

Hurricane Risk 3

Jennifer Collins
James Done
Yi-Jie Zhu
Paul Wilson *Editors*

Advances in Hurricane Risk in a Changing Climate

 Springer

Hurricane Risk

Volume 3

Series Editor

Jennifer M. Collins, School of Geosciences, NES 107, University of South Florida,
Tampa, FL, USA

Hurricanes are one of nature's most destructive agents and widespread interest surrounds the possibility that future hurricanes will increase in both frequency and intensity, causing devastation to vulnerable communities effecting their way of life and livelihoods. The Risk Prediction Initiative has organized a unique series of conferences bringing a new focus to the subject of impacts and risks from hurricanes, and how they may be changing under evolving climate regimes. The goals are to advance the understanding of risk, rather than solely the meteorology of storms and the observation and modelling of the climate.

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Paul Wilson
Editors

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Editors

Jennifer Collins
School of Geosciences, NES 107
University of South Florida
Tampa, FL, USA

James Done
MMM
NCAR
Boulder, CO, USA

Yi-Jie Zhu
Department of Geosciences
Florida Atlantic University
Boca Raton, FL, USA

Paul Wilson
Securis Investment Partners LLP
London, UK

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Foreword

Until relatively recently, estimates of tropical cyclone hazard risk used by governments and industry, particularly insurance and re-insurance firms, were based exclusively on historical tropical cyclone records, usually bootstrapped by various means. This has proved unsatisfactory for two essential reasons: First, historical records, even in the Atlantic region where they are longest, are not long enough to robustly estimate hazard risk. Second, climate change has already changed the underlying statistics enough to seriously compromise historically based risk estimates, especially for the most destructive events.

Into this breach has stepped a small but growing army of hurricane scientists who, in an earlier era, had focused all their efforts on the science of tropical cyclones but who now seek to bring their knowledge and training to bear on estimating current and future hazard risk. The reader will find herein enticing and informative chapters on topics ranging from changing ocean heat transport in the hurricane-prone North Atlantic to advanced efforts to better communicate hurricane risk in a changing environment.

The adverse effects of climate change on human and natural ecosystems result mostly from extreme weather events. The growing contribution of the scientific community to hazard risk assessment and communication will better communicate both the immediate threats and the long-term risks of tropical cyclones, providing people with the knowledge they need to better cope with immediate threats and to adapt to and mitigate future risk.

Professor Emeritus of Atmospheric
Science, New Harbor, ME, USA

Kerry Emanuel

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Jennifer Collins
James Done
Yi-Jie Zhu
Paul Wilson

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Contributors

Poulomi Chakravarty Global Climate Association, Patna, India

Hung-Ming Cheung School of Energy and Environment, City University of Hong Kong, Hong Kong, China

Jung-Eun Chu School of Energy and Environment, City University of Hong Kong, Hong Kong, China

Pao-Shin Chu Department of Atmospheric Sciences, School of Ocean and Earth Science and Technology, University of Hawaii at Manoa, Honolulu, HI, USA

Jennifer Collins School of Geosciences, NES 107, University of South Florida, Tampa, FL, USA

Yolanda Cordero-Nieves School of Public Administration, University of Puerto Rico at Río Piedras, San Juan, Puerto Rico

Dipanjjan Dey School of Ocean and Earth Science, University of Southampton, Southampton, UK
School of Earth, Ocean and Climate Sciences, Indian Institute of Technology, Bhubaneswar, India

Sandra M. Fábregas Latino Center for Bioethics and Humanities, San Juan, PR, USA

Sai Gattupalli University of Massachusetts Amherst, Amherst, MA, USA

Jeremy Grist National Oceanography Centre, Southampton, UK

Elizabeth Harris School of Ocean and Earth Science, University of Southampton, Southampton, UK
Ariel Re, Bermuda, Hamilton, Bermuda

Saige Hill Old Dominion University, Norfolk, VA, USA

Meagan M. Jordan Old Dominion University, Norfolk, VA, USA

Gary L. Kreps George Mason University, Fairfax, VA, USA

Indira Luciano-Montalvo Department of Economics, University of Puerto Rico at Río Piedras, San Juan, Puerto Rico

Soumya Ranjan Mahapatra National Atmospheric Research Laboratory, Department of Space, Indian Space Research Organization, AP, India

Robert Marsh School of Ocean and Earth Science, University of Southampton, Southampton, UK

Sylvia Martínez-Mejías Department of Psychology, University of Puerto Rico at Río Piedras, San Juan, Puerto Rico

Mirelsa Modestti-González Latino Center for Bioethics and Humanities, San Juan, PR, USA

Laura Myers University of Alabama, Tuscaloosa, AL, USA

Xiao Pan Collaborative Innovation Center on Forecast and Evaluation of Meteorological Disasters (CIC-FEMD)/Key Laboratory of Meteorological Disaster, Ministry of Education (KLME)/Joint International Research Laboratory of Climate and Environmental Change (ILCEC), Nanjing University of Information Science and Technology, Nanjing, China

Jagabandhu Panda Department of Earth and Atmospheric Sciences, National Institute of Technology, Rourkela, Odisha, India

Debashis Paul Department of Earth and Atmospheric Sciences, National Institute of Technology, Rourkela, Odisha, India

Leilani D. Paxton School of Geosciences, NES 107, University of South Florida, Tampa, FL, USA

Kesley J. Richardson School for Continuing and Professional Studies, Loyola University of Chicago, Chicago, IL, USA

Hilda Rivera-Rodríguez Graduate School of Social Work, University of Puerto Rico at Río Piedras, San Juan, Puerto Rico

Eileen Segarra-Alméstica Department of Economics, University of Puerto Rico at Río Piedras, San Juan, Puerto Rico

Kasturi Singh Department of Mathematics and Statistics, University of Exeter, Exeter, UK

Federico Subervi-Vélez University of Wisconsin–Madison, Madison, WI, USA

Geo Tom Department of Earth and Atmospheric Sciences, National Institute of Technology, Rourkela, Odisha, India

Akiyoshi Wada Department of Typhoon and Severe Weather Research, Meteorological Research Institute, Tsukuba, Ibaraki, Japan

Wataru Yanase Department of Typhoon and Severe Weather Research, Meteorological Research Institute, Tsukuba, Ibaraki, Japan

Juita-Elena (Wie) Yusuf Old Dominion University, Norfolk, VA, USA

Chapter 1

Modeling Return Periods of Tropical Cyclone Winds in the Vicinity of Hawaii—A Revisit



Xiao Pan and Pao-Shin Chu

Abstract The return periods of the maximum wind speed (MWS) for tropical cyclones (TC) in the vicinity of Hawaii from 1966 to 2022 were examined. After testing a suite of potential predictors, a significant correlation between the ocean heat content (OHC) and TC frequency was observed. Using the OHC, MWS and striking date, together with a Poisson regression, generalized extreme value distribution, and kernel density estimation to fit TC frequency and MWS, we developed a modern statistical model to determine the return periods of MWS. Results showed that the uncertainty of the return periods became larger as the MWS increased. Compared to the previous results based on datasets from 1970 to 1995, the return periods of MWS based on the updated data and modern statistical techniques shortened considerably, suggesting an increased risk of damaging wind associated with TCs in the vicinity of Hawaii in recent decades.

Keywords Return periods · Tropical cyclones · Maximum wind speed · Frequency

1.1 Introduction

Tropical cyclones (TC) are one of the most devastating and intense disasters in the tropics, which may cause catastrophic damage and loss of life through powerful wind speed, torrential rainfall and flooding, high oceanic waves and storm surges, and wildfires (Cervený and Newman 2000; Phadke et al. 2003; Storch and Woth

X. Pan

Collaborative Innovation Center on Forecast and Evaluation of Meteorological Disasters (CIC-FEMD)/Key Laboratory of Meteorological Disaster, Ministry of Education (KLME)/Joint International Research Laboratory of Climate and Environmental Change (ILCEC), Nanjing University of Information Science and Technology, Nanjing, China
e-mail: panx@nuist.edu.cn

P.-S. Chu (✉)

Department of Atmospheric Sciences, School of Ocean and Earth Science and Technology, University of Hawaii at Manoa, Honolulu, HI, USA
e-mail: chu@hawaii.edu

2008; Bloemendaal et al. 2018). In August 2023, a destructive firestorm occurred in Lahaina on west Maui due to the extremely strong downslope winds caused by a high-pressure gradient from Hurricane Dora passing to the south of Hawaii and the unusually strong subtropical high-pressure system to the north of Hawaii. Before this event, Maui was already abnormally dry. The dried-out vegetation on west Maui provided fuel for ignition. It is suspected that downed power lines caused by destructive downslope winds initially sparked ignition in an environment where the humidity was very low and the ground was covered by dry grasses and pasture. Hawaii is a group of volcanic islands located in the central Pacific, and its unique geographic location makes the local economy and people's lives highly susceptible to TCs. Therefore, it is crucial to estimate the return periods of TC and identify the high-intensity events to develop appropriate mitigation measures.

The return period of the maximum wind speed (MWS) associated with TCs refers to the average period in which an event is expected to recur once (Chu and Wang 1998). Previous studies were mainly based on the standard statistical distributions fitted to estimate the return periods of TC (Russell 1971; Batts et al. 1980; Georgiou et al. 1983; Neumann 1987; Jagger et al. 2001); however, the results depended on the tail shape of the hypothetical distribution (Emanuel and Jagger 2010). Darling (1991) and Chu and Wang (1998) avoided this limitation by using the empirical distribution of the relative intensity (RI) to deduce the return periods of the MWS of local TCs. Moreover, a generalized extreme value (GEV) distribution was proposed to describe the distribution of MWS, which solved the difficulty of the tail of the distribution and could be extrapolated to longer return periods (Jagger and Elsner 2006). During the process, the method of generating a large sample size of synthetic data and calculating the return periods was commonly used (Vickery et al. 2000; Emanuel et al. 2006), especially the Monte Carlo method, which was used to simulate TC wind or intensity sequence (Batts et al. 1980; Neumann 1987; Chu and Wang 1998).

Previous studies have also pointed out that TC frequency and intensity are related to various climate and environmental variables. For example, the annual TC frequency or intensity may be related to the Pacific Decadal Oscillation (PDO) (Scoccimarro et al. 2021), Atlantic Multi-decadal Oscillation (AMO) (Goldenberg et al. 2001), North Atlantic Oscillation (NAO) (Elsner and Jagger 2004), Pacific Meridional Mode (PMM) (Murakami et al. 2017), Antarctic Oscillation (AAO) (Ho et al. 2005; Song et al. 2022), Quasi-Biennial Oscillation (QBO) (Gray et al. 1992; Ho et al. 2009), South Oscillation Index (SOI) (Chu and Wang 1998; Clark and Chu 2002), and ENSO related oceanic indices (Clark and Chu 2002; Zhao and Wang 2019; Lin et al. 2020). Besides, large-scale environmental conditions may also favor TC genesis and development, such as low-level relative humidity, low-level relative vorticity, vertical wind shear, sea surface temperature (SST) and OHC (Gray 1968; Clark and Chu 2002; Chu 2002; Emanuel and Nolan 2004; Murakami and Wang 2010; Kaplan et al. 2015; Wang and Murakami 2020; Shan et al. 2023).

In this study, we will analyze the characteristics of TCs in the vicinity of Hawaii, applying GEV distribution to fit the distribution of MWS of TCs, developing a new modern statistical model to estimate the return periods of the MWS of TCs,

elucidating the new situation of TC related risks in Hawaii, and providing valuable insights for decision-makers, and the entire scientific community. The materials and methods are introduced in Sect. 1.2. Section 1.3 is the detailed process of the modern statistical model to estimate the return periods. Section 1.4 analyzes the results and makes a comparison with the previous study. Finally, the conclusions are given in Sect. 1.5.

1.2 Materials and Method

1.2.1 Data

The tropical cyclone datasets during 1966–2022 that are used in this chapter are taken from the International Best Track Archive for Climate Stewardship version 4 (IBTrACS v4) (Knapp et al. 2010, 2018), which contains the start date, end date, latitude, longitude and MWS of tropical cyclones. During 1966–2022, there were a total of 42 TCs passing through the vicinity of Hawaii, which is defined as a scan radius of 250 n mi from Honolulu (27.32°N, 157.86°W), as shown in Fig. 1.1. The annual TC frequency shows that there are 30 years with no TCs, 18 years with one TC, 5 years with two TCs, 2 years with three TCs and 2 years with four TCs (Fig. 1.1b). Detailed information can be seen in Table 1.1. The peak season of TC is from July to November.

As discussed in Sect. 1.1, eleven climate indices (PDO, AMO, NAO, PMM, AAO, QBO, SOI, Ni ñ o3 index, Ni ñ o4 index, Ni ñ o3.4 index and Ni ñ o1 + 2 index) may exert an impact on TC activity, which are derived from the National Oceanic and Atmospheric Administration (NOAA) website (<https://psl.noaa.gov/data/climateindices/list/>). All indices cover 1966–2022 except the AAO index which covers 1979–2022.

The monthly atmospheric specific humidity, zonal and meridional wind, and sea surface temperature are taken from the European Center for Medium-Range Weather

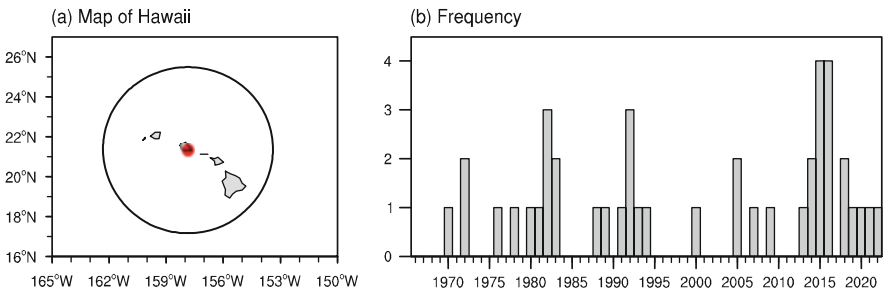


Fig. 1.1 (a) Map showing the vicinity of Hawaii and (b) the time series of the seasonal (JASON) frequency of tropical cyclones near Hawaii during 1966–2022. The red dot in (a) denotes Honolulu (27.32°N, 157.86°W). The radius of the circle is 250 n mi (~463 km)

Table 1.1 Statistics of the tropical cyclones in the vicinity of Hawaii in JASON during 1966–2022

Year	Name	Type	Start date	End date	Lat (°N)	Lon (°W)	Maximum wind speed (kt)
1970	Maggie	Tropical Storm	20-Aug	27-Aug	14.8	138.3	45
1972	Diana	Hurricane	11-Aug	20-Aug	16.7	129.5	60
	Fernanda	Hurricane	20-Aug	1-Sep	17.7	123.3	45
1976	Gwen	Tropical Storm	5-Aug	18-Aug	10.2	119.3	25
1978	Fico	Hurricane	9-Jul	30-Jul	15	115	100
1980	Kay	Hurricane	16-Sep	30-Sep	17	113.9	30
1981	Jova	Hurricane	14-Sep	21-Sep	17.4	134	35
1982	Daniel	Hurricane	7-Jul	22-Jul	14.7	114.9	25
	Gilma	Hurricane	26-Jul	2-Aug	15.7	135.8	30
	Iwa	Hurricane	19-Nov	25-Nov	21.5	161.4	80
1983	Gil	Hurricane	23-Jul	5-Aug	11.8	113.8	40
	Raymond	Hurricane	8-Oct	20-Oct	12.4	121.2	30
1988	Gilma	Tropical Storm	28-Jul	3-Aug	15.9	136.2	20
1989	Dalilia	Hurricane	9-Jul	21-Jul	14	137.9	55
1991	Fefa	Hurricane	29-Jul	8-Aug	16.6	122.7	25
1992	Georgrtte	Hurricane	14-Jul	27-Jul	16	109.2	30
	Orlene	Hurricane	2-Sep	14-Sep	14.4	123.1	25
	Iniki	Hurricane	5-Sep	13-Sep	19.5	160	125
1993	Eugene	Hurricane	15-Jul	25-Jul	15.4	123.6	30
1994	Emilia	Hurricane	16-Jul	25-Jul	11.7	149.6	85
2000	Daniel	Hurricane	23-Jul	5-Aug	14.5	122.4	60
2005	Jova	Hurricane	12-Sep	25-Sep	16	143.3	20
	Kenneth	Hurricane	14-Sep	30-Sep	14.2	129.2	25
2007	Flossie	Hurricane	8-Aug	16-Aug	13.2	141.7	50
2009	Felicia	Hurricane	3-Aug	11-Aug	14.7	130.1	30
2013	Flossie	Tropical Storm	25-Jul	30-Jul	17.7	138.4	35
2014	Ana	Hurricane	13-Oct	26-Oct	17.5	157	75
	Iselle	Hurricane	31-Jul	9-Aug	16.1	136.9	50
2015	Ela	Tropical Storm	8-Jul	10-Jul	17.2	143.4	20
	Guillermo	Hurricane	29-Jul	7-Aug	12.5	133.9	35
	Ignacio	Hurricane	25-Aug	4-Sep	17.1	147.7	60
	Jimena	Hurricane	26-Aug	9-Sep	12.2	124.4	30
2016	Celia	Hurricane	6-Jul	15-Jul	15.1	125.8	40
	Darby	Hurricane	11-Jul	25-Jul	17.9	124.4	35
	Howard	Tropical Storm	31-Jul	3-Aug	18	127	25
	Lester	Hurricane	24-Aug	7-Sep	17.7	137	70

(continued)

Table 1.1 (continued)

Year	Name	Type	Start date	End date	Lat (°N)	Lon (°W)	Maximum wind speed (kt)
2018	Lane	Hurricane	15-Aug	28-Aug	14.5	154.3	105
	Olivia	Hurricane	1-Sep	14-Sep	18.9	129.2	45
2019	Flossie	Hurricane	28-Jul	5-Aug	13.3	123.8	30
2020	Douglas	Hurricane	20-Jul	29-Jul	14.6	138	80
2021	Linda	Hurricane	10-Aug	19-Aug	18.6	115.5	40
2022	Darby	Hurricane	9-Jul	17-Jul	14.6	124.3	35

Forecasts (ECMWF) Re-Analysis 5 (ERA5; Hersbach et al. 2019) with a horizontal resolution of $0.25^{\circ} \times 0.25^{\circ}$. The ocean heat content (OHC) is the measure of the integrated vertical temperature from the sea surface to the depth of the 26°C isotherm and computed from the altimeter-derived isotherm depths in the upper ocean relative to 20°C , which is calculated based on the monthly mixed-layer ocean temperature analyses from Simple Ocean Data Assimilation, version 2.2.4 (SODAv2.2.4) (Carton et al. 2000), at a $0.5^{\circ} \times 0.5^{\circ}$ horizontal resolution and 40 vertical levels during 1966–1979, and the NCEP Global Ocean Data Assimilation System (GODAS) (Saha et al. 2006) at a 1° zonal resolution, $1/3^{\circ}$ meridional resolution, and 40 vertical levels with a 10-m resolution in the upper 105 m during 1980–2022. All the datasets are interpolated into $1^{\circ} \times 1^{\circ}$ resolution via bilinear interpolation, and the research period is from July to November (JASON) during 1966–2022.

1.2.2 Statistical Methods

1.2.2.1 Poisson Process

The Poisson distribution is a common statistical method to describe the numbers of discrete events that occur in a series or a sequence and is only applicable to count data that can take nonnegative integer values (Wilks 2019). The annual TC frequency fits well with the Poisson distribution (Ross 1996; Parisi and Lund 2000, 2008) because (1) the TC occurred independently from year to year and (2) two distinct TCs are rarely striking simultaneously in a limited region.

The annual Poisson mean parameter, denoted by λ , which is called the arriving rate, not only depends on a suite of climate indices but also could be affected by the environmental factors as introduced in Sect. 1.1, therefore the λ can be reconstructed through a Poisson regression method with one or more independent indices.

1.2.2.2 Kernel Density Estimation

Kernel density estimation is a non-parametric way to estimate the probability density function of a random variable (Bowman and Azzalini 1997). The striking date of a

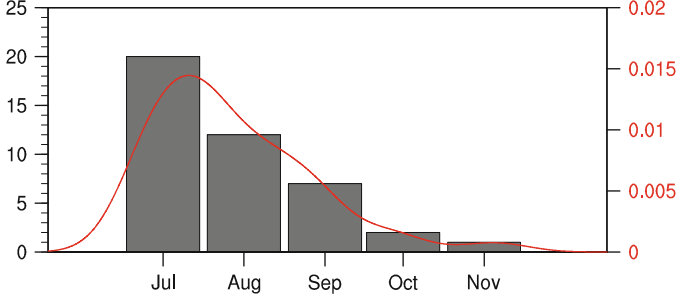


Fig. 1.2 The histogram (bar) of the striking date of 42 TCs during 1966–2022 and the fitted PDF using kernel density estimation (line)

TC in a year is defined as the date of the TCs when the maximum wind speed occurs in the vicinity of Hawaii and can be fitted by the kernel density estimation (Parisi and Lund 2008). The probability density function (PDF) of the kernel density estimation is as follows:

$$f(d) = \frac{1}{nh} \sum_{j=1}^n K\left(\frac{d-d_j}{h}\right), 0 \leq d < 365 \quad (1.1)$$

where n , h , and d_j denote the sample size, the smoothing parameter, and the striking date of the j th TC, respectively. $h = \frac{\min\{0.9s, \frac{2}{5} * IQR\}}{n^{1/5}}$ (Silverman 1986), where s is the standard deviation of the sample data and IQR is the interquartile range (75% percentile minus 25% percentile). K is a Gaussian kernel function as $K(t) = (2\pi)^{-1/2} e^{-\frac{t^2}{2}}$, where $t = \frac{d-d_j}{h}$.

In this study, $n = 42$ and $h = 12.63$. The fitted PDF and the histogram of the TC striking date are shown in Fig. 1.2. We can see that most TCs occur in July and August, and fewer in October and November. The kernel density estimation fits well with the distribution of the TC striking date.

1.2.2.3 Generalized Extreme Value (GEV) Distribution

The GEV distribution is often used to model the smallest or largest value among a large set of independent, identically distributed random values representing measurements or observations. Here we used it to fit the distribution of MWS referring to Jagger and Elsner (2006) and Chu et al. (2018). The PDF of the GEV distribution is as follows:

$$f(x) = \frac{1}{\beta} \left[1 + \frac{k(x-\xi)}{\beta} \right]^{-1-\frac{1}{k}} e^{-\left[1 + \frac{k(x-\xi)}{\beta} \right]^{-\frac{1}{k}}} \quad (1.2)$$

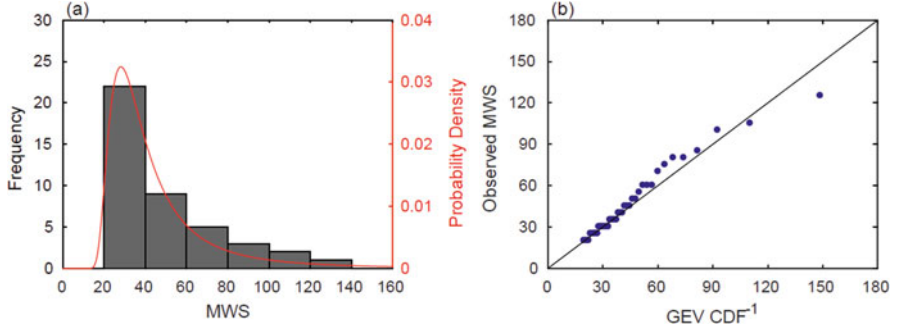


Fig. 1.3 (a) The histogram (bar) of the MWS of 42 TCs during 1966–2022 and the fitted PDF using the GEV (line), (b) Q-Q plot of the MWS, with the x-axis being the theoretical MWS and the y-axis being the observed MWS

where β , ξ , k denote the scale parameter, location parameter and shape parameter, respectively. The cumulative density function (CDF) of the GEV is as follows:

$$F(x) = e^{-\left[1 + \frac{k(x-\xi)}{\beta}\right]^{-\frac{1}{k}}} \quad (1.3)$$

The quantile function, which is the inverse of the CDF, is derived as follows:

$$x' = \xi + \frac{\beta}{k} \left\{ \left[-\ln F(x) \right]^{-k} - 1 \right\} \quad (1.4)$$

In our study, the 42 TCs' MWS fits GEV distribution with $\beta = 12.31$, $\xi = 32.28$ and $k = 0.44$. The histogram of the distribution of MWS and the fitted GEV PDF are shown in Fig. 1.3a, presenting a good fit. Furthermore, the quantile-quantile (Q-Q) plot also shows that most points align closely to the 45° line, indicating the GEV distribution fits well with the observed MWS data (Fig. 1.3b).

1.3 Modern Statistical Model to Estimate the Return Periods

1.3.1 Procedures for Selecting Variables as Predictors

As seen from Fig. 1.1, a total of 42 TCs passed through the vicinity of Hawaii during 1966–2022, with TC frequency reaching its peak (i.e., 4 incidences in each year) in 2015 and 2016, followed by 1982 and 1992 (3 incidences in each year). It is clear that the clusters around the 2015 and 1982 El Nino years (i.e., 2013 ~ 2016 and 1980 ~ 1983 years) contribute greatly to the TC frequency near Hawaii during 1966–2022, which indicates the ENSO influence is of vital importance (Chu and

Table 1.2 Correlation between TC frequency and climate indices. Bold values denote that they exceed the 95% significance level using t-test

	PDO	AMO	NAO	PMM	SOI	AAO	QBO	Ni ñ o3	Ni ñ o4	Ni ñ o3.4	Ni ñ o1 + 2
Cor	0.33	0.10	0.11	0.19	-0.32	-0.02	0.00	0.30	0.26	0.25	0.33

Wang 1997). In addition, there have been no TCs passing through the vicinity of Hawaii in 30 out of 57 years. In this section, we aimed to determine optimal predictors to establish the relationship between the TC frequency and external factors.

The correlation coefficients between the TC frequency and 11 climate indices from 1966 to 2022 indicated that the PDO, SOI, Ni ñ o3, Ni ñ o4 and Ni ñ o1 + 2 indices are significantly correlated with TC frequency (Table 1.2). The threshold correlation coefficient is 0.26 with 95% significance level using t-test. However, these five indices are highly correlated with each other; therefore, the TC frequency is reconstructed through Poisson regression by the five indices individually. For example, for the PDO index, we reconstructed the TC frequency or arriving rate by $\lambda_t = e^{\beta_{00} + \beta_{01} PDO_t}$, where λ_t is the TC frequency in year t , PDO_t is the PDO index in year t , β_{00} and β_{01} are the regression coefficients.

To train the Poisson regression model, a leave 1-year out cross validation (LOOCV) method is applied. First, leave 1-year data out and perform the Poisson regression between climate index and TC frequency using the remaining 56-year data. Second, calculate the TC frequency in the excluded year using the excluded 1-year climate index based on the regression coefficients derived from the first step. Third, repeat the above two steps 57 times to obtain 57 years of reconstructed TC frequency.

After reconstructing the TC frequency with five highly-correlated climate indices (PDO, SOI, Ni ñ o3, Ni ñ o4 and Ni ñ o1 + 2 index) respectively and comparing the results with the observed TC frequency, we can see that all five indices could not well reproduce the observed TC frequency, especially in 1992, 2015 and 2016 (Fig. 1.4). The Ni ñ o3 and Ni ñ o1 + 2 indices even simulated a fake TC frequency peak in 1997. As a result, all the climate indices could not accurately represent the inter-annual variation of TC frequency and its peak.

Given that TC formation requires favourable large-scale environmental conditions (Gray 1968; Emanuel and Nolan 2004; Murakami and Wang 2010; Chu and Murakami 2022), the correlation coefficients between the TC frequency and the environmental factors, such as relative vorticity at 850 hPa (RV), relative humidity integrating from 1000 hPa to 700 hPa (RH), vertical wind shear between 200 hPa and 850 hPa (VWS), SST and the OHC are examined. The VWS is defined as $VWS = \sqrt{(u_{200} - u_{850})^2 + (v_{200} - v_{850})^2}$, where u_{200} is the zonal wind at 200 hPa, and so on. The OHC formula is $OHC = c_p \int_{D26}^0 \rho(z) [T(z) - 26] dz$ (Shan et al. 2023), where $c_p = 4000 J kg^{-1} K^{-1}$ is the specific heat at constant pressure, $\rho = 1015 kg m^{-3}$ is the density of the ocean, $D26$ denotes the vertical coordinate of 26 °C isotherm, and $T(z)$ is the ocean temperature.

The spatial correlation coefficients between SST and TC frequency near Hawaii show that the SST in the central and eastern Pacific is positively correlated with TC

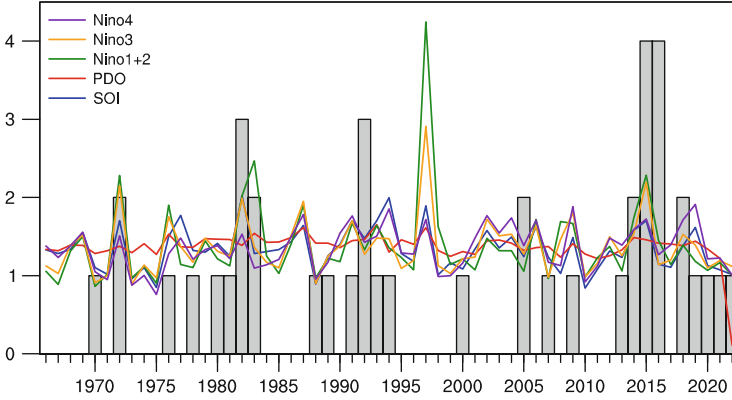


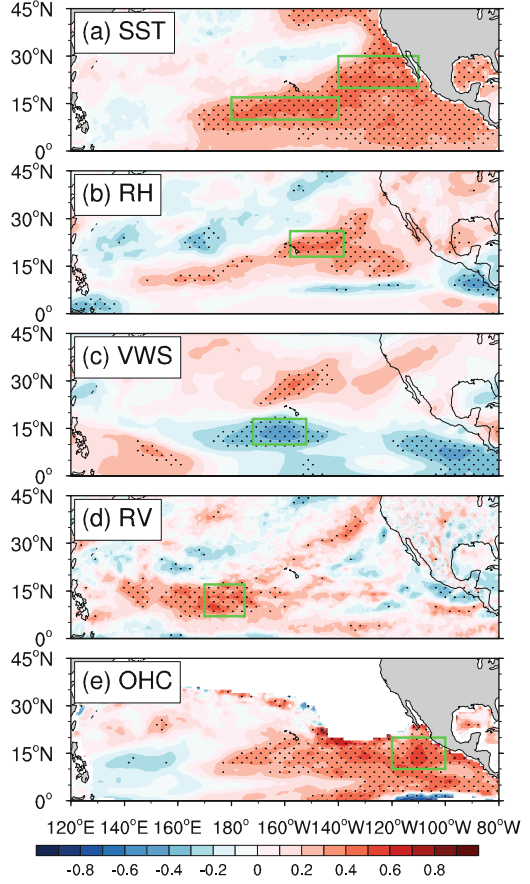
Fig. 1.4 The observed seasonal (JASON) TC frequency (bar) and the reconstructed seasonal TC frequency by SOI, PDO, Niño1 + 2, Niño3 and Niño4 indices, respectively (coloured lines)

frequency (Fig. 1.5a), which means the warm SST is favourable for TC genesis and development. Besides, TC frequency is significantly correlated with the increasing RH in the vicinity and to the east of Hawaii and the decreasing RH to the west of Hawaii (Fig. 1.5b). The increase in the depth of the moisture layer is probably attributed to the increased moisture fluxes from the warmer ocean surface in the central/eastern North Pacific. More moisture in situ contributes to TC formation. As mentioned in Zhao et al. (2018), the VWS should not be excessively large or small for TC generation. The results implied that to the south (north) of Hawaii, the VWS is negatively (positively) correlated with TC frequency (Fig. 1.5c). The smaller VWS in the south of Hawaii contributes to more TCs. In addition, RV is another important factor for TC genesis and development. The positive correlation between RV and TC frequency in the central Pacific implies that the stronger the relative vorticity at 850 hPa, the more TCs will appear in the vicinity of Hawaii (Fig. 1.5d). Lastly, OHC is also beneficial for TC activity. The positive correlation in the tropical eastern Pacific implies that stronger OHC in the tropical eastern Pacific may lead to more TCs near Hawaii (Boucharel et al. 2016).

Therefore, we select the key regions that contain the most significant correlation information between environmental factors and TC frequency. The environmental indices are SST averaged over (10° – 17° N, 180° – 140° W, SST1) and (20° – 30° N, 140° – 110° W, SST2) respectively, integrated RH averaged over (18° – 26° N, 158° – 138° W), VWS averaged over (10° – 18° N, 172° – 152° W), RV850 averaged over (7° – 17° N, 170° E– 175° W) and OHC averaged over (10° – 20° N, 120° – 100° W).

By calculating the correlation coefficient between any two environmental indices, it was found that they are not independent of each other. Therefore, the similar Poisson regression method and LOOCV are used to obtain the reconstructed TC frequency from these critical environmental factors respectively. Here we used two metrics, i.e., the temporal correlation coefficient (TCC) and the root-mean-square error (RMSE) to measure the skill of the reconstructed TC frequency by different

Fig. 1.5 The correlation coefficients between the observed seasonal (JASON) TC frequency near Hawaii and seasonal (a) SST, (b) integrated relative humidity from 1000 hPa to 850 hPa (RH), (c) vertical wind shear (VWS), (d) relative vorticity at 850 hPa (RV) and (e) ocean heat content (OHC) across the Pacific basin. The black dots denote the correlation exceeding the 95% significance level, and the green boxes represent the key regions



environmental variables. The larger the TCC, the smaller the RMSE, and the closer the reconstructed TC frequency is to the observation. The results suggest that the OHC is the best predictor to reproduce the inter-annual variation of the TC frequency and the peak year in 2015 (Fig. 1.6).

One may wonder whether the selection of key regions for environmental variables will influence the results. To address this concern, another approach is taken to consider the averaged input variables that exceed the 95% significance level. For VWS and RH, using all the significant positive regions minus all the significant negative regions as the indices, the results showed that the OHC is still the best predictor to reproduce TC frequency (figure not shown).

Therefore, in the following, we identified the OHC index as the optimal predictor to simulate TC frequency. The Poisson regression equation between the TC frequency (λ_t) and OHC is as follows:

$$\lambda_t = e^{\beta_0 + \beta_1 OHC_t} \quad (1.5)$$

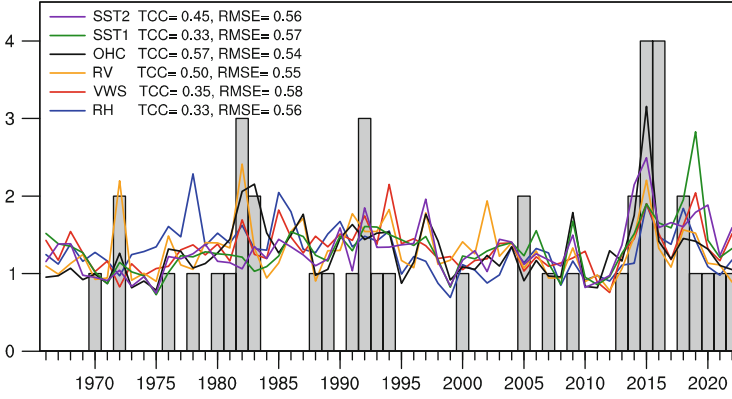


Fig. 1.6 The observed seasonal TC frequency (bar) and the reconstructed seasonal TC frequency by RH, VWS, RV, SST and OHC averaged over their key regions shown in Fig. 1.5 (coloured lines). The TCC and RMSE between the observed and reconstructed TC frequency are shown in the upper left corner

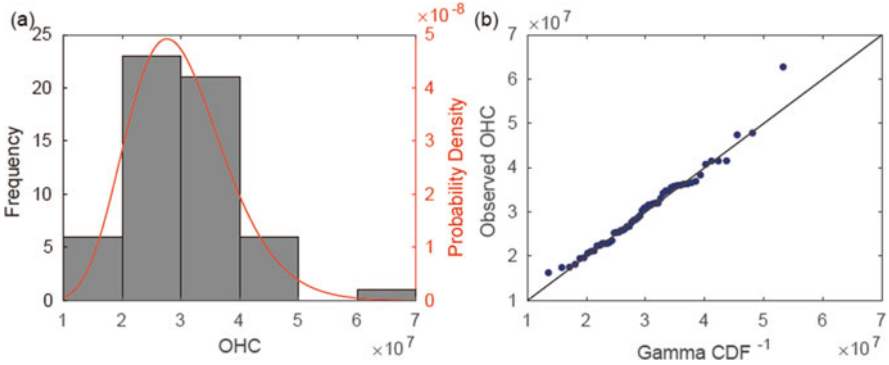


Fig. 1.7 (a) The histogram (bar) of the OHC and the fitted PDF using gamma distribution (line), (b) Q-Q plot of the OHC, with the x-axis being the theoretical OHC and the y-axis being the observed OHC

where $\beta_0 = -0.76$, $\beta_1 = 3.21 \times 10^{-8}$. The correlation coefficient between the reconstructed TC frequency by OHC and the observation is 0.6, exceeding the 95% significance level using t-test. The RMSE is 0.54 and p -value is 0.0007.

It was found that the distribution of OHC is positively skewed, while the gamma distribution is a continuous probability distribution function that can model right-skewed data. Here we use gamma distribution to fit the distribution of OHC. As shown in Fig. 1.7, the PDF of gamma distribution fits well with the histogram of OHC and the Q-Q plot also shows that most points align along the 45° line. The parameters of gamma distribution are $a = 12.79$ and $b = 2.34 \times 10^6$, representing the shape parameter and scale parameter respectively.

1.3.2 Statistical Model to Estimate the Return Periods

After reconstructing the TC frequency, a modern statistical model to calculate the return periods of the MWS was conducted, which is comprised of the gamma distribution, Poisson regression, kernel density estimation and GEV distribution (Fig. 1.8). The flow chart encapsulates the step-by-step processes.

The first step of the statistical model is to simulate the OHC in year t (OHC_t) with gamma distribution ($a = 12.79$ and $b = 2.34 \times 10^6$). The second step is calculating the TC frequency (λ_t) in year t using Poisson regression eq. (1.5). The third step is simulating the MWS ($w_i, i = 1, 2, \dots, \lambda_t$) and the striking date ($d_i, i = 1, 2, \dots, \lambda_t$) of each TC with GEV distribution and kernel density estimation in year t . The parameters in GEV and kernel density estimation are based on the observed 42 TCs

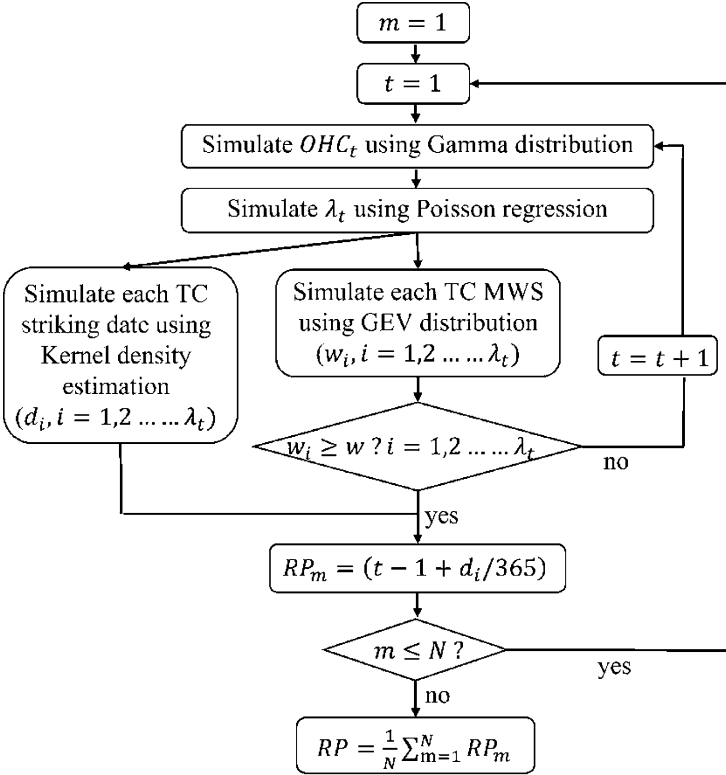


Fig. 1.8 Flow chart of the statistical model to calculate the return periods of the maximum wind speed. m is the iteration number. t denotes the year. OHC_t and λ_t are the OHC and the frequency of TC in year t . The model can simulate the MWS and the striking date in year t , i.e., w_i ($i = 1, 2, \dots, \lambda_t$) and d_i ($i = 1, 2, \dots, \lambda_t$). If the MWS (w_i) in year t is no less than w (the reference MWS), then the return period (RP_m) is printed out. In this model, the repeat time (N) of the whole process is set to 1000, and the return period (RP) is the ensemble mean of the N times' results ($RP_m, m = 1, 2, \dots, N$)

referring to eqs. (1.1) and (1.2). The final step is to make a judgement. If the MWS (w_i) for any event in year t meets or exceeds the preset MWS threshold (w , e.g., 34, 50, 64, 80, 100, 110, 125 knots), then the return periods (RP_m) of the MWS threshold (w) can be obtained by $(t - 1 + \frac{d_t}{365})$ yr., where m is the iteration number. In the final step, if the MWS (w_i) is less than the MWS threshold (w), then let $t = t + 1$, and repeat the processes.

To enhance the robustness of the return period estimates, the model iteratively simulates the above processes by N times, here N is set to 1000. The return period (RP) for a preset MWS threshold (w) is determined by the ensemble mean of the outcomes of all N simulations ($RP_m, m = 1, 2, \dots, N$), providing a statistically reliable estimate of the MWS return period.

An uncertainty analysis is needed and conducted to estimate the confidence interval of the return periods. A Monte Carlo random sampling method is applied by constructing the artificial data batches with replacements from the original data of size 42. In each replacement, the parameters of GEV distribution and kernel density estimation are newly generated. Repeating a large number of times, here we select 1000 times, and the range of the central 95% samples' results is considered the 95% confidence interval of the return periods.

1.4 Results

Table 1.3 lists the return periods of the MWS equal to or greater than 34, 50, 64, 80, 100, 110 and 125 knots, respectively. 34 knots is the minimum tropical storm intensity; 64 knots is the minimum hurricane intensity; 100 and 125 knots are the MWS of Hurricane Fico in 1978 and Hurricane Iniki in 1992 (Table 1.1). Compared to the previous results presented by Chu and Wang (1998), the simulated return periods for weak MWS are quite similar (2.1 years for 34 knots, 3.8 years for 50 knots, and 5.7 years for 64 knots). In contrast, the return periods of the current study are much shorter for MWS exceeding 80 knots. More specifically, the return periods decreased from 42 years to 14.9 years for 100 knots, from 81 years to 17.6 years for 110 knots, and from 202 years to 24.5 years for 125 knots, which is a

Table 1.3 Return periods and confidence interval simulated by the modern statistical model, compared with the results in Chu and Wang (1998)

MWS (knots)	Return periods (year)	Confidence interval (year)	Chu and Wang 1998 (year)
34	2.1	1.9–2.7	3.2
50	3.8	2.8–5.4	4
64	5.7	4.1–10.3	6.6
80	8.8	6.0–20.4	13
100	14.9	8.8–42.4	42
110	17.6	10.2–52.6	81
125	24.5	12.3–68.7	202

striking decrease compared to Chu and Wang (1998). It is understandable that the updated return period has significantly shortened because much more TCs have occurred since 1998, especially with the clustering of events around 2015. Different statistical models used in the current study and our previous paper may also contribute to the difference in return period estimation. In addition, the ocean heat content is used to simulate TC frequency in the current study while no such consideration was given in the previous analysis.

Besides, the confidence interval for each return period is estimated, which ranges from 6.0 to 20.4 years for the return period of 80 knots, 8.8 to 42.4 years for the return period of 100 knots, 10.2 to 52.6 years for the return period of 110 knots, 12.3 to 68.7 years for the return period of 125 knots. These results suggest that the estimated return periods are closer to the lower boundary of the 95% confidence interval and also indicate that the larger the MWS, the greater the uncertainty of the confidence interval.

Compared to the previous study (Chu and Wang 1998), the estimated return periods in this study were significantly shortened, indicating that more TCs with considerable intensity have occurred in the vicinity of Hawaii in recent years and are likely to have a destructive impact on the local economy and lives.

1.5 Conclusions and Discussion

In this article, the statistics of 42 TCs passing through the vicinity of Hawaii during 1966–2022 were analyzed. More TCs occurred in July and August, and fewer in October and November. By calculating the correlation coefficients between the TC frequency and climate indices or environmental factors, the highly-correlated indices and key regions of environmental factors are identified as potential predictors to reconstruct TC frequency, respectively through the Poisson regression method. The results indicated that the optimal predictor to reconstruct TC frequency is OHC and the Poisson regression equation is shown as Eq. (1.5).

The distribution of observed OHC is positively skewed and can be fitted by the gamma distribution. Besides, the kernel density estimation and GEV distribution could be used to fit the striking date and MWS of TCs. The histogram of the distribution and the PDF of the fitting function showed a good fitting relationship. The Q-Q plot was also applied to determine the fitting effect based on whether the empirical values and observed values are aligned along the 45° line.

Using the OHC, MWS and the striking date, together with a Poisson regression, GEV distribution and kernel density estimation to fit TC frequency and MWS, the return periods of MWS were estimated by conducting a modern statistical model. The ensemble-mean of a large number of repeating times' (i.e., 1000 times) results is considered as the final return period of a preset MWS threshold (w knots). In addition, the Monte Carlo method was applied to calculate the confidence interval of the return periods. Results show that the return periods of maximum wind speeds equaling to or greater than 125, 110, 100, 80, 64, 50, and 34 knots are estimated to be

24.5, 17.6, 14.9, 8.9, 5.7, 3.8, and 2.1 years, respectively, with 95% confidence interval of 12.3–68.7 years, 10.2–52.6 years, 8.8–42.4 years, 6.0–20.4 years, 4.1–10.3 years, 2.8–5.4 years, and 7.9–2.7 years. The results implied that the larger the MWS, the greater the uncertainty of its confidence interval.

Compared to the previous study that used data from 1970 to 1995 (Chu and Wang 1998), the return periods in this study are significantly shortened. For example, the return period decreased from 202 years to 24.5 years for the MWS of 125 knots and from 42 years to 14.9 years for 100 knots. The shorter return periods compared to Chu and Wang (1998) may be primarily attributed to the clustering of events around 2015, which reminds us to pay attention to the ENSO impacts on TC. A further question of how ENSO affects TC frequency and MWS through OHC needs to be explored. Other factors contributing to this difference is due to the different statistical models used between the two studies and the inclusion of the upper ocean heat content in the current study.

Note that there are 57 years of data with only one incidence of wind speed greater than 110 kt. One may wonder why the calculated return period for 125 kt is 24 years, not something like 57 years or longer? Our study is based on the theoretical model, not the empirical data, which is rather limited in length and cases. This finding points to a worrying trend that the return periods of MWS have notably decreased, indicating a higher likelihood of intense wind events that could lead to increased hurricane damage in the vicinity of Hawaii.

This research evaluates the return periods of MWS for TCs near Hawaii through an extensive analysis spanning from 1966 to 2022, which is critical for measuring the potential damage from TCs and providing a contemporary perspective on TC wind risk assessment. The implications of these findings are profound, with potential impacts on infrastructure planning, disaster preparedness, and climate change adaptation policies. By providing a more detailed understanding of TC risk, especially the MWS return periods, this research contributes a vital piece of knowledge to the complex puzzle of global climate change and its local impacts on TC frequency and intensity.

Although the results may depend on the selection of three statistical distributions (gamma, GEV distribution and kernel density estimation), we believe the chosen models are perhaps the best modern statistical methods to estimate the return periods of TC intensity and could be applied to other regions in future studies.

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Competing Interests The authors declare that they have no conflict of interest.

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Chapter 2

Extratropical Transition of Tropical Cyclones in a Changing Climate



Jung-Eun Chu and Hung Ming Cheung

Abstract The chapter discusses the transformation of tropical cyclones into extratropical storms in midlatitude baroclinic environments, a process known as extratropical transition (ET). During ET, storms typically decrease in maximum wind speed but increase in size, resulting in higher integrated kinetic energy. As such, the damage caused by ET can match or even exceed that caused by tropical cyclones. As the climate warms, tropical cyclones are expected to intensify and last longer. However, the accurate representation of ET events in climate models and their future projections in a changing climate remains a challenge. This chapter intends to (1) introduce the characteristics and a method for quantitatively measuring ET events, known as the cyclone-phase-space diagram, and (2) summarize the projections of high-resolution models in a warmer climate. In short, while there is no agreement among the models on the changes in the number of ET events in the North Atlantic, most models concur that the proportion and intensity of ET events will increase in the future, suggesting potentially stronger impacts of ET in a warmer climate.

Keywords Tropical cyclones · Extratropical transition · Extratropical storm

2.1 Introduction

Tropical cyclones (TCs), as their name suggests, originate in the tropical ocean and often progress toward the midlatitudes, resulting in severe devastation along coastal regions. When a TC moves in highly varying midlatitude environments, it typically undergoes a significant change in its characteristics and structure, losing its tropical nature. This transformation process is known as extratropical transition (ET) (Jones et al. 2003; Klein et al. 2000). During ET, a cyclone often produces heavy rain and strong wind and exhibits a rapid translation speed. Furthermore, its interaction with

J.-E. Chu (✉) · H. M. Cheung

School of Energy and Environment, City University of Hong Kong, Hong Kong, China

e-mail: jungeun.chu@cityu.edu.hk; [huncheung4@cityu.edu.hk](mailto:hunceung4@cityu.edu.hk)

Table 2.1 Estimated damage related to ET events that impacted North America and made landfall after ET completion in the last 20 years. Only cases with available references regarding the estimated loss are included

Hurricane (Year)	Estimated loss	Source
Fiona (2022)	2 direct deaths; 1 indirect death; CAD \$660 million; more than 500,000 customers lost power	Insurance Bureau of Canada (2019b) and Reinhart (2023)
Dorian (2019)	CAD \$105 million; 410,000 customers without power	Insurance Bureau of Canada (2019a) and Silver et al. (2022)
Nestor (2019)	3 indirect deaths; USD \$125 million; more than 10,000 customers without power	Hagen et al. (2020)
Olga (2019)	USD \$400 million; about 130,000 customers without power	Pasch et al. (2020)
Leslie (2012)	45,000 homes without power for about 6 h	Stewart (2013)
Sandy (2012)	72 direct deaths; 87 indirect deaths; USD \$50 billion; about 8.5 million customers lost power	Blake et al. (2013)
Noel (2007)	190,000 homes and businesses in eastern Canada and about 80,000 homes in the northeastern United States lost electricity	Brown (2007)

the midlatitude flow can influence the development of high-impact weather events downstream. Consequently, the damages resulting from ET can be comparable to, or in some cases even surpass, those associated with TCs. Hurricane Sandy in 2012, for example, made landfall along New Jersey after completion of ET and transformation into an extratropical cyclone. During the ET of Hurricane Sandy in 2012, heavy precipitation located left of track over Appalachia in conjunction with an upper-level trough and devastating storm surges from New Jersey to Rhode Island driven by the deepening of surface low pressure resulted in 72 deaths and economic damages over \$50 billion US dollars (Blake et al. 2013). In addition to Sandy in 2012, many other hurricanes have resulted in losses and fatalities after the completion of ET (Table 2.1). Although Table 2.1 only contains the estimated loss caused by landfalling storms after ET is completed, it is important to note that storms making landfall before or during ET can also cause severe damage due to the mixed tropical and extratropical characteristics, like Hurricane Irene (2011) (Murnane and Elsner 2012).

TCs obtain their energy from warm ocean waters through wind-driven evaporation and resultant release of latent heat through deep and moist convection near the cyclone core (Emanuel 1986; Rotunno and Emanuel 1987; Evans et al. 2017). As a consequence, the storm develops a non-frontal warm-core structure that indicates a relatively symmetric TC in gradient wind balance (see Fig. 2.1a). In contrast, extratropical cyclones primarily originate within the midlatitude regions due to the temperature and moisture gradients and wind shear intrinsic to those latitudes. These baroclinic environments lead to highly asymmetric wind and rainfall distributions, especially along the frontal boundaries that divide warm, moist air from cool, dry air. Once a cyclone occludes as a cold front overtakes a warm front, it often exhibits a

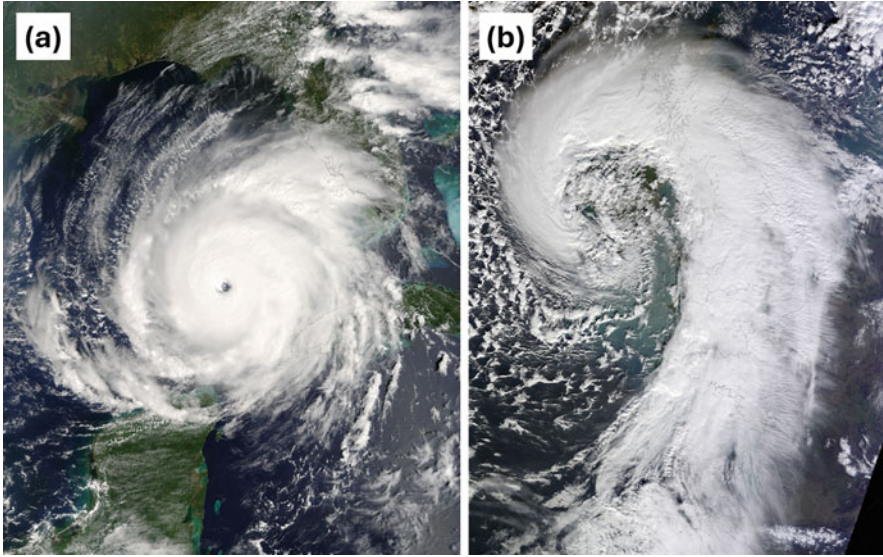


Fig. 2.1 (a) A symmetric tropical cyclone (TC) Rita (2005) over the Gulf of Mexico and (b) an asymmetric extratropical cyclone Tini (2014) over the United Kingdom. Images are obtained from NASA Earth Observatory taken on September 21, 2005, and February 12, 2014, respectively

comma-like shape of mid-tropospheric cloudiness (see Fig. 2.1b). In the Northern Hemisphere, the wind field of an extratropical cyclone rotates counterclockwise with the strongest winds on the cold/poleward side of warm fronts and wind speed increasing with height due to the cold-core structure. In summary, unlike TCs with symmetric and warm-core structures, extratropical cyclones exhibit asymmetric and cold-core structures in response to the baroclinic midlatitude environments. Most TCs lose their symmetric structure first during ET, before a cold-core structure eventually replaces a warm-core structure (Evans and Hart 2003; Hart et al. 2006). These structural changes result in high-impact weather over a larger area associated, directly and indirectly, with the transitioning cyclone.

Until the early 2000s, an objective description of ET was limited due to the lack of observed data with sufficient resolution. Klein et al. (2000) presented a two-stage conceptual model of ET based on satellite imagery of storms in the western North Pacific: the *transformation stage* when the outer circulation of a TC interacts with the pre-existing baroclinic zone resulting in asymmetry in cloud and precipitation pattern and *reintensification stage* when the post-transformation storm deepens as an extratropical storm. Based on the two-stage classification of ET by Klein et al. (2000), Hart (2003) suggested cyclone-phase-space (CPS) diagnostics to quantitatively measure ET events using three-dimensional geopotential height fields. There have also been other methods for identifying the onset and completion of ET. Harr and Elsberry (2000) introduced a scalar frontogenesis metric by taking the average over the northeast and northwest quadrants of a storm at 500 hPa to define the onset of transition. Demirci et al. (2007) determined the onset of ET by detecting

the interaction between an open wave in the 500-hPa geopotential height fields and the mid-latitude trough. Kofron et al. (2010) defined ET onset using a local minimum of 330-K Ertel's isentropic potential vorticity (IPV), averaged within 500 km radius of the storm center, while ET completion was indicated by exceeding an IPV threshold of 1.6 PVU ($1 \text{ PVU} = 10^{-6} \text{ K kg}^{-1} \text{ m}^2 \text{ s}^{-1}$). An evaluation was conducted by Wang et al. (2012) to assess four different ET detection methods for Typhoons Mindulle (2004) and Yagi (2006). Their findings revealed that the scalar frontogenesis and open wave methods lacked reliability in determining the completion of ET, whereas the CPS and IPV methods were able to determine the onset and completion times of ET. However, Wang et al. (2012) also acknowledged that there is substantial variability in the results among different datasets when using the CPS method. Additionally, Li and Wang (2013) found that the IPV metric was not effective in determining the onset and completion times of ET in higher-resolution datasets. Despite the existing limitations in the CPS method, it has demonstrated effectiveness and has been extensively applied to many studies to diagnose ET events in reanalysis, observational, and model-forecast datasets (Baker et al. 2021; Bieli et al. 2019a, b; Evans et al. 2017; Evans and Hart 2003). This book chapter will primarily focus on the CPS method. A comprehensive explanation of the CPS method will be presented in Sect. 2.2.2.

As climate warms, TCs are anticipated to become more intense and have a longer duration (Bacmeister et al. 2018; Emanuel 2021; Hill and Lackmann 2011; Knutson et al. 2010, 2020a, b; Walsh et al. 2016). Consequently, there is a greater chance of TCs persisting for a longer time beyond the tropical or subtropical regions due to their higher moisture-holding capacity, possibly impacting the frequency of ET events. Despite the growing availability of high-resolution models, a significant challenge remains in accurately representing ET events in climate models and projecting their future change under a changing climate. This chapter seeks to provide a brief overview of the development and identification of ET using the CPS diagram (Sect. 2.2) and potential future changes projected by high-resolution models, with a primary focus on the North Atlantic and eastern North Pacific (Sect. 2.3). Section 2.4 contains a summary and discussion.

2.2 Evolution and Detection of ET

2.2.1 *Evolution of ET*

When a TC moves toward higher latitudes, it often encounters environmental conditions conducive to transformation into an extratropical cyclone. Its changing environment includes but is not limited to:

- Decreasing sea-surface temperature (SST)
- Strong SST gradient
- Strong moisture gradient

- Increased vertical wind shear and baroclinicity
- Upper-level troughs
- Increasing Coriolis parameter
- Increased surface drag after landfall
- Orography.

In response to these environmental changes, TCs can experience:

- Decreased TC intensity
- Increased forward motion
- Asymmetries in wind, thermal structure, moisture field, cloud, convection, precipitation, surface fluxes
- Increased spatial extent of gale-force winds
- Rapid wave growth, large wave heights
- Loss of warm-core.

The evolution of ET has been well summarized in the previous review papers (Evans et al. 2017; Evans and Hart 2003; Jones et al. 2003). According to the ET classification proposed by Evans and Hart (2003), the process of ET can be divided into two stages: the *onset stage* and the *completion stage*. The onset stage of ET occurs when a TC begins to undergo structural changes in response to environmental factors. This phase indicates the initial transformation of the TC as it adapts to the evolving conditions. The completion stage of ET depicts the point at which a TC has fully transformed into an extratropical cyclone. During this stage, the TC has undergone significant structural changes and adopted the characteristics associated with extratropical cyclones. It should be noted that not all TCs that initiate the onset stage of ET fully complete the transition process. Approximately 50% of North Atlantic and western North Pacific TCs undergo ET (Bieli et al. 2019b). Some TCs complete the ET process and become extratropical cyclones, and the remaining TCs decay in the tropics and do not complete transformation (Hart and Evans 2001).

During ET, a TC can interact with pre-existing extratropical systems, such as an upper-level potential vorticity anomaly, mature extratropical low, and/or surface baroclinic zone, and develop extratropical characteristics. Alternatively, a TC can develop its extratropical characteristics by having a frontal structure and vertical tilting, independent of pre-existing systems. The resultant extratropical cyclones after ET completion can experience a steady decay in the extratropics or sometimes re-intensify as an extratropical system. The interaction between ET and midlatitude flows is well summarized in Jones et al. (2003).

2.2.2 Detection of ET: Cyclone Phase Space

The CPS (Hart 2003) employs a set of three parameters to describe the physical structures of a cyclone, namely symmetry/asymmetry and warm/cold core. One advantage of this method is that all three parameters can be simply derived by

analyzing geopotential height fields at different atmospheric levels. This section will briefly introduce the methodology and interpretation of the CPS diagram.

2.2.2.1 Parameter B: Symmetry Vs Asymmetry

The first parameter, B, represents the storm-motion-relative thickness asymmetry calculated using the difference in geopotential thickness between the 900 hPa and 600 hPa levels on the right and left sides of the TC with respect to its motion direction.

$$B = h \left(\overline{Z_{600 \text{ hPa}} - Z_{900 \text{ hPa}}} \Big|_{\text{right}} - \overline{Z_{600 \text{ hPa}} - Z_{900 \text{ hPa}}} \Big|_{\text{left}} \right) \quad (2.1)$$

where Z refers to the geopotential height, h is a hemispheric sign parameter that equals +1 in the Northern Hemisphere and -1 in the Southern Hemisphere, and the overbar denotes the spatial average within a radius of 500 km from the storm center. The radius of 500 km is consistent with the average radius over which cyclonic, convergent inflow is observed for TC (Frank 1977).

As this parameter is the thickness difference between the left and right of the TC, the larger value of B indicates a greater asymmetry and frontal structure, as shown before and during the ET event of Hurricane Sandy in 2012 (Fig. 2.2). A mature or developing front typically has a B value greater than 10 meters (Evans and Hart 2003). Conversely, symmetric and non-frontal TC has a B value of less than 10 meters. Therefore, the 10-meter threshold serves as a practical indicator to differentiate between symmetric and asymmetric storms in the CPS. The 10-meter threshold roughly translates to a 0.85°C temperature difference averaged over a cyclone layer (Evans et al. 2017).

A critical indicator that ET may have started is decreasing symmetry, meaning its shape becomes less circular and more elongated or distorted. This asymmetry is reflected in the CPS by an increase in the value of B. In the Northern Hemisphere, it is generally observed that an increase in parameter B leads to the advection of cold air into the rear of the cyclones, while warm air advects poleward to the right of the cyclone's motion. Consequently, the thickness on the right side of the cyclone tends to be much greater than that on the left side, which results in the B value of the CPS becoming positive or even exceeding 10 m.

During the progression of Hurricane Sandy in 2012, the warm core of TC was encompassed by cold and continental polar air while it moved in a northwestern direction (Fig. 2.2a). As Sandy underwent ET, the geopotential thickness field between 900 and 600 hPa displayed the warm seclusion on the right side of the cyclone's motion, resulting in an increase in the B value. This warm seclusion or occlusion event is often observed in highly intense extratropical cyclones (Hart 2003), which occur in approximately one-third of ET events (Kitabatake 2008).

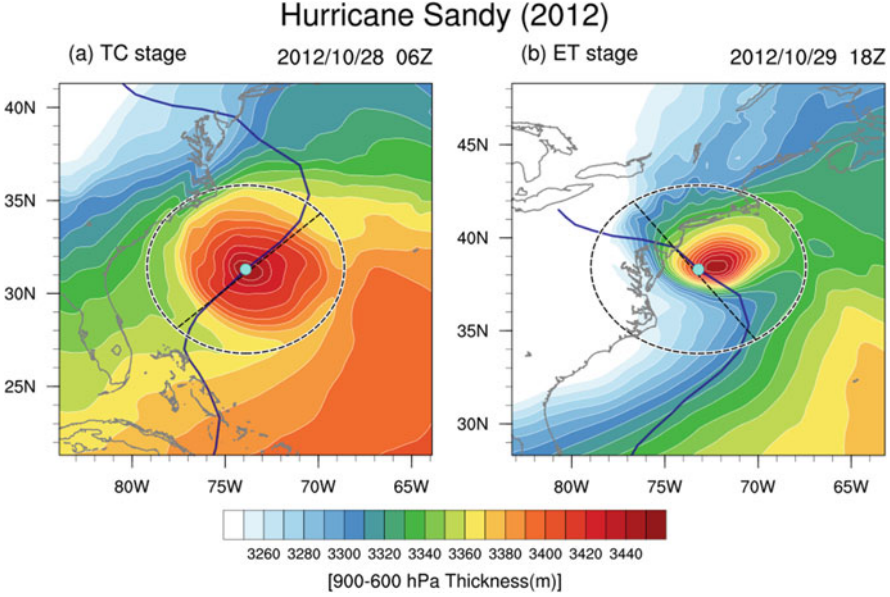


Fig. 2.2 900–600 hPa geopotential thickness (shading) for Hurricane Sandy (2012) at (a) symmetric TC stage on 28 October 2012 and (b) asymmetric extratropical cyclone stage on 29 October 2012. The thick solid line indicates the track of the Sandy, and the dashed circle indicates a 500 km radius from the storm center. The dashed bisecting line shows the direction of motion. TC track is obtained from the International Best Track Archive for Climate Stewardship (IBTrACS) best track database version 4 (Knapp et al. 2010). The geopotential height field is from the European Centre for Medium-Range Weather Forecasts Reanalysis v5 (ERA5) (Hersbach et al. 2020)

2.2.2.2 Parameters — V_T^L and $-V_T^U$: Warm-Core Vs Cold-Core

The second and third parameters represent the warm-core versus cold-core via the thermal wind relationship between two tropospheric layers of equal mass. Specifically, these parameters evaluate the thermal wind in the 900–600 hPa ($-V_T^L$) and 600–300 hPa ($-V_T^U$) by computing linear regression of ΔZ , the difference between the maximum ($Z_{\max}$) and minimum ($Z_{\min}$) geopotential height at the same pressure level within 500 km of the TC center.

$$-|V_T^L| = \frac{\partial(\Delta Z)}{\partial \ln p} \bigg|_{900 \text{ hPa}}^{600 \text{ hPa}} \quad (2.2)$$

$$-|V_T^U| = \frac{\partial(\Delta Z)}{\partial \ln p} \bigg|_{600 \text{ hPa}}^{300 \text{ hPa}} \quad (2.3)$$

Following Hart (2003), we used seven pressure levels, ranging from 900 to 600 hPa and 600 to 300 hPa, with a 50 hPa increment. Positive values of $-V_T^L$ and $-V_T^U$, which represent the weakening of geopotential wind with height, suggest the existence of a warm core within that layer. Conversely, negative values are linked

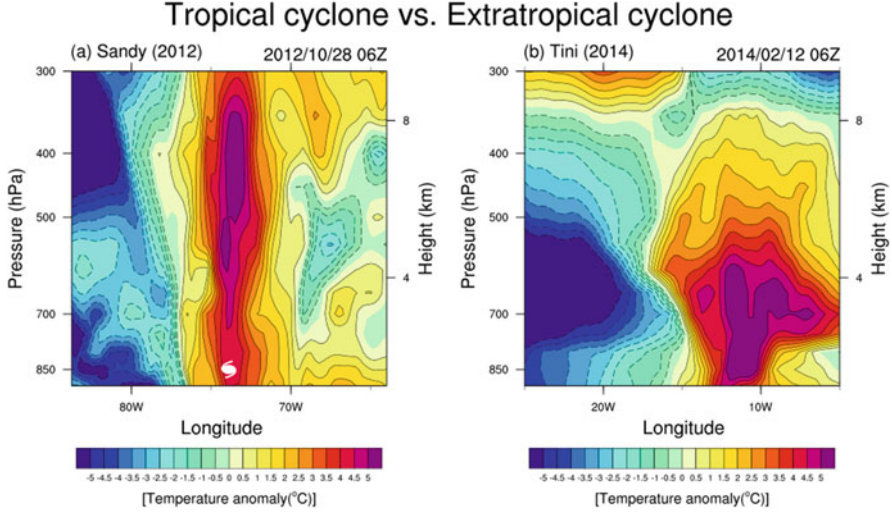


Fig. 2.3 Longitude-height cross-section of the air temperature anomaly ($^{\circ}\text{C}$) for (a) tropical cyclone Sandy on 28 October 2012 (06 UTC) at a latitude of 31.25°N in and (b) extratropical storm Tini on 12 February 2014 (06 UTC) at a latitude of 48°N . The white marker in Fig. 2.3a indicates the center of the Sandy, which corresponds to the blue dot in Fig. 2.2a. Anomaly is calculated as a deviation from the zonal mean within $\pm 10^{\circ}$ from the center. The temperature fields at different vertical levels are from the ERA5

to systems with a cold core and stronger winds with height. Due to limited data availability, other studies used fewer pressure levels to compute these two parameters and found that the results are comparable (e.g., Liu et al. 2017).

Figures 2.3, 2.4 and 2.5 illustrate the vertical cross-sections of temperature and geopotential height anomalies, as well as ΔZ for tropical cyclone Sandy (2012) and extratropical cyclone Tini (2014). Hurricane Sandy is characterized as a warm-core system (see Fig. 2.3a), wherein it exhibits a negative anomaly in geopotential thickness near the storm center (see Fig. 2.4a). The magnitude of the cyclone isobaric height gradient around the surface cyclone center (i.e., geostrophic wind magnitude) increases with height (see Fig. 2.5a). Consequently, the CPS shows a positive value for the parameter $-V_T^L$, indicating a larger perturbation at 900 hPa compared with 600 hPa, and therefore, a stronger near-surface wind. Similarly, $-V_T^U$ also exhibits a positive value, suggesting the presence of a deeply developed warm-core structure.

For a comparison with warm-core TC structure, Fig. 2.3b and Fig. 2.4b show an asymmetric and tilted frontal structure of extratropical cyclone Tini (2014). Extratropical cyclones are typically cold-core systems characterized by a negative geopotential thickness anomaly near the center and a stronger upper-level wind. This negative anomaly results in a negative value for $-V_T^L$ and $-V_T^U$ (Fig. 2.5b). Therefore, the sign and magnitude of $-V_T^L$ in the CPS provides a distinction between warm-core and cold-core storms, based on the geopotential thickness anomaly near their centers.

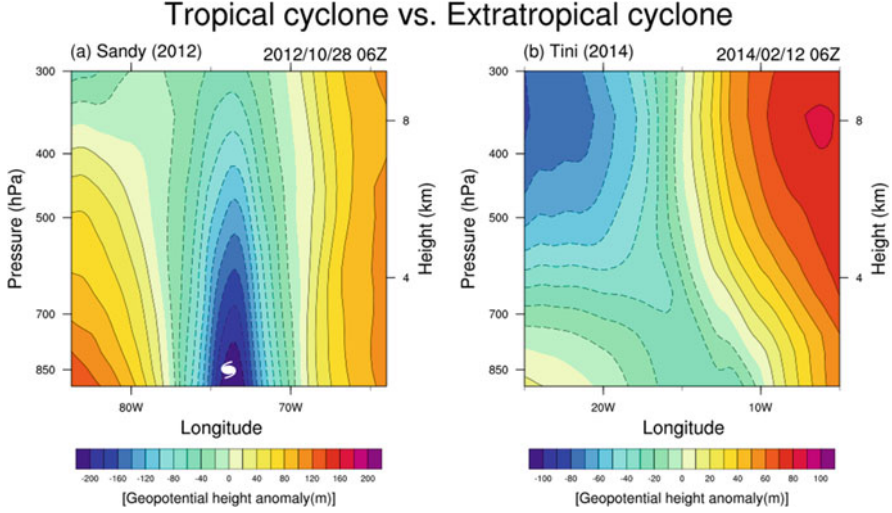


Fig. 2.4 Same as in Fig. 2.3 but for geopotential height anomaly (m)

2.2.2.3 Diagnostics of ET Onset and Completion

Based on the three parameters mentioned in Sect. 2.2.2, the various stages of a cyclone can be defined and visualized using two-dimensional cross sections between two parameters: B versus $-V_T^L$ and $-V_T^U$ versus $-V_T^L$ (Fig. 2.6). The trajectory of a cyclone through the phase diagram defines its evolution over time.

TCs exhibit a high degree of symmetry and a warm-core structure; they have small B values and positive $-V_T^L$ values, placing their trajectory in the right-bottom quadrant of the diagram (Fig. 2.6a). In the example of Fig. 2.6a, ET starts with the loss of thermal symmetry and ends with the formation of a cold core. The *onset* of ET is defined as when the cyclone develops its asymmetry but remains warm-cored. In other words, the trajectory moves from the bottom-right quadrant to the top-right quadrant, and onset is the time when it reaches a B value higher than 10 m between 900 and 600 hPa pressure levels (Evans and Hart 2003). This transition point is often associated with low-level frontogenesis, a process involving the generation or intensification of a frontal zone near the cyclone (Harr and Elsberry 2000). The transition is *completed* when the vertical storm structure corresponds to a cold-core vortex in the lower troposphere and moves into the left-top quadrant (i.e., a negative value of $-V_T^L$). However, not all ET events follow this typical path. In some cases, a TC may initially develop a cold-core structure before losing its symmetry, or it may exhibit both asymmetry and cold-core characteristics simultaneously (Evans and Hart 2003). In such cases, the *onset* of transition is defined as the first time step when the TC moves out of the bottom-right quadrant in the B versus $-V_T^L$ CPS diagram. The *completion* of transition is identified when the TC moves into the left-top quadrant of the diagram.

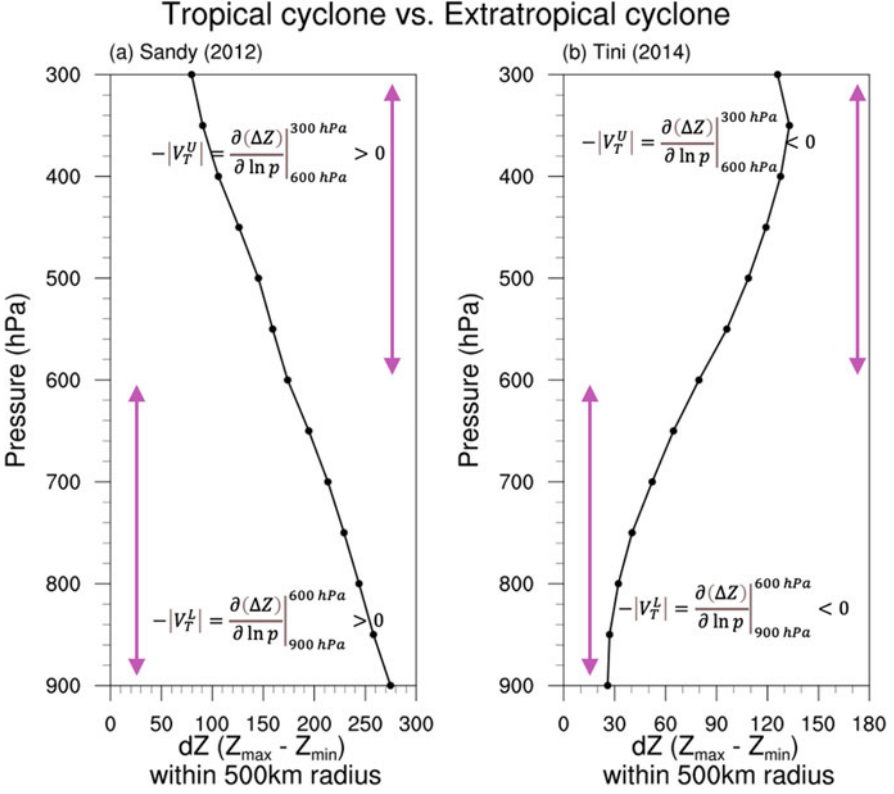


Fig. 2.5 The vertical profile of the ΔZ from Fig. 2.4 calculated by the difference between the maximum ($Z_{\max}$) and minimum ($Z_{\min}$) geopotential height within a 500-km radius from the storm center

According to Evans and Hart (2003), thermal wind in the lower troposphere offers a more robust criteria for ET transition because the upper troposphere typically cools before the lower troposphere. Many subsequent studies have detected ET based on $B > 10 \text{ m}$ and $-V_T^L < 0$ conditions (Hart et al. 2006; Liu et al. 2017; Wood and Ritchie 2014). Using k-means clustering analysis, Studholme et al. (2015) found that the mean value of B during the onset of ET varies across different basins. They identified that the mean value in the Northern Hemisphere is approximately 11 m, while the Atlantic Basin exhibits a value greater than 13 m. For this reason, some studies have adopted different thresholds of B in their studies. For example, Bieli et al. (2019a, b) used a threshold of 11 m, while Cheung and Chu (2023) and Zarzycki et al. (2017) employed a higher threshold value of 15 m. Zarzycki et al. (2017) stated that a greater threshold for B can avoid “brief and false alarm ET events at low latitudes” when high-resolution dataset is used. Bieli et al. (2019a, 2019b) also added $-V_T^U < 0$ condition in detecting ET events from reanalysis data. They argued that exclusion of $-V_T^U$ would lead to an overestimation of ET events,

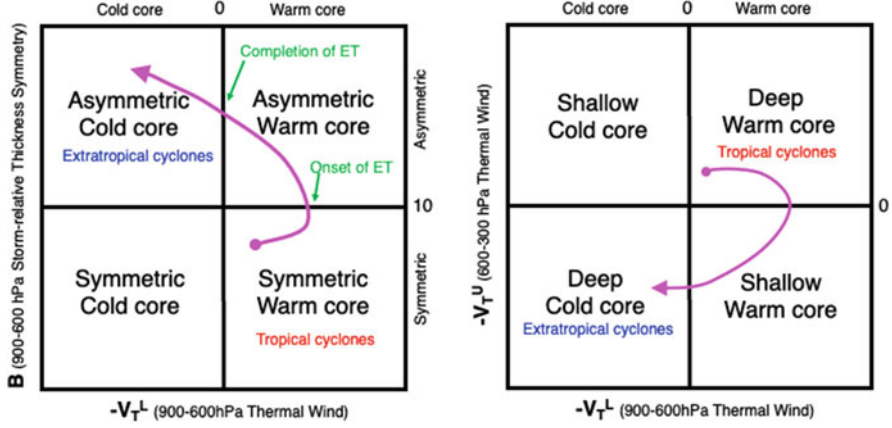


Fig. 2.6 The Cyclone Phase Space diagram proposed by Hart (2003) that illustrates an idealized transition from a symmetric and warm-core structure to an asymmetric cold-core structure. Cross section of (left) B versus $-V_T^L$ and (right) $-V_T^U$ versus $-V_T^L$

suggesting that the formation of a cold-core in the upper troposphere does not always precede that of a lower tropospheric cold-core.

The CPS (Hart 2003) has a limitation in that it does not provide detailed information about a cyclone's inner-core structure. For a better understanding of the changes in storm structure during ET, more in-situ observation through field campaign is necessary. In addition, the quality of CPS diagnostics relies heavily on data sources such as numerical weather prediction products, reanalysis datasets, or satellite retrievals (Jones et al. 2003). For example, even when employing the same CPS parameters for a given storm, the magnitude of CPS parameter values varies to some degree depending on the reanalysis datasets used for computation (Bieli et al. 2019a, b; Zarzycki et al. 2017). CPS can also have an issue with correctly identifying the completion of ET with high-resolution datasets. Jung & Lackmann (2021) found that model storms retained their warm core in the lower troposphere despite the development of thermal asymmetry, and thus CPS failed to capture the completion of ET. Nonetheless, the CPS classification correlates well with the best track classification and is reasonably close to reanalysis data, encouraging its use for climatological research (Bieli et al. 2019b).

2.3 Future Changes in ET Events

2.3.1 ET Events Represented in High-Resolution Models

The accurate simulation of ET events in climate models is fundamentally dependent on the model's ability to represent TC statistics as well as storm structure because poorly resolved TCs in a model can have an adverse impact on the subsequent

transition process. TC intensity is closely correlated with horizontal resolution (Walsh et al. 2007, 2015). Studies have demonstrated that a minimum grid spacing of 50 km is necessary to realistically represent TC climatology (Bengtsson et al. 2007; Zhao et al. 2009). Furthermore, Davis (2018) demonstrated that a grid spacing coarser than $\sim 0.25^\circ$ may not allow numerical models to realistically simulate the frequency of intense TCs (category 4 and 5). Recently, high-resolution models are becoming increasingly available despite their computational expense. Roberts et al. (2020) evaluated climate models that participated in the High Resolution Model Intercomparison project (HighResMIP) with varying grid spacing, ranging from coarser (50–200 km) to finer grid spacing (25–50 km). They demonstrated that high-resolution models exhibit more accurate spatial distribution of TC tracks and allow the formation of more intense TCs, although only one of them could simulate TCs stronger than category 3.

To showcase how efficiently a high-resolution model captures the characteristics of the ET event, Fig. 2.7 shows a simulated TC undergoing ET in one of the highest-resolution fully coupled model simulations with a horizontal grid spacing of 0.25° in the atmosphere and 0.1° in the ocean (Chu et al. 2020; Cheung and Chu 2023). During the TC stage, the storm displays an axisymmetric wind field with a maximum wind speed of 61 m/s (Fig. 2.7b) and precipitation well confined within 100 km from the center (Fig. 2.7f). As it moves northward, the storm encounters the midlatitude baroclinic zone and begins ET. During the transformation stage of ET, the storm loses its symmetric characteristics and obtains a cold-core structure (Fig. 2.7e). The wind speed weakens with the maximum speed of 43 m/s, however, the area with winds stronger higher than 17 m/s expands radially outward, indicating an increase in the spatial extent of strong winds within the storm (Fig. 2.7c).

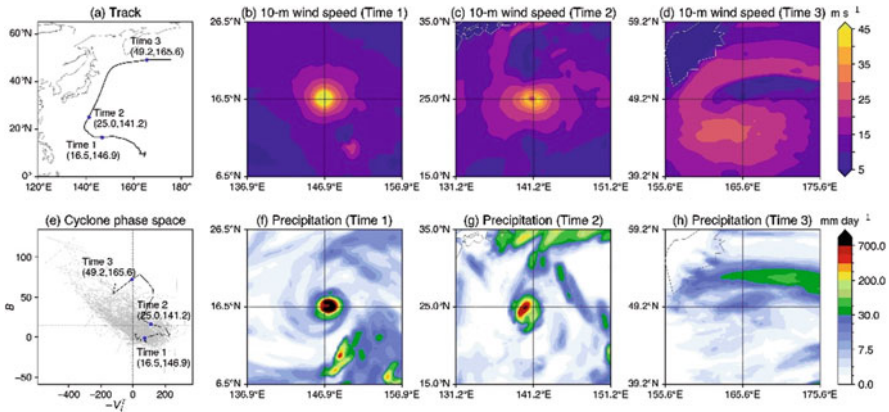


Fig. 2.7 A simulated TC that undergoes extratropical transition. (a) Track of the TC, (b–d) 10-m instantaneous wind speed, (e) the trajectory of the TC on the Cyclone Phase Space diagram, and (f–h) total precipitation (b and f) before the ET onset (Time 1), (c and g) during the ET (Time 2), and (d and h) after the ET completion (Time 3)

The asymmetry during the ET is also well represented in the precipitation pattern, with a maximum core observed to the left of the storm center (Fig. 2.7g). This precipitation asymmetry holds significant implications for re-intensification after ET. Typically, when atmospheric conditions favor re-intensification post-ET, precipitation is more common on the left side of the track (Atallah et al. 2007; Evans et al. 2017; Milrad et al. 2009). In the CPS diagram shown in Fig. 2.7e, there is an increase in the warm core parameter ($-V_T^L$) after Time 2, indicating the potential for re-intensification. These conditions typically include an intensified mid to upper-tropospheric ridge above and downstream of the storm (Fig. 2.7h), along with a negatively tilted upstream trough near the TC. Conversely, instances with maximum precipitation on the right side of the track typically either do not complete the ET process or rapidly decay soon after becoming extratropical (Milrad et al. 2009).

The 0.25° grid spacing model used in this simulation holds promise as it successfully depicts the realistic evolution of ET. Furthermore, incorporating a realistic orographic effect is also important, as it influences anomalous ascending motion and geostrophic frontogenesis. For example, the interaction of upper-level cold air with the western side of the Appalachian Mountains during Hurricane Sandy (2012) led to as much as 900 mm of snowfall (Keighton et al. 2016). An in-depth examination of severe rainfall events triggered by ET in the model will ultimately improve the prediction of flood risks associated with ET in a more timely manner.

2.3.2 *Future Changes in ET Events in the North Atlantic and Eastern North Pacific*

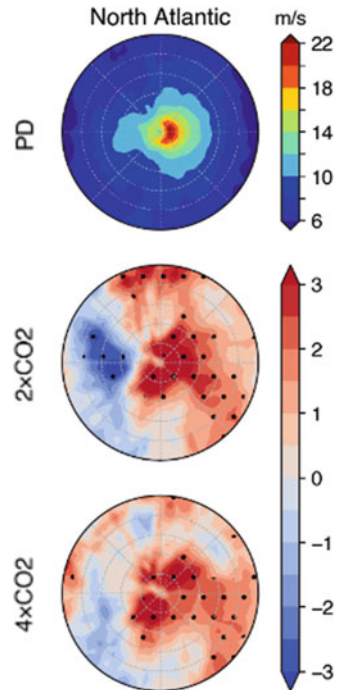
There is a growing consensus among high-resolution climate models that the global number of TCs is expected to decrease, while their intensity is expected to increase in a warmer climate (Chu et al. 2020; Emanuel 2021; Knutson et al. 2020a, b; Sobel et al. 2016). Following the Clausius-Clapeyron relationship, the atmosphere can retain more moisture as the temperature increases, implying that TCs may maintain their strength and persist for longer periods beyond the tropics or subtropics. Studies of the potential changes in ET activities in response to anthropogenic warming using climate models have emerged in recent years. Understanding the changes in ET activities is crucial for predicting the behavior and impacts of transitioning TCs in the future, which can help improve TC forecasting and risk assessment. In this section, we provide an overview of high-resolution modeling studies that employ global or regional models to predict the changes in ET activities focusing on the North Atlantic and eastern North Pacific. Considering the potential modification in circulation and downstream impacts on North America due to ET events in the western North Pacific (Keller et al. 2019), changes in ET events over the western North Pacific are also summarized.

Cheung and Chu (2023) conducted an analysis using the high-resolution Community Earth System Model (CESM) 1.2.2 to investigate potential changes in ET

activities under greenhouse warming. They used century-long simulations with a horizontal grid spacing of 0.25° in the atmosphere and 0.1° in the ocean, with the fixed CO_2 concentrations: present-day level (367 ppm), double CO_2 (734 ppm), and quadruple CO_2 (1468 ppm) (Chu et al. 2020). Their findings revealed that the number of ET events over the North Atlantic does not change significantly with increasing CO_2 concentration. However, the ET fraction, which is the ratio of TCs that undergo transition to the total number of TCs, increases with CO_2 concentrations (+8% under $2 \times \text{CO}_2$ and +14% under $4 \times \text{CO}_2$) over the North Atlantic due to the decrease in TC frequency. Upon completion of ET, the composite near-surface wind speed shows a significant increase over the inner-core region in the greenhouse warming simulation (Fig. 2.8). They clarified that the spatial distribution of the maximum Eady growth rate, an indicator of atmospheric baroclinic instability, remains relatively unchanged in each simulation (Fig. 2.9). Therefore, the large-scale environments that promote ET do not change in response to increased CO_2 levels.

Similar conclusions were made by Liu et al. (2017), who used the flux-adjusted version of the Forecast-oriented Low Ocean Resolution (FLOR-FA) with atmosphere and land components at a horizontal grid spacing of 50 km and ocean and sea ice components at a grid spacing of 100 km. The Representative Concentration Pathway (RCP) 4.5 scenario is used for the future simulation (2006–2100), and five ensemble members are analyzed for the period 2056–2100. Their analysis showed a

Fig. 2.8 Composited 10-m wind speed at the completion of ET for the present-day simulation (upper) and differences between increased CO_2 experiments and present-day (middle and bottom) over the North Atlantic. Stippling represents a statistically significant increase or decrease in mean wind speed at a 90% confidence level. The figure is adjusted from Cheung and Chu (2023, their Fig. 4)



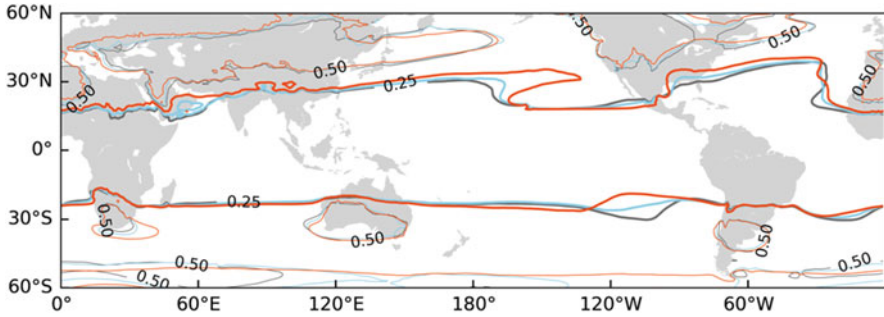


Fig. 2.9 Maximum Eady growth rate averaged over each hemisphere summer. Thick and thin contours indicate the maximum Eady growth rate value of 0.25 and 0.5 day^{-1} for the present-day (gray), doubling (blue), and quadrupling CO_2 (red) experiments, respectively. Northern Hemisphere summer is from July to November and Southern Hemisphere summer is from December to April. The figure is adapted from Cheung and Chu (2023, their supplementary Fig. 2)

significant increase in ET fraction, although the total number of TCs decreases, and the number of ET events does not exhibit significant changes. Geographically, a dipole pattern is observed, with a reduction of ET events over the western North Atlantic and an increase over the tropics or subtropics in the eastern part. This resulted in more TCs transitioning toward the northeastern United States or recurving toward Western Europe. They also concluded that these changes are attributed to the increase in SST and decrease in vertical wind shear that creates a conducive environment for TC development and subsequent ET.

Bieli et al. (2020) employed the same model and framework as Liu et al. (2017) but focused specifically on the North Atlantic region during the shorter period (2071–2100). In order to address unrealistic grid-scale features caused by high-resolution datasets, the study implemented additional modifications to the CPS parameter. Their analysis revealed no change in the ET fraction in the North Atlantic but a robust increase in the eastern North Pacific. There was a slight equatorward shift in the latitude of ET onset in both ocean basins. Geographically, more TCs in the central and eastern North Atlantic undergo transition in the future simulations, similar to the findings of Liu et al. (2017), although the increase is not statistically significant. The signal over the eastern North Pacific is mixed.

In contrast to the studies mentioned earlier that relied on a single model, Baker et al. (2022) utilized an ensemble of four global climate models for future climate simulations (2015–2050). These models—CNRM-CM6.1, EC-Earth3P, HadGEM3-GC3.1, and MPI-ESM 1.2—were part of the CMIP6 HighResMIP (Haarsma et al. 2016). The study included both atmosphere-only and fully coupled versions of the models at coarser (50–142 km) and finer (25–50 km) grid spacings. The simulations used similar forcings such as greenhouse gas concentration and anthropogenic aerosol forcing, except that the atmosphere-only models are forced by HadISST2 daily SST for the present climate and SST at a warming rate derived from an ensemble mean of CMIP5 RCP8.5 simulations for the future climate. The track density of ET events simulated by atmosphere-only models shows an increase across

the North Atlantic, with the exception of the United States' east coast. While similar distributions of change in ET track density are observed in both low- and high-resolution models, there is not always agreement between models in regions with significant changes. For fully coupled models, the climate change response in ET track density varies based on horizontal resolution: the geographical distribution in low-resolution models is similar to those from atmosphere-only models, though weaker in magnitude; for high-resolution coupled simulation, the region with a reduction in track density extends to the central North Atlantic without extensive area of increase in track density. A statistically significant increasing trend in the annual fraction of ET events during August–November, a period with consistent model behavior in seasonality, is observed in the high-resolution atmosphere-only models. The latitudes of ET completion in the North Atlantic shift equatorward in the atmosphere-only models, but the opposite is observed in the fully coupled models. Over the eastern North Pacific, a decrease in ET events is simulated by the low-resolution atmosphere-only models, but the response in the high-resolution version is unclear. However, an increase in ET events is observed in the high-resolution fully coupled models, while a weak signal is detected in the low-resolution version.

A configuration with variable resolution has also been employed in the global simulation to increase the horizontal resolution over the specific area. Michaelis and Lackmann (2019) used the Model for Prediction Across Scales–Atmosphere (MPAS-A) at a horizontal grid spacing of 15 km across the Northern Hemisphere. In their future climate simulations, pseudo-global warming (PGW) method is applied, fixing the CO₂ concentration at 936 ppm and applying temperature changes derived from an ensemble of CMIP5 models following the RCP8.5 scenario to the present-day simulation. Their analysis showed an increase in the number of TCs (+18%), ET events (+40%), and the fraction of ET events (+6%) in the North Atlantic, consistent with the weakened vertical wind shear, increased SST, and greater maximum potential intensity (MPI). The study also observed substantial changes in the central North Atlantic and the Caribbean, with an overall poleward shift in the location of ET onset and completion by approximately 4°, consistent with a significant poleward shift in the latitude of TC genesis and lifetime maximum intensity (Torres-Vazquez 2018). Regarding the changes in intensity, the study found a strengthened lower-tropospheric warm-core and deepened sea-level pressure during the TC stage, while changes in the overall ET processes are minimal in future simulations. In a subsequent study, Michaelis and Lackmann (2021) examined post-transformation cold-core ET events. The analysis revealed that storms in future simulations are closer to the entrance of a stronger upper-level jet, resulting in enhanced trough-TC interaction and increased post-transition storm intensity, including potential vorticity, precipitation, and 10-m wind speed. The results hint at a potential for increased impact of post-ET events on downstream regions under future climate conditions.

Case studies have also been conducted to investigate the impact of climate change on single ET event. Jung and Lackmann (2019) simulated Hurricane Irene (2011), which was a strong ET event with severe flooding in the Northeastern United States,

using the Weather Research and Forecasting (WRF) model with seven ensemble members. The PGW approach was applied, and the simulations showed increased storm intensity, enhanced precipitation rates exceeding Clausius–Clapeyron scaling, and longer ET duration. Liu et al. (2020) studied Hurricane Irene as well using the WRF model with 9 km and 3 km nested domains and realistic topography. Their study emphasized an increase in rain rate as well as a shift in rainfall structure from the inner core at the TC stage to outer rainband regions at the ET stage, highlighting the increased flood risk in the future.

In summary, several studies and models concur on certain aspects regarding the North Atlantic: an increased ET fraction, more ET activities over the central/eastern North Atlantic, less ET activity over the western North Atlantic, and enhanced storm intensity and precipitation. Changes in the total number of TCs and ET events in the basin, as well as the average latitude of TC genesis, ET onset, and ET completion, are less consistent. Due to the small number of observed and simulated ET events in the eastern North Pacific, comprehensive analyses in this region are rare.

2.3.3 Future Changes in ET Events in the Western North Pacific

Given that ET processes can alter the circulation patterns in the midlatitudes and have downstream impacts (Keller et al. 2019), it is important to consider the potential effects of ET events in the western North Pacific on North America. Therefore, changes in ET events in the western North Pacific under warming scenarios will be briefly explained in this section. Since background information on most of the studies was mentioned in the previous section, we will refrain from repeating it again. Instead, this section will focus on explaining the findings related to the changes in ET events in the western North Pacific and their potential implications for North America.

In the study conducted by Cheung and Chu (2023), the occurrence and fraction of ET events in the western North Pacific did not significantly change under doubling or quadrupling CO₂ concentration experiments. However, there were notable poleward shifts in the latitudes of TC genesis and ET onset. Interestingly, unlike other basins, the study observed a decrease in 10-m wind speed at ET completion, particularly at locations further from the storm center by approximately 2°. Contrary to the conclusions drawn by Cheung and Chu (2023), Bieli et al. (2020) found a significant increase in ET fraction and equatorward shift (by approximately 2°) in ET onset latitude over the western North Pacific. However, the study mentioned that the increase in ET activity is sensitive to the parameters used in the CPS, with a significant increase in their modified parameter and no change in the original form. The multi-model study conducted by Baker et al. (2022) indicates a significant decrease in track density for the TCs undergoing ET in both atmosphere-only and fully coupled models. This decrease is particularly pronounced over the Kuroshio region. While the frequency of ET events shows a clear pattern of decrease, the study

reveals less consistent results when it comes to changes in intensity-related variables across different models and resolutions. In the PGW time-slice simulations of Michaelis and Lackmann (2019, 2021), it was found that warming leads to an increase in the number of TCs and ET events, but the fraction of ET remains unchanged. The spatial distribution of ET tracks did not show consistent changes, except for an increase near the Korean Peninsula. The intensity of storms showed minimal differences, with a slight decrease in the intensity due to the weakening of upper-level trough inhibiting trough-TC interaction during and after ET. Additionally, there was an increase in precipitation near the storm center before and during ET, albeit below the Clausius–Clapeyron rate. A case study of Typhoon Songda (2004) was conducted by Ito et al. (2016) using the WRF model with a 1 km grid spacing and PGW approach. Their PGW conditions are derived from MRI-AGCM under the Representative Concentration Pathway 8.5 (RCP8.5) scenario. Their study found that the change in simulated TC tracks in response to global warming is negligible. However, a reduction in surface wind speed is observed over the Hokkaido area under PGW conditions. The study explained this phenomenon by the reduced meridional temperature gradient and weakened baroclinicity in the midlatitudes, which provides unfavorable conditions for ET events.

In summary, studies on the ET events in the western North Pacific show less consistent changes in characteristics such as ET fraction and intensity. Nevertheless, compared to the Atlantic Ocean, a greater number of models indicate a decrease in the intensity of ET events in the western North Pacific region. These findings suggest that the impacts of ET events in the western North Pacific on North America might be less pronounced or potentially reduced compared to those in the Atlantic Ocean. Further research is needed to determine whether downstream effects can be amplified regardless of a decrease in ET events.

2.4 Summary and Discussion

In this chapter, we provide insights into the potential changes in extratropical transition (ET) events of tropical cyclones (TCs) under global warming, simulated by high-resolution climate models. ET events can cause significant damage, sometimes exceeding that of TCs, due to their larger size and greater integrated kinetic energy, as we learned from Hurricane Sandy (2012). This chapter also presents an overview of the cyclone-phase-space (CPS) diagnostics (Hart 2003) and future changes in characteristics of ET events. Overall, studies indicate an increase in ET fraction and storm intensity during ET in the North Atlantic, suggesting stronger impacts of ET in a warmer climate. However, there is less consistency in the total number of ET events and their average latitude of onset and completion. In the western North Pacific, studies show inconsistent changes in ET fraction but a consistent decrease in ET events intensity, implying complex effects on North America.

High-resolution models generally exhibit smaller errors in simulated TCs and ET densities (Baker et al. 2022; Roberts et al. 2020). It is worth emphasizing that both

low-resolution and high-resolution models exhibit similar performance concerning the fraction of ET events. This suggests that the sensitivity of ET to resolution is primarily influenced by the resolution sensitivity of TC frequency rather than environmental conditions favorable for ET. However, the magnitude of ET events is not well reproduced by the typical resolution of the CMIP6 models, especially for the high-intensity tail of the warm-core distribution. In other words, thermodynamics associated with moist adiabatic rise of air and associated release of latent heat are still the keys in improving the structure of TCs as well as ET events. Consequently, employing a higher resolution model offers the potential to realistically simulate deep warm-core cyclones.

Another important aspect worth investigating is the impact of ET events in the future in terms of strong winds and precipitation. Cheung and Chu (2023) indirectly incorporated changes in the area of strong winds by considering integrated kinetic energy. Although the specific changes in the number of ET events may vary across different models and basins, it is anticipated that under conditions of higher water vapor levels in the future, convectively driven extreme rainfall will increase at a similar (or higher) rate as predicted by the Clausius-Clapeyron relation. Therefore, a better understanding and management of water resources and future disaster mitigation will necessitate considering the potential increase in winds and precipitation related to ET.

Since an ET event cannot develop without a TC forming in the first place, improving the simulation of TC is crucial for accurately representing the statistics of ET events in changing climate. The lack of intense model TCs in Cheung and Chu (2023), which agrees with Davis (2018), can explain the underestimation of the overall number of ET events in the same study. As climate models continuously improve towards the kilometer scale (e.g., Stevens et al. 2019), the inner core of simulated TCs is expected to be better resolved.

Several studies have hinted at the potential problem of CPS when it is applied to high-resolution datasets; Bieli et al. (2020) noticed strong local maxima in the geopotential height fields that required data pre-processing before the use of CPS, and Jung & Lackmann (2021) discerned the persistence of strong remnant warm-core vortex that caused CPS failed to determine the completion of ET. As a result, it is recommended to improve the detection of ET events by CPS by further understanding how high-resolution models can impact the outcome of CPS diagnostics and how data pre-processing should be performed in order to use CPS.

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Chapter 3

Rainfall Contribution by Cyclonic Disturbances Over India In Two Epochs During 1901–2021 and Risk Assessment



Jagabandhu Panda, Kasturi Singh, Geo Tom, Soumya Ranjan Mahapatra, and Debashis Paul

Abstract The peninsular Indian subcontinent bounded by the Bay of Bengal and the Arabian Sea is highly vulnerable to destruction induced by cyclonic disturbances (CDs). Besides the stronger devastating winds generated by the CDs, the torrential rainfall imparts floods and landslides over the places of landfall. To characterize the repercussions owing to the warming climate, trends of rainfall contributions from the CDs (CDR) over India for both the pre-warming (PWP: 1901–1946) and the current warming (CWP: 1947–2021) periods were examined. The CDs considered either crossed or grazed the Indian coastline, and the rainfall within a radius of 5° from the storm center has been considered. The average CDR for PWP is about 60–70 mm/year, while the CWP accounts for over 110 mm/year, with an increasing trend during the pre-monsoon season. The CDR percentage contribution analogous to the seasonal rainfall over India is within 30% for PWP; however, it is nearly 80% for CWP. Additionally, for the post-monsoon season, the average rainfall is <80 mm/year and exceeds 140 mm/year for PWP and CWP, respectively. The variability in percentage contribution is like the pre-monsoon, even though there is an increasing trend for both epochs. Subsequently, the risk induced by the CDR in the coastal states of India is estimated using a statistical approach. The return levels characterize the probable annual maximum CDR via best-fit extreme value theory (EVT) model configuration. The EVT model results exhibit an analogous near-future trend in the eastern coastal states of India, i.e., Odisha, Andhra Pradesh, and Tamil Nadu. The EVT results indicate that these eastern coastal states would exceed the extremely heavy rainfall threshold induced by CDs in <10 years. However, the corresponding timeframe for

J. Panda (✉) · G. Tom · D. Paul

Department of Earth and Atmospheric Sciences, National Institute of Technology, Rourkela, Odisha, India

e-mail: pandaj@nitrkl.ac.in

K. Singh

Department of Mathematics and Statistics, University of Exeter, Exeter, UK

S. R. Mahapatra

National Atmospheric Research Laboratory, Department of Space, Indian Space Research Organization, Gadanki, AP, India

the western coastal states would be >20 years. Also, the western coastal states of Karnataka, Kerala, and Maharashtra could become prone to excessive hazards induced by extreme CDR in the far future.

Keywords Cyclonic Disturbance (CD) · CDs contributed rainfall (CDR) · North Indian Ocean (NIO) · Warming climate

3.1 Introduction

Cyclonic disturbances (or CDs) are globally ranked as the second major cause of severe fatalities among all kinds of natural disasters (Breña-Naranjo et al. 2015). In the North Indian Ocean (NIO) basin, the CDs encompass depressions (with maximum sustained wind (MSW) 17–33 kts or 31.5–62 km.hr.⁻¹) and tropical cyclones (TCs) with MSW of 34 kts (~63 km.hr.⁻¹) and more (Goyal et al. 2013). These systems gained importance because of the destruction associated with their strong wind, storm surge, coastal flash floods, and heavy rainfall. When these devastating systems approach the coast, the combined effect of storm surge, torrential rain, and severe winds cause massive devastation. While the CDs travel inland, apart from the wind and intensity, these systems pour significant rainfall even after several hours of landfall. Since the NIO basin is partially landlocked and is comparatively small, most of the systems make landfall (Singh et al. 2019a, 2020b) over the landmass of India. A large percentage of the population resides along the coastal regions of India, which makes it more vulnerable to CD-related disasters.

The cyclone season over NIO is bimodal, i.e., the highest number of CDs form in the post-monsoon season (October to December), and the second-highest genesis occurs in the pre-monsoon season (March to May). Singh et al. (2019b) observed that although the trend in annual frequency of CDs is decreasing over NIO, the rate of intensification of depressions to severe CDs has increased under the impact of a warming climate. About 60% of systems intensify into severe ones in the current climate conditions over NIO. Out of the total number of systems formed over the Bay of Bengal (BOB) and Arabian Sea (AS), ~84.8% and 34% make landfall, respectively, over the eastern and western coastal places of India (Singh et al. 2019a). These systems generate heavy rainfall over the coastal areas and sometimes in the interior districts of India (Singh et al. 2020b).

The seasonal reversal of the monsoon wind systems (south-west and north-east monsoons), the tremendous influx from riverine discharges, and the reversal of ocean currents are the apparent features of NIO (Shetye 1998; Monolisha et al. 2018; Albert and Bhaskaran 2020). Also, the sea surface temperature (SST) and ocean heat content (OHC) are some of the important factors that make the ocean more favorable for TC formation (Tiwari et al. 2022). The tropical warm waters present in the NIO basin that is signified by an increase in SST make it more active for cyclogenesis (Singh et al. 2019a, b; Tiwari et al. 2022; Mohan et al. 2021; Panda et al. 2023). The occurrence of cyclones influences ocean currents, surface waves, temperature, salinity, and biological activities. On the surface, it causes the upper

ocean near-inertial currents, increases strong surface waves, decreases SST, and increases the salinity; however, in the sub-surface, it leads to warming of the sub-surface ocean, decreases salinity, and causes phytoplankton blooms (Zhang et al. 2021). Chowdhury et al. (2020b) highlighted that the increase in chlorophyll concentration and a noticeable interaction of cyclone Madi with the cold core eddies reduced the upper-ocean heat content in BOB, which led to a track reversal. Similarly, Chowdhury et al. (2020a) highlighted a reduction in SST and an increase in chlorophyll concentration after the passage of the extremely severe cyclones Chapala and Megh formed over AS. Besides, the concurrent occurrence of TCs, Titli in the BOB, and Luban in the AS showed variability in the upper ocean response (Chowdhury et al. 2021) as well. Thus, an interactive feedback mechanism exists between the upper ocean characteristics and the cyclones formed over the respective basins, which governs the intensification process and, indirectly, the CD contributed rainfall (CDR).

Climate patterns such as El Nino Southern Oscillation (ENSO) modulate the TC activity globally. Since the large-scale environmental factors primarily direct the TC characteristics (i.e., their genesis, track, intensity, and landfall), and the climate modes significantly alter the atmospheric and ocean conditions, in effect, they influence the TC activity (Camargo and Hsiang 2015; Zheng et al. 2015). The atmospheric variabilities include changes in vertical wind shear, humidity, low-level vorticity, the strength and position of subtropical highs, and the ocean parameters include SST, upper-ocean heat content, etc. (Lin et al. 2020). The effects of ENSO are also experienced beyond the Pacific Ocean owing to atmospheric teleconnections. In the Western North Pacific basin, a normal or above normal TC activity is experienced in the El-Nino years, whereas La-Nina years exhibit a normal or below normal activity (Chan 1985). Over the NIO basin, the influence of ENSO on TC activity is majorly observed during the post-monsoon season. Like the other global basins, BOB shows less intense TCs during the El-Nino years and intense TCs during the La-Nina years (Singh et al. 2000). Like ENSO, the Indian Ocean Dipole (IOD) has a significant role in regulating TC activity over the NIO. During the positive (negative) phase of IOD, the SST anomalies are positive (negative) in the west and negative (positive) in the eastern part of NIO. The reduced (enhanced) convection results in lower (higher) TC genesis and inhibits (favors) the TC occurrence probability in NIO (Yuan and Cao 2013). Besides ENSO and IOD, sub-seasonal factors such as Madden-Julian oscillation (MJO) modulate the TC activity in all the basins (Klotzbach and Oliver 2015). The TC activity in BOB is observed to be enhanced during the active phase of MJO located over the eastern Indian Ocean and the Maritime Continent (Tsuboi and Takemi 2014; Girishkumar et al. 2015; Bhardwaj et al. 2019). Singh et al. (2021) reported that MJO and anomalously higher SST generate a conducive dynamic and thermodynamic condition for the genesis of extremely severe cyclone Fani. MJO influences various factors associated with NIO TCs, viz., their numbers, lifetime, accumulated cyclone energy (ACE), power dissipation index (PDI), genesis location, tracks, etc. (Bhardwaj et al. 2019) as well. Since ENSO, IOD, and MJO impact the NIO TC activity and the

associated thermodynamics and dynamics, it may be said that these convective events would indirectly influence the CDR.

Several pieces of literature are available that examine the CDR variability over different countries (Larson et al. 2005; Knight and Davis 2009; Yokoyama and Takayabu 2008; Jiang and Zipser 2009; Dare et al. 2012). For Australian regions, during the peak season (January–March), ~40% of rainfall is contributed by TCs along the coastal regions west of 120°E, while during December, the contribution is approximately 60–70% in the west of 115°E (Dare et al. 2012). Knight and Davis (2009) observed that TCs contributed ~15% of the total TC season rainfall over Carolinas (North and South) from 1980 to 2004. Along the USA, Gulf, and Mexican coasts, 15–20% of rainfall is contributed by TCs during 1950–80 (Larson et al. 2005). Yokoyama and Takayabu (2008) found that the annual rainfall contribution by TCs between 35°N and 35°S is 3.3%. TCs contribute ~30% of total rainfall during the NIO TC season over southeast coastal regions of Oman and south coastal areas of the Pakistan and Indian border (Jiang and Zipser 2009). Globally, the CDR variability and its significance reported by various studies, therefore, indicate an appreciable percentage of contribution over the associated landmass concerning respective basins.

The inter-annual variation of the CDR was noticeable over the coastal regions of BOB (i.e., Tamil Nadu, Andhra Pradesh, Odisha, and West Bengal) from 1998 to 2016 (Uddin et al. 2019), and over the NIO region, it was ~5% during 1998–2006 (Jiang and Zipser 2009). The cyclones developed over the BOB contribute significant rainfall over Kerala during the post-monsoon season (Krishnakumar et al. 2009). The correlation between rainfall received during monsoon season and the frequencies of CDs is very low, i.e., ~0.08 (Dhar et al. 1980); however, a deficiency in rainfall is evident in the absence of CDs during September. Notably, the amount of rainfall contributed by CDs is less correlated to the annual CD frequency.

India is prone to landfalling cyclones along its BOB and AS coasts (Singh et al. 2019a). In the case of the Fani cyclone (in 2019), which made landfall over the Odisha coast (20.95°N, 85.09°E), the rainfall occurred at a rate of 25 mm/hour in rainbands around the center (<https://blogs.nasa.gov/hurricanes/tag/fani-2019/>). Though the loss of life was comparatively less because of well-preparedness by different government agencies and the residents of coastal regions, the property and economy-related damage was very high. Moreover, in one of our recent studies, the average CDR over the Indian region is found to be up to 100 mm/year during the pre-monsoon season and 140–180 mm/year during the post-monsoon season in the current climate scenario (Singh et al. 2020b). Similarly, the percentage contribution is up to 70% during pre-monsoon and 60% during post-monsoon season. The study focused on the variation in CDR, specifically in a warming climate, and the importance of having a comparative analysis of the corresponding variabilities during pre- and post-warming scenarios was realized, which would enhance further understanding in this direction. Although the climatological variation in NIO CD activity is well-documented (Mohanty et al. 2012; Mohapatra 2015; Singh et al. 2019a, b, 2020b), the alteration in CDR still needs to be addressed properly.

Various methodological frameworks were used to address the future risks associated with extreme events. Initially, empirical models were used to quantify the extreme hurricane wind speed by assigning a certain threshold; however, it could be appropriate for wind speed estimations greater than 100 years only (Darling 1991). Later, a statistical probabilistic technique by adopting extreme value theory (EVT) was widely applied and seemed to be a valuable tool for estimating the probability of occurrence of random events (Ahmad et al. 2023). The EVT models have been generally applied to estimate the return period of TC extreme wind speeds. For instance, Rupp and Lander (1996) employed the technique to estimate the return period over Guam Island in the North Pacific. A reverse Weibull distribution incorporated with a peak-over threshold method was adopted to quantify the hurricanes' extreme wind speed across the coastline of the US (Heckert et al. 1998). Similarly, the TC's extreme wind speed risk over BOB has been quantified by Bhardwaj et al. (2020) by adopting a probabilistic estimation approach that considers the maximum sustained wind speed experienced over the region. It utilized EVT and adopted a specific distribution to categorize the sectorial risk variability over the BOB region. The study introduced certain indices, including probable annual maxima, the maximum expected number of TCs, return period, etc., to quantify risk. To incorporate the higher variabilities, the EVT via frequentist and Bayesian estimations using block maximum and peak over the threshold (POT) approaches have been utilized (Coles et al. 2001; Bücher et al. 2019; Ahmad et al. 2022) as well.

Thus, developing efficient disaster impact mitigation strategies and capacity-building frameworks to effectively bridle losses and damages, as well as reliable and potent information regarding possible future catastrophic events, is essential. Therefore, this study intends to perform a comparative analysis of CDR over India during the current and pre-warming conditions by considering the bimodal aspect of NIO CD activity during 1901–2021. The risk induced by CDR has been estimated in the coastal states of India using a statistical probabilistic approach.

3.2 Data used and Techniques Adopted

3.2.1 Datasets Used

To perform a comparative analysis of rainfall contribution by CDs during the pre-warming and current warming climate, it is necessary to divide the whole period of 121 years into two separate epochs. For the said purpose, the sea surface temperature (SST) from the International Comprehensive Ocean-Atmosphere Data Set (ICOADS; <http://icoads.noaa.gov/>) has been used in our earlier studies (Singh et al. 2019a, b) to determine the two epochs, i.e., pre-warming period (PWP) and current warming period (CWP). Accordingly, the period from 1947 onwards has been considered CWP, and the period earlier, i.e., from 1880–1946, has been taken as PWP. Notably, the positive SST anomaly trend starting in 1947 became the

determining factor of these two periods, and thus, the classification is based only on ocean warming.

The best track dataset is obtained from the India Meteorological Department (IMD) archive (<https://rsmcnewdelhi.imd.gov.in/>) and has been used to get the position and center of CDs. The cyclone e-atlas is available at 5° horizontal grid spacing, and the details of the data set may be learned from the IMD technical note version 2.0/2011 (IMD 2011). Notably, Singh et al. (2020b) comprehensively analyzed the robustness of best-track data and associated cyclone activity over the NIO basin during and before the satellite era. The study noted that data from 1961 onwards is adequately robust with the advent of satellite technology. Also, it specifies an undercount of severe cyclones during the pre-satellite era. However, these errors can be considered negligible, given the comparatively smaller size of the NIO basin. Therefore, the IMD best track data can be regarded as acceptable enough for analyzing cyclone activity in this basin, especially on a climatological scale. Moreover, several studies have used and referred to the IMD best track and e-atlas datasets for the climatological analysis (Singh et al. 2019a, b; Kumar et al. 2021, 2023). Similarly, the rainfall values are obtained from the gridded IMD product available at a spatial resolution of $0.25^\circ \times 0.25^\circ$ (https://www.imdpune.gov.in/cmpg/Gridddata/Rainfall_25_NetCDF.html). Several studies have been conducted to ensure the accuracy of IMD gridded rainfall products by comparing them with other existing observational and reanalysis products (Pai et al. 2014; Kishore et al. 2016; Prakash et al. 2015). Some studies (Chakra et al. 2023; Pai et al. 2015; Singh et al. 2020a; Panda et al. 2024) also incorporated the IMD gridded rainfall product for long-term analysis. Therefore, it is reasonable to consider the IMD gridded rainfall product to comprehend the spatio-temporal variability in a climatological context over India, and the choice of the data is very well justified.

3.2.2 Methodologies and Techniques Adopted

The CDR is computed partly following the methodology described by Dare et al. (2012) and Singh et al. (2020b). The rainfall within a radius of 5° from the center of the CD is considered to be associated with the storm and the surrounding rainbands (Singh et al. 2020b). The choice of 5° is consistent with Larson et al. (2005), Kim et al. (2006), Lee et al. (2010), Lonfat et al. (2004), Lau et al. (2008), Yokoyama and Takayabu (2008), Jiang and Zipser (2009), Nogueira and Keim (2010). Notably, the average size of the CDs over NIO lies within 600 km (Kumar et al. 2021; <http://rsmcnewdelhi.imd.gov.in/>), and hence, the choice of 5° radius minimizes the chances of over-estimation of CDR. Therefore, the rainfall contribution for each CD is considered only when its center is located within 500 km of the Indian sub-continent and covers more than half of the area of the nearby grid boxes. Also, the CDR values are collected along the path of travel after the landfall of CDs.

The 'F test' is conducted at a 95% confidence level, to test the significance of the results obtained for annual variations of CDR. It is a variance test that determines

whether the variability of two groups differs. In this study, the F test helped determine whether the warming climate impacts the CDR contribution.

To capture the future probabilities and risks associated with CDR over the coastal states of India, statistical techniques primarily based on EVT have been adopted. The probable annual maximum CDR is regarded as a proxy to indicate the risk and physical vulnerability of each coastal state of India. The generalized extreme value (GEV) models in frequentist and Bayesian inferences and different parameter estimation scheme configurations, i.e., maximum likelihood estimation (MLE), generalized MLE (GMLE), and linear moment (L-mom) are used. Also, the gamma model in the block maximum method, the generalized Pareto (GP), and the exponential models using the peak over threshold (POT) model are employed in the study. The POT approach applies a cut-off level and considers all values above it as a secondary sample, whereas the block maximum splits the data into equal-sized chunks and allows only the maximum of each block as a secondary sample. In the present work, the annual maximum daily CDR over each coastal state is considered a block and used as input to the statistical models. Moreover, the POT approach over the block maximum is also used to examine the characteristics of model fitting. The prior technique excludes the tails generated via insignificant annual CDR values. The gamma, GP, and exponential models are configured with the MLE parameter estimation scheme for the current study. Similarly, the parameters for the Bayesian framework are executed using the GEV with MLE via the non-informative priors (NIPs) concept. The cumulative distribution function of GEV (Park et al. 2011; Hossain et al. 2021) is given as follows:

$$G(Y; \theta) = \exp \left\{ - \left[1 + \xi \left(\frac{Y - \mu}{\sigma} \right) \right]^{\frac{-1}{\xi}} \right\} \quad (3.1)$$

where Y represents the annual maximum rainfall data, and $\theta(\mu, \sigma, \xi)$ represents the location, scale, and shape parameters of the GEV distribution, respectively. According to the values of the shape parameter, the distribution can be of three types (Martins and Stedinger 2000), i.e., Gumbel

$$G(Y; \theta) = \exp \left\{ - \exp \left(- \frac{Y - \mu}{\sigma} \right) \right\}; \xi = 0 \quad (3.2)$$

Fréchet

$$G(Y; \theta) = \exp \left\{ - \left(\frac{Y - \mu}{\sigma} \right)^\alpha \right\}; \xi > 0 \quad (3.3)$$

and Weibull distribution

$$G(Y; \theta) = \exp \left\{ - \left[- \left(\frac{Y - \mu}{\sigma} \right) \right]^\alpha \right\}; \xi < 0. \quad (3.4)$$

The cumulative density function of gamma distribution (Dagpunar 2019) is given as follows:

$$f(y; \alpha, \beta) = \frac{y^{\alpha-1} e^{-\frac{y}{\beta}}}{\Gamma(\alpha) \beta^\alpha} \quad (3.5)$$

where y represents the annual maximum rainfall data, α and β represent the location and rate, respectively. $\Gamma(\alpha)$ indicates the gamma function. If $\alpha = 1$, the function tends to be exponential, and if $\beta = 1$, the function becomes standard gamma distribution. The cumulative density function of GP distribution (Andrade et al. 2017) can be written as:

$$G(x; \xi, \sigma) = \left\{ 1 - \exp\left(-\frac{x}{\sigma}\right) \right\}; \xi = 0 \quad (3.6)$$

$$G(x; \xi, \sigma) = \left\{ 1 - \left[1 + \xi \left(\frac{x}{\sigma} \right) \right]^{-\frac{1}{\xi}} \right\}; \xi \neq 0 \quad (3.7)$$

Further details regarding the models, parameter estimation techniques, inferential statistics, etc., relevant to this study are included in Sect. 3.10.

To quantify the uncertainties and select the best-fit model for the region under consideration, several error estimations, viz., root mean square estimates (RMSE), relative absolute error (RAE), and model assessment techniques quantile (Q-Q), probability (P-P) fit tests were carried out. The estimated parameters for different models were also assessed by analyzing standard errors (SE), confidence interval (CI), Akaike information criterion (AIC), and the Bayesian information criterion (BIC).

Based on earlier studies (e.g., Mohanty et al. 2012; Singh et al. 2019a, b), the years before 1947 may be considered as PWP, i.e., the epoch 1901–1946 is referred to as PWP for the current study. Notably, the consideration is bounded by the availability of the IMD gridded rainfall product from 1901. Starting from 1947, the epoch is referred to as CWP to discuss the results obtained. Also, the bimodal nature of CD activity during pre-monsoon and post-monsoon months enriches the comparative analysis.

3.3 Crossed and Grazed CDs to Indian Coast

The CDR contribution over India is basically from the systems that crossed or grazed the coast. Therefore, before analyzing the CDR statistics, it is necessary to examine the CDs that crossed or grazed the Indian coast. Here, “crossing system” means the CDs crossing the coast, and grazing means the systems are located within 500 km of the coast without crossing it (Dare et al. 2012). The track of the systems crossing or grazing India during the warming climate is represented in Fig. 3.1.

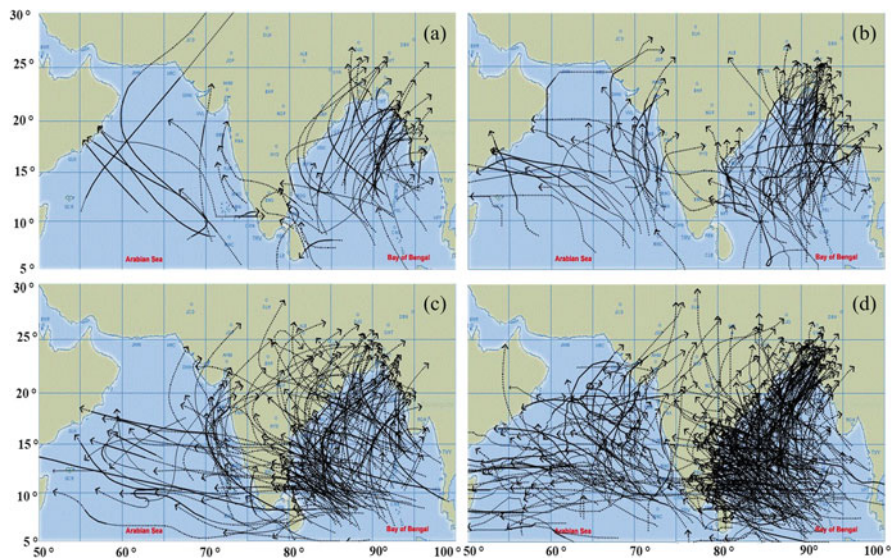


Fig. 3.1 Tracks of CDs crossing or grazing the Indian coast during pre-monsoon (a, b) and post-monsoon (c, d) seasons for PWP and CWP. The first column represents PWP and the second column represents CWP. The figure has been generated using the Cyclone eAtlas portal of the India Meteorological Department (<http://14.139.191.203/Login.aspx>)

During pre-monsoon season, 64 numbers of systems were observed, out of which 53 CDs either crossed or grazed the coast, i.e., 83% either crossed or grazed the coast during PWP. However, during CWP, 111 CDs are observed over the NIO region in the pre-monsoon season. Out of these, about 86 (77.47%) systems crossed or grazed the Indian coast. However, during the post-monsoon season, 195 CDs formed in PWP over the NIO region, out of which 89% (174 systems) either crossed or grazed the Indian coast. NIO region experienced 355 CDs during the post-monsoon months of CWP, and about 80.84% (287) of them crossed or grazed the Indian coast.

During CWP, the number of systems crossing or grazing the Indian coastal states has increased compared to PWP for pre-monsoon season. A higher number of BOB CDs are observed to be making landfall over southern and eastern coastal areas of the Indian region. Similarly, for western coastal places of India, a greater number of grazing systems are observed during pre-monsoon seasons of CWP in comparison to that of PWP (Fig. 3.1b), and enhanced genesis over AS is evident near south-western coastal places (Singh et al. 2019a). In post-monsoon season, the number of CDs crossing interior northeastern Indian states was more during PWP when compared to CWP (Fig. 3.1c). During CWP, the landfall of CDs over the southeastern parts of India has increased (Fig. 3.1d).

3.4 Average CDR and CD Frequency

During the pre-monsoon season of PWP, the rainfall trend is observed to be appreciably increasing along with the number of crossing or grazing CDs (Fig. 3.2a). The rainfall activity increased during PWP in the early 1920s for the pre-monsoon season. During CWP, the number of CDs either crossing or grazing the Indian coastline displays a decline, whereas an appreciable rise in CDR is observed (Fig. 3.2c). The average CDR value ranges to 55 mm in recent climate conditions for pre-monsoon season. The F-test for CDR variation during PWP and CWP shows that the null hypothesis for both epochs is rejected, i.e., the variances of the two epochs are unequal. The F-statistics is found to be 2.967, the F-critical is 1.686, and $p = 0.00044$. The results are statistically significant since the F- statistics are higher than F-critical and have a lower p-value. Specifically, the variances for PWP and CWP are 129.954 and 385.671 mm², respectively. In the CWP epoch, a significantly high variance of average CDR, i.e., almost three times higher compared to PWP, can be observed. Notably, the variance indicates the dispersion of the parameter considered. Thus, the results indicate that the average CDR rate has a noticeable variability in the CWP and can be due to the impact of a warming climate.

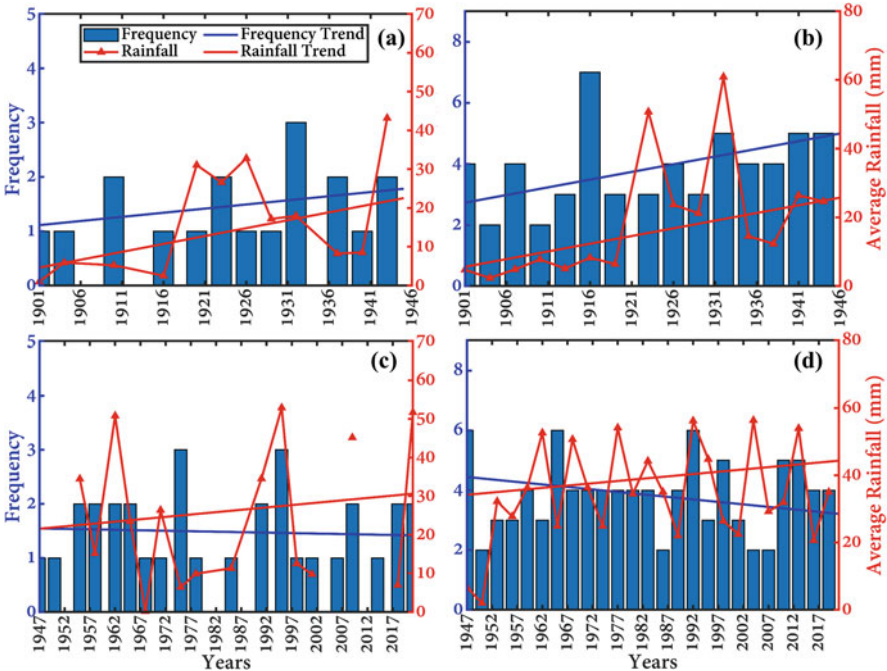


Fig. 3.2 Average CD rainfall (red) and crossed/grazed CDs count (blue) during PWP (a, b) and CWP (c, d) for pre-monsoon and post-monsoon seasons. The first column represents the pre-monsoon season, and the second column represents the post-monsoon season

During post-monsoon season, CDR contribution and crossing or grazing CD frequency are observed to increase during PWP (Fig. 3.2b). However, during CWP, the crossing or grazing CD frequency is decreasing. The average CDR contribution is maintaining a slight increase (Fig. 3.2d). The current findings are allied with the inferences by Deshpande et al. (2021); the past decades account for a significant (insignificant) increase in the frequency of cyclonic storms (CS; 18–24 m. s⁻¹) and very severe cyclonic storms (VSCS; 33–46 m.s⁻¹) in AS (BOB); however, a few are crossing the east coast of India, and the majority are traveling northward or recurving to the east. Thus, the prevalence of severe TCs for a longer duration generates heavy rainfall in the current climate scenario. The rainfall contribution by CDs in PWP and CWP ranges up to 78 mm in the post-monsoon season, which is comparatively higher than the pre-monsoon months over India. The crossing or grazing CD frequency during post-monsoon season shows a trend similar to pre-monsoon; both seasons account for a maximum of 7 CDs per year. Therefore, the possibility of higher CDR contribution with more peaks during the post-monsoon season of CWP lies in the contribution by individual CDs (Singh et al. 2020b) besides the increased CD frequency. For the post-monsoon season, the variances for PWP and CWP are 155.19 and 231.97 mm², respectively, and a large variation in rainfall is also evident during CWP than in PWP from Fig. 3.1. The F-test results for the post-monsoon season show an F-statistics of 1.494, F-critical to be 1.586, and p value of 0.0757.

3.5 Spatial Variability of Average CDR Contribution

A distinct impact of the warming climate on CDR spatial distribution over India can be realized when Figs. 3.3a–d are compared. During pre-monsoon season, the CDR contribution is relatively higher over the eastern and southwestern states of India when compared to other parts during PWP. However, the CDR contribution over eastern parts of India, specifically Andhra Pradesh, Odisha, Tamil Nadu, and West Bengal, increased during CWP in the pre-monsoon season (Fig. 3.3b). The western parts of Rajasthan and Gujarat received a considerably enhanced amount of CDR during CWP (Fig. 3.3b) compared to PWP (Fig. 3.3a). The maximum average CDR during pre-monsoon season shows ~60–70 mm during PWP and above 110 mm during CWP. In the pre-monsoon season of CWP, a significant increase is observed over coastal Andhra Pradesh, North-Eastern Odisha, western Rajasthan, and Gujarat, coastal belts of Kerala, Karnataka, and Goa regions in comparison to PWP.

In post-monsoon season, most of the interior places over southern, central, and North-Eastern India were observed to receive appreciable CDR during PWP (Fig. 3.3c), while during CWP, the North–Western regions also accounted for a higher contribution of CDR (Fig. 3.3d). However, the CDR contribution increased over some of the Northern regions of India during CWP (Fig. 3.3d). Coastal Andhra Pradesh, Tamil Nadu, and Odisha received higher CDR in the CWP epoch, and the maximum average CDR contribution is observed to be ~140 mm. In PWP, the western coastal regions received higher CDR with a maximum of ~60 mm. The

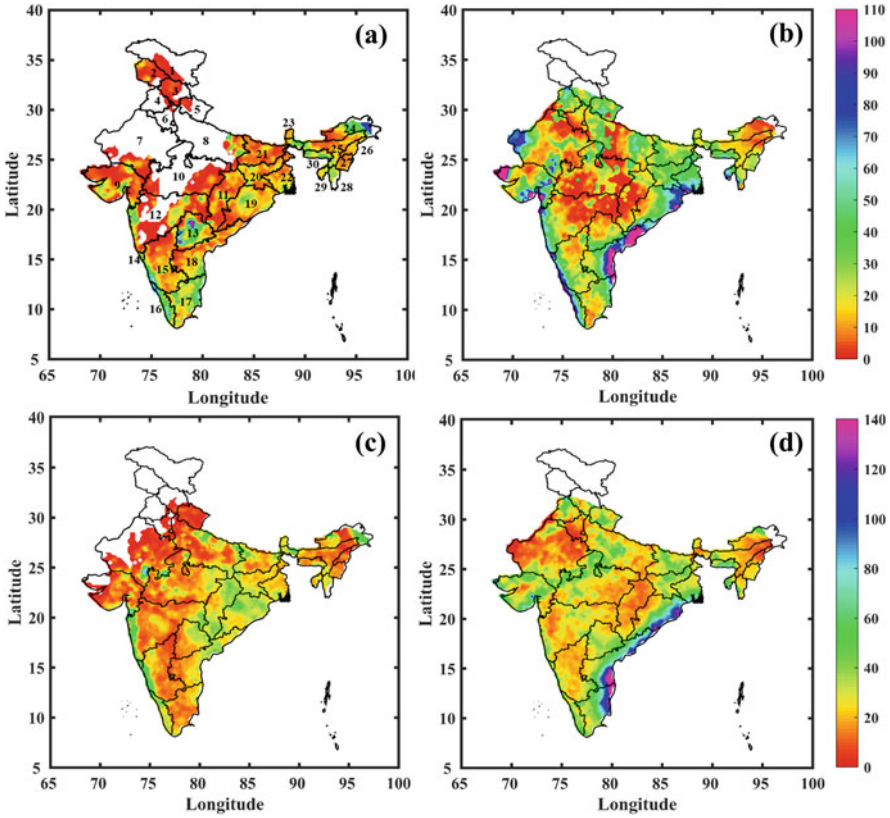


Fig. 3.3 Average accumulated CD rainfall during pre-monsoon (a, b) and post-monsoon season (c, d) for PWP and CWP. The left column represents PWP, and the right one represents CWP. The numbers in (a) signify different states or regions of India, i.e., 1-Ladakh, 2-Jammu and Kashmir, 3-Himachal Pradesh, 4-Punjab, 5-Uttarakhand, 6-Haryana, 7-Rajasthan, 8-Uttar Pradesh, 9-Gujarat, 10-Madhya Pradesh, 11-Chhattisgarh, 12-Maharashtra, 13-Telangana, 14-Goa, 15-Karnataka, 16-Kerala, 17-Tamil Nadu, 18-Andhra Pradesh, 19-Odisha, 20-Jharkhand, 21-West Bengal, 22-Bihar, 23-Sikkim, 24-Arunachal Pradesh, 25-Assam, 26-Nagaland, 27-Manipur, 28-Mizoram, 29-Tripura, and 30-Meghalaya

CDR contribution is observed to have increased over Jammu and Kashmir, Himachal Pradesh, and Punjab region, indicating increased CD dissipation over these places during CWP (Fig. 3.3d).

3.6 Spatial Variability of CDR Percentage Contribution

The percentage CDR contribution over India is generally higher over Gujarat during pre-monsoon and post-monsoon seasons irrespective of the epoch considered, except over some areas for the post-monsoon season of PWP (Figs. 3.4a–d). In

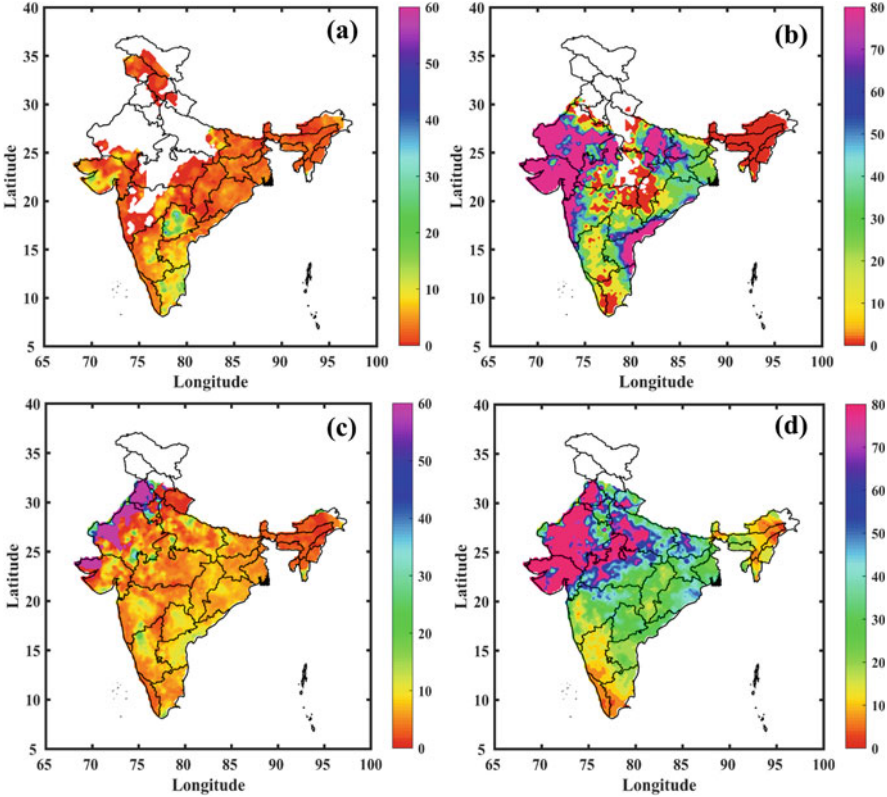


Fig. 3.4 Percentage contribution of CDR to the seasonal rainfall during pre-monsoon (a, b) and post-monsoon (c, d) months for PWP (left column) and CWP (right column)

pre-monsoon season, the percentage contribution of CDR over Gujarat is nearly up to 30% during PWP, and during CWP, the considered percentage ranges up to 80%. Rajasthan is also observed to receive ~80% of rainfall contributed by CDs during CWP, which was less (up to 10%) during PWP. As observed by Praveen et al. (2020), a highly positive trend was detected in the Rajasthan region, with little increase in rainfall over the region in a few years. They argued that a positive trend over Rajasthan does not guarantee an increased rainfall occurrence, although the region has received almost consistent amounts of rainfall throughout the period considered. The current analysis indicates an increase in the percentage of CDR contribution from PWP to CWP in pre-monsoon season, and the enhancement in CDR positively supports the total rainfall increment over Rajasthan. The east coast of India also receives considerably higher CDR contribution in CWP; however, the percentage maxima is seen over the eastern parts of Andhra Pradesh (Fig. 3.4b).

In the post-monsoon season, the highest percentage of CDR contribution is ~80% over Gujarat and Rajasthan during CWP, but the comparatively lower percentage contribution was observed over the region during PWP (~30%). Nearly 10–20% of

rainfall contribution was observed over most Indian states except the Northern regions of India in the post-monsoon seasons of PWP. The spatial distribution of percentage CDR contribution shows an increase during the CWP phase, majorly over eastern, central, and north-western regions (Fig. 3.4d). The increment in percentage contribution can be attributed to the intensity and life span (Deshpande et al. 2021), while an increase in rain intensity and storm radius is observed with the rise in TC intensity (Ankur et al. 2020). Thus, CDs are observed to generate higher contributions and cover more spatial extents in the CWP epoch of both seasons (Fig. 3.2d).

3.7 Spatial Distribution of CDR Trend

The spatial distribution of the trend of CDR over different places of India is observed to be increasing during PWP, primarily over the southern and slightly over the north-eastern parts (Fig. 3.5a). However, over most regions, a significantly increasing trend of CDR has been observed during the warming climate scenario. Over coastal Odisha, north-eastern Andhra Pradesh, West Bengal, and western Gujarat, the trend is increasing type during CWP, i.e., 0.4 to 0.8 mm/year (Fig. 3.5b). The CDR trend over western coastal regions and southern parts of Andhra Pradesh is decreasing by -0.4 to -0.6 mm/year.

During the post-monsoon season, the trend of CDR was increasing over the eastern and southern parts of India during PWP. The highest rise in CDR is observed over southern Andhra Pradesh and northern parts of Tamil Nadu, i.e., up to 1.4 mm/year (Fig. 3.5c). During CWP, the rainfall trend is slightly positive over Indian states; however, the eastern states account for a significant increase of ~ 0.4 – 0.6 mm/year. A reduction in CDR by -0.4 to -0.8 mm/year is observed over coastal places of Andhra Pradesh, Tamil Nadu, and Kerala during the CWP phase (Fig. 3.5d). Praveen et al. (2020) observed that the north-eastern states such as Nagaland, Mizoram, Manipur & Tripura, eastern Madhya Pradesh, Jharkhand, eastern Uttar Pradesh, Chhattisgarh, and Kerala experienced highly negative trends of rainfall during post-monsoon season. The trend of CDR over these states is nearly stable except in the eastern coastal states, where a positive trend in CDR is seen during both PWP and CWP. It indicates that the rainfall from other sources is decreasing over these states during the post-monsoon season, which is responsible for the decrease in the trend in total rainfall.

3.8 Variation of Seasonal CDR Percentage Contribution

The percentage contribution of CDR to total rainfall is observed to vary significantly during PWP and CWP for the pre-monsoon season (Fig. 3.6a). In PWP, most years have a CDR contribution of $<10\%$, whereas a considerably higher contribution can

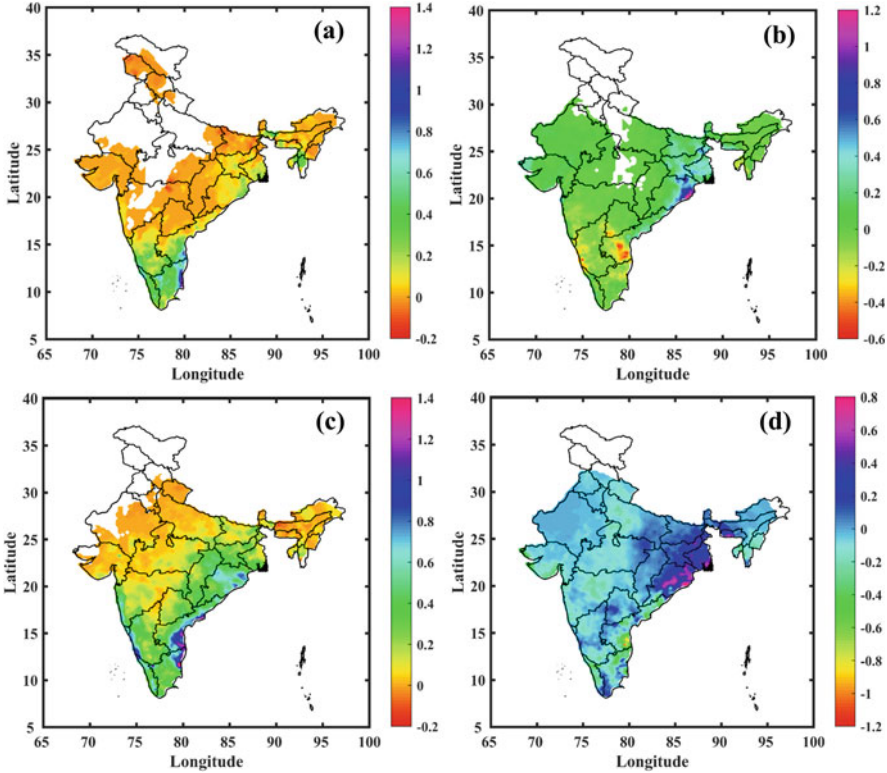


Fig. 3.5 Spatial distribution of trend of CDR during pre-monsoon (a, b) and post-monsoon season (c, d) for PWP and CWP. The left side represents PWP and the right column represents CWP

be observed in the CWP. Moreover, the bi-decadal trend over the pre-monsoon season reveals that the CWP epoch exhibits a significant incline in the CDR contribution, especially after the 1980s, whereas a slight increase is realized in the first two decades of PWP. During the post-monsoon season (Fig. 3.6b), the CDR trend is slightly stable in the first two decades of PWP; however, the percentage is nearly similar to the pre-monsoon season. The trends during the post-monsoon season of CWP indicate a significantly higher percentage of CDR contribution with an average of $>20\%$ compared to PWP. Similar bi-decadal trends can be observed in both seasons of CWP. While increasing CDR contribution trends are observed after 1980, a decline is visible during 1960–1980 in both seasons of the CWP epoch. Singh et al. (2020b) observed a stable trend in CDR when the crossing or grazing CDs during CWP are decreasing (Fig. 3.2d), indicating that some CDs contribute very heavy rainfall during the current climate. The percentage contribution upsurges during CWP (Fig. 3.6), while the actual CDR trend increases with decreased crossing or grazing CDs (Fig. 3.2d). However, most of the studies observed an increasing trend in the intense TCs in recent decades (Elsner 2020;

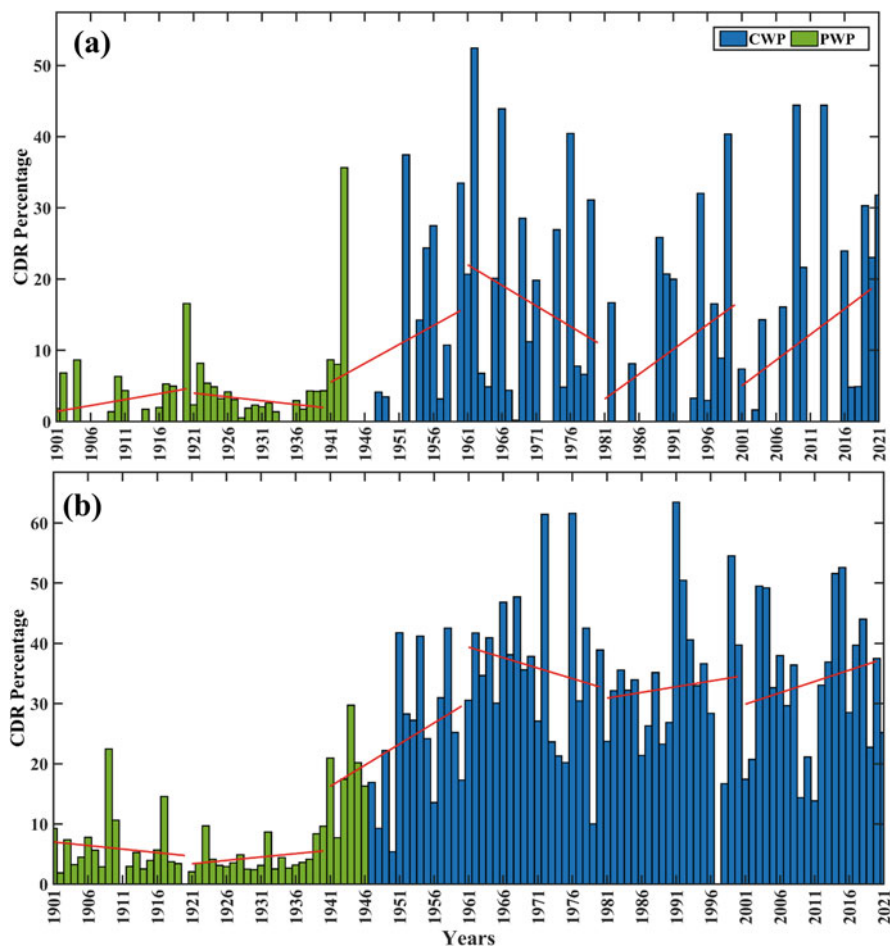


Fig. 3.6 Variation of CD rainfall percentage during pre-monsoon (a) and post-monsoon (b) seasons for PWP and CWP. The red line represents a linear trend for blocks of 20 years

Balaji et al. 2018) that effectively increases the rain intensity (Ankur et al. 2020), leading to a higher percentage contribution of CDR during CWP.

The results for the F-test for pre-monsoon seasons are $F\text{-statistics} = 5.339$, $F\text{-critical} = 1.686$ with $p\text{-value} = 4.547e-07$. The variances are 38.887 and 207.65 mm^2 , respectively, for PWP and CWP during pre-monsoon season. The results are statistically significant since the $F\text{-statistics}$ are higher than $F\text{-critical}$ and have a lower $p\text{-value}$. The current results show that the CWP epoch exhibits a higher range of variabilities in the percentage contribution of seasonal CDR compared to PWP. The statistical analysis for seasonal CDR percentage variation is found to be significant at a 95% confidence level for the post-monsoon season. The values of $F\text{-statistics}$ and $F\text{-critical}$ are 4.088 and 1.5865, respectively, with $p\text{-value}$

=1.0410e-06 for post-monsoon season. The corresponding variances for PWP and CWP are 41.622 and 170.1833 mm², respectively. Like the pre-monsoon, post-monsoon variabilities are significantly higher during the CWP epoch. Thus, the seasonal variation in the percentage contribution of CDR during CWP was quite large in comparison to PWP. In most years, CDs are responsible for a significant rainfall contribution, especially during the post-monsoon season.

3.9 Trend of Average CDR Over the Indian Coastal States

During the pre-monsoon season, the number of years with CD contributed rainfall over India are found to be significantly less (Figs. 3.7 and 3.8). However, during the PWP epoch, the CDR trend is increasing over the coastal states of India during the pre-monsoon season, with an abrupt increase over Tamil Nadu. The maximum seasonal CDR observed over the eastern coastal states of India, such as West Bengal, Odisha, Andhra Pradesh, and Tamil Nadu, is 86, 33, 40, and 101 mm, respectively. The corresponding values for the western coastal states of India are 10, 18, 46, 68, and 64 mm, respectively, for Gujarat, Maharashtra, Karnataka, Kerala, and Goa (Fig. 3.7). However, during CWP, the CDR trend declines over most coastal states except West Bengal, Odisha, and Gujarat. A significant decline can be observed over the southern coastal states of India, with a maximum over Goa. The effect of the warming climate over Kerala is reasonable, where a decreasing trend is observed during CWP. Over Odisha, the considered trend exhibits a rise (slope values are 0.10 and 0.28, respectively, during PWP and CWP) during CWP (Figs. 3.7 and 3.8). The

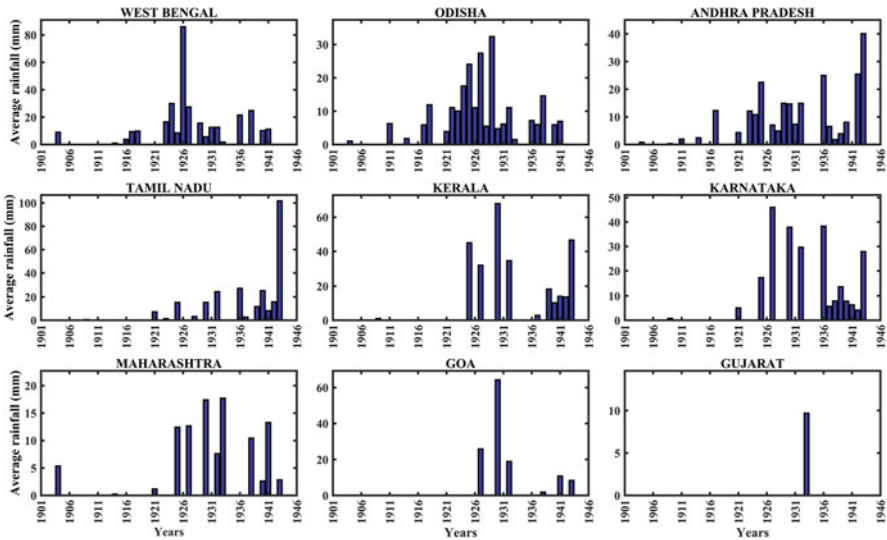


Fig. 3.7 Average rainfall over the coastal states of India during the pre-monsoon months of PWP

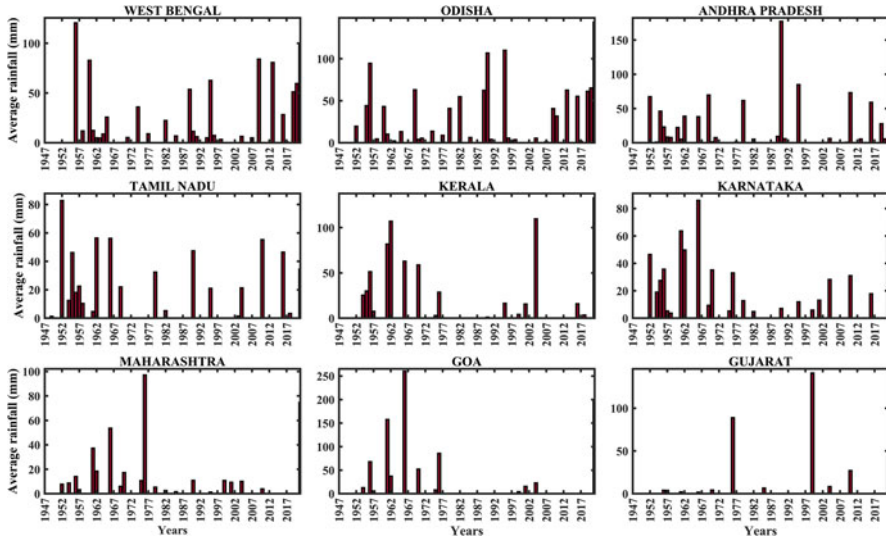


Fig. 3.8 Average rainfall over the coastal states of India during the pre-monsoon months of CWP

maximum CDR over coastal states of India during the pre-monsoon season of CWP is nearly 120, 109, 177, 82, 141, 97, 86, 107, and 260 mm, respectively, over West Bengal, Odisha, Andhra Pradesh, Tamil Nadu, Gujarat, Maharashtra, Karnataka, Kerala, and Goa.

During the post-monsoon season of PWP, the trend for CDR is observed to be increasing for all the eastern and western coastal states such as West Bengal, Odisha, Andhra Pradesh, Tamil Nadu, Maharashtra, Karnataka, Kerala, and Goa, while Gujarat accounts for limited CDR contributions and comparatively insignificant annual trend (Fig. 3.9). Over West Bengal, Odisha, Andhra Pradesh, Tamil Nadu, Gujarat, Maharashtra, Karnataka, Kerala, and Goa, the maximum CDR value for the post-monsoon season was nearly 110, 125, 71, 45, 56, 53, 71, 115, and 150 mm respectively during PWP as observed in Fig. 3.9.

The linear trend for CDR over the western coastal states of India and Tamil Nadu is decreasing during the post-monsoon season of CWP (Fig. 3.10). However, the trend was nearly stable over Andhra Pradesh and increased over Odisha and West Bengal during the post-monsoon months of CWP. The coastal states of Odisha, West Bengal, and Andhra Pradesh are more prone, whereas Maharashtra, Kerala, and Karnataka were observed to be least prone to TCs in recent decades (Singh et al. 2019a, b, 2020b; Kantamaneni et al. 2022; Boragapu et al. 2023). During the post-monsoon seasons of CWP, the maximum annual CDR observed over West Bengal, Odisha, Andhra Pradesh, Tamil Nadu, Gujarat, Maharashtra, Karnataka, Kerala, and Goa is nearly 140, 166, 196, 206, 205, 61, 103, 154 and 215 mm, respectively.

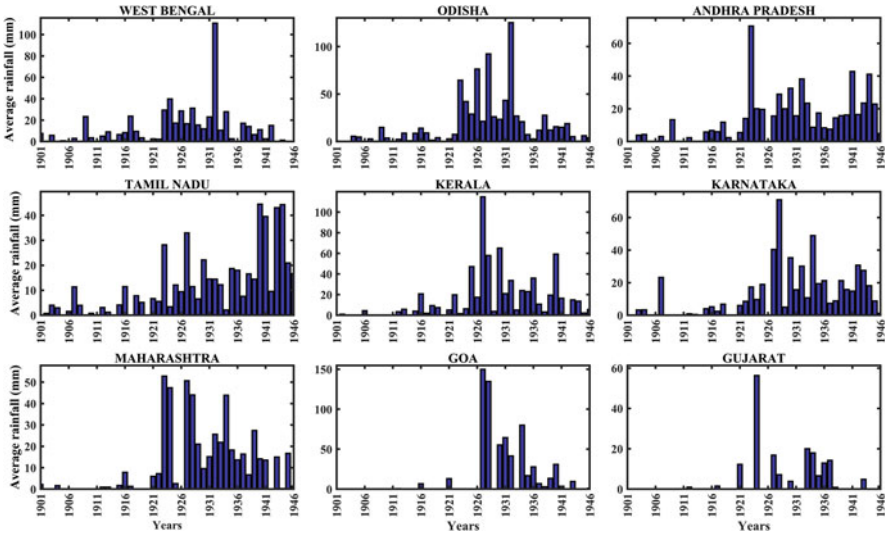


Fig. 3.9 Average rainfall over the coastal states of India during the post-monsoon months of PWP

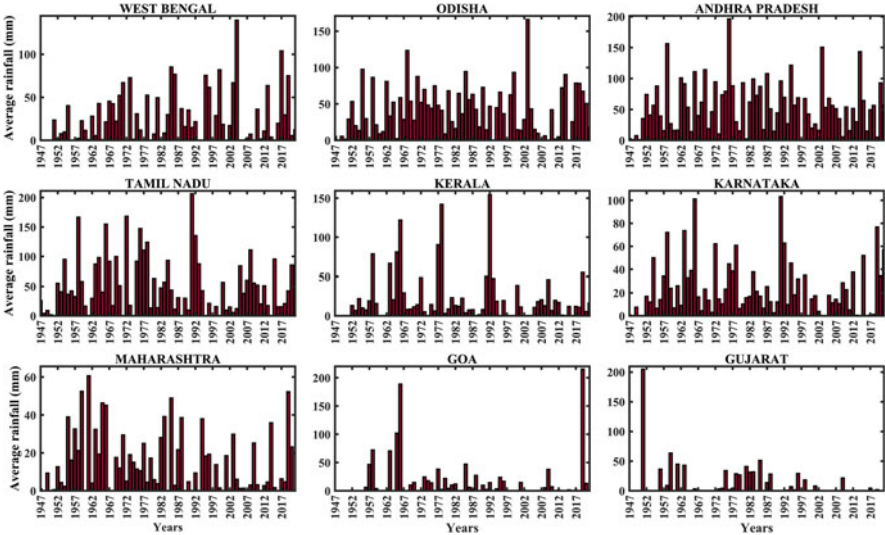


Fig. 3.10 Average rainfall over the coastal states of India during the post-monsoon months of CWP

3.10 Quantifying the Future Risks Using a Probabilistic Approach

To quantify the future risks concerning CDR, extreme value models are applied to the long-term data regionally. For this purpose, the annual maximum rainfall experienced over each state is calculated. The coastal states of India, viz., West Bengal, Odisha, Andhra Pradesh, Tamil Nadu, Kerala, Karnataka, Goa, Maharashtra, and Gujarat, are considered the coastal hotspots that are highly vulnerable to the impacts of CDR (Mohapatra 2015; Singh and Panda 2022). The coastal states account for an incessant annual trend in crossed or grazed CDs over the last centennial, except for Gujarat and Goa. To employ the theory, the data is assumed to be homogeneous, i.e., the impacts of influential factors are regarded to be persistent over the space and time frame of observation and for the period for which extrapolations are made. Based on the assumption of stationarity and to overthrow ambiguity due to discontinuity in data, the minimum of the long-term maximum annual CDR experienced over the region has been assumed to represent the particular year under consideration. As rainfall occurred over a domain of $\sim 7.85 \times 10^5 \text{ km}^2$ from the center of the CDs is regarded to be CDR, significant variability in yearly maxima is observed. Hence, the annual maximum daily CDR over the regions is limited from the very light to extremely heavy rainfall category within the time frame. The eastern and south-western districts account for more intense CDR during the CWP epoch than they did prior. In contrast, the states of Maharashtra, Gujarat, and Goa reveal a significant uncertainty in the data due to approximations. Thus, a 121-year sample sequence has been generated to perform the probabilistic assessment of CDR. Subsequently, the parameters for different models are estimated using frequentist and Bayesian approaches, and the uncertainties are quantified to find the best-suited model for each region.

3.10.1 *Parameter Estimation for Probabilistic Model Configurations*

Initially, the parameters of the GEV distribution are computed using MLE, L-moments, and GMLE estimation techniques in frequentist configuration. The location, scale, and shape define the characteristics of a random probabilistic distribution. In the MLE approach, the parameter vectors are determined by maximizing the negative log-likelihood concerning the unknown parameters (Ahmad et al. 2022; Hossain et al. 2021). However, generally, it underestimates negative values of the shaped parameter and is comparatively biased for small to moderate sample sizes (Coles and Dixon 1999). The L-moment utilizes linear combinations of probability-weighted moments that portray the distribution's shape (Hosking 1990). It produces more effective estimations of the characteristics, is less sensitive to variability and outliers in data, and is essentially unbiased to small sample sizes (Hosking 1990;

Hossain et al. 2021). Moreover, the GMLE estimation scheme is grounded on the basic MLE (Park 2005), but the limitations on the shorter sample are overwhelmed by comprising a further constriction to the shape parameter to avoid the large negative invalid values generated from the MLE (Yoon et al. 2010). This approach includes extra priori information on shape parameters to overcome bias. Distinct from the frequentist approach, the Bayesian method is a statistical inference technique incorporating prior knowledge about the probability model parameters. So, the method essentially bears a prior distribution and a likelihood function that generates a posterior distribution based on the Bayes theorem integrating both sources' combined weights (Coles and Tawn 2005; Ahmad et al. 2022). It can overcome the limitations due to small sample sizes in extreme time series data if reliable prior knowledge about the distribution is available. Also, the block maxima approach is extended to assess the model fit and parameter estimation capability of the gamma model in MLE configuration, commonly used to model the continuous distribution that exhibits positively skewed characteristics (Bhaumik et al. 2009). A two-parameter gamma distribution that uses a shape and inverse of the scale parameter, viz., the rate parameter, defines the distribution trait. Gamma distribution is considered a flexible model that captures positively skewed distribution effectively and can model various shapes (Husak et al. 2007; Chaudhuri and Sharma 2021), including exponential, chi-square, etc. The peak-over-threshold modeling techniques, with the MLE estimation scheme, are used along with the block maxima method. GP and exponential distributions are built to model the excess values over the threshold instead of maxima. The GP distribution is defined by two parameters, i.e., shape and scale, and is more sensitive to modeling the tails of a distribution (Andrade et al. 2017). In contrast, the exponential model uses a single scale parameter to describe the characteristics of the model distribution. The minimum of the annual maximum CDR is considered as the threshold to implement the POT approach on the annual extreme value technique. Hence, various model configurations by interchanging estimation techniques and statistical inference methods are adopted for the parameter estimation concerning risk assessment, and the uncertainties in estimated parameters are examined by standard error and confidence interval.

3.10.2 *Model Assessment*

The characteristics of the extreme value time series of the CDR incorporated with each coastal state show significant variations in the trend. To accommodate variability and reduce the bias in extrapolating future probabilities, all the model configurations discussed earlier are fitted to each coastal state under consideration. The GEV distribution, a combination of three extreme value distributions, i.e., Gumbel, Freshet, and Weibull distribution, has been fitted to the distribution based on the nature of the shape parameter. If the shape tends to zero, a positive or negative value defines the Gumbel, Freshet, or Weibull distribution, respectively (Coles et al.

2001). The GEV with Bayesian configuration in non-informative prior (NIP) mode has been adopted as well. The NIPs for the GEV are built by incorporating a parameterization to scale parameter, i.e., a logarithmic transformation to secure a positive constraint. Again, marginal independent NIPs with a mean zero and a larger variance, i.e., $N(0, 10,000)$, are used (Annazirin et al. 2012; Diriba and Debusho 2020; Ahmad et al. 2022). These are known as independent Gaussian prior, and the greater variance values are integrated to produce flat marginal priors, which display the absence of external information. A Markov Chain Monte Carlo (MCMC) combined with Metropolis Hasting (M-H) algorithm generates the posterior distribution. Moreover, Gamma and the POT models in MLE settings, i.e., GP and exponential, are tested over the domain.

The RMSE and RAE associated with each model fit are provided in Table 3.1, and the marginal distribution curves for each state are depicted in Figs. 3.11 and 3.12. The empirical cumulative distribution function and the modeled cumulative distribution function or the marginal distribution are computed from the actual data and the model parameter estimates, respectively. For West Bengal, Gamma MLE and GEV L-moment perform comparatively better; however, GEV with MLE, GMLE, and Bayesian underestimates in the later stages (Fig. 3.11b). The GP in MLE configuration displays a more significant bias in the initial and middle stages, although the exponential model shows a poor fit to actual estimates. In the cases of Odisha (Fig. 3.11c), Kerala (Fig. 3.12a), and Karnataka (Fig. 3.12b), the GEV L-moment indicates the best fit followed by Gamma MLE models.

The block maxima approach with frequentist estimation schemes generally better fits CDR in most regions under consideration. The Bayesian inference in NIP mode cannot capture the variability compared to the frequentist models. The state of Gujarat shows a higher departure owing to more significant model errors (Fig. 3.12e). The optimal extreme value distribution was selected as the marginal distribution for the following estimations.

3.10.3 *Estimate Return Levels for Annual Maximum CDR*

The assessment is extended to compute the maximum probable CDR or the return levels corresponding to various recurrence intervals. The return period or recurrence interval is the expected time break (or interval) between two consecutive occurrences of a given event. The estimation is executed for 2, 5, 10, 20, 50, 100, 300, and 500 years of recurrence intervals. Each coastal state's previously selected marginal distributions based on the lowest values of errors (Table 3.1) are used to estimate the return levels. Figures 3.13 and 3.14 show the estimated return level curves (solid lines) for the regions under consideration. The confidence interval corresponding to the marginal distributions is depicted as dotted lines in these figs. A narrow confidence interval range represents a relatively stable output. The marginal distribution that provides a minimum confidence interval range (least range of uncertainty) in return levels and minimal errors (Table 3.1) is used to filter the robust distribution.

Table 3.1 Comparison of the models and estimation of uncertainties by RMSE and RAE over coastal states under consideration. (Marginal distribution results are represented in *italics*)

Study Locations	GEV—MLE		GP—MLE		Exp.—MLE		Gamma—MLE		GEV—L-moments		GEV -GMLE		GEV Bayesian	
	RMSE	RAE	RMSE	RAE	RMSE	RAE	RMSE	RAE	RMSE	RAE	RMSE	RAE	RMSE	RAE
West Bengal	0.0967	0.4689	0.0547	0.1651	0.0720	0.2805	0.0338	0.1594	0.0369	0.1504	0.0444	0.1989	0.0806	0.3958
Odisha	0.0501	0.2009	0.0833	0.2460	0.1001	0.3310	0.0520	0.1991	0.036	0.1241	0.0493	0.1987	0.0486	0.1974
Andhra Pradesh	0.0335	0.1194	0.1042	0.2914	0.1228	0.3779	0.0664	0.2329	0.0258	0.0904	0.0317	0.1083	0.0321	0.1142
Tamil Nadu	0.0442	0.1921	0.0783	0.247	0.0902	0.3128	0.0395	0.1744	0.0341	0.1355	0.0439	0.191	0.0431	0.1909
Kerala	0.0545	0.2735	0.0751	0.2523	0.0928	0.3445	0.0272	0.099	0.0258	0.0939	0.0359	0.1636	0.0626	0.3221
Karnataka	0.0367	0.1725	0.0608	0.1657	0.0644	0.1875	0.0351	0.1367	0.0224	0.0839	0.0368	0.1729	0.038	0.1814
Goa	0.0536	0.4475	0.0822	0.7568	0.0454	0.3727	0.0343	0.1903	0.0478	0.3099	0.0487	0.3196	0.0527	0.4502
Maharashtra	0.1372	0.8859	0.0348	0.1468	0.0808	0.6100	0.0342	0.1420	0.0362	0.1439	0.0375	0.1665	0.1366	0.8824
Gujarat	0.0460	0.5350	0.0625	0.6258	0.0640	0.6519	0.0559	0.4314	0.0564	0.4645	0.0564	0.4645	0.1431	1.9095

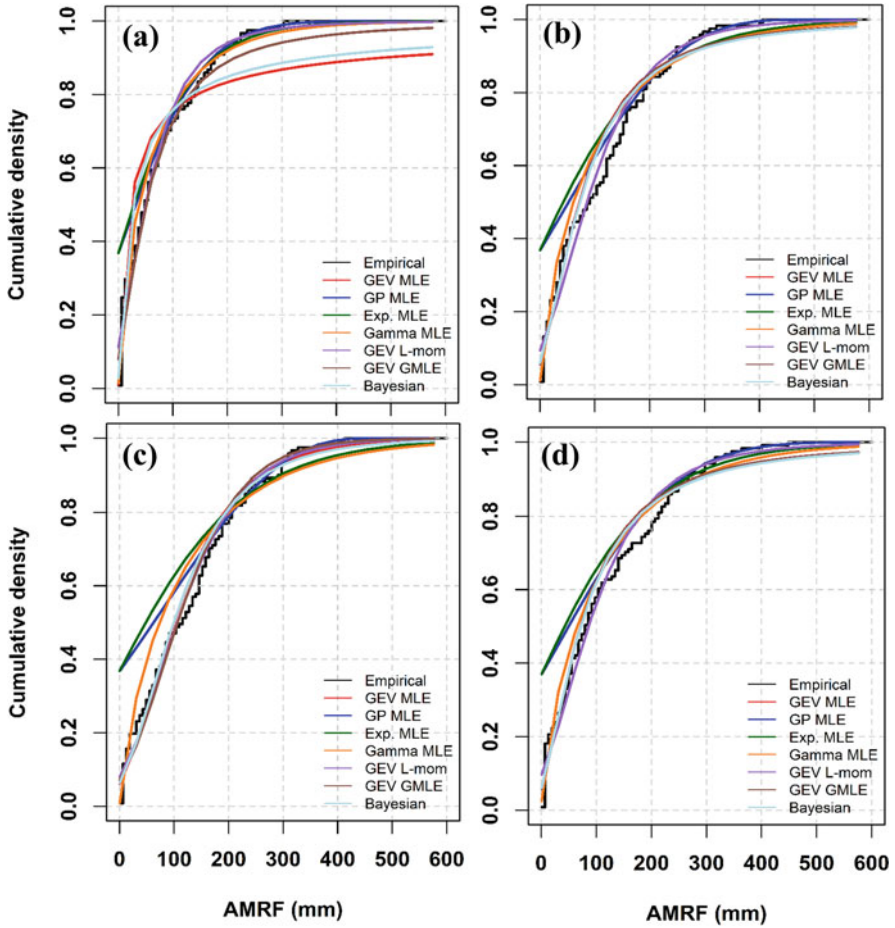


Fig. 3.11 Comparison of the model fitting results by the cumulative probability distribution curves for annual maximum CDR over eastern coastal states of West Bengal (a), Odisha (b), Andhra Pradesh (c), and Tamil Nadu (d)

Subsequently, the prior selected distribution is utilized to quantify the return levels for each coastal state of India (Table 3.2).

For West Bengal (Fig. 3.13a), the return levels are computed for Gamma-MLE and GEV-L-mom, and the outcomes are comparatively similar. However, the uncertainty is higher for the Gamma-MLE approach. GEV-L-mom is therefore used to estimate the return level for West Bengal. From the results (Table 3.2), the probable maximum CDR exceeds the extremely heavy rainfall (> 244.5 mm/day) once in <20 years. Likewise, the state might experience CD-induced heavy rainfall (64.5–124.4 mm/day) once in 5 years.

For Odisha (Fig. 3.13b), GEV L- mom is only considered since the prior distribution provides an acceptable range of uncertainty. Like West Bengal, Odisha

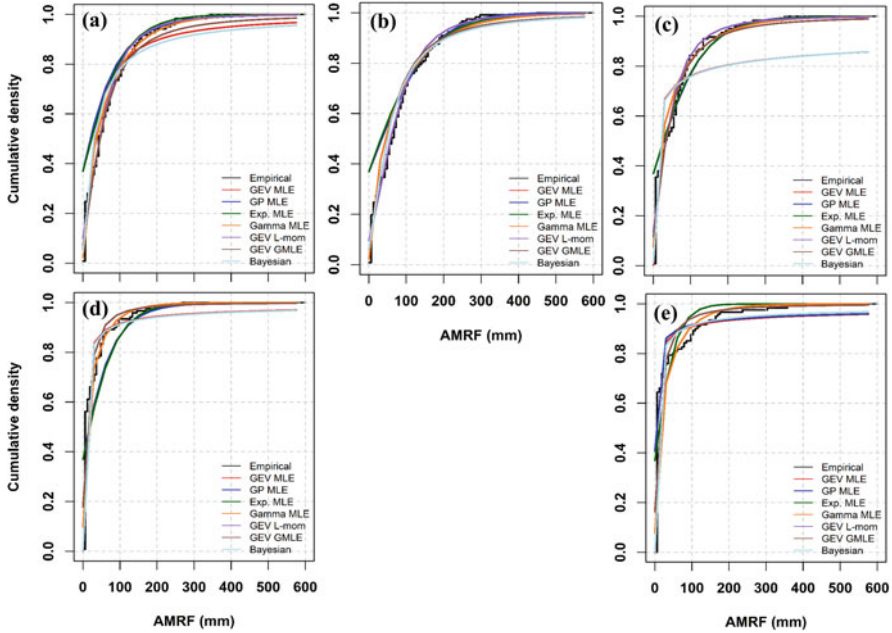


Fig. 3.12 Comparison of the model fitting results by the cumulative probability distribution curves for annual maximum CDR over western coastal states of Kerala (a), Karnataka (b), Maharashtra (c), Goa (d), and Gujarat (e)

also experiences extreme heavy rainfall in <20 years; however, the state exceeds very heavy rainfall (124.5–244.4 mm/day) in <5 years. Besides, GEV in MLE, L-mom, and GMLE parameter estimation schemes are selected as marginal distributions for Andhra Pradesh (Fig. 3.13c). Similarly, GEV in L-mom and Gamma in MLE configurations are adopted for Tamil Nadu (Fig. 3.13d). The GEV-Lmom exhibits lower uncertainty and the least error for both states. The results further indicate that both states surpass the extremely heavy rainfall category in <10 years and very heavy rainfall in <5 years. The results also align with the previous observations (in sections discussing CDR contributions). The eastern coastal states of Andhra Pradesh and Tamil Nadu are more vulnerable to extreme rainfall events in the near future than West Bengal and Odisha. Except for West Bengal, all three eastern coastal states are susceptible to very heavy rainfall events in <5 years.

Gamma MLE and GEV L-mom exhibit considerably better estimates with lower levels of uncertainties over the western coastal states of Kerala (Fig. 3.14a), Karnataka (Fig. 3.14b), and Maharashtra (Fig. 3.14c). However, GEV L-mom shows more robust results than Gamma MLE. Similarly, these states exceed the very heavy rain category in <10 years. In contrast to other western coastal states, Gamma MLE produced a preferable estimate of return level with a lower range of confidence for Goa (Fig. 3.14d) and Gujarat (Fig. 3.14e). The state of Gujarat exceeds the very heavy rain category in <20 years, whereas Goa exceeds the said class of rainfall in

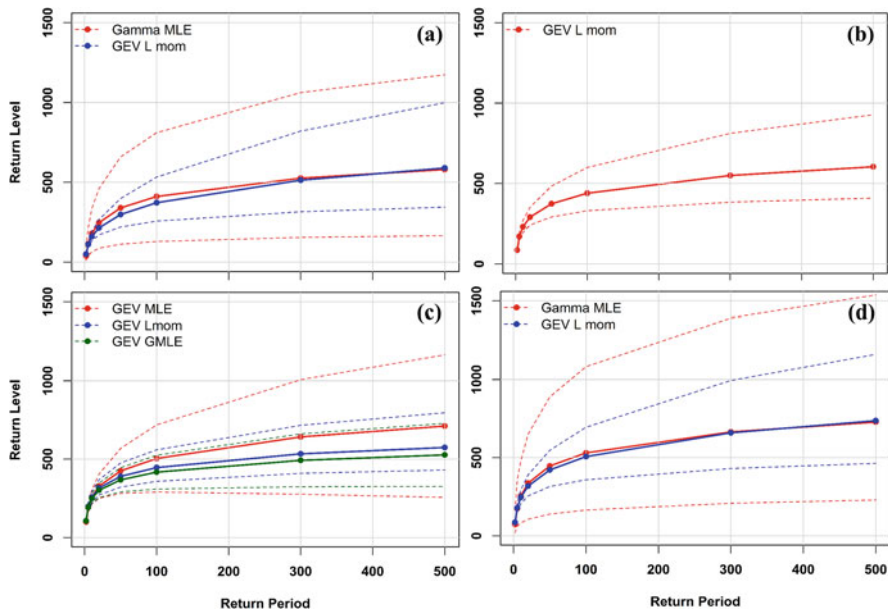


Fig. 3.13 Return level estimates based on marginal distributions for annual maximum CDR over eastern coastal states of West Bengal (a), Odisha (b), Andhra Pradesh (c), and Tamil Nadu (d). The solid lines represent estimated return level and the dotted lines signify the corresponding confidence interval

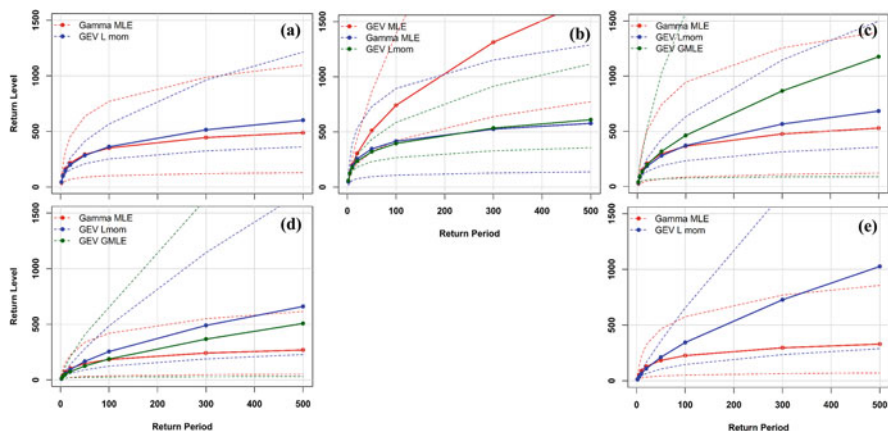


Fig. 3.14 Return level estimates based on marginal distributions for annual maximum CDR over the western coastal states of Kerala (a), Karnataka (b), Maharashtra (c), Goa (d), and Gujarat (e). The solid lines represent the estimated return level and the dotted lines signify the corresponding confidence interval

Table 3.2 Estimated return levels for CDR of different coastal states in India using a selected marginal distribution probabilistic model

Study Locations	2	5	10	20	50	100	300	500
West Bengal	49.3932	110.6725	159.7624	214.4506	298.2529	372.3392	512.9659	589.7681
Odisha	85.3100	170.3557	230.4059	290.9804	373.9542	439.6946	550.0615	604.1891
Andhra Pradesh	105.4582	197.2309	257.7805	315.7032	390.4492	446.2918	534.133	574.7841
Tamil Nadu	85.7544	177.6276	246.0684	318.0716	421.4898	507.3252	659.0962	737.0123
Kerala	44.3432	99.9779	146.3463	199.646	284.2727	361.7105	514.5408	600.8642
Karnataka	58.0144	124.4459	176.6544	233.9446	320.2454	395.2814	535.0642	610.1727
Goa	11.2688	41.6524	70.7857	102.8215	147.9322	183.4527	241.4101	268.8764
Maharashtra	33.1149	83.621	128.9935	184.3479	278.3883	370.2527	565.5598	683.118
Gujarat	15.0131	53.1519	88.9967	128.1057	182.9065	225.9303	295.9884	329.1469

<50 years. It is noteworthy to mention that the south-western coastal states are more prone to heavy rainfall events in the near future in comparison to Gujarat and Goa. Singh et al. (2020b) also observed that the coastal states of Odisha, Andhra Pradesh, and Tamil Nadu in the east and Karnataka and Kerala in the west coasts of India account for the highest CDR in pre- and post-monsoon seasons.

The current results indicate that the estimated future probabilities in the trends of annual maximum CDR follow historical patterns over the eastern coastal states. The eastern coastal states are expected to be more susceptible to frequent extreme rainfall events associated with CDs. However, the western coastal states of Karnataka, Kerala, and Maharashtra also tend to be more prone to extremely heavy CDR in the far future. Several studies display an apparent increment in the frequency and duration of cyclonic storms (Deshpande et al. 2021; Simpkins 2021) over AS, and the enhanced activity could make the western coastal states highly hazardous to extreme CDR activities in the future.

3.11 Concluding Remarks

In this chapter, the impact of the presence and absence of the warming climate on CDR over India is primarily emphasized. Several numerical modeling studies on CDs in a warmer climate suggest that CD associated rainfall rates are likely to increase (Knutson and Tuleya 1999; Knutson et al. 2010; Zhang et al. 2013). Although several studies focus on extreme rainfall events over India, those emphasizing on CDR over India (Singh et al. 2020b) are limited, and the changes in CDR rate have not been well understood.

The impact of a warming climate is significantly evident during the pre-monsoon season, where higher annual CDR is frequently observed for most of the years of CWP. During PWP, trends for both the annual frequency of CDs and CDR are observed to be increasing for the post-monsoon season. However, although the CD frequency shows a decreasing trend during post-monsoon season in CWP, the annual CDR indicates an increased nature signifying increased rainfall associated with CDs. The F-test indicates that the trend of annual CDR is significant at a 95% confidence level for pre-monsoon season, and the variance is higher during CWP than PWP.

The spatial distribution of the average annual CDR indicates that the highest rainfall values, exceeding 110 mm/year, are found in the eastern and western Indian coastal states of Andhra Pradesh, Odisha, and Karnataka in the NIO region during CWP. The CDR is 60–70 mm/year during the pre-monsoon season of PWP. Values in average CDR are generally smaller over most parts of India than those observed in the eastern coastal regions for the post-monsoon season, with the largest contributions (nearly 140 mm/year) along Andhra Pradesh, Tamil Nadu, and Odisha during the CWP. The CDR has increased during the pre-monsoon season over western coastal states such as Gujarat, Rajasthan, and Maharashtra during CWP, which was insignificant during PWP. The northern parts of India, covering Himachal Pradesh,

Punjab, and the Uttarakhand region, receive a good amount of rainfall due to the dissipation of CDs during the post-monsoon season of CWP.

In terms of percentage, the CDR contributions are 20–30% during PWP and nearly 80% during CWP for the pre-monsoon season. For the pre-monsoon season, the highest contribution is over Gujarat, and the spatial extent of higher CDR percentage contribution over the eastern region of India is limited to Andhra Pradesh and Tamil Nadu during the warming climate. During the post-monsoon season, the percentage contribution has increased to up to 80% in CWP, from 10–30% in PWP. The linear trend for annual percentage is increasing for pre-monsoon and post-monsoon seasons in the warming climate. The F-test for annual variation of CDR contribution between PWP and CWP shows the variance during PWP is less than CWP for the post-monsoon season. During pre-monsoon, the annual percentage has enhanced to ~53% from 36% under the influence of the present climate condition. The maximum annual percentage contribution has increased to nearly 60% during CWP from 30% during PWP for the post-monsoon season. The annual average CDR trend for the pre-monsoon season over the coastal states of India is decreasing except for West Bengal and Odisha during CWP. Similarly, for the post-monsoon season, the annual accumulated CDR trend is decreasing over the coastal states except in West Bengal, Odisha, and Andhra Pradesh, where an increasing trend is observed in the current climate.

The inferences obtained from the estimated return levels via the probabilistic approach exhibit a similar trend (as stated earlier) in the eastern coastal states for the near future, i.e., the states of Odisha, Andhra Pradesh, and Tamil Nadu exceed the extremely heavy rainfall with a periodicity of <10 years; while the western coastal states account for >20 years to surpass the extremely heavy rainfall-induced by CDs. However, the western coastal states of Karnataka, Kerala, and Maharashtra could also become prone to excessive hazards induced by extreme CDR in the far future. The analysis presented in this chapter will be highly beneficial for future disaster management plans for coastal areas since India has been experiencing developmental growth in due course with better living conditions.

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Chapter 4

Meridional Heat Convergence Will Increase Tropical North Atlantic Heat Content Available for Hurricane Intensification



Elizabeth Harris, Dipanjan Dey, Robert Marsh, and Jeremy Grist

Abstract Ocean heat content available for hurricane intensification is expected to increase in a warming world. Mechanisms for growth of the Atlantic Warm Pool to 2050 are examined in a high-resolution coupled ocean and atmosphere model with greenhouse gas forcing. The model warm pool increases in depth as well as northern and eastern extent. While net heat flux from the atmosphere remains stable through the forced model run, heat convergence from reduced heat transport by ocean currents drives growth of the warm pool. While atmospheric heat flux and oceanic heat convergence both contribute to anomalous warm water for hurricane development at present, high resolution ocean modelling suggests that, when atmospheric conditions allow for hurricane formation, increased potential for intensification from a warmer ocean will primarily be due to reduced meridional heat transport.

Keywords Climate change · Heat content · Hurricanes · Meridional transport · Warm pool · Heat convergence

Key Points:

- The volume of warm water increases to the north, east, and in depth, in a high-resolution ocean model with high emissions forcing.

E. Harris (✉)

School of Ocean and Earth Science, University of Southampton, Southampton, UK

Ariel Re, Bermuda, Hamilton, Bermuda

e-mail: elizabeth.harris@arielre.com

D. Dey

School of Ocean and Earth Science, University of Southampton, Southampton, UK

School of Earth, Ocean and Climate Sciences, Indian Institute of Technology,
Bhubaneswar, India

R. Marsh

School of Ocean and Earth Science, University of Southampton, Southampton, UK

J. Grist

National Oceanography Centre, Southampton, UK

- Convergence of ocean heat transport between 10 °N and 30 °N drives this increase.
- This additional ocean heat content could be available for potential hurricane intensification if atmospheric conditions allow.

4.1 Introduction

Recent US landfalling hurricanes have resulted in more than 40 billion USD in damage (NCEI 2023) in 5 of the last 7 years (2017–2023), bringing to the forefront the need to understand how anthropogenic warming may have contributed to the intensity of these events, and how major hurricanes could develop in a future, warmer climate.

An increasing area of warm tropical Atlantic sea surface temperature (SST) since the 1970s has provided a larger energy source for hurricane intensification (Saunders and Lea 2008). The Atlantic Warm Pool (AWP) has maintained feedback loops resulting in lower wind shear and a moist atmosphere (Wang and Lee 2007). Annual Atlantic basin major hurricane counts exhibit an increasing trend in the last few decades (Vecchi et al. 2021), mainly due to a recovery from anomalously low activity in the 1970s and 80s, compared with subsequent decades (Nyberg et al. 2007; Rousseau-Rizzi and Emanuel 2022). Recent high major hurricane landfall activity since 2017 (Murakami et al. 2018) marked a return to expected behaviour due to warming Atlantic SSTs, after an unusual gap in the record (Hall and Hereid 2015). When changes in the observational network are accounted for, there remains significant multidecadal variability, but little upward trend since the 1850s (Vecchi et al. 2021). There is also no upward long-term trend in US landfalling major hurricanes since 1900 (Klotzbach et al. 2018), a record which offers reasonable consistency since the onset of anthropogenic warming, as few of these storms are likely to have been missed.

Observed multi-decadal variability in Atlantic major hurricane activity has been explained by a cool period in the North Atlantic resulting from a combination of sulphate aerosol emissions (Dunstone et al. 2013) and natural variability in ocean circulation (Yan et al. 2017; Zhang et al. 2019). It is difficult to separate the potential impact of climate change on major hurricane frequency from these other atmospheric and oceanic factors which have influenced activity on multidecadal timescales; for example, while Kang and Elsner (2015) found a recent increase in global tropical cyclone (TC) intensity, they do not attribute it to climate change. More generally, while a recent review (Knutson et al. 2019) found mixed evidence to support conjectures that an increase in major hurricane activity has already occurred, continued warming of the tropical ocean due to greenhouse gas forcing could provide the potential for additional hurricane intensification in future decades, provided atmospheric conditions permit tropical cyclone development.

Climate models systematically underestimate the number and strength of tropical cyclones (Walsh et al. 2016). Tropical cyclone activity is simulated in

high-resolution climate modelling, HADGEM3-GC31-HH, but projected changes for the North Atlantic are inconclusive, particularly as major hurricanes are not produced by even the highest resolution climate models (Roberts et al. 2020a; Davis 2018). A number of future model projections using downscaling techniques predict a lower frequency of global tropical cyclones, and an increase in the proportion of the most intense storms (Knutson et al. 2020). In general, the reliability of future projections is challenged by the low annual frequency and large variability of TCs (Yoshida et al. 2017). While truly understanding the mechanisms of TC frequency and resolving extreme TCs accurately within climate models remains elusive (Sobel et al. 2021), they can provide insight into the processes which will drive future TC changes.

For example, the Atlantic Meridional Overturning Circulation (AMOC) is predicted to decrease in strength due to increased freshwater at high latitudes reducing deep water formation (Madan et al. 2023), as polar ice caps melt. This allows accumulation of heat in the tropical Atlantic. Variation in inter-model AMOC strength remains a major factor in future climate uncertainty (Bellomo et al. 2021). Liu et al. (2013) consider the historical runs of 19 CMIP5 models, many of which exhibit a cold SST bias in the tropical Atlantic. While this cold bias still exists in CMIP6, higher resolution models more realistically represent ocean processes, so the impacts of continued greenhouse gas warming can be anticipated with greater confidence. Han et al. (2021) examined 33 CMIP6 models and found that model reanalysis skill for tropical cyclone predictor climatology and interannual variability improves with higher horizontal resolution, including tropical SST. This is likely due to the better representation of northwards heat transport via the AMOC (Roberts et al. 2020b), due to increased ocean resolution, as well as improvements in parameterization of the surface mixed layer and interior mixing processes.

Climate models provide projections of the atmospheric variables relevant to hurricane activity, including atmospheric stability, humidity, and vertical wind shear (VWS) (DeMaria et al. 2001). Tang and Camargo (2014) propose an index for tropical cyclone activity including VWS, entropy, and potential intensity, from analysis of CMIP5 models. Tropical Atlantic VWS, the strength of which is associated with the El Niño Southern Oscillation (ENSO) on interannual timescales, is stronger in climate model projections (Vecchi and Soden 2007; Emanuel 2021), inhibiting hurricane development (Lin et al. 2020). Atlantic VWS exhibits Interseasonal and intraseasonal variability (Aiyyer and Thorncroft 2006), leaving windows of opportunity for hurricane development, given existing disturbances and warm SSTs.

Historically, a warmer tropical Atlantic has been linked with increased hurricane activity (Goldenberg et al. 2001; Moharana and Swain 2023). Warm water is primarily defined here as warmer than 26.5 °C. This has been identified as the threshold temperature for most hurricane development in previous studies (Dare and McBride 2011; McTaggart-Cowan et al. 2015). Johnson and Xie (2010) note covariability in tropical SST and convection in satellite precipitation, while Dare and McBride (2011) find that the temperature threshold directly related to tropical cyclogenesis has not been observed to have changed significantly during

1981–2008. However, based on climate model analyses, it has been proposed that the temperature threshold for tropical deep convection could vary with the climate state (Evans and Waters 2012; Korty et al. 2012; Sugi et al. 2015). Nevertheless, many studies confirm the importance of ocean heat content as a critical ingredient of increased tropical cyclone activity and in model TC simulation (Chan et al. 2021; Hallam et al. 2021; Domingues et al. 2019; Pfleiderer et al. 2022). The goal here is not to resolve this issue but to diagnose the source of increased ocean heat which will be available for potential TC development when atmospheric conditions allow.

In general, there is low confidence in observed long-term change in major hurricane frequency and uncertainty in their future projections. However, further growth in the amount of warm water available to fuel intense hurricanes would be one factor which could impact Atlantic basin activity in the next few decades. Climate models using high-resolution ocean models can improve projections of hurricane climate predictors, particularly the region of warm water available for hurricane development. In this study, the potential future change in the volume of warm water available for hurricane development is quantified using the HadGEM3-GC31-HH high-resolution climate model with prescribed greenhouse gas forcing following the Shared Socioeconomic Pathway 585 (SSP585) high emissions scenario.

In summary, although climate models suggest that variables other than SST may drive future tropical cyclone frequency, increasing ocean heat content is widely understood to explain recent increases in hurricane activity. Hence the drivers of warm water volume variability in an increasingly warm, forced climate are examined here, including air-sea heat flux into the ocean, and advective heat convergence across the tropical Atlantic. The robustness of the advective heat convergence trend is tested by extending the analysis to three other high-resolution climate models.

4.2 Data and Methods

4.2.1 CMIP6 HighResMIP (High-Resolution Model Intercomparison Project)

High-resolution coupled climate model output is analysed from experiments described by Haarsma et al. (2016). These models start with a short spin-up period of 30 to 50 years and then are run from 1950 through 2050. The control run external forcing is at 1950 levels. Historical forcing is used in years 1950 to 2014. The SSP585 high emissions scenario forcing, where radiative forcing increases to 8.5 Wm^{-2} by 2100, is applied during 2015 to 2050.

Our primary focus in this study is analysing the outputs from the high-resolution ocean and atmosphere model HadGEM3-GC31-HH (Roberts et al. 2019), which includes the project's (HighResMIP) highest resolution ocean configuration, at $1/12^\circ$. The ocean model is the Nucleus for European Modelling of the Ocean

Table 4.1 HighResMIP Model configurations

Model	Resolution name	Ocean model	Horizontal resolution	
			Ocean	Atmosphere (km)
HadGEM3-GC31	HH	NEMO 3.6	1/12°	50
HadGEM3-GC31	HM	NEMO 3.6	1/4°	50
EC-Earth3P	HR	NEMO 3.6	1/4°	50
CESM1-3	HH	POP	1/10°	25

(NEMO) version 3.6 (Madec et al. 2017), with 75 levels. Atmospheric resolution is 50 km.

To sample the diversity of model configuration and resolution, we compare data from three other high-resolution models (Table 4.1), including HadGEM3-GC31-HM with a lower resolution ocean model, at 1/4° (HM), EC-Earth3P (ECE), with a similar configuration to HM (Haarsma et al. 2020), and CESM1-3 (CESM), which uses the POP ocean model at 1/10° horizontal resolution (Danabasoglu et al. 2012; Small et al. 2014), with 25 km atmospheric resolution.

4.2.2 Ocean Data

The observed volume of Atlantic water warmer than specific temperature thresholds, north of 10 °N, was calculated using the UK Met Office Hadley Centre EN4 subsurface ocean temperature analysis, which provides ocean analysis data from 1900 to the present (Good et al. 2013). This dataset contains gridded subsurface temperature at 42 discrete depths, at 1° latitude longitude horizontal resolution, from 1900 to the present, from 83 °S to 90 °N. While this dataset offers a longer record than other datasets, direct observations used are increasingly scarce with depth and further back in time.

The mean decadal observed depth of the 26.5 °C isotherm, north of 10 °N, was calculated using the National Center for Environmental Prediction (NCEP) Global Ocean Data Assimilation System (GODAS) ocean reanalysis product (Behringer and Xue 2004). This dataset contains gridded global potential temperature at 40 discrete depths, at 1/3° latitude and 1° longitude spacing, from 1980.

4.2.3 Atmospheric and Surface Flux Data

ERA5 (Hersbach et al. 2020) is produced by the Copernicus Climate Change Service (C3S) at the European Centre for Medium-Range Weather Forecasts (ECMWF). It is the fifth generation ECMWF atmospheric reanalysis of the global climate covering the period from January 1940 to the present. Hourly 30 km grid data is aggregated to

monthly averages. Surface latent heat flux, net solar and longwave radiation, and sensible heat flux are used in this analysis.

4.2.4 Hurricane Data

Annual North Atlantic basin major hurricane counts are collected from the International Best Track Archive for Climate Stewardship (IBTrACS) (Knapp et al. 2010; Knapp et al. 2018) Version 4 dataset for the Atlantic basin. This data consists of storm-centred point data from 1851, which includes maximum 1 min mean winds at 6-hourly intervals over the ocean, more frequent near land, rounded to the nearest 5 knots. Unique storms reaching greater than 96 knots of maximum wind speed in their lifetime during 1980 to 2022 are identified here, as recorded by the National Hurricane Center (NHC).

4.2.5 Water Mass Transformation

From the original formulation of Walin (1982), the Water Mass Transformation (WMT) framework (Groeskamp et al. 2019) is applied in temperature space, quantifying volume fluxes across isotherms associated with variations of heat fluxes in that property space. With this diagnostic, we attribute variations in warm water volume to variations in surface heat exchanges. The net surface heat flux, Q_{net} , combines surface net solar radiation (Q_{sw}), net longwave radiation (Q_{lw}), sensible heat flux (Q_{sh}), and latent heat flux (Q_{lh}). Throughout this study, the convention is that all heat fluxes are positive into the ocean:

$$Q_{net} = Q_{sw} + Q_{lw} + Q_{sh} + Q_{lh} \quad (4.1)$$

Across temperature space, the volume of water transformed by Q_{net} is calculated over the North Atlantic, north of 10 °N, where tropical storms are able to form due to sufficient Coriolis acceleration. Firstly, the Diathermal Temperature Flux, $Q_{in}(T)$ ($^{\circ}\text{C m}^3 \text{ s}^{-1}$) (2), is found by area-integrating Q_{net} , where SST is at or above a given value of temperature, T , then dividing by reference density, ρ_0 , and specific heat capacity, c_p :

$$Q_{in}(T) = \frac{1}{\rho_0 c_p} \int_{x_w}^{x_e} \int_{y_s}^{y_n} Q_{net}(x, y) \Gamma(SST(x, y), T) dx dy \quad (4.2)$$

where x, y are distance in west (w) to east (e) and south (s) to north (n) directions, and Γ is a sampling function; $\Gamma = 1$ where $SST > T$, otherwise $\Gamma = 0$. Q_{net} values at the potential temperature grid points are found using bilinear interpolation.

The thermal water mass transformation rate, $F_T(T)$ (m^3s^{-1}), can then be arrived at by taking differences between $Q_{in}(T)$ across two temperature surfaces:

$$F_T(T - \Delta T/2, T + \Delta T/2) = \frac{Q_{in}(T - \Delta T/2) - Q_{in}(T + \Delta T/2)}{\Delta T} \quad (4.3)$$

The WMT framework is used here to diagnose the contribution of heat flux trends from air-sea interaction to the evolving volume of warm water in the tropical North Atlantic in a warming future climate.

4.2.6 Back-Tracking Warm Water (TRACMASS)

The TRACMASS Lagrangian trajectory code has been designed for use with gridded weather and climate models to track water paths and associated heat and salt fluxes (Aldama-Campino et al. 2020; Döös et al. 2017). One of the unique characteristics of TRACMASS is that it uses differential equations and mass transport fields at the grid cell walls to analytically calculate the trajectory path through grid boxes. The use of mass transport in a grid cell makes TRACMASS a mass-conserving algorithm. From changes in temperature along each path, we obtain Lagrangian heat divergences, which are ensemble-averaged to obtain heat input to the northward flow across tropical latitudes. Here we track water paths backwards from latitudes currently relevant to hurricane development for water warmer than 26.5 °C. Water parcels are seeded so there is at least one water path start point per HadGEM3-GC31-HH grid cell.

4.3 Results

4.3.1 Future Trends in Available Heat Content

In this section, we investigate HadGEM3-GC31-HH 1950–2050 predicted changes in the amount of heat potentially available for hurricane intensification. We first evaluate changes in the AWP at various temperature thresholds at the peak of hurricane season in the high-resolution model, referencing observational data for model validation. Timeseries of total volume and area of warm water are presented. Maps of the decadal mean depth of the 26.5 °C isotherm are included to highlight the regional extent of warm water through the forced model run.

The total model volume of water in the North Atlantic north of 10 °N and warmer than 26.5 °C, 27.5 °C and 28.5 °C is summed for the month of September, and plotted over time, in Fig. 4.1. September is the peak of the hurricane season; 48% of major hurricanes intensified to 96 knots or above in this month during 1900–2023. The forced run is compared with the control run and EN4 observations.

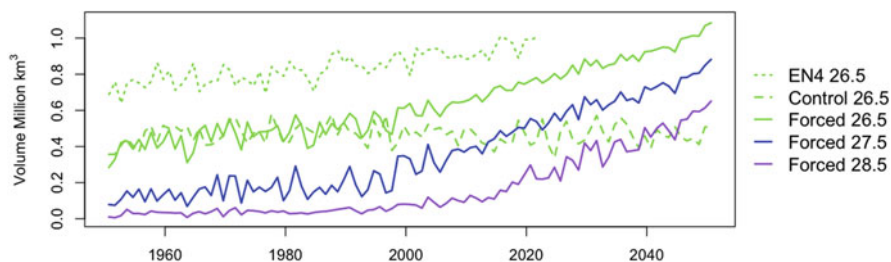


Fig. 4.1 September HadGEM3-GC31-HH 1950–2050 forced run mean monthly volume (million km^3) in the North Atlantic north of 10°N of water warmer than 26.5°C (green, solid), 27.5°C (blue), and 28.5°C (purple); warmer than 26.5°C in the control run (green, dashed), and EN4 1950–2022 (green, dotted)

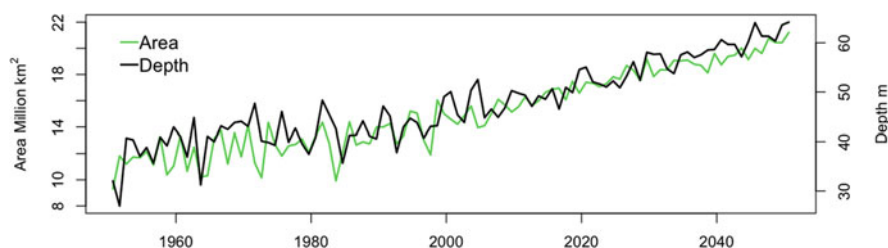


Fig. 4.2 September mean monthly area of water (million km^2) warmer than 26.5°C in the North Atlantic north of 10°N : HadGEM3-GC31-HH 1950–2050 forced run (green) and depth of the 26.5°C isotherm (black)

The HadGEM3-GC31-HH September volume of warm water ($> 26.5^\circ\text{C}$) increases gradually from 1950 to around 2000, after which it increases rapidly with additional external forcing in the model high emissions forced years. The 1950–1959 September mean monthly volume warmer than 26.5°C is 0.40 million km^3 . In the final decade of the years with historical forcing, 2005–2014, the mean September volume of warm water has reached 0.64 million km^3 , an increase of 0.04 million km^3 per decade. The rate of change increases with time in the forced run. The model predicts 0.96 million km^3 by 2040–2049, an increase of 0.08 million km^3 per decade compared with the volume at the end of the period with historical forcing. Hence, the model predicts 56% more warm water by the middle of the twenty-first century, with high emissions forcing. The trend in observed September volume of water warmer than 26.5°C is an increase of 0.003 million km^3 per year. The model cool bias in the tropical North Atlantic is clear, as the EN4 monthly mean warm water volume ($> 26.5^\circ\text{C}$) is nearly twice as large as the warm water volume in the high-resolution model.

HadGEM3-GC31-HH mean monthly area and depth of water warmer than 26.5°C in the North Atlantic north of 10°N in September is shown in Fig. 4.2. As with warm water volume, the area at the surface also increases, with an increase in the rate of change in the forced run. The mean depth of the September 26.5°C

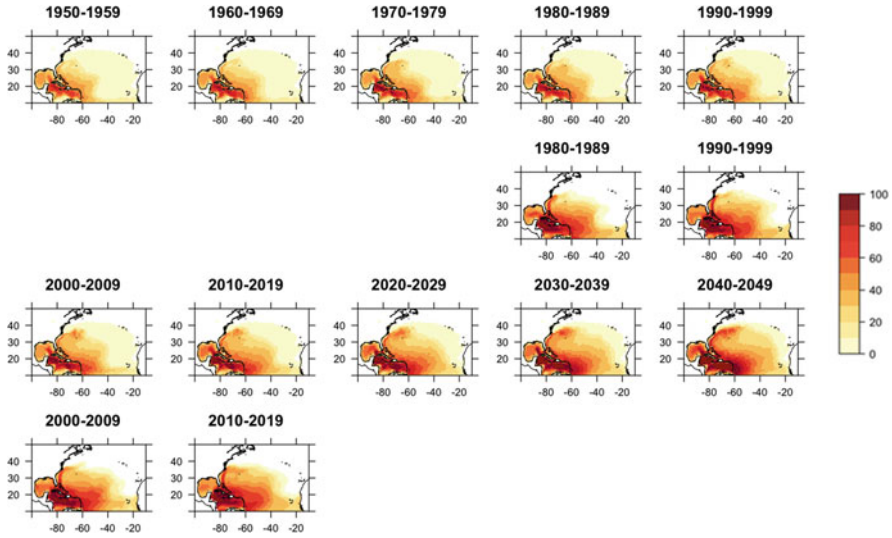


Fig. 4.3 Depth of the September 26.5 °C isotherm (m) in the North Atlantic north of 10 °N by decade 1950–2049 HadGEM3-GC31-HH forced run (rows 1 and 3) and 1980–2019 GODAS (rows 2 and 4)

isotherm north of 10 °N also continues to increase in the high emissions years of the forced run. Both the area and depth of the warm water pool increases, so volume changes are not only the result of both increasing area and depth of the 26.5 °C isotherm with atmospheric forcing.

The depth of the HadGEM3-GC31-HH forced September 26.5 °C isotherm is plotted by decade, providing spatial insight into the depth and extent of the AWP (Fig. 4.3, rows 1 and 3). The warm water area expands to the north and east over time and deepens in the Caribbean Sea and western tropical Atlantic. This is compared with GODAS (rows 2 and 4). A larger area of warm water extending vertically to 100 m is evident in the observational data than in the model, due to the HadGEM3-GC31-HH cold bias. A thin layer of warm water (light yellow) extends further to the north and east in the HasGEM3-GC31-HH maps due to higher resolution of vertical levels near the surface than in the GODAS data. GODAS vertical levels have a 10 m resolution in the top 100 m. The much higher resolution of HH vertical levels near the surface do not average out very shallow warm temperatures in surface layers.

The HadGEM3-GC31-HH model predicts a high emissions scenario future with a much larger volume of deep warm water extending further north and east than the present day. In the following sections, we analyse changes in the mechanisms of heat transfer into the tropical North Atlantic, to diagnose which processes drive the projected increase in warm water in high resolution forced models, with a focus on HadGEM3-GC31-HH.

4.3.2 Changes in Atmospheric Heat Flux

Heat exchange between the atmosphere and ocean is a major driver of interannual variability in the volume of warm water in the tropical North Atlantic, particularly through latent heat flux (Hallam et al. 2019). Similarly, an increasing trend in heat flux into the ocean over surface water which flows through the tropical Atlantic would result in an increase in warm water volume. Additional absorption of heat from the atmosphere could be a result of, for example, higher humidity surface conditions decreasing latent heat flux from the ocean by reducing evaporation, and/or decreased cloudiness, allowing additional short-wave radiation absorption into the ocean.

We inspect the main drivers of heat accumulation in the tropical North Atlantic in HadGEM3-GC31-HH, to explain these changes in the warm water pool. HadGEM3-GC31-HH heat flux in the North Atlantic between 10 °N and 30 °N is examined. This covers the region of 26.5 °C water, where 90% of hurricanes intensify into major hurricanes (Fig. 4.4). We then calculate the volume of water transformed across isotherms, using the WMT framework, to quantify the ocean-atmosphere heat exchange driving AWP volume changes.

Figure 4.5 shows a small upward trend in Q_{net} into the ocean in HadGEM3-GC31-HH over the Atlantic between 10 °N and 30 °N in the forced model run. The mean 2015–2050 Q_{net} is 0.04 W m^{-2} higher than the 1950–2014 mean. This small change in Q_{net} is a consequence of large but compensating changes in the component fluxes (not shown here) in the model. The small change in Q_{net} then suggests that transfer of additional heat from the atmosphere into the ocean at these latitudes is not the driver of increasing AWP by 2050 in the high-resolution model.

Observed (ERA5) Q_{net} is higher into the ocean and exhibits more variability than the model on multidecadal timescales. ERA5 heat input into the ocean has a negative trend in this period of -0.04 W m^{-2} per year. Mayer et al. (2023) likewise observe a negative trend for a sample location in the tropical North Atlantic, which they suggest is due to global warming.

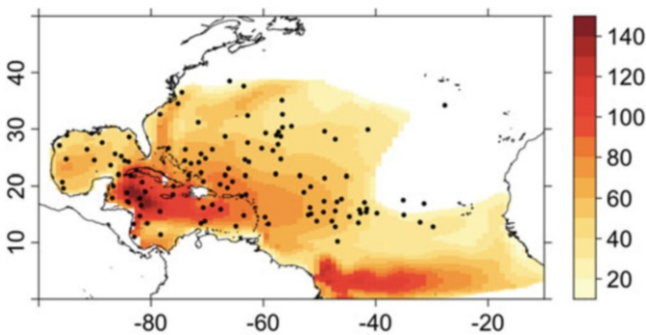


Fig. 4.4 1980–2022 Mean depth of GODAS September 26.5 °C isotherm (m) and IBTrACS points 1980–2022 where hurricanes intensified into major hurricanes

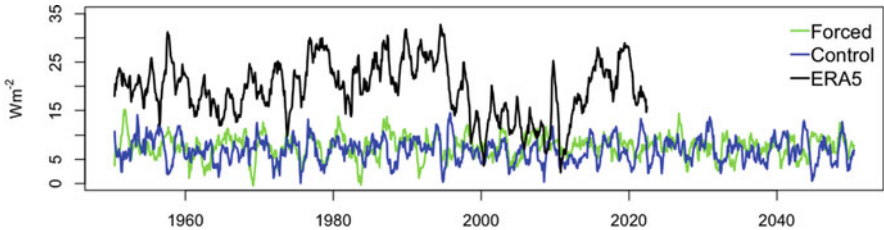


Fig. 4.5 Mean monthly Q_{net} into the Atlantic Ocean (Wm^{-2}) 10 °N to 30 °N with 12-month centred moving average: HadGEM3-GC31-HH 1950–2050 forced run (green) and control (blue), compared with observed ERA5 (black)

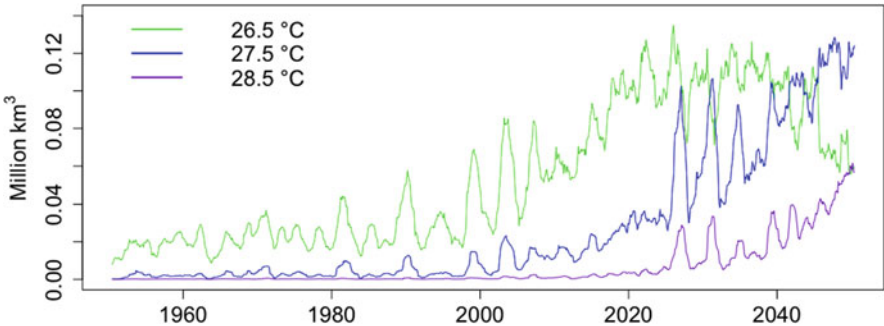


Fig. 4.6 Mean monthly volume (million km^3) of water transformed across the 26.5 °C (green), 27.5 °C (blue) and 28.5 °C (purple) isotherm, with 12-month centred moving average

The volume of water transformed across the isotherms which have historically been relevant to hurricane development in the North Atlantic north of 10 °N can be calculated using the WMT framework (Harris et al. 2022). This metric diagnoses the additional volume of water warmer than these temperature thresholds. The total volume increases due to both deepening of the 26.5 °C isotherm and a larger area of water warmer than 26.5 °C, over which the heat flux into the ocean warms the AWP.

Figure 4.6 indicates the amount of water transformed across the 26.5 °C, 27.5 °C, and 28.5 °C isotherms. For each temperature threshold, the transformed volume is positive from 1950–2050 in the forced run. Using this framework, the rate at which water is transformed by atmospheric heat flux increases around 2000. The transformed volume peaks in the mid-2020s and then begins to decline towards the end of the simulation for water transformed across 26.5 °C, as much of the tropics and subtropics reach this temperature, but continues to increase for higher temperature thresholds.

As the WMT framework calculates the volume transformed by heat flux bounded by the area of water at that temperature, the increase in transformed volume of 26.5 °C water over time must be due to an increasing area of water over which the transformed volume is calculated, rather than an increase in the heat flux into the

ocean, as suggested by the absence of a trend in HadGEM3-GC31-HH atmospheric heat exchange (Fig. 4.5).

The significant increase in the size of the AWP by 2050 in the HadGEM3-GC31-HH forced run cannot be attributable to additional absorption of net heat transfer from the atmosphere as greenhouse gases continue to increase (from Fig. 4.5). Hence, next, we consider the contribution of advective heat flux by ocean currents.

4.3.3 *Climate Change and Tropical Atlantic Advective Heat Flux*

In this section, the advective component of warm water volume changes in the tropical Atlantic in the HadGEM3-GC31-HH forced run are discussed. Warm water volume convergence between 10 °N and 30 °N is analysed across a suite of ‘HighResMIP’ ocean models. These models differ by resolution and ocean model, adding robustness to our results. Employing a complementary technique, we also use TRACMASS Lagrangian analysis applied to HadGEM3-GC31-HH forced simulation output to analyse ocean properties and heat convergence along trajectories, and hence, diagnose mechanisms of advective heat transfer into the tropical Atlantic. These trajectories are calculated backwards from 20 °N in the Atlantic for 6 months prior to June 30, near the beginning of the hurricane season.

Figure 4.7 shows the warm water volume convergence between 10 °N and 30 °N. This has been calculated using meridional mass transport from four high-resolution ocean climate models. All models show an increase in warm water convergence between these latitudes at these temperatures. Convergence of water warmer than 26.5 °C increases after 2000 and begins to decrease after 2030. At this time there is still a larger volume of water warmer than 26.5 °C transported across 10 °N than 30 °N. However, the difference between the transport across the higher and lower latitudes decreases, as the AWP extends this far north most of the time by the end of the simulation. At higher temperature thresholds, warm water convergence increases through the model run as the amount of water warmer than these temperatures steadily increases between these latitudes.

HadGEM3-GC31-HM behaves in a similar fashion, although the decline in convergence of 26.5 °C and warmer water is less pronounced than in the HadGEM3-GC31-HH model. The ECE model convergence of 26.5 °C plateaus in the forced run, rather than declines. The CESM model, on the other hand, shows less increase in convergence at any temperature threshold, which may be due to its near-surface warm bias (Roberts et al. 2020b).

Analysis of output of this suite of high-resolution forced ocean models shows an increase in the volume of water warmer in the region of recent hurricane development. The increase in greenhouse gases in the HadGEM3-GC31-HH forced run results in a greater reduction in ocean transport via weakening of the AMOC

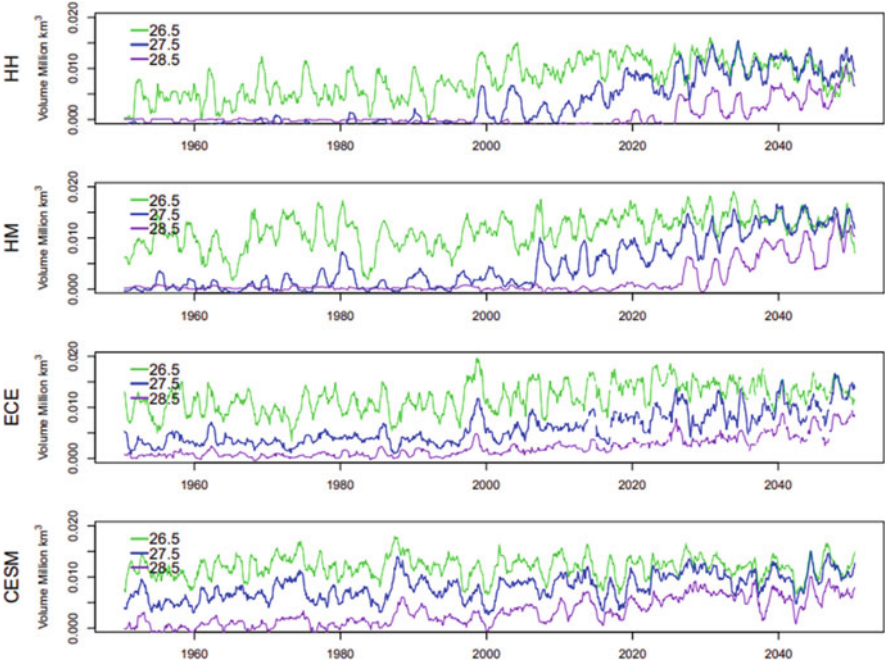


Fig. 4.7 Monthly meridional convergence of warm water volume (million km³) convergence between 10 °N and 30 °N with 12-month centred moving average for water warmer than 26.5 °C (green), 27.5 °C (blue), and 28.5 °C (purple) in HadGEM3-GC31-HH, HadGEM3-GC31-HM, ECE and CESM

(Roberts et al. 2020b), when compared to lower resolution ocean models. An oceanic decrease in heat transfer to higher latitudes allows heat to accumulate in the tropical Atlantic, and the AWP consequently expands northward and eastward.

To confirm and develop these findings, Lagrangian trajectory analysis of warm water flow into the tropical North Atlantic is undertaken. TRACMASS calculations using output from the HadGEM3-GC31-HH forced run are obtained as 6-month backwards trajectories from particles seeded at 20 °N, on June 30 of each of 10 years in 3 decades: 1951–1960, 2001–2010, and 2041–2050. This latitude is in the middle of the region of warm water analysed in previous sections. The choice of start date, near the beginning of the hurricane season, is motivated by the fact that the observed interannual variability at June 30 is higher than in September (Harris et al. 2023), during which time much of water at this latitude is warmer than 26.5 °C in most historical years. The variability is significantly correlated with annual major Atlantic basin hurricane counts over 1980–2022, with Pearson Correlation Coefficient of .44, significant at the 95% level (Fig. 4.8).

The mean January–June temperature of warm water (warmer than 26.5 °C) particle tracks ending at 20 °N at the end of June in the HadGEM3-GC31-HH forced run is plotted in Fig. 4.9 (right) for the 3 decades representing pre-industrial

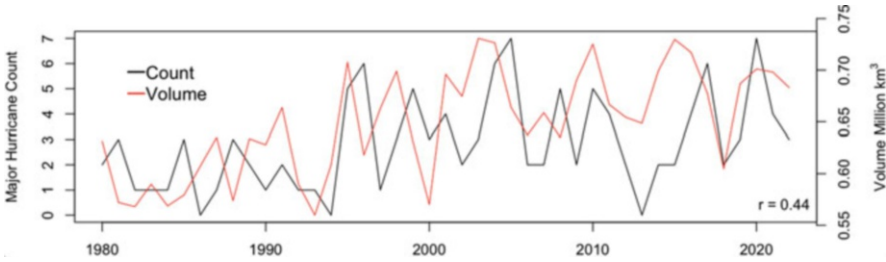


Fig. 4.8 GODAS July 1 volume (million km³) of water warmer than 26.5 °C between 10 °N and 30 °N (red) and annual major hurricane count (black) 1980–2022

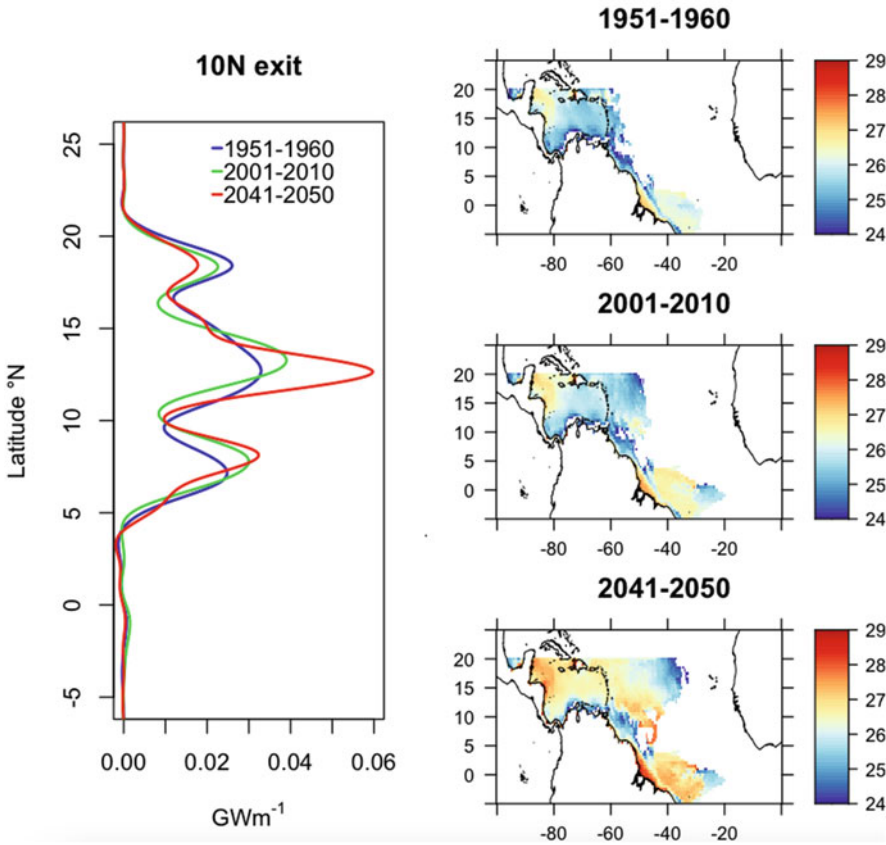


Fig. 4.9 Left: Smoothed mean zonally integrated January–June heat flux into particles backtracked from 20 °N, which cross 10 °N (GWm⁻¹ positive for heat gain) by latitude, averaged over 1951–1960 (blue), 2001–2010 (green), and 2041–2050 (red). Right: January–June mean particle temperature (°C) within 0.5 degree grid boxes averaged over a decade; 1951–1960 (top), 2001–2010 (middle), and 2041–2050 (bottom)

conditions at the start of the model run, 1951–1960 (top), 2001–2010, near the end of the historical forcing (middle), and the last decade of the high emissions forcing, 2041–2050 (bottom). Particle temperatures at all time stamps through the experiment of particles which are located within 0.5 degree grid boxes are averaged, and then averaged over 10 years to smooth interannual variability. The mean temperature of warm water arriving at 20 °N by July 1 is notably warmer near the coast of central America and in the Amazon outflow region in the 2000s than the 1950s. Warm water sources extend 20 degrees further east of the Caribbean. By the 2040s, warm water sources are 2 °C degrees warmer over most of the Caribbean Sea, and 3 °C warmer near the coast of central America and in the Amazon outflow region. Warm water sources extend as far east as 30 °W in the North Atlantic.

The zonally integrated heat flux for particle tracks ending at 20 °N after 6 months, which cross 10 °N, summarises total energy into warm water sources from other regions. This is plotted by latitude in Fig. 4.9 (left). Across all latitudes, the total heat flux along these particle tracks changes very little from the first historical decade (1951–1960, 3.8 GW) to the later historical decade (2001–2010, 3.7 GW). By the final future forced decade (2041–2050), the total heat accumulation along particle tracks crossing 10 °N and ending at 20 °N after 6 months, which are warmer than 26.5 °C, is 14% higher than final historical forced decade (4.2 GW).

Heat flux along these tracks peaks between 12 °N and 14 °N. There is 0.01 GWm⁻¹ more zonally-integrated heat convergence at the latitude of smoothed peak heat flux by the present-day decade than the pre-industrial decade, and an additional 0.02 GWm⁻¹ of smoothed peak heat flux by the near-future decade than the present-day. In summary, HadGEM3-GC31-HH predicts that more heat will move through the tropical Atlantic from south of 10 °N over the next few decades, with the peak heat flux convergence just north of 10 °N.

This accumulation of heat in the tropical Atlantic is evident in the mean sea temperature map of the 2040s (Fig. 4.9, bottom right), where much warmer water, with temperatures greater than 27 °C, reach 20 °N in the previous 6 months than in the earlier decades, the 1950s and 2000s, where there is less change in the temperature of water parcels approaching 20 °N by July 1.

In summary, two techniques are used here to quantify changes in ocean currents leading to future accumulation of heat in HadGEM3-GC31-HH over the region of recent hurricane development. Advective heat convergence between 10 °N and 30 °N is quantified and compared with other high-resolution models. A complementary technique, Lagrangian heat convergence analysis backwards from 20 °N, is used to confirm findings. Both methods highlight the role of reduced meridional ocean transport in the next few decades, allowing more heat accumulation into the tropical Atlantic by the middle of the century, beginning around the present-day.

4.4 Conclusions

We have quantified changes in the volume of warm water related to increasing ocean heat content, which could be available for hurricane intensification in the tropical North Atlantic in the forced run of a high-resolution ocean model. The pool of warm water becomes more widespread to the north and east, as well as deepening. Quantification of changes in tropical North Atlantic mechanisms, leading to heat accumulation in a high-resolution forced ocean model, provide insight into one factor which could impact future hurricane risk, due an increase in deeper, more extensive pool of warm water which would be available for development of major hurricanes when atmospheric conditions are conducive to tropical deep convection.

This warm water volume is shown here to be positively correlated with annual major Atlantic hurricane counts in the observational record, though climate models suggest lower hurricane frequency in a warmer climate. The HadGEM3-GC31-HH volume of water warmer increases steadily towards 2050, at a higher rate than has been observed, albeit from a lower starting point in the model. This indicates that more intense hurricanes are possible in a warmer climate when atmospheric conditions allow.

While net heat flux into the tropical Atlantic does not increase in the HadGEM3-GC31-HH forced run, the amount of water transformed across warm isotherms does increase, due to the larger surface area of warm water just below these temperatures. However, this increase in the area is itself not expanding because of heat transfer mechanisms from the atmosphere, but due to oceanic processes.

Heat accumulation in this expanding region of warm water in the North Atlantic stems from slower ocean circulation in HadGEM3-GC31-HH. This is quantified by the increasing volume of heat convergence between 10 °N and 30 °N, which is also found in in 3 other high-resolution climate models. Likewise, Lagrangian heat convergence analysis for water arriving at 20 °N by July 1 shows a dramatic increase in warm water parcels by the 2040s, relative to the difference between the changes from the 1950s to the present day. HadGEM3-GC31-HH has the highest climate model ocean resolution available and the largest increase in warm water between latitudes currently relevant to major hurricane development, suggesting that, from an ocean heat perspective, there will be more potential for future hurricane intensification not found in previous climate model studies using lower resolution models.

Ocean heat content is projected to increase due a larger volume of warm water in the tropical Atlantic, driven by slower ocean circulation, if greenhouse gas emissions continue at the present rate. Future climate model runs at even higher resolutions could better resolve oceanic and atmospheric pathways for heat transfer into the tropical Atlantic, as well as detecting intense hurricanes themselves, and overcoming SST biases, which would increase confidence in future hurricane activity projections.

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Chapter 5

Is the Increasing Trend in the Environmental Upper-Ocean Heat Content in the Northwest Pacific Strengthening Tropical Cyclone Intensity?



Akiyoshi Wada and Wataru Yanase

Abstract The IPCC Sixth Assessment Report (AR6) indicates that the global proportion of Category 3–5 tropical cyclones (TCs) has increased over the past four decades. One of the possible reasons is an increase in the upper-ocean heat content (UOHC). However, it is questionable to explain the long-term trend only based on the upper-ocean warming because Category 3–5 TCs enhance the ocean response in the form of sea surface cooling. Here we calculated a new heat content metric by using 2-m air and dew-point temperatures from 2000 to 2021 with oceanic reanalysis data under the consideration of atmospheric baroclinicity. Since 2000, the new heat content from July to December has not significantly increased in the tropical and subtropical Northwest Pacific (NWP). Although the median for conventional UOHC calculated based on the 26 °C-isotherm depth has increased significantly, the trends in the median and extreme values of TC central pressures obtained from multiple best track datasets were consistent with the trends of the new heat content metric. The results suggest that upper ocean warming alone cannot explain an increase in extremely intense TCs, while new heat content has a potentially closer relationship with TC activity than conventional UOHC.

Keywords Tropical cyclone · Upper-ocean heat content · Ocean warming

5.1 Introduction

The Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Report (AR6) indicated that the global proportion of Category 3–5 six-hourly intensity estimates during the lifetime of each tropical cyclone (TC) has increased over the past four decades (IPCC 2021). This assessment is partly based on studies that used

A. Wada (✉) · W. Yanase

Department of Typhoon and Severe Weather Research, Meteorological Research Institute,
Tsukuba, Ibaraki, Japan

e-mail: awada@mri-jma.go.jp

two TC best track datasets in the Northwest Pacific (NWP) archived by the Regional Specialized Meteorological center (RSMC) Tokyo in the Japan Meteorological Agency (JMA) and the U.S. Department of Defense Joint Typhoon Warning Center (JTWC) (Mei and Xie 2016). One of the possible reasons for the increase in the proportion of intense TCs is an increase in the TC heat potential (TCHP), a measure of the upper-ocean heat content (UOHC) from the surface to the 26 °C-isotherm depth (Liu and Chan 2022; Song et al. 2021; Wada and Chan 2021). Since the energy source for TC development is turbulent heat fluxes transported from the ocean to the atmosphere (Emanuel 1986), however, it is questionable to explain the long-term trend based only on upper-ocean warming.

As one of the oceanic environmental factors, the importance of sea surface temperature (SST) has been recognized as one of the factors in the energy source for the generation and development of TCs (Gray 1968; Merrill 1988; Miller 1958; Palmén 1948). SST is one of the explanatory variables in TC intensity forecast guidance (DeMaria et al. 2005; Shimada et al. 2018) and is also used in the calculation of maximum potential intensity (DeMaria and Kaplan 1994; Emanuel 1986; Holland 1997; Miller 1958). SSTs beneath a TC, on the other hand, are known to decrease due to dynamics and thermodynamics in the upper ocean such as vertical turbulent mixing and upwelling as well as turbulent heat fluxes from the ocean to the atmosphere (Price 1981; Wada 2002; Yablonsky and Ginis 2009). The amount of sea surface cooling is determined by the intensity, the size, the speed of movement and the upper-ocean stratification beneath a TC. Although it is difficult to observe SSTs directly in the vicinity of TC in real time, even with microwave satellites (Wentz et al. 2000), we can infer that SSTs beneath a TC are less likely to decrease when a TC passes over the area where the preexisting oceanic mixed layer is relatively thick such as the area with warm mesoscale eddies and a warm-pool area east of the Philippines.

TCHP is an oceanic metric firstly proposed in the 1970s (Leipper and Volgenau 1972). In the 1990s, TCHP, but not SST, was shown to explain TC maximum intensity and intensity changes (Goni and Trinanes 2003; Shay et al. 2000). In the 2000s, the relationship between TCHP and TC maximum intensity was statistically studied (Wada and Usui 2007). Now, TCHP is also one of the explanatory variables in TC intensity forecast guidance (DeMaria et al. 2005; Shimada et al. 2018) as well as SST. However, the relationship between TCHP summed from the genesis time to the time a TC first reaches its lifetime minimum central pressure differed between the Northeast Pacific and NWP (Moon et al. 2022; Wada et al. 2012). This suggests that TC intensity is affected not only by the oceanic environment but also by the atmospheric environment specific to ocean basins such as vertical wind shear, static stability and synoptic conditions such as baroclinicity and pressure patterns.

Therefore, an attempt was made to change the criterion for calculating TCHP from a simple integration of water temperatures to the 26 °C-isotherm (Leipper and Volgenau 1972) to a temperature that accounts for atmospheric variables such as 2-m air and dew-point temperatures and accounts for atmospheric baroclinicity (Wada 2016). The modified TCHP in Wada (2016) was shown to be more closely related to the TC maximum intensity (minimum central pressure and 10-min-average

maximum sustained wind speed) than the conventional TCHP (Leipper and Volgenau 1972; Shay et al. 2000; Wada and Usui 2007) (Hereafter in this chapter, the conventional TCHP is referred to as ‘the conventional UOHC’). However, the method did not always ensure consistent results because the reference temperature determined from 2-m air and dew-point temperatures was set to ‘24 °C’ or higher. Thus, the reference depth for calculating the modified TCHP in Wada (2016) was always shallower than the 24 °C-isotherm depth. In this chapter, we propose an updated heat content metric that uses 2-m air and dew-point temperatures and accounts for atmospheric baroclinicity to produce more consistent values than the modified TCHP in Wada (2016).

Recently the relationship between TC rapid intensification and ocean metrics such as SST and the conventional UOHC has been studied (Hong and Wu 2021; Liu and Chan 2020; Song et al. 2020, 2021; Zhao et al. 2018). These studies used a single TC best track dataset or multiple TC datasets. There are four official internationally-recognized best-track datasets for TCs in the NWP, archived by the China Meteorological Administration’s Shanghai Typhoon Institute (CMA), Hong Kong Observatory (HKO), JTWC, and JMA. Since each institute conducts its own analysis using its own data, methods, and criteria (Lowry 2009), there is no guarantee that the trends of TC rapid intensification and the lifetime maximum intensity analyzed by using one of the best-track datasets are reflected in the others. To eliminate as much uncertainty as possible arising from analysis by an unspecified number of forecasters and to increase the uniformity of the dataset, the JMA has recently conducted a Dvorak reanalysis (Nishimuta et al. 2023). In the reanalysis dataset, the increasing trend in the number of Saffir-Simpson category 3–5 TCs was not significant (Kawabata et al. 2023). Furthermore, uncertainties associated with certain datasets also apply to other correlated datasets, such as an SST dataset (Tomita et al. 2019) and a conventional UOHC dataset (e.g. Wada 2021). Due to lack of in-situ observations not only in the inner core of TCs but also in the surrounding environments, studying the relationship between TCs and the ocean is still challenging. Even under these difficult circumstances, the results based on a consensus of analyses among multiple datasets would be more robust than those based on a single dataset in elucidating the relationship between TC activity and the oceanic environment. In addition, we must scientifically explain the contradiction that ocean heat content has increased where TCs are active despite the fact that an increase in stronger TCs is considered to enhance sea surface cooling.

The purposes of this chapter are as follows. First, the relationship between the increasing trend in TC intensity and the oceanic metrics such as SST and the conventional UOHC is reexamined using the four best track datasets along with two SST and two oceanic reanalysis datasets from July to December during 2000–2021, when the quality of data seems to be relatively homogeneous. This period follows an abrupt regime shift since 1998 (Zhao et al. 2018), and the first half of the period corresponds to the warming hiatus period (Trenberth 2015). Second, a new heat content is derived from the atmospheric and oceanic reanalysis data by accounting for the effect of turbulent heat fluxes from the ocean to the atmosphere and considering atmospheric baroclinicity. In addition, we assess the uncertainties of

the relationship between ocean warming and increases in TC intensity using the new heat content in NWP.

The rest of this paper consists of the following sections. Section 5.2 described data and method used in this study. In particular, Sect. 5.2 describes the derivation of a new heat content metric proposed in this study. Section 5.3 shows the results of examining the timeseries of best track TC central pressures, heat contents derived from the SST, conventional UOHC and new heat content. Section 5.4 discusses the interpretation of the results. Section 5.5 is devoted to the concluding remarks.

5.2 Data and Methods

Our analysis used four TC best track datasets, three SST datasets, two oceanic reanalysis datasets, and three atmospheric reanalysis datasets. We obtained the TC best track datasets from the International Best Track Archive for Climate Stewardship dataset (Knapp et al. 2010). The dataset includes four best track datasets from the JTWC, JMA, CMA, and HKO. The 6-hourly latitude, longitude, and central pressure were used for analyses. This study used the 6-hourly central pressure as a measure of TC intensity instead of the maximum wind speed because of the difference in the definition of averaging period for the maximum wind speed among the four datasets (i.e., 1 min (JTWC), 2 min (CMA) and 10 min (JMA and HKO)). It should be noted that there is no record of central pressure in the JTWC best track data prior to 2001, so the analysis period of the JTWC best track data is from 2001 to 2021. Also, the JMA maximum sustained wind speed was used to determine the time at which the TC occurred. Since the definition of maximum sustained wind speed differs among the four datasets, it is possible that the maximum sustained wind speed of the other datasets may not reach 35 kt at the genesis time determined from the JMA dataset. Only best track data for which all four centers have a record for the same time are selected and analyzed (i.e., a homogeneous comparison).

The two SST datasets used in this study are the Merged Satellite and In-situ Data Global Daily Sea Surface Temperatures (MGDSST) dataset (Kurihara et al. 2006), and the Microwave Optimally Interpolated SST (OISST) (Wentz et al. 2000). These are daily SST products with a spatial resolution of 0.25° .

The two oceanic reanalysis datasets are the extended three-dimensional variational daily ocean reanalysis dataset for the North Pacific (Wada and Chan 2021) based on the Four-dimensional variational Ocean ReAnalysis (FORA) dataset for the NWP (Usui et al. 2017) and the Japan Coastal Ocean Predictability Experiment (JCOPE)-Forecast Global Ocean (JCOPE-FGO) daily oceanic reanalysis dataset (Kido et al. 2022). The horizontal resolution of the FORA dataset used in this study is 0.5° and that of the JCOPE dataset is 0.1° . The two datasets cover the area from 100°E to 180° and from 0 to 60°N , which is the area of responsibility of the RSMC-Tokyo.

Three atmospheric reanalysis datasets are the Japanese 55-year Reanalysis (JRA-55) (Kobayashi et al. 2015), the Japanese Reanalysis for Three Quarters of a

Century (JRA-3Q) (Kobayashi et al. 2021), and the European Centre for Medium-Range Weather Forecasts Reanalysis version 5 (ERA-5) (Hersbach et al. 1997). The horizontal resolution of JRA-55 and JRA-3Q used in this study is 1.25° and that of ERA-5 is 0.25° . Since the temporal resolution of the three datasets used in this study is shorter than a day, the data for 00 UTC are used in this study. Thus, new heat content is a once-daily dataset.

We calculated the following three oceanic heat contents (Q_{SST} , Q_{TCHP} , Q_{NEW}):

$$Q_{SST} = \rho C_p (T_{SST} - 26) \times 1 \quad (5.1)$$

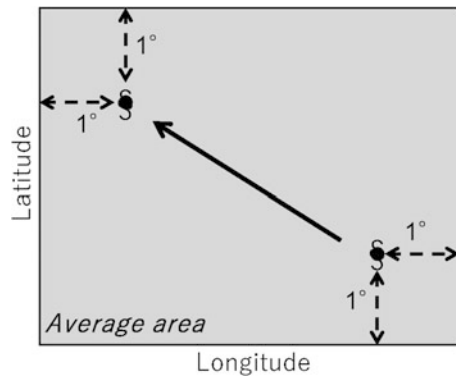
$$Q_{TCHP} = \sum_{i=1}^{i=i_{D26}} \rho_i C_p (T_i - 26) \Delta Z_i, \quad (5.2)$$

$$Q_{NEW} = \sum_{i=1}^{i=i_{DREF}} \rho_i C_p (T_i - T_{ref}) \Delta Z_i, \quad (5.3)$$

where i is the number of vertical layers, ρ is the water density, C_p is the specific heat capacity of liquid water at constant pressure, T_{SST} is the sea surface temperature, T_i is the water temperature at the i^{th} layer, ΔZ_i is the layer thickness of the i^{th} layer. In eq. (5.1), the sea surface temperature at 1-m depth is assumed (Kawai and Wada 2007).

The spatial average of three ocean heat contents is calculated for the rectangle-shaped area shown in Fig. 5.1. An area for calculating the spatial average is determined by using two locations of a TC at the analysis time and 6 h before. In addition, an edge of 1° is considered in the rectangle-shaped area. It is important to note that the ocean reanalysis data is on a daily time scale, whereas the TC data set is on a 6-h time scale. Ocean reanalysis cannot capture rapid decreases in water temperature that occur on time scales shorter than a day. It may lead to overestimating the ocean heat content within the inner core of a TC, particularly in the case of slow-moving TCs.

Fig. 5.1 Schematic diagram of the rectangle-shaped area over which the spatial average is calculated. Two TC marks show the locations of the TCs at the analysis time (upper left) and 6 h before (lower right). An arrow shows the direction of movement. The length of the arrow indicates the moving distance for 6 h



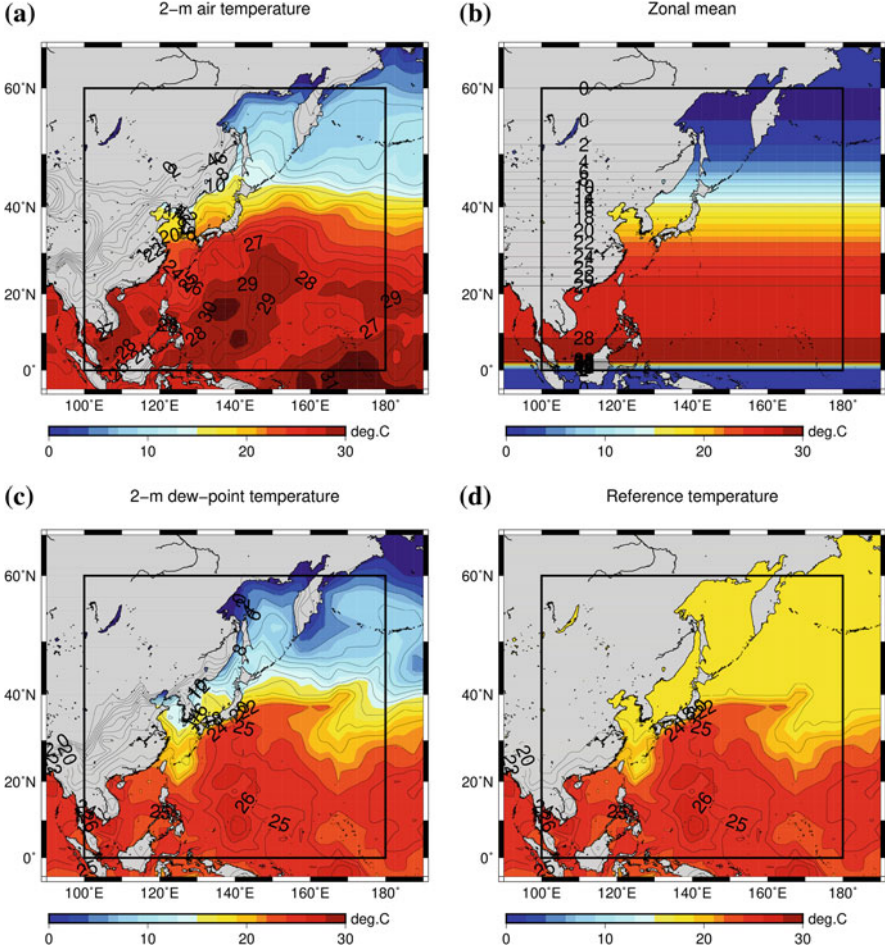


Fig. 5.2 An example of the parameters from the JRA-55 dataset used to calculate a reference temperature for the ocean reference depth. These panels show the distribution on 11 October in 2019. (a) Horizontal distribution of 2-m air temperature; (b) Horizontal distribution of zonal mean 2-m air temperature; (c) Horizontal distribution of 2-m dew-point temperature; and (d) Horizontal distribution of the reference temperature. The unit is degrees Celsius

The index i_{DREF} in Eq. (5.3) is determined based on the isotherm depth of T_{ref} in each oceanic reanalysis dataset. Figure 5.2 shows an example of the procedure for calculating a reference depth ($Z(i_{DREF})$) that is necessary for calculating the new heat content metric. First, the 2-m air temperature (Fig. 5.2a) was zonally averaged over the 20-day period preceding the analysis day. The zonal mean temperature $T_a(j)$ is a

function of latitude (Fig. 5.2b) where j is a latitudinal grid. $T_a(j)$ was calculated over the area from 100°E to 180° and from 0 to 60°N, the area of responsibility of the RSMC-Tokyo. After the following value L was calculated, the latitude corresponding to the maximum value of L (j_{Lmax}) was determined:

$$L = (-T_a(j-1) + 2T_a(j) - T_a(j+1)) \times T_a(j) \quad (5.4)$$

Equation 5.4 contains the Laplacian in the meridional direction of 2-m temperature. This enables extracting the latitude where the largest temperature gradient exists, which could be between the mid-latitude and the pole. To ensure that the latitude with the largest temperature gradient between the subtropics and mid-latitudes is extracted, the Laplacian is multiplied by the zonal mean temperature.

The maximum of either $T_a(j_{LMAX})$ or 2-m dew-point temperature in each grid (Fig. 5.2c) is selected as a grid's reference temperature T_{ref} (Fig. 5.2d). Therefore, the value of Q_{NEW} is affected by both oceanic and atmospheric reanalysis datasets, unlike Q_{TCHP} .

In previous studies (Moon et al. 2022; Wada and Usui 2007; Wada 2016), accumulated ocean heat content is used. In this study, however, the time average during the interval from the first record is used for analysis instead.

$$\overline{Q}_{SST} = \frac{1}{t} \sum_{t=0}^t Q_{SST}(t), \quad (5.5)$$

$$\overline{Q}_{TCHP} = \frac{1}{t} \sum_{t=0}^t Q_{TCHP}(t), \quad (5.6)$$

$$\overline{Q}_{NEW} = \frac{1}{t} \sum_{t=0}^t Q_{NEW}(t), \quad (5.7)$$

where the overbar denotes the time average from the first record of the RSMC-Tokyo best track maximum wind speed. The interval is determined every 6 h based on the first record of the maximum wind speed commonly recorded in all the four best track datasets.

We focus on the relationship between TC intensity and the upper-ocean environment in the tropical and subtropical oceans from July to December during 2000–2021. The analysis region is confined to a square from 5–20°N and 110–170°E corresponding to the primary rapid intensification zone in summer and autumn (Sasaki and Motoi 2022). The number of samples collected from the 6-hourly best track data is shown in Fig. 5.3, which is the same among the four TC best track datasets. Over the area of 5–20°N and 110–170°E, there is no clear trend but a decadal variation in the number of samples.

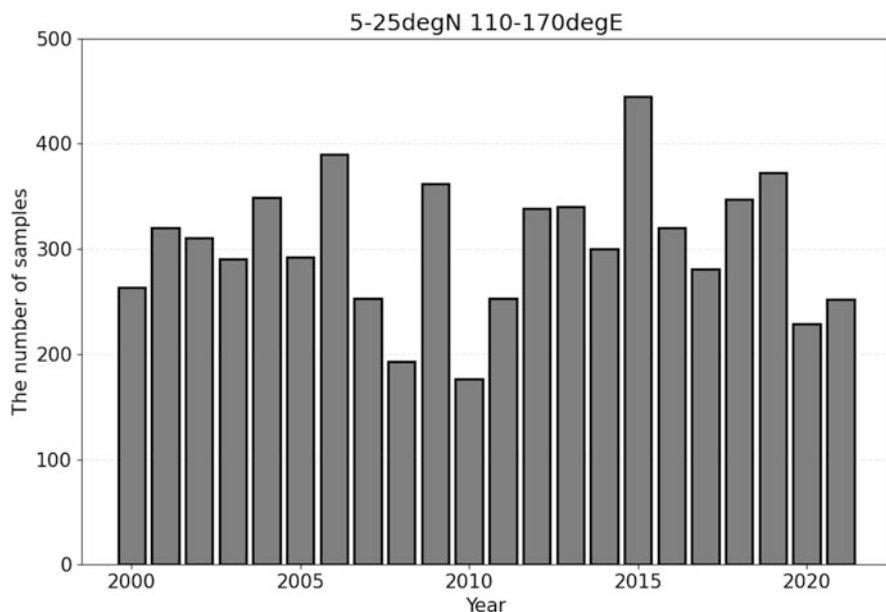


Fig. 5.3 Timeseries of the number of TC samples used in this study

5.3 Results

5.3.1 Trends in TC Best-Track Central Pressures

Figure 5.4 shows the timeseries of best-track central pressures from the four datasets from July to December during 2000–2021 (2001–2021 for JTWC) as a Box and Whisker plot. Linear regression analysis was conducted for the upper quartile (75%), median (50%), lower quartile (25%), and extreme value (0.5%), respectively. A color shade in each panel indicates the range of values calculated from the two linear regression functions and is considered to show a range between the upper and lower quartiles (25–75%). A dashed line shows a linear regression function for the median, a middle value in the number of samples in a year. The range of the slope per year was from 0.11 (CMA) and 0.51 (JTWC) for the median and from -0.86 (CMA) to 0.48 (JTWC) for the extreme value. The slopes for the median in the JTWC and HKO datasets were significant at the 90% significance level, while the others were not significant at that level. Although the consensus among the four datasets is not obtained, the median central pressure tends to increase in NWP from July to December 2000–2021. However, there is no evidence of a statistically significant decrease in the central pressure of extremely strong TCs at all. In addition, we clearly found differences in the trend of extreme values between JTWC and the other three institutions. Moreover, even within the three best-track datasets (HKO, KMA, JMA), we found differences to a greater or lesser extent for the extreme value.

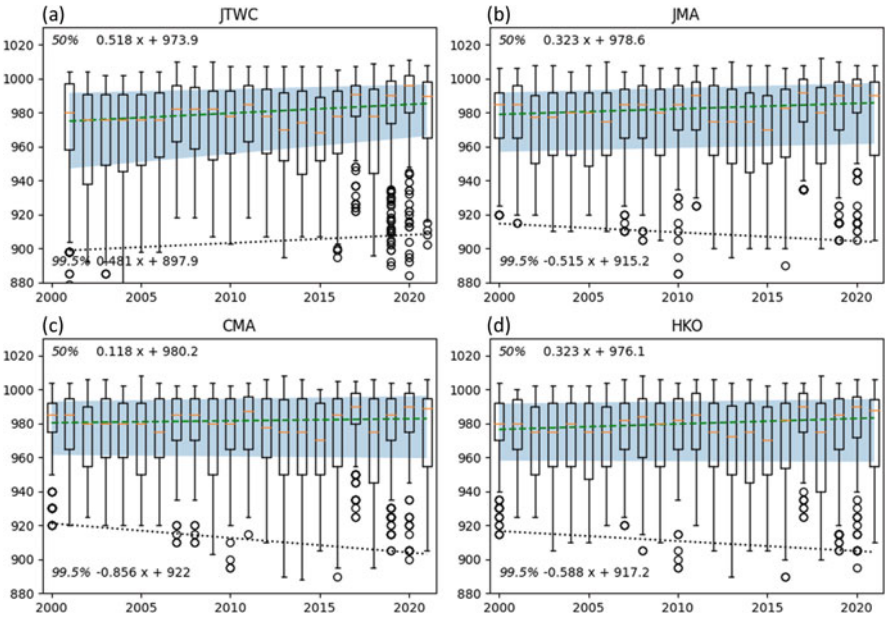


Fig. 5.4 Box and Whisker plots for the TC central pressure in the (a) JTWC, (b) JMA, (c) CMA, and (d) HKO best track datasets. The horizontal axis shows year and the vertical axis shows sea-level pressure. Green dashed lines show linear regression values for the median (orange bars for individual years) and dotted lines for the extreme value (0.5%). Blue shades indicate the range of linear regressions between the upper and lower quartiles. Circles show the outliers in each year. The linear regression equation shown in the upper left in each panel is for the median and the equation in the lower left is for the extreme value

5.3.2 Trends in SST and Conventional UOHC

5.3.2.1 SST

Figures 5.5 and 5.6 show the timeseries of heat content for daily bulk SST beneath a TC (Fig. 5.1) over the analysis region from July to December 2000–2021 calculated from Eq. (5.5) with OISST (Fig. 5.5) and MGDSSST (Fig. 5.6) datasets as Box and Whisker plots. The increasing rate of the median heat content was approximately 0.11 kJ cm^{-2} (OISST) and 0.09 kJ cm^{-2} (MGDSST) per decade, which was almost the same among the four best-track datasets. The increasing rates for the median were significant at the 99% (OISST) and 95% (MGDSST) significance levels. In addition, the increasing rate of the extreme values (99.5%) were consistent with those for the median, and significant at the 90% (OISST) and 99% (MGDSST) significance levels. The heat content of MGDSSST shown in Fig. 5.6 tended to be higher than that of OISST, while the increase rate in the heat content of OISST tended to be larger than that of MGDSSST. A common feature of the two SST datasets among the four best-track datasets is that the SSTs beneath a TC have been

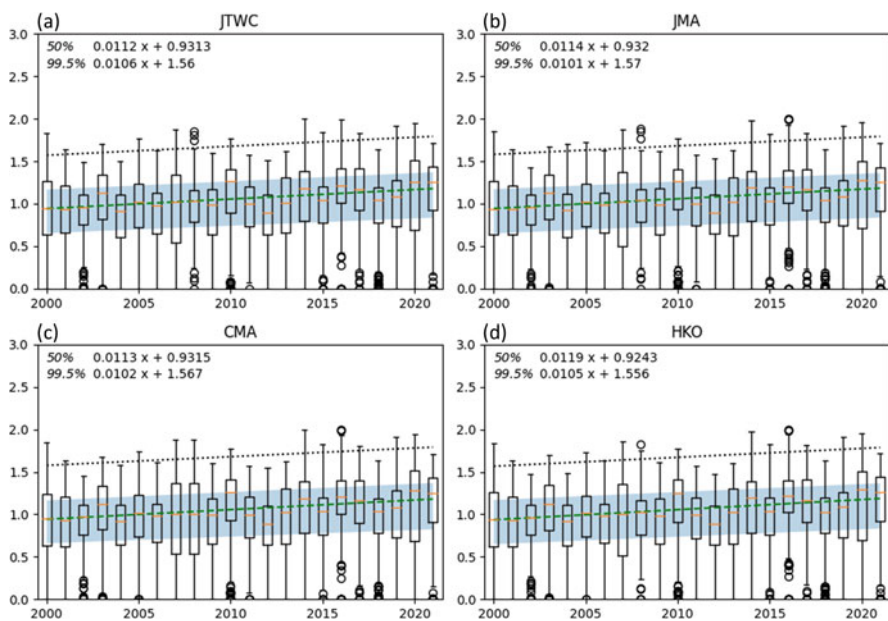


Fig. 5.5 Box and Whisker plots for the heat content of OISST calculated with Eq. (5.5) using the (a) JTWC, (b) JMA, (c) CMA, and (d) HKO best track datasets. The horizontal axis shows year and the vertical axis shows heat content (kJ cm^{-2}). A 1°C difference between SST and 26°C corresponds to approximately 1 kJ cm^{-2} . Green dashed lines show linear regression values for the median (Orange bars) and dotted lines for the extreme value (99.5%). Blue shades indicate the range of linear regression values between the upper and lower quartiles. Circles show the outliers in each year. The linear regression equations shown in the upper left in each panel is for the median and for the extreme value (99.5%), respectively

increasing over the analysis region in NWP from July to December during 2000–2021.

5.3.2.2 UOHC

Figures 5.7 and 5.8 show the timeseries of the conventional UOHC over the analysis region from July to December 2000–2021 calculated from Eq. (5.6) with the FORA and JCOPE datasets as Box and Whisker plots. The increasing rate of the median conventional UOHC was approximately $8.5\text{--}8.8 \text{ kJ cm}^{-2}$ (FORA) and $9.9\text{--}10.3 \text{ kJ cm}^{-2}$ (JCOPE) per decade. The increasing rates for the median were significant at the 95% (FORA) and 99.5% (JCOPE) significance levels. However, the increasing rate for the extreme value (99.5%) was not significant in the two datasets. The results suggest that TCs tend to occur over an area where the SST and conventional UOHC have been increasing during the analysis period. On the other hand, the median value of the best track central pressure has been increasing during the analysis period, indicating that a typical TC is weaker in recent years. The result

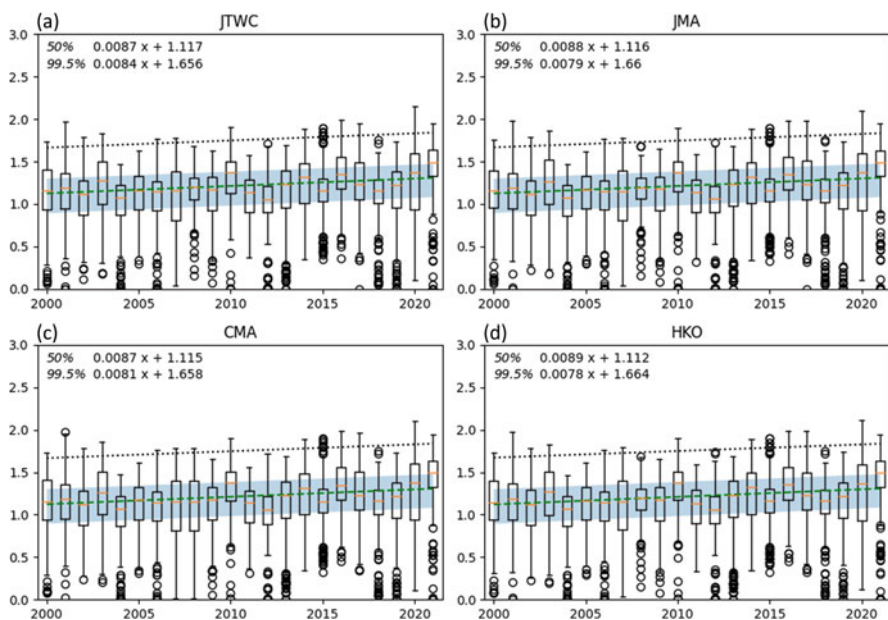


Fig. 5.6 Same as Fig. 5.5 except showing the heat content derived from the MGD SST dataset

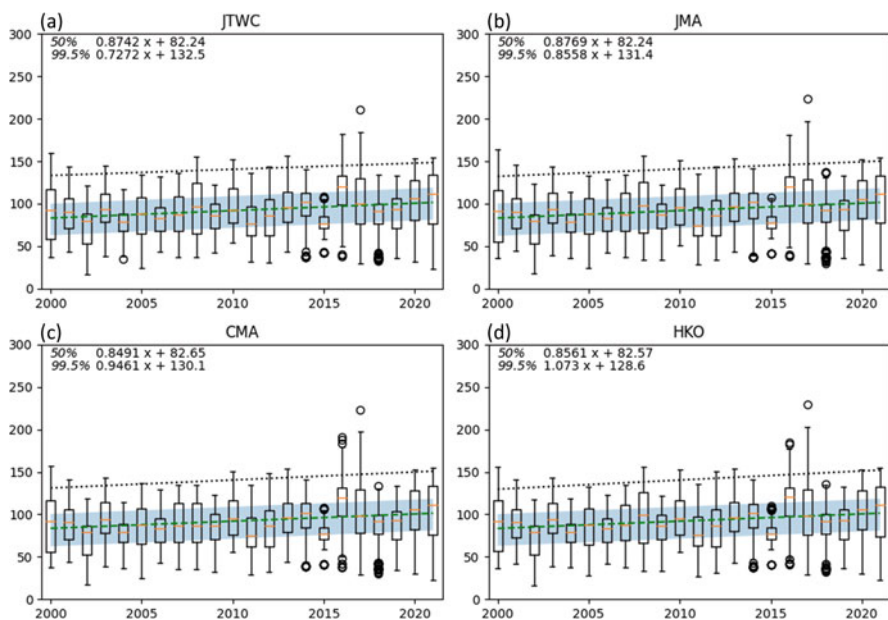


Fig. 5.7 Box and Whisker plots for the conventional UOHC of FORA calculated in Eq. (5.6) using the (a) JTWC, (b) JMA, (c) CMA, and (d) HKO best track datasets. The horizontal axis shows year and the vertical axis shows the value of conventional UOHC (kJ cm^{-2}). Green dashed lines show linear regression values for the median (orange bars for individual years) and dotted lines for the extreme value (99.5%). Blue shades indicate the range of linear regressions between the upper and lower quartiles. Circles show the outliers in each year. The linear regression equations shown in the upper left in each panel are for the median and for the extreme value (99.5%), respectively

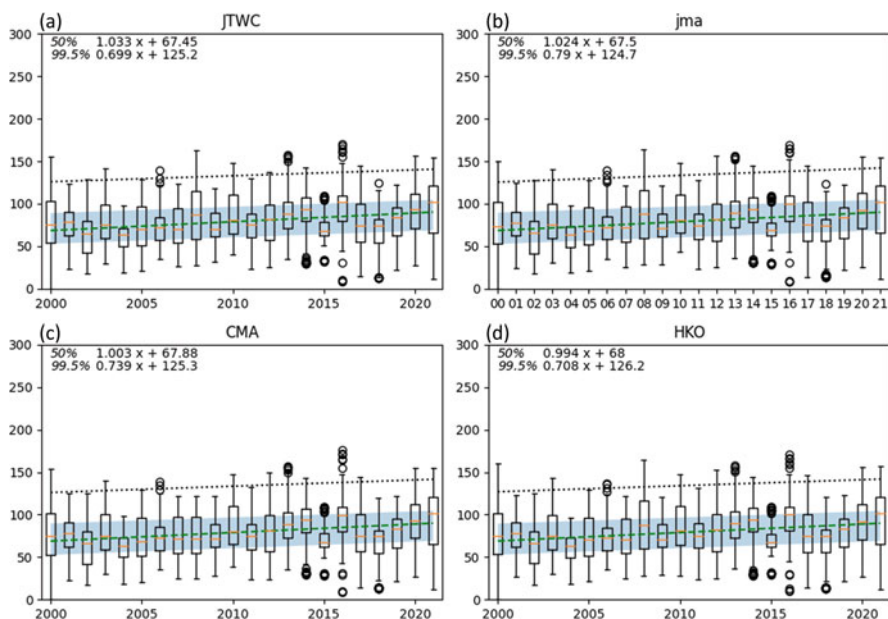


Fig. 5.8 Same as Fig. 5.7 except showing the conventional UOHC derived from the JCOPE dataset

seems to differ from previous studies (Elsner 2020; Elsner et al. 2008) that have shown that the increase in the intensity of the strongest TCs during 2007–2019 was related to rising SSTs and conventional UOHC. The difference depends on whether the analysis sample is the strongest TCs (0.5% percentile for central pressures) or typical TCs (the median) that occur in a year. It is important to argue here that not all TCs during the intensification phase can reach an extreme intensity, a statistical outlier, even though the TC passes over a region where SSTs and conventional UOHC have increased significantly. This is similar to the discussion regarding TC potential intensity (Emanuel 1988) frequently used in studies on TC climatology and projections of a future climate.

The contradictory result would be explainable if we consider that turbulent heat fluxes transported from the ocean to the atmosphere are more important for TC intensification than SST and conventional UOHC. A weakening TC results in lighter surface winds within the TC inner core and thereby reduces turbulent heat fluxes around the TC. Since the energy supply to a TC is reduced, the central pressure will become higher so that the surface wind speeds within the inner core do not increase but may decrease. The weakening of surface winds around the TC results in a reduction in the vertical turbulent mixing in the upper ocean, resulting in more upper-ocean stratification due to a higher near-surface water temperature than would be observed under strong wind conditions. This process is favorable for sustaining relatively high upper-ocean heat content beneath the TC but is not always associated with an extremely intense TC. Thus, the increase in conventional UOHC is not an optimal indicator to explain the increase in TC intensity. Another indicator closely

related to air-sea turbulent heat fluxes is required to describe the relationship between TC activity and oceanic environment if TC intensity and intensification is strongly influenced by the wind induced surface heat exchange mechanism (Emanuel 1986).

5.3.2.3 New Ocean Heat Content

Figures 5.9, 5.10 and 5.11 show the timeseries of new heat content from July to December 2000–2021 calculated from Eq. (5.7) based on the JCOPE dataset with the JRA-55 (Fig. 5.9), JRA-3Q (Fig. 5.10), and ERA-5 (Fig. 5.11) datasets as Box and Whisker plots. The increasing rate of new heat content for the median was approximately $5.4\text{--}5.6\text{ kJ cm}^{-2}$ for JRA-55, $5.1\text{--}5.3\text{ kJ cm}^{-2}$ for JRA-3Q and $6.0\text{--}6.3\text{ kJ cm}^{-2}$ for ERA-5 per 10 years, respectively. The increasing rates for the median were significant at the 95% significance level, but the statistical significance was confirmed for new heat content based on the JCOPE dataset with the JRA-55 dataset and the JTWC, JMA and CMA best track datasets (Table 5.1). The significance was also found for new heat content based on the FORA dataset with the

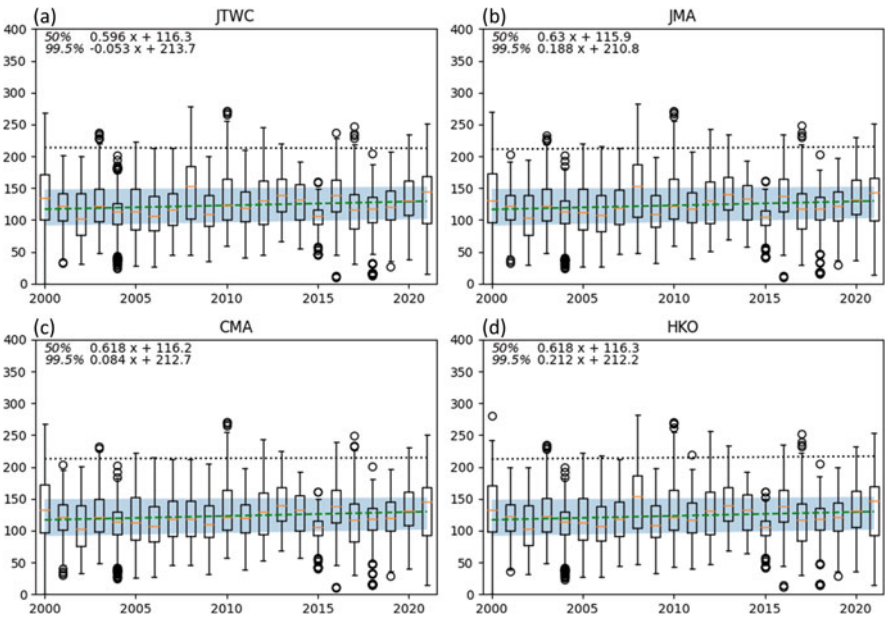


Fig. 5.9 Box and Whisker plots for the new heat content of JCOPE with JRA-55 calculated with Eq. (5.7) for the (a) JTWC, (b) JMA, (c) CMA, and (d) HKO best track datasets. The horizontal axis shows year and the vertical axis shows new heat content (kJ cm^{-2}). Green dashed lines show linear regression values for the median (orange bars for individual years) and dotted lines for the extreme value (99.5%). Blue shades indicate the range of linear regressions between the upper and lower quartiles. Circles show the outliers in each year. The linear regression equations shown in the upper left of each panel are for the median and for the extreme value (99.5%), respectively

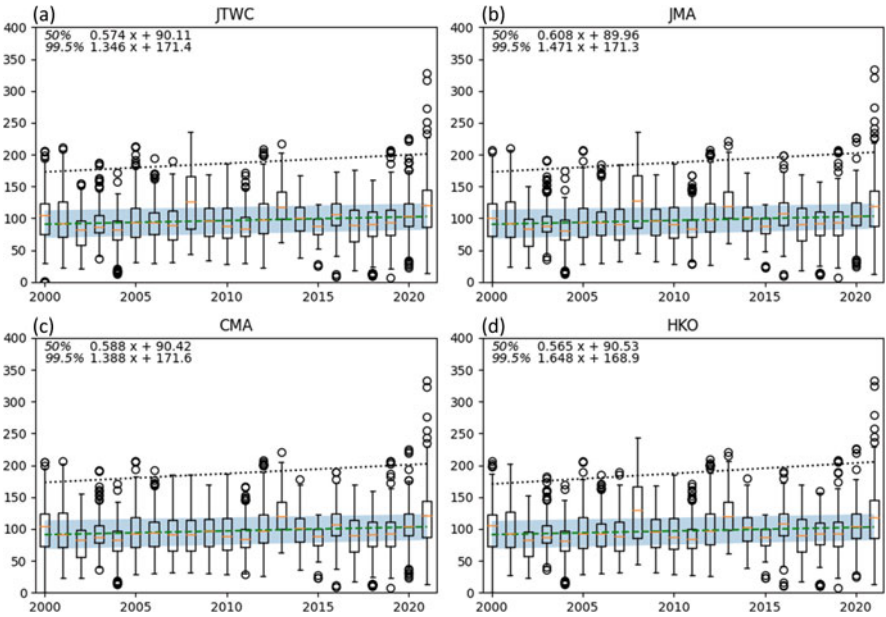


Fig. 5.10 Same as Fig. 5.9 except showing the new heat content from the JCOPE and JRA-3Q datasets

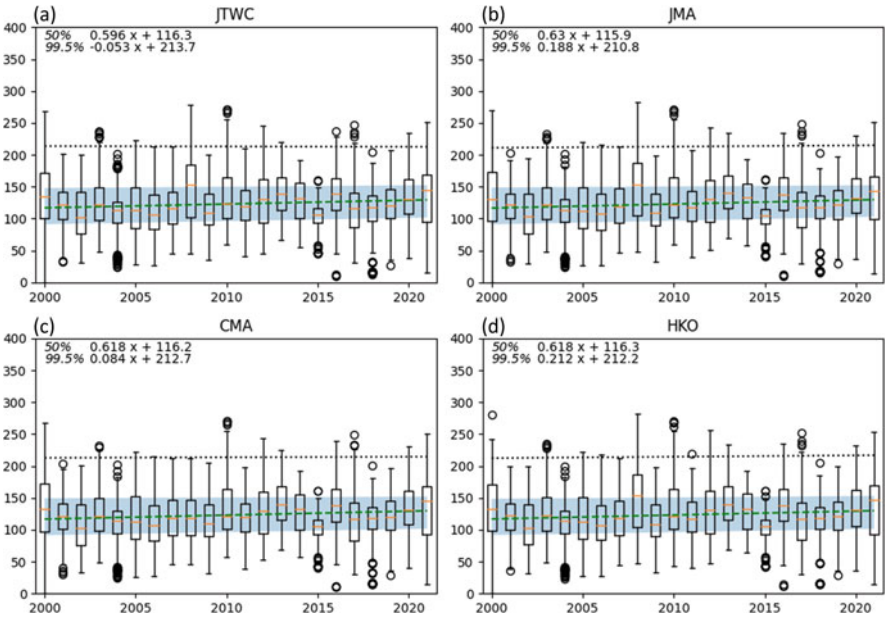


Fig. 5.11 Same as Fig. 5.9 except showing the new heat content from the JCOPE and ERA-5 datasets

Table 5.1 Slopes and intercepts in regression functions for the median of new heat content

Oceanic reanalysis dataset	Atmospheric reanalysis dataset	Institute	Slope	Intercept
JCOPE	JRA-55	JTWC	0.54*	185.3
		JMA	0.54*	185.1
		CMA	0.55*	184.7
		HKO	0.56	182.1
	JRA-3Q	JTWC	0.53	189
		JMA	0.53	188.7
		CMA	0.53	188.3
		HKO	0.51	186.6
	ERA-5	JTWC	0.60	213.7
		JMA	0.63	210.8
		CMA	0.62	212.7
		HKO	0.62	212.2
Fora	JRA-55	JTWC	0.65**	160.3
		JMA	0.66**	160.0
		CMA	0.66	159.7
		HKO	0.62	159.1
	JRA-3Q	JTWC	0.43	184.8
		JMA	0.42	184.3
		CMA	0.40	183.8
		HKO	0.41	183.4
	ERA-5	JTWC	0.54	229.8
		JMA	0.53	227.9
		CMA	0.62	227.8
		HKO	0.59	228.5

*95% significance level **90% significance level

JRA-55 dataset and the JTWC and JMA best track datasets. While there is consensus among the datasets that new heat content was increasing during 2000–2021, the statistical significance depends on the dataset used. However, the increasing rate for the extreme value (99.5%) was not significant in any of the timeseries shown in Figs. 5.9, 5.10 and 5.11.

The increasing rates of new heat content was lower than those of the conventional UOHC, although the significance of the rates of new heat content depended on the dataset used. The relatively low increasing rate for new heat content is due to the fact that the reference temperature over the analysis area (Fig. 5.1) has been rising recently as well as the SST and conventional UOHC. In other words, turbulent heat fluxes from the ocean to the atmosphere may not have increased as much as the increase in conventional UOHC. The increases in both TC central pressures (Fig. 5.4) and reference temperatures also suggest that the energy supplied for TC intensification has not been increasing in recent years even though the conventional UOHC has been increasing (Figs. 5.7 and 5.8).

As a precaution for use, the new heat content proposed in this study is affected by the quality of the atmospheric reanalysis dataset; ERA-5 had the highest new heat

content and JRA-55 had the lowest among the three atmospheric datasets (Table 5.1). We infer that the reference temperature in the JRA-55 dataset was the highest, while that in the ERA-5 dataset was the lowest over the analysis area (Fig. 5.1). This suggests that quantitative discussions for new heat content must take the uncertainties in the atmospheric dataset into account as well as the uncertainties in the ocean dataset. Although the horizontal resolution differs between JCOPE and FORA, the impact of the difference on the value of new heat content is not clear. While finer horizontal resolution of oceanic reanalysis data is expected to improve the representation of oceanic mesoscale eddies (Wada 2021), the finer horizontal resolution of atmospheric reanalysis data is expected to improve the representation of the inner-core structure of a TC such as a cold pool caused by downdrafts in the eyewall clouds (Houze Jr. 2010). These factors related to horizontal resolution may impact the new heat content uncertainty due to the complex involvement of finer-scale atmospheric and oceanic phenomena.

5.3.2.4 Relationship Between New Heat Content and TC Central Pressure

In this subsection, we address the relationship between TC central pressure and new heat content as well as conventional UOHC. The number of samples for each bin of central pressure is shown in Fig. 5.12 for each best track dataset. The number of samples for which central pressure was lower than 900 hPa in the JTWC best track dataset was much greater than that in the other datasets. This is partly consistent with a previous study (Nakazawa and Hoshino 2009) showing that the TC intensity estimates derived from the Dvorak method (Dvorak 1984) current intensity (CI) number in the JTWC dataset were generally higher than those in the JMA dataset (Koba et al. 1990) during 2000–2005, which corresponds to the latest 5 years of the analysis period from 1987 to 2006 in Nakazawa and Hoshino (2009). In other words, the characteristic of higher CI numbers in the JTWC dataset continues until 2021.

The followings are analysis results based on the JCOPE oceanic reanalysis dataset and the JRA-3Q atmospheric reanalysis dataset. The Box and Whisker plots of conventional UOHC (Fig. 5.13) and new heat content (Fig. 5.14) for each TC central-pressure bin show that the range of values of both the conventional UOHC and new heat content over the analysis area (Fig. 5.1) became narrower when the central pressure was lower than 940 hPa. In addition, as the central pressure deepens from 940 hPa, the median for new heat content tends to increase for the CMA (Fig. 5.14c) and HKO (Fig. 5.14d) best track datasets and conventional UOHC tends to increase for the JMA (Fig. 5.13b), CMA (Fig. 5.13c) and HKO (Fig. 5.13d) datasets. The increasing median central pressure trend is not noticeable in new heat content values for the JMA dataset (Fig. 5.14b). Also, the increasing trend is not noticeable for either new heat content or conventional UOHC for the JTWC dataset (Figs. 5.13a and 5.14a).

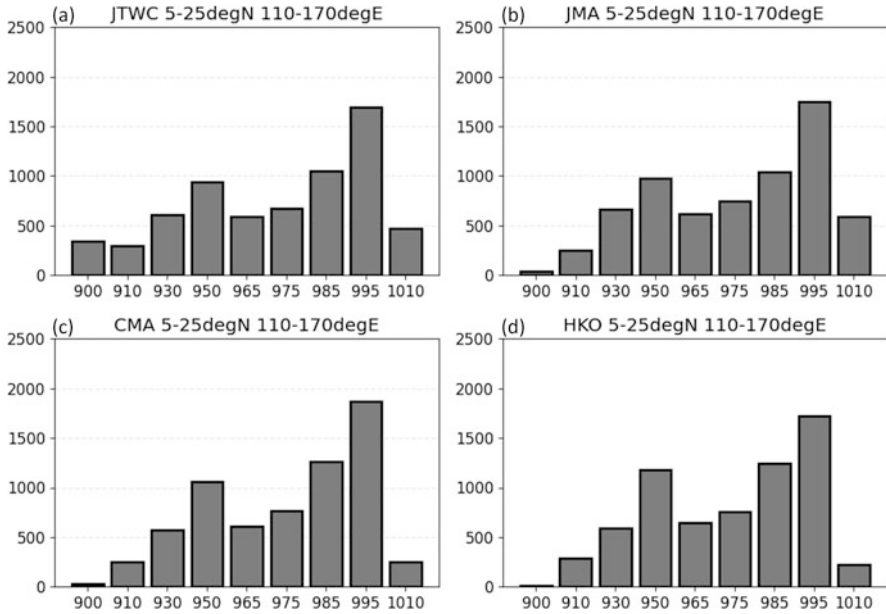


Fig. 5.12 Bar plots of the number of samples for each central-pressure bin for the (a) JTWC, (b) JMA, (c) CMA, and (d) HKO best track datasets over the area of 5–20°N, 110–170°E from July to December 2000–2021. The range of each bin is <900 hPa (900), 900–920 hPa (910), 920–940 hPa (930), 940–960 hPa (950), 960–970 hPa (965), 970–980 hPa (975), 980–990 hPa (985), 990–1000 hPa (995), >1000 hPa (1010)

With the exception of the results for the JTWC dataset, the number of samples for which central pressure is lower than 900 hPa is extremely low compared to the other central-pressure bins. JMA, CMA and HKO tended to analyze relatively high central pressures of TCs over the analysis area where the value of the conventional UOHC is lower than 70–80 kJ cm^{-2} and that of new heat content is approximately 90 kJ cm^{-2} . Thus, the number of samples for which central pressure is lower than 900 hPa was small in the JMA, CMA, HKO datasets and the value of the median for both new heat content and conventional UOHC tends to increase when the central pressure is lower than 900 hPa.

5.3.2.5 Case Study: Typhoon HAGIBIS (2019)

HAGIBIS rapidly enlarged from its genesis at 18 UTC on October 5 in 2019 (15.1° N, 157.4° E) during its rapid intensification phase, usually defined as the 95th percentile of all 24 h over-water intensity changes, corresponding to approximately +15 m s^{-1} or greater (Kaplan and DeMaria 2003). From 00 UTC on 6 October to 00UTC on 8 October, while Hagibis moved west-northwestward, it rapidly intensified and reached the minimum central pressures of 915 hPa in the

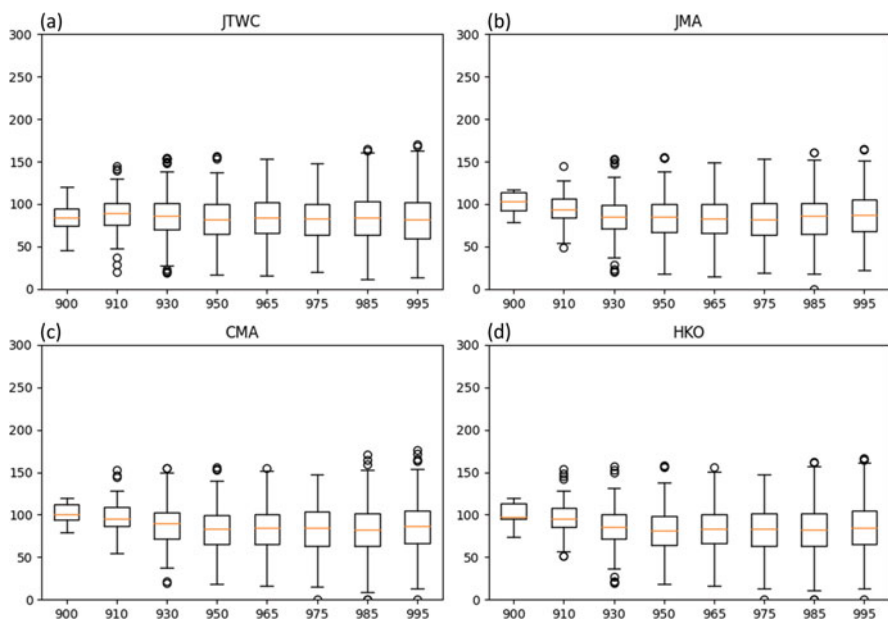


Fig. 5.13 Box and Whisker plots of conventional UOHC for each central-pressure bin in the (a) JTWC, (b) JMA, (c) CMA, and (d) HKO best track datasets over the area of 5–20°N, 110–170°E from July to December 2000–2021. The range of each bin is <900 hPa (900), 900–920 hPa (910), 920–940 hPa (930), 940–960 hPa (950), 960–970 hPa (965), 970–980 hPa (975), 980–990 hPa (985), 990–1000 hPa (995), >1000 hPa (1010)

JMA, CMA, and HKO best track dataset and 890 hPa in the JTWC dataset (Fig. 5.15).

Wada and Chan (2021) reported that Hagibis became an extremely intense TC due to an increase in TCHP caused by oceanic internal variability. However, Wada et al. (2022) noted that the analyzed central pressure of Hagibis was different between JMA and JTWC. In addition, the numerical simulations and climate sensitivity experiments conducted in Wada et al. (2022) supported the above-mentioned conclusion of Wada and Chan (2021), but Wada et al. (2022) only changed the oceanic initial condition without changing the atmospheric initial and boundary conditions. Of interest is the extent to which T_{ref} affects the Hagibis's central pressure. Therefore, Hagibis is taken up as a case study.

Figure 5.16a shows the time series of mean conventional UOHC calculated with the FORA and JCOPE data for the case of HAGIBIS. The values remained high or increased up to the 72-h integration time, and then the values rapidly decreased after the 72-h integration time (Fig. 5.16a). Considering that conventional UOHC was a daily dataset, the tendency was in good agreement with that of the best-track central pressures shown in Fig. 5.15a. For HAGIBIS, the differences in best-track central pressure among the institutions were more pronounced than the differences in conventional UOHC attributable in the differences in TC positions among the

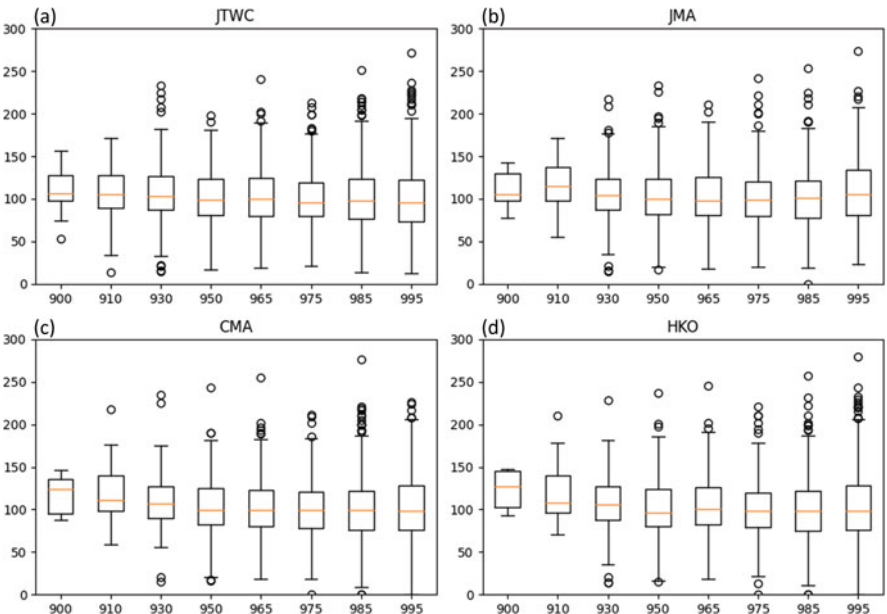


Fig. 5.14 Same as Fig. 5.13 except for the Box and Whisker plots of the new heat content for each central-pressure bin in the (a) JTWC, (b) JMA, (c) CMA, and (d) HKO best track datasets. The new heat content is calculated based on the JCOPE oceanic reanalysis dataset and the JRA-3Q atmospheric reanalysis dataset

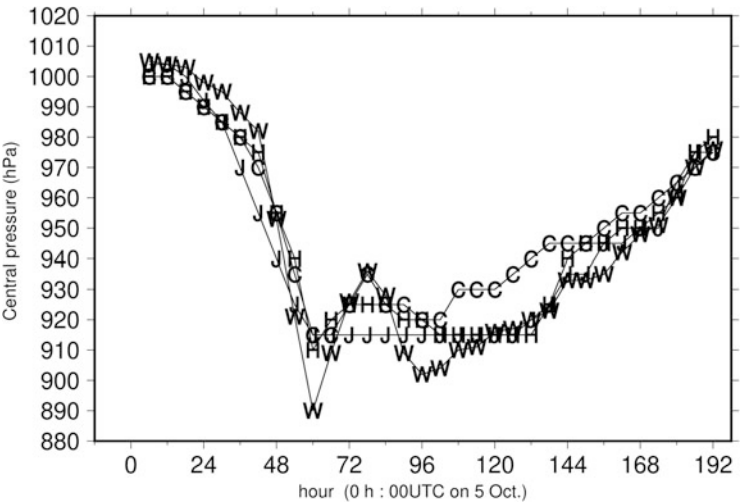


Fig. 5.15 Time series of the central pressure of HAGIBIS (2019) in the JTWC (W), JMA (J), CMA (C), and HKO (H) best track datasets. The horizontal axis shows the integration time from 00UTC on 5 October in 2019

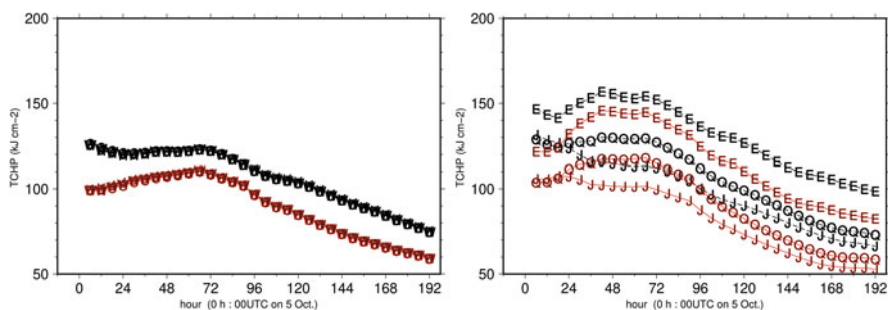


Fig. 5.16 (a) Same as Fig. 5.15 except for the time average of conventional UOHC calculated in Eq. (5.6) with the FORA (black) and JCOPE (red) data. (b) Time series of new heat content of HAGIBIS (2019) for the JMA (J) best track datasets using the FORA (black) and JCOPE (red) data. ‘J’ indicates the result with the JRA-55 dataset, ‘Q’ with the JRA-3Q dataset, and ‘E’ with the ERA-5 dataset

institutions. Figure 5.16b shows the time series of mean new heat content calculated with Eq. (5.7) using the FORA and JCOPE oceanic datasets and the JRA-55, JRA-3Q, and ERA-5 datasets, respectively. As in Fig. 5.16a, the tendency of new heat content was consistent with that of the best-track central pressure shown in Fig. 5.15. This means that HAGIBIS intensified over the ocean where new heat content was relatively high during its lifetime. As the new heat content beneath HAGIBIS decreased, HAGIBIS stopped intensifying and transitioned to mature and decaying phases. In addition, the range of new heat content shown in Fig. 5.16b was larger than that of the conventional UOHC shown in Fig. 5.15. This suggests that during the decaying phase, the temperature difference at the interface between the atmosphere and the ocean may have affected the change in TC central pressure in addition to the upper-ocean heat content. Thus, the new heat content could be a better metric to explain intensity changes and phase transition of TCs than conventional UOHC.

5.4 Discussion

Conventional UOHC has been used as a metric of the oceanic environment to infer the potential intensity of TCs (Wada and Usui 2007; Wada 2015). TC lifetime maximum intensity is significantly correlated with accumulated TCHP, represented by the accumulation of the UOHC beneath a TC from genesis to the lifetime minimum central pressure time (Moon et al. 2022; Wada 2016; Wada and Usui 2007; Wada et al. 2012). Both SSTs and conventional UOHCs are routinely used for NWP TC monitoring and intensity prediction guidance (Shimada et al. 2018). As shown in this study, both SSTs and conventional UOHCs in the tropical and subtropical NWP from July to December have increased significantly during 2000–2021. However, in terms of median annual central pressure trends, TC

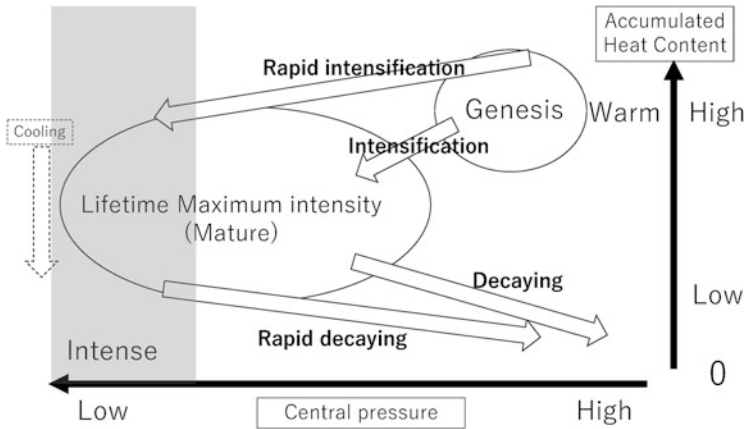


Fig. 5.17 Schematic diagram of the relationship between central pressure (horizontal axis) and accumulated heat content (vertical axis). Gray highlights the zone of most significant uncertainty in the best track datasets (see Fig. 5.14). Extratropical transition may be included at the head of the ‘decaying’ arrow

intensity has weakened during the period, although some datasets do not show a significant weakening trend. In addition, in this study, extremely intense TCs are statistically classified as outliers. For an extremely intense TC, a case study rather than a statistical analysis like this study may be more appropriate to determine whether the cause of such TCs can be attributed solely to characteristics of the oceanic environment such as the upper-ocean warming. Moreover, we should note that the results of the analysis for the outliers must account for the fact that there is not always agreement among the best track datasets.

The relationship between TC intensities and oceanic environments needs to account for the phase of a TC, including genesis, intensification, maturing, decaying and extratropical transition (Fig. 5.17). The process of TC genesis and intensification is explained by a structural change in the inner core from asymmetric to axisymmetric (Wada 2009) and from the monopole and ring-like pattern (Hardy et al. 2021). In these phases, the strength of convection in the TC inner core is one of the crucial factors that determines TC intensity via frictional convergence and upward transport of moist air to the upper troposphere at the TC center/eyewall (Wada 2021). When SSTs and conventional UOHCs underlying a TC are higher, the amount of convective heat transport to the atmosphere is expected to be greater. When a TC establishes an axisymmetric structure, an adiabatic heating process through downward flow at the TC center starts in the upper troposphere within the TC inner core. In this phase, from late intensification through maturity, stronger convection is needed to further intensify the TC. On the other hand, as a TC continues to intensify, the upper-ocean temperature decreases along the TC track particularly on the right side of the direction of motion in the Northern Hemisphere mainly due to turbulent mixing when the speed of TC movement is faster than the phase speed of the first baroclinic mode in the ocean (approximately 3 ms^{-1}) (Price 1981; Shay et al. 1998; Wada

2002). Sea surface cooling induced by a TC stabilizes the lower atmosphere (Lee and Chen 2013; Wada 2021), resulting in suppression of TC intensification or weakening. Inner core structure changes from axisymmetric to asymmetric in the mature and decaying phases (Wada 2021). During these phases, relatively low central pressure is analyzed under low conventional UOHC particularly in the JTWC best track dataset (Fig. 5.14a). During the decaying phase, the central pressure increases as a TC moves over the relatively low conventional UOHC region.

The range from lower to upper extremes in both conventional UOHC and new heat content for a given central-pressure bin is relatively wide because the analysis does not account for differences in TC phase. It is more appropriate to examine the relationship between TC intensity change and both conventional UOHC and new heat content only in the intensification phase (Wada 2015; Wada 2016; Wada and Usui 2007; Wada et al. 2012). If convection and surface friction are crucial physical processes that determine TC intensity change in the intensification phase (Wada 2021), it would be more appropriate to evaluate the heat and moisture transports from the ocean to the atmosphere within the TC inner core rather than characteristics of the upper-ocean environment alone. Based on the above-mentioned discussion, we develop new heat content from the modified TCHP of Wada (2016). The effect of heat and moisture transports from the ocean to the atmosphere is included in the estimate of new heat content in a more objective way: the atmospheric baroclinicity is determined through a calculation that does not use a 24 °C threshold. The relationships between the new heat content metric and TC intensity are consistent with those for conventional UOHC, while the results of the timeseries analysis of new heat content follow the trend of TC central pressure change better than that of the conventional UOHC.

As a metric for studies of TC climatology, the new heat content metric would be more useful for studying the drivers of TC activity in both current and future climates that are related to global warming. However, the new heat content metric depends not only on the quality of the ocean analysis dataset, but also on the quality of the atmospheric reanalysis dataset. As shown in Table 5.1, there are large differences in the value of new heat content among the datasets used. The difference in values could result in TC intensity prediction errors if new heat content is used as a predictor in TC intensity guidance, for instance. Another issue is the uncertainties associated with TC best track datasets. There are very few atmospheric and oceanic in-situ observations, particularly in the environment of extremely intense TCs. Although the amount of data available for objective analysis has been increasing due to the widespread use of satellite observations, the data observed by satellites are limited in time, space, and observation elements. Therefore, TC intensity analysis over the open ocean still relies on the subjective Dvorak analysis based on geostationary meteorological satellite data (Dvorak 1984; Koba et al. 1990). However, a recent numerical modeling study has shown that the main modes of variation in brightness temperature within the inner core of a TC in the intensification phase can explain at most only 70% of the total variance (Wada et al. 2022). Moreover, the differences in analysis among institutions are largely due to the unique practices of each institution (Lowry 2009). The Dvorak reanalysis dataset would be useful to

reduce the uncertainties (Nishimuta et al. 2023), but it should be noted that the dataset only includes a CI number that represents TC intensity instead of the maximum wind speed and central pressure. The procedure for converting CI number to the maximum wind speed and central pressure has also increased the uncertainty of TC data due to unique rules every institute and changes in the quality of observation data. We should keep in mind that the quality of the observational data used to analyze central pressure has changed over the analysis period (Shimada et al. 2020), and that the wind-pressure relationship used to evaluate best-track central pressure has also changed during 2000–2021 (Bai et al. 2019; Knapp et al. 2013). In addition, the JMA has changed the conversion procedure from the CI number of a TC based on Koba's table (Koba et al. 1990) from the central pressure (JMA 2016) to the maximum sustained wind speed (JMA 2017). The improvement of recent observation data includes the possibility that relatively high central pressure could be analyzed at a given CI number by cross-referencing new, high-quality data. It is also worth pointing out that the results of the analysis of relatively high central pressures may also affect the analysis of the upper ocean warming through atmospheric forcings.

Factors responsible for the increase in the conventional UOHC in the summer and autumn seasons in the analysis area (Sasaki and Motoi 2022) are not directly addressed in this study. However, as far as new heat content is concerned, no association with extreme strong TCs is inferred. Rather, a decreasing trend in TC intensity seems to be a contributing factor to the increase in the conventional UOHC due to a decrease in vertical turbulent mixing in the upper ocean. This is consistent with the recent study (Zhang et al. 2022) showing that the strengthening of the upper-ocean stratification due to global warming resulted in a reduction in TC-induced sea surface cooling and vertical turbulent mixing in the upper ocean.

Future work includes applying the new ocean heat dataset to studies of TC intensity relationships in the South China Sea and mid-latitudes. In addition, the metric may also be useful in global-warming studies such as the project of Earth System Modelling and Observations in World Climate Research Program.

5.5 Concluding Remarks

The IPCC Sixth Assessment Report (AR6) indicated that it is likely that the global proportion of Category 3–5 TC has increased over the past four decades. One of the possible reasons is an increase in the conventional UOHC. However, since the energy source for TC development is turbulent heat fluxes from the ocean to the atmosphere, it is questionable to explain the long-term trend in TC intensity only based on the upper-ocean warming. To replace the conventional UOHC, we calculated a new heat content metric using the reference temperature determined by atmospheric air temperature, dew point temperature and baroclinicity in the mid-latitudes instead of sea water temperature of 26 °C. The idea is based on Wada (2016), but the method is improved in a more objective way. While the

conventional UOHC beneath a TC has increased in the tropics and subtropics NWP from July to December 2000–2021, there is no evidence that new heat content beneath a TC has increased significantly even though multiple atmospheric reanalysis datasets were used. This implies that atmospheric warming represented by the increases in 2-m air and dew-point temperatures affects the calculation of new heat content.

The four best-track datasets in the NWP region tend to show anomalously low central pressures in recent years (particularly the JTWC best track dataset) while the median central pressure in the best track data has been increasing. Although most datasets show an increasing trend at extreme intensity, the results imply that overall TC intensity has weakened recently. The median for the conventional UOHC has increased significantly. However, there is no evidence of a trend particularly in the extremely low values for the best-track central pressures in any of the four best track datasets in NWP from July to December 2000–2021, which is more consistent with the trend in new heat content. Therefore, upper-ocean warming is likely not a direct cause of TC strengthening, and the reduction in TC activity may reinforce upper-ocean warming in the tropical and subtropical NWP. The increase in the number of extremely strong TCs is only the result of analyzing outliers in a statistical way. However, the trends in central pressure and conventional UOHC may make favorable environments for abruptly occurring and strengthening extremely strong TCs. While it is conceivable that the number of outliers will increase in the future to the point that the increase affects the evaluation of statistical significance, it is difficult to support such a possibility with the datasets used in this study. The weakening of TCs and the associated upper-ocean warming may have led to the emergence of extremely intense TCs as outliers in recent years. We should recognize that TC risk in a global warming world may be that the statistically explainable recent TC inactivity and its associated upper-ocean warming can be a crucial factor in causing extremely intense TCs that are classified into outliers.

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Chapter 6

Integration of Indigenous Traditional Knowledge and AI in Hurricane Resilience and Adaptation



Poulomi Chakravarty and Sai Gattupalli

Abstract With the incidences of increasing hurricanes and cyclone intensity and frequency driven by climate change, Indigenous communities have become vital actors in advancing effective adaptation strategies. This chapter focuses on the synergy between traditional Indigenous knowledges and modern scientific approaches to predict and respond to tropical storms such as hurricanes. Utilizing case studies from literature, we explore how Indigenous communities have successfully harnessed their knowledge, including traditional weather forecasting methods, to enhance community-based disaster preparedness and resilience against hurricanes. We emphasize the intricate process of integrating Indigenous Traditional Knowledge (ITK) in disaster risk reduction and climate change adaptation efforts, highlighting the essential role of building trust, nurturing relationships, and respecting the deep-seated values embedded in Indigenous practices. Additionally, the chapter investigates the challenges these communities face in advocating for their cyclone/hurricane adaptation strategies within formal disaster risk reduction policies. We highlight initiatives that empower Indigenous communities to prepare for hurricanes, including partnerships with governments, NGOs, and international organizations. In doing so, we offer an understanding of the multifaceted adaptation strategies employed by Indigenous communities in the face of a changing climate and highlight their critical role in strengthening regional resilience to hurricanes. Apart from Indigenous Traditional Knowledge we try to amalgamate the research on current scientific practices involving machine learning and artificial intelligence approaches along with traditional practices for reduction in disaster risk related to tropical storms and increased resilience of communities. We also present the *Climate Communication Channels* (3C) Model, a conceptual framework for effective true knowledge transfer between local communities via scientists, researchers,

P. Chakravarty (✉)
Global Climate Association, Patna, India
e-mail: poulomi@globalclimateassociation.org

S. Gattupalli
University of Massachusetts Amherst, Amherst, MA, USA
e-mail: sgattupalli@educ.umass.edu

knowledge processing centers, educators, and learners for curated localized climate resilience and adaptation strategies.

Keywords Hurricane · Climate change · Disaster risk and resilience · Climate change adaptation · AI · Indigenous traditional knowledge

6.1 Convergence of Knowledge

Climate variability and extreme weather events have become a norm in the era of global boiling (United Nations 2023; Chakravarty 2023). The diverse nature of the impacts of the changing climate makes it difficult to decipher and categorize systematically (Turner and Clifton 2009). The Sixth Assessment Report of Intergovernmental Panel on Climate Change (IPCC) warns the world of the impending doom that awaits us (IPCC 2023). To alleviate the general air of anxiousness that surrounds the ill effects of climate change and related socioeconomic impact, swift and comprehensive action must be taken, integrating all available resources and effectively communicating these efforts to the public. These sources include current modern technologies such as artificial intelligence (AI) and ancient wisdom of nature.

6.1.1 Overview of Hurricanes

The climate of a particular region is the driving force behind the survival of the living organisms residing within that ecosystem. The climate might be varied or stable, but its impact on the species is constant (Ng et al. 2018). With the changing climate, the entire ecosystem and living conditions of societies are under threat. Extreme weather events are one of the major adverse impacts of climate change. Tropical cyclones, including hurricanes and typhoons, are among Earth's most destructive weather systems. These extreme events are devastating weather systems that impact regions that are closer to the coasts (Lau et al. 2022). The spinning storms originate over warm tropical oceans, deriving energy from the evaporation of seawater and latent heat release during water vapor condensation. As they organize and intensify, wind speeds can exceed 74 mph, classifying them as hurricanes or typhoons depending on the ocean basin as described by the National Oceanic and Atmospheric Administration (NOAA). These storms originating from warm, low-pressure coastal waters are termed as hurricanes in the Atlantic, tropical cyclones in Asia, and typhoons in the Pacific regions. Tropical cyclones are categorized in terms of wind speed, wind pressure, frequency of occurrence, and financial losses and are scrutinized depending on casualties. As these powerful storms make landfall, they pose substantial threats to coastal populations, infrastructure, and economies through intense rainfall, storm surge flooding, high winds, and tornadoes (Lau et al. 2022).

Key environmental factors controlling tropical cyclone formation and intensification include sea surface temperature, vertical wind shear, mid-level moisture, and ocean heat content, which determine the thermodynamic potential intensity (Singh and Roxy 2022). Historical records of tropical cyclone occurrence and intensity relied heavily on ship-based observations before modern satellite monitoring, beginning in the 1970s (Chan and Kepert 2010). The datasets reveal considerable natural variability and multidecadal fluctuations in tropical cyclone activity over individual ocean basins (Velden and Hawkins 2010). However, limitations and inconsistencies in climate monitoring make detecting long-term trends difficult, significantly earlier in the twentieth century. Nonetheless, recent studies have identified increases in global proportions of major hurricanes and storm power dissipation energy, indicating an anthropogenic climate change fingerprint (Strauss et al. 2021). At the same time, natural oscillations like the Atlantic Multidecadal Oscillation contribute significantly to observed variability, complicating attribution efforts (Yeager and Robson 2017). Looking ahead, climate model projections under continued greenhouse gas forcing suggest likely increases in global tropical cyclone rainfall rates, intensity, and frequencies of major storms. However, substantial uncertainties remain regarding the timing, magnitude, and regional details of changing tropical cyclone behavior due to model biases, internal climate system variability, and competing effects like aerosol-induced cooling. Beyond maximum winds, shifts in prevailing tropical cyclone tracks could profoundly alter regional risks. For example, projections indicate a poleward shift in western Pacific storms, exposing East Asian coasts to greater threats, and an eastward shift in Atlantic storms, raising U.S. landfall likelihood (Tran et al. 2022). Regardless of storm behavior changes, rising sea levels will amplify coastal flooding during tropical cyclones and hurricane landfalls (Anderson et al. 2022).

Ongoing population growth and development in vulnerable regions are increasing exposure to such extreme events. This combination of climatic and societal changes points to growing hurricane impacts in the coming decades, underscoring the global need for expanded preparedness and adaptation efforts (Birkmann et al. 2022). In particular, underserved and Indigenous communities in developing nations face acute risks from hurricanes but often lack adequate resources for protective infrastructure and early warning systems (Climate change and the health of Indigenous populations, US EPA 2022). Extreme rainfall and inland flooding also pose major threats that can persist long after storm passage. Understanding what drives changes in tropical cyclones and hurricane behavior remains an active area of research, relying on improvements in long-term historical records, high-resolution modeling, and analysis of environmental controls (Camargo et al. 2023). There are many open questions about the relative roles of natural variability, anthropogenic climate change, and their interactions in recent observed trends. Addressing these knowledge gaps can help constrain projections of future changes and their uncertainties. Well-informed risk assessment and adaptation planning will be critical for enhancing community resilience and reducing hurricane impacts (Stephenson et al. 2019).

6.1.2 The Role of Indigenous Communities in Hurricane Resilience

Indigenous communities often inhabit tropical and subtropical regions prone to hurricane impacts (Kronik and Verner 2010). Their profound connection to ancestral lands and livelihoods dependent on local ecosystems make these communities highly vulnerable to storm damages (Pearson et al. 2021). However, centuries of accumulated knowledge, cultural practices, and adaptation strategies also impart unique resilience that can inform hurricane preparedness beyond Indigenous regions. Many native traditions evolved and adapted to promote safety and sustain vital resources during hurricane seasons. For example, elevated stilt home construction protected Central American communities from flooding, while Polynesian oral histories tracked cyclical storm patterns to guide sailing routes (Walter et al. 2017). Indigenous groups from Guatemala to Nicaragua track astronomical cycles or natural cues like bird migrations to anticipate impending hurricane threats (Garcia 2022). Traditional meteorological knowledge and forecasting methods remain important where they can work with modern weather technology. Indigenous communities have also cultivated storm-resistant crops like cassava, developed agroforestry systems with flexible tree species, and reserved emergency food supplies (Mcguigan 2022). Their localized knowledge of drainage patterns, prevailing winds, and shelter locations in familiar terrains further aids survival during hurricane strikes. However, Indigenous resilience practices face increasing challenges in modern times. Factors like climate change, ecosystem degradation, globalization, and displacement from ancestral lands due to colonization are eroding Indigenous traditional knowledge (ITK) (Wane 2008). Many communities also lack resources or access to natural resources due to institutional barriers, commercial projects, and structural scarcity, resulting in failure to fully implement adaptive strategies or recover post disasters (Climate change and the health of Indigenous populations, US EPA 2022). Still, efforts to integrate Indigenous knowledges with formal policies offer mutually beneficial opportunities to reinvigorate and expand life-saving practices. For instance, the Miskitu people's expertise improved hurricane impact models for Nicaragua's North Caribbean Coast (Kain 2018). The Mayan elders' insights helped align disaster management priorities with local needs in Guatemala (Fox 2021). Partnerships facilitating open knowledge exchange, rather than extraction, enable Indigenous communities to retain authority over sharing wisdom on their terms while ensuring data sovereignty, thus building trust among all parties. At the international level, frameworks like the UN Sendai Declaration increasingly recognize Indigenous knowledges as crucial for disaster resilience (Pimprikar et al. 2023). Looking ahead, Indigenous resilience practices honed over generations offer invaluable insights that can strengthen hurricane preparedness worldwide.

6.1.3 Intersection of AI and Indigenous Knowledge

As climate change escalates hurricane threats, respectfully integrating Indigenous knowledges with modern AI and machine learning (ML) techniques can enhance disaster resilience worldwide (Chen et al. 2020). Indigenous communities possess place-based wisdom honed over generations of adapting to local hurricane risks that provide key insights. Meanwhile, AI offers vast data processing capabilities to uncover patterns and model complex hurricane behaviors (Clemente et al. 2023). Though from different traditions, joining these complementary strengths can forge new solutions. A foremost priority is digitizing endangered Indigenous knowledges to preserve hurricane resilience practices and make them accessible. Community-led efforts to collate oral histories, experiential insights, forecasting methods, survival strategies, and damage mitigation approaches into digital databases enable organized storage along with acknowledging data sovereignty for future generations. This way, the original source of knowledge retains authority, credibility, and opens access to all resources in the process. For instance, several Ecosystem-based Adaptation (EbA) strategies can be witnessed worldwide, such as in the island of Fiji, where the iTaukei community implements mangrove management strategies as custodians of local wetlands (Pearson et al. 2020). These strategies can be digitized to preserve and customized for other similar areas. AI techniques like natural language processing can help systematically extract, translate, and analyze Indigenous knowledges content at scale (such as Robles et al. 2024). Although only a few languages are currently available for such translations this scenario will likely improve in the future. Modern hurricane tracking and forecasting systems still have trouble anticipating rapid intensification events (Z. Sun and Huang 2023). However, some Indigenous techniques can detect early signs of strengthening storms (Nurzaman et al. 2020). Integrating these observational cues with AI-processed satellite imagery and meteorological data through ML could enhance prediction accuracy (Orlove et al. 2020). AI can also determine optimal ways to present forecast information that aligns with Indigenous communication customs (Wei et al. 2023).

However, climate change is altering hurricane patterns in ways beyond historical Indigenous experience. AI modeling leveraging both scientific climate projections and community observations of environmental changes can anticipate new hurricane risks (Panda et al. 2023). Indigenous dwellings upgraded for contemporary hazards using AI-optimized engineering techniques maintain cultural continuity (Pimprikar et al. 2023). Ultimately, blending Indigenous wisdoms and AI capabilities could uncover synergies that strengthen resilience to mounting hurricane threats. The same collaborative model applies to disaster response. AI chatbots delivering emergency alerts in native languages are able to improve communication (Chan and Tsai 2023). Drones guided by AI and community feedback accelerate damage assessments (Kerle et al. 2019; Calantropio et al. 2021). ML triage of hurricane impacts helps rapidly mobilize Indigenous-led recovery efforts, and Indigenous communities can direct AI resilience priorities based on experiential insights. With climate change projected to expand hurricane destruction worldwide, joining Indigenous

knowledges and AI is key to empowering vulnerable regions. This fusion honors Indigenous resilience while democratizing AI to serve local needs.

6.2 Case Studies: Traditional Practices in Hurricane Prediction and Response

Indigenous communities possess holistic worldviews that foster deep connections to the lands they inhabit. Their traditional knowledge systems reflect generations of place-based observations, experiences, and spiritual relationships with local environments. This produces a sophisticated understanding of ecosystem changes that can provide early warnings of impending hurricanes. For instance, the Native Hawaiian chants record cyclical hurricane patterns noted during navigation centuries ago (Enos 2015). Memorizing these chants imparted life-saving environmental knowledge to sailors crossing the Pacific. Other Pacific Islanders crafted predictive models of hurricane season risks by tracking sun, moon, and star positions. In various parts of India, ancient traditional wisdom is recorded and passed on through couplets or rhymes which inform about the upcoming monsoon, yield quality, impending disasters, storm events and drought periods (Pareek and Trivedi 2011; Acharya 2011). These examples showcase how Indigenous knowledge systems cultivate acute environmental awareness and disaster prediction capacities (Table 6.1). Blending Indigenous forecasting practices with modern meteorological data could uncover new synergies for early warning and climate adaptation.

The integration of ITK in environmental management and disaster resilience is exemplified across various Indigenous communities globally, each employing unique strategies tailored to their local ecosystems and cultural heritage. The iTaukei people utilize mangrove management as part of their ecosystem-based adaptation strategies, effectively safeguarding coastal areas against environmental threats (Pearson et al. 2020). In Rajasthan, India, tribes like the Banjara, Bhil, Meena, Kanjar, Kathodi, Rabaris, and Sansar employ local sayings and poems to accurately predict weather and seasons, aiding in agricultural planning (Pareek and Trivedi 2011). Similarly, tribes in British Columbia, Canada, have developed a knowledge bank of natural disasters through storytelling and artifacts, preserving crucial information for future generations (Turner and Clifton 2009). The Brahman Sutras of ancient India offer insights into monsoon and drought predictions by interpreting cloud formations, a method crucial for agricultural productivity (Pareek and Trivedi 2011). In Vietnam, the Yao people of Bac Kan Province employ cultivation strategies that closely monitor animal behaviors and vegetation patterns, adapting their agricultural practices to climatic stresses (Son et al. 2019). Farmers in Tripura, India, use the phenology of night flowering jasmine to guide crop planting, showcasing an intimate understanding of plant life cycles (Acharya 2011). Navigation and prediction methods of Native Hawaiians, involving memorizing chants that record cyclical hurricane patterns, demonstrate an advanced understanding of environmental

Table 6.1 Examples of traditional ecological knowledge from literature: indigenous approaches to weather forecasting and environmental management

Indigenous community	Purpose	Strategy	Reference
iTaukei community Fiji Island	Mangrove management	For instance, several Ecosystem-based Adaptation (EbA)	Pearson et al. (2020)
Banjara, Bhil, Meena, Kanjar, Kathodi, Rabaris and Sansar tribes of Rajasthan, India	Weather, season, and disaster prediction	Local sayings and poems predict upcoming seasonal behavior accurately. “ <i>Pawan baje suryo, to hali halav kim puryo</i> ”- winds from North-west indicate heavy rains therefore farmers warned against ploughing fields	Pareek and Trivedi (2011)
Tribes of British Columbia, Canada	Disaster related knowledge bank creation through ancient stories and tales of survival	Storytelling, ceremonies and inclusion of artifacts such as totems of natural disasters like floods, volcanic eruptions, earthquakes, and extreme weather conditions. These stories of survival during devastation help effective customization of climate adaptation	Turner and Clifton (2009)
Brahman Sutras of ancient India	Monsoon and drought predictions	Cloud shapes decides the nature of monsoon rains and drought periods	Pareek and Trivedi (2011)
Yao people of Bac Kan Province, Vietnam	Cultivation strategies based on native species, climate change adaptation, and resilience	Monitoring animal behaviors, vegetation patterns, and weather indicators for early warning. Utilizing native plant and animal species for better adaptation during climatic stresses such as floods and droughts	Son et al. (2019)
Farmers in Tripura, India	Agricultural planning	Observing phenology of night flowering jasmine to guide crop planting	Acharya (2011)
Native Hawaiians	Navigation and prediction	Memorizing chants recording cyclical hurricane patterns	Enos (2015)
Pacific Islanders	Predictive modeling	Tracking sun, moon, and star positions for hurricane season risks	
Caribbean Island Communities	Storm preparedness	Observing changes in sea conditions and bird behaviors	Kronik and Verner (2010)
Maori Tribes (Indigenous Australians)	Environmental monitoring	Using knowledge of land, sea, and atmospheric conditions for prediction	King et al. (2008)
Indigenous Amazonians	Flood prediction	Recognizing specific flora and fauna behaviors as flood indicators	Bauer et al. (2022)

rhythms (Enos 2015). Skilled in predictive models, Pacific Islanders track celestial bodies to anticipate hurricane season risks, a testament to their navigational prowess (McDonald 2023). In the Caribbean Islands, communities observe sea conditions and bird behaviors to prepare for storms, illustrating a deep connection with their natural surroundings (Kronik and Verner 2010). The Māori Tribes and Indigenous Australians utilize their comprehensive knowledge of land, sea, and atmospheric conditions for environmental monitoring, a practice integral to their cultural heritage (King et al. 2008). The Indigenous Amazonians' ability to predict floods through specific flora and fauna behaviors showcases their acute awareness of ecosystem indicators and highlights the importance of such knowledge in disaster preparedness (Bauer et al. 2022). These examples reflect the richness and diversity of Indigenous ecological knowledge and underscores its importance in contemporary environmental management and disaster resilience efforts. These practices, refined over generations, emphasize a sustainable and holistic approach to living in harmony with nature, providing valuable lessons for broader application in addressing today's environmental challenges.

6.2.1 The Scientific Basis of Indigenous Knowledge

While Indigenous Knowledge Systems and Western scientific methodologies arise from keen observations and intricate relationships with the environment, they are each grounded in distinct worldviews. Indigenous knowledges, cultivated over generations, offer a holistic understanding of local ecosystems and environmental patterns, including those relevant to hurricanes. This knowledge, deeply intertwined with cultural and spiritual elements, complements Western science's more analytical and hypothesis-driven approach. Increasingly, empirical research recognizes the value of these traditional practices, validating their insights and integrating them for a more comprehensive approach to understanding and adapting to hurricanes. Work by Meena et al. (2023) shows that the "majority of the farmers expressed the need for blending TK and modern science for addressing location-specific problems." Studies have confirmed the accuracy of Mayan forecasts based on monitoring plant and animal behaviors in anticipating cyclones in Central America (Zeiger 2019). Likewise, computational modeling validated structural engineering principles in traditional wooden housing designs that minimize wind damage in Caribbean communities (Kuś et al. 2024). Aerodynamic forms and flexible joints allow these dwellings to withstand hurricane-force winds (Gan Chowdhury et al. 2017). Scientists also discovered Indigenous Australian burning practices produced Savanna ecosystems more resilient to cyclone impacts (Ibanez et al. 2022). Patchy, low-intensity fires created habitat mosaics and prevented fuel buildup, mitigating storm damages. Indeed, integrating the two knowledge systems for disaster risk reduction has become a major priority of UN initiatives like the Sendai Framework

(Pearson and Pelling 2015). This synthesis acknowledges the intrinsic value of Indigenous practices and their profound contribution to scientific research and policymaking. By combining the depth of Indigenous understanding with other knowledge systems, we aim to enrich the overall approach to disaster risk reduction, ensuring that the unique insights and wisdom inherent in Indigenous practices are recognized and integrated into a holistic framework of resilience. Empirical demonstration of ITK systems is upending conceptions of traditional wisdom as anecdotal or folkloric, revealing its vital role in navigating an uncertain climate future.

6.3 Modern Scientific Approaches: AI and Machine Learning

As climate change drives more destructive tropical cyclone seasons, advanced computing technologies like AI and ML offer new tools to enhance disaster prediction, response, and resilience (Fan et al. 2021; Sun et al. 2020; Yu et al. 2018). Recent advances allow AI systems to rapidly analyze vast meteorological datasets (Fathi et al. 2021), identify patterns key to hurricane genesis and intensification (Martinez-Amaya et al. 2022), boost forecast model performance, and optimize emergency operations (Huang et al. 2021). Though not a panacea, judiciously applied AI can generate actionable insights to aid vulnerable communities, complementing existing research and policy efforts. In weather forecasting, ML algorithms are uncovering nonlinear relationships in historical meteorological data that improve real-time tropical cyclone tracking and intensity prediction. For instance, neural network models can process records of past storm behaviors to determine the likelihood of rapid hurricane intensification based on current environmental conditions (such as Xie et al. 2023; Tapiador et al. 2022). These AI-enhanced forecasts provide earlier warnings to prompt protective actions. Likewise, AI geospatial analytics enable rapid disaster needs assessments after landfalls by synthesizing satellite imagery with on-the-ground damage reports (Liu et al. 2023; Yu et al. 2018). Kikin et al. (2019) use ML techniques to prioritize response logistics by mapping infrastructure impacts, flooding, and lifeline service outages. AI-directed disaster drones further support search-and-rescue, infrastructure repairs, and humanitarian aid delivery to isolated communities (Heidari et al. 2023). However, careless application of AI may encode biases, breach privacy, or exacerbate inequities (Schwartz et al. 2022). Equitable and reciprocal collaboration with frontline communities is vital to ensure AI adoption empowers local actors. AI constitutes one piece of the puzzle for building hurricane resilience, complementing but not supplanting human knowledge, preparedness policies, and disaster response capacities.

6.3.1 AI Advances in Hurricane Forecasting and Prediction

The emergence of advanced AI and ML technologies has ushered in a new era in meteorology, particularly in hurricane forecasting and weather prediction (Donner et al. 2022). Table 6.2 represents a selection of cutting-edge AI tools, designed to enhance our understanding and predictive capabilities regarding tropical cyclones, hurricane intensity, and broader weather phenomena. These tools, developed through collaborative efforts of scientists, technologists, and researchers, showcase the fusion of high-level computational power with meteorological science. Their diverse applications range from analyzing the intricate dynamics of hurricanes to leveraging historical data for accurate weather forecasting, demonstrating the transformative impact of AI and ML in tackling some of the most challenging aspects of climate and weather prediction.

Meanwhile, AI simulation of past storms under projected climate scenarios provides risk projections at a finer scale than current forecast models. AI can also continuously assess infrastructure vulnerability and community disaster readiness using real-time satellite data (W. Sun et al. 2020). Immediate damage estimates after landfall enable optimized humanitarian response planning and resource allocation (Jung et al. 2020). AI is a powerful new tool for improving hurricane predictive abilities, risk awareness, and disaster preparedness.

Table 6.2 Examples of innovative AI tools in meteorology: revolutionizing hurricane forecasting and weather prediction

AI Tool	Purpose	Application	Reference
Hurricast	Tropical cyclone forecasting	Multimodal ML framework combining various techniques for intensity and track forecasting of tropical cyclones	Wang et al. (2022) and Boussieux et al. (2022)
Data-based models for hurricane evolution prediction	Hurricane evolution prediction	Deep learning approach for forecasting hurricane evolution, particularly trajectory forecasting	Bose et al. (2023)
Machine learning for hurricane intensity prediction (JPL NASA)	Predicting hurricane intensity	Utilizing machine learning to analyze complex internal dynamics of hurricanes, focusing on ice water content and outflow temperatures	JPL NASA (2020)
Google DeepMind GraphCast	Weather prediction	Utilizes ML to analyze historical weather data for quick and accurate predictions of various weather variables	Lam et al. (2023)
Huawei’s Pangu-weather	Weather forecasting	AI-based system for meteorological data analysis and weather prediction	Bi et al. (2023)

6.4 Challenges and Opportunities

While integrating Indigenous knowledges, technology, and scientific data holds tremendous potential to enhance hurricane resilience, realizing synergistic solutions also faces obstacles (Loch and Riechers 2021; Hemmerling et al. 2019; Mitchell et al. 2016). Overcoming systemic barriers, building trust, and securing resources require confronting complex social challenges. However, doing so brings possibilities to fundamentally transform disaster readiness through inclusive, participatory processes. Here, we explore impediments that must be recognized, along with openings to catalyze positive change. Elucidating this dual landscape illuminates prudent pathways toward just, equitable collaboration. With a commitment to open dialogue and power sharing, challenges can become opportunities to empower vulnerable communities in the face of intensifying hurricane risks. Table 6.3 provides an overview of the benefits and challenges of integrating AI and ITK in hurricane resilience efforts.

6.4.1 *Barriers in Recognizing Indigenous Knowledge*

Integrating Indigenous knowledges into disaster management faces obstacles rooted in colonization, historical marginalization, and dismissal of native wisdom. Dominant policies and practices that overlooked holistic Indigenous worldviews created barriers, including:

- Lack of mechanisms for documenting oral knowledge or accounting for experiential insights. This can render native wisdom invisible to formal decision-making (Grenier 1998; Berkes 2017; Adade Williams et al. 2020).
- Legal structures that don't recognize collective Indigenous ownership of knowledge or deference to traditional governance. This hinders community authority over knowledge sharing (Sherry and Myers 2002; Tobin 2014).
- Paternalistic attitudes dismiss Indigenous practices as folklore rather than sophisticated knowledges. This prevents reciprocal exchange and co-creation (Jeffes 2020).
- Extraction of Indigenous knowledges without consent, attribution, or benefits for native communities. This exacerbates power imbalances (Chapman and Schott 2020; Marinova and Raven 2006).

Transforming these systemic biases requires seismic shifts in awareness, accountability, rights regimes, and governance. However an expanding global movement led by Indigenous groups provides hope for overcoming entrenched obstacles through truth-telling, power sharing, and institutional reforms (Lauderdale 2009; Stavenhagen 2009; World Bank Group 2020).

Table 6.3 Benefits and challenges of using AI and ITK in hurricane resilience

Aspect	AI in Hurricane Resilience	ITK in Hurricane Resilience
Benefits		
Early warning systems	AI models analyze historical data, satellite imagery, and oceanic conditions to predict hurricane paths and intensities, enabling timely warnings for evacuation, and preparedness	Local wisdom includes insights about weather patterns and signs of impending storms, based on generations of observations.
Damage assessment	AI-driven assessments rapidly identify affected areas and damaged infrastructure using deep learning models to process satellite images.	Traditional practices include knowledge of local terrain and ecosystems that aid in quick assessment and recovery actions.
Resource allocation	AI algorithms optimize resource distribution during response and recovery, determining efficient aid delivery and power restoration routes.	Community-based adaptation strategies often involve sustainable resource management practices honed over generations.
Adaptive decision-making	AI systems adapt to changing conditions, considering real-time data for dynamic adjustments during evolving scenarios.	Traditional building techniques and local adaptation methods are inherently flexible and resilient, developed through centuries of local experience.
Risk assessment	AI assesses vulnerabilities, exposure, and potential impacts, allowing communities to plan proactively.	Indigenous ecological knowledge provides a deep understanding of local environmental risks and vulnerabilities.
Challenges		
Scalability and data needs	AI models require large datasets and computational resources, potentially limiting their applicability in data-scarce regions.	ITK is often specific to certain regions or cultures and may not be easily transferable to different contexts.
Environmental changes	AI's effectiveness can be hindered by rapidly changing climate patterns that disrupt familiar data patterns.	ITK may struggle to adapt to rapid ecological changes brought about by modern climate change.
Integration	Harmonizing AI with local contexts can be complex, especially in diverse cultural settings.	Scientific validation and integration of ITK into formal policy and decision-making can be challenging.

6.4.2 *Advocating Indigenous Strategies in Formal Policies*

Meaningful incorporation of Indigenous knowledges into disaster management policies is vital but faces barriers, including:

- Lack of formal decision-making roles for Indigenous authorities and reluctance to recognize traditional governance. This excludes native voices from policy processes (Rosenthal 2006; Udofia et al. 2017).
- Perceived tensions between Indigenous practices and bureaucratic rules or scientific approaches. This discourages integration (Mertens and Cram 2016).

- Difficulty codifying holistic, experiential Indigenous knowledges into rigid policy frameworks. Nuance may be lost translating oral wisdom into written decrees (Hossain and Ballardini 2021).
- Politicization of Indigenous rights, representation, and knowledge systems. This creates conflicts obstructing collaboration (Manuel-Navarrete et al. 2021).

Addressing these hurdles requires inaugurating structural reforms that center Indigenous leadership in policy spaces. Fostering cultural humility among decision-makers and balanced frameworks for knowledge integration can seed evolution toward inclusive governance.

6.4.3 Opportunities for Enhancing Indigenous Voices

Despite obstacles, expanding avenues exist to amplify Indigenous perspectives, including:

- Grassroots movements mobilizing to assert Indigenous sovereignty and leadership, forcing spaces for dialogue and dissent (such as Dreher et al. 2015).
- Mounting legal precedents and frameworks like the UN Declaration on the Rights of Indigenous Peoples affirming native rights and status (United Nations 2007; Barelli 2009).
- Increasing Indigenous representation in scientific bodies, collaborations with academics, and higher education attainment growing native expertise (Bang et al. 2010; Adams et al. 2014; Moore 2021).
- Communication technology that enables Indigenous groups to share knowledge globally and organize transnationally to advance collective interests (i.e. using social media).

Skillfully utilized, these openings offer potential levers for systemic reforms that dismantle barriers to Indigenous knowledges, catalyzing a rebalancing of power toward just solutions crafted locally by communities at the frontlines of climate threats.

6.5 A Call for International Collaboration and Communication to Address Climate Change

Our planet is experiencing “Global boiling” (United Nations 2023; Chakravarty 2023). Rising seas, scorching heat, rampaging storms, failing crops, and vanishing species—the impacts of climate change have arrived at our doorstep. No corner of the world remains untouched by this existential threat looming over humanity’s future. The necessity for urgent, decisive action has never been more pressing or non-negotiable. The time for incremental measures has passed; transformative

change is now imperative. The interest in climate change and its associated impact has caused a surge in demand for producing and providing climate information at decision relevant spatial and temporal scales (Kirchhoff et al. 2018). This means the information must be pertinent to distinct geographic locales and aligned with the time frames pertinent to those areas' planning and response needs. The first step towards climate change adaptation and resilience is understanding the science behind climate change and how it affects ecosystems and vice versa. It is necessary to engage climate stakeholders (locals and indigenous communities, policymakers, resource managers, educators, and learners) as facilitators for developing and communicating relevant climate information to produce "actionable science" as usable knowledge, effective in developing climate adaptation strategies (Bamzai-Dodson et al. 2021).

Central to this transformation is education, to empower communities on the frontlines with the knowledge, tools, and agency to build resilience against escalating climate disruptions (IPCC AR6 Report 2023). Top-down policies devised in ivory towers will not suffice anymore; climate adaptation demands decentralized, grassroots strategies tailored to local, culturally relevant, and meaningful contexts (Aronson and Laughter 2016; Chakravarty 2023). Therefore, it is necessary to take climate- relevant information and knowledge from the community level and integrate it with current scientific research thus creating a knowledge bank strongly based on scientific rigor and culturally-responsive community wisdom. This will help create a "channel" of locally adaptive and meaningful climate education curricula that is diverse, to the point, and can be used as teaching material in both formal and informal, online and in-person formats, and assist in making more informed and educated decisions for a climate- resilient future. This research proposes the *Climate Communication Channels* as a first-of-its-kind utilitarian and adaptive model where climate facilitators (facilitators are people who are part of the local communities, researchers, educators, research and academic institutions, and finally the learner community as end users) participate to create a community or "channel" of relevant climate information providers with an ultimate goal of creating climate- resilient communities. The model focuses on the role of localized, culturally relevant community knowledge, researcher and educator's use, climate literacy initiatives, and AI-based tools and techniques for climate information dissemination.

6.5.1 The Climate Communication Channel: A Model for Collaborative Hurricane Readiness

The *Climate Communication Channels* (3C) Model gains unprecedented urgency in light of the sixth IPCC Assessment Report's findings, revealing that human-induced global warming has led to a 1.1 °C temperature rise since the pre-industrial era (IPCC AR6 Report 2023). With current policies poised to propel temperatures beyond the critical threshold of 1.5 °C, the 3C Model becomes an essential conduit

for disseminating the urgent adaptations and mitigations needed across all sectors. No community, whether urban or rural, coastal or inland, rich or poor, exists outside the climate crisis's far-reaching impacts. Yet awareness, understanding, and agency to take action vary immensely based on access to scientific information and resources. Bridging this climate literacy gap through education and community participation represents an ethical imperative and pragmatic necessity. Accurate scientific understanding motivates learner engagement (Pintrich 2003; Marley et al. 2022), stressing the urgency for both systemic and community-level interventions. According to Lehtonen et al. (2018), climate education cultivates critical thinking skills to evaluate solutions, and identify misinformation that exploits fear and confusion (Baker et al. 2020).

To address the current world issues such as climate change- induced extreme events, we need to understand the causes, impacts, impacted stakeholders, and sources of solutions. This can be achieved by creating open-access knowledge banks for issues such as hurricane risk and resilience for a particular region. We must understand that these local knowledge pockets gathered from Indigenous communities, scientific research, knowledge centers and government bodies must be effectively communicated for maximum benefit.

We propose the *Climate Communication Channels* (3C) Model that provides a conceptual model for actualizing holistic hurricane readiness through interconnected knowledge sharing as one of its applications (Chakravarty 2023). Developed for climate education contexts, the 3C model also offers a promising template for collaborative hurricane preparation. Central to the 3C approach is gathering and validating Indigenous and local knowledges, then dynamically translating insights into practical resilience strategies through community-engaged education and capacity building. Partnerships across public, private, and civil society sectors enable adaptation solutions tailored to local cultural and geographic realities. Figure 6.1 maps the key components of the 3C model, outlining how its core principles of inclusive knowledge co-production and multilateral collaboration can be applied to enhance hurricane readiness globally. The model provides a guidepost for the participatory development of disaster resilience solutions that synthesize diverse ways of knowing and empowering vulnerable communities.

6.5.2 Model Overview: Conceptual Framework for Collaborative Resilience

The 3C model provides a conceptual roadmap for bringing diverse voices together to co-develop locally relevant hurricane readiness strategies. It emphasizes gathering endangered Indigenous knowledges and engaging scientific partners to validate and enhance community insights. These partnerships inform the creation of tailored educational resources that help impart ancestral wisdom to new generations.

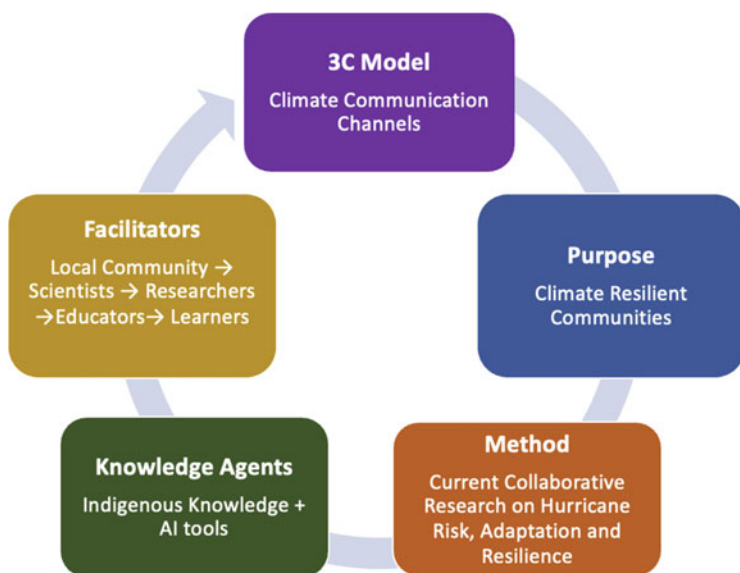


Fig. 6.1 Overview of climate communication channels (3C Model)

Sustained dialogue and knowledge sharing within this ecosystem empower the continuous refinement of grassroots solutions attuned to cultural realities. The model envisions interconnected processes of collective learning that synthesize modern and Indigenous ways of knowing to meet escalating hurricane threats.

The five stages of the 3C model commence with Stage 1, where the *realization* of existing knowledge in the natural world, Indigenous and local communities takes place; in Stage 2, scientists and knowledge workers (researchers, educators, and communicators) gather these *pockets of knowledge* and validate them for authenticity and accuracy and finally record their findings and communicate them via research publications, research conferences, open online public repositories for community benefit (Fig. 6.2). In Stage 3, AI researchers and scientists are involved in *integration, customization, and channelizing* the validated knowledge from Indigenous communities and the natural world via effective research and communication platforms. Stage 4 involves facilitator involvement, where the curated knowledge and information is passed through *knowledge processing centers*, and further customization takes place by educators to make the customized knowledge and strategies adaptable to their local areas. Resource managers and government administrators are also involved in the facilitation process, where the communicated and channelized information is used to develop *tailored strategies for resilience and adaptation*. In Stage 5, the ultimate *testing* followed by *adaptation* of the curated strategies in local areas is executed in partnership with educators, learners, resource managers, government agencies and finally the communities. In this model framework, effective communication and channelisation of valid scientifically AI-curated Indigenous and

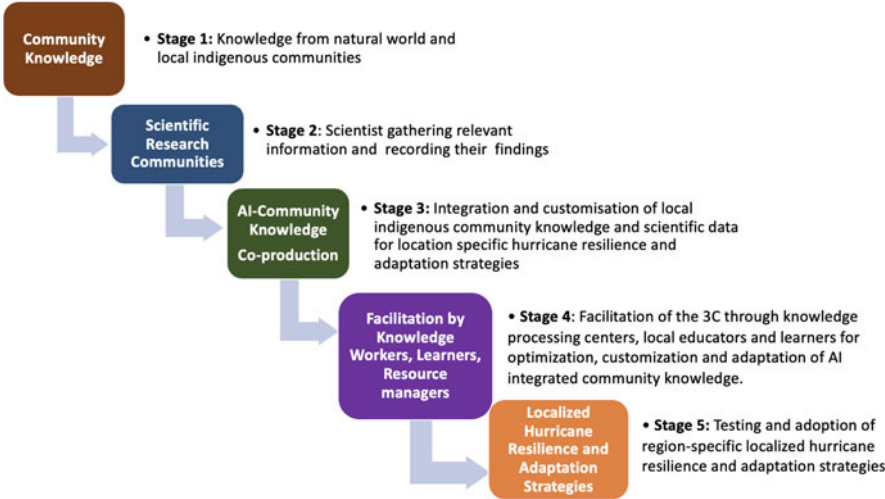


Fig. 6.2 Conceptual framework of the climate communication channels (3C) Model

natural knowledges are of essence. Therefore, snag-free communication channels are required. We aim to establish a system where validated *true knowledge* reaches all lines of the channel and the local communities are not just mere stakeholders but *facilitators* in strategizing for hurricane and climate resilience and adaptation.

6.5.2.1 Community and Natural Knowledge

We recognize the profound value that community and natural knowledge contribute to our understanding of climate change and its mitigation. This knowledge, derived from centuries of intimate interaction with the natural environment, encompasses a deep understanding of ecological processes, sustainable resource management, and biodiversity conservation (Wyllie de Echeverria and Thornton 2019). Yet, in contemporary discourse, these insights often remain underappreciated, if not altogether overlooked, in favor of more conventional scientific research. Community and natural knowledge are critical components of the cultural fabric that includes language, systems of classification, resource use practices, social interactions, rituals, and spirituality. It offers a foundational platform for sustainable development that is culturally congruent and locally appropriate. We argue for the inclusion of this knowledge in global climate science and policy processes, as evidenced by UNESCO’s Local and Indigenous Knowledge Systems (LINKS) program (Petzold et al. 2020; Wyllie de Echeverria and Thornton 2019) program. LINKS has been instrumental in ensuring the voices and wisdom of indigenous knowledge holders are incorporated into science-policy dialogues on biodiversity, climate change, and sustainable development (Duvic-Paoli 2017; Roué et al. 2022; Climate Change

2023). Climate change's impacts are particularly acute for over 370 million Indigenous Peoples globally, who have historically thrived in diverse environmental contexts through their adeptness at working with nature and climate variability. However, their remarkable adaptability also renders them exceedingly vulnerable to the unprecedented changes wrought by a warming planet. To counter these challenges, Indigenous Peoples and local communities are increasingly called upon to harness and enhance their traditional knowledge to adapt to extreme weather events and the slow onset effects of climate variability.

Through this lens we examine the importance of indigenous responses to climatic variances, which have enabled Indigenous Peoples to sustain themselves in various ecosystems. The paper highlights how indigenous and local communities are key to successful conservation efforts, as demonstrated by research conducted by the University of East Anglia and its partners (Roué et al. 2022). This systematic review of 169 conservation projects worldwide has shown that equitable conservation strategies that empower Indigenous Peoples and local communities are more likely to yield long-term positive outcomes for both nature and the people. Dawson et al.'s research (2021) further underscores the criticality of local governance in conservation, arguing that the current paradigm of conservation efforts, often led by international organizations and governments, can infringe upon local communities rights and cultural diversity. Similarly, for the global climate change crisis, we advocate for a shift in conservation strategies that acknowledges and prioritizes indigenous and local knowledge systems and tenure arrangements. This approach is not just ethical; it is pragmatic, as it has been shown to be more effective in achieving conservation goals. We emphasize that true conservation success is contingent upon recognizing and integrating local cultural practices and decision-making. The paper calls for a reorientation of conservation strategies towards stewardship by Indigenous Peoples and local communities, suggesting that such a shift is imperative for the creation of more equitable and effective conservation outcomes using the 3C model where the stewardship of the climate adaptation strategies is shared by all the facilitators and knowledge keepers starting from the local communities at *Stage 1* to the next levels. This reorientation is about conserving the environment and upholding the rights, knowledge, and cultural integrity of those who have been its stewards for millennia.

6.5.2.2 Scientific Research Communities

The pursuit of knowledge through scientific inquiry has long stood as a defense against the encroaching tide of climate change, with research communities at the vanguard of this quest. These communities, comprising a global network of dedicated scientists, are the sentinels and scribes of our changing world, meticulously documenting the shifts in our climate and deciphering the complex interactions within our ecosystems (Hubbell and Ryan 2021). Their endeavors are underpinned by a commitment to empirical evidence and methodological rigor, ensuring that the data they collect and the analyses they perform are of the highest integrity, providing

a bedrock upon which policymakers and educators can build strategies for mitigation and adaptation. The role of scientific research communities is multifaceted, engaging not only in the act of discovery but also in the dissemination of knowledge. These communities operate as interdisciplinary collectives, where climatologists, ecologists, oceanographers, and other specialists converge (Hulme 2014). Through collaborative efforts, they synthesize wide-ranging data sets into cohesive narratives that illustrate the multifarious impacts of climate change. This holistic approach is critical for devising comprehensive strategies that address climate change's environmental, social, and economic dimensions. Leading the charge in climate research are esteemed institutions like the National Aeronautics and Space Administration (NASA), the National Oceanic and Atmospheric Administration (NOAA), and the Intergovernmental Panel on Climate Change (IPCC), which work in concert with universities worldwide. Prestigious universities such as the Massachusetts Institute of Technology (MIT), the University of East Anglia, and the Australian National University are notable for their groundbreaking research and influential publications that shape our understanding of climate dynamics. We suggest scientific research community participation as *Stage 2* of the 3C model that bridges the gap between local and indigenous knowledge and scientific research, advocating for a more inclusive and culturally sensitive approach to climate science. The imperative for scientific research communities is not merely to understand the present state of the climate crisis but to project and prepare for future scenarios. Their work in modeling and forecasting plays a crucial role in anticipating climatic shifts, allowing communities and nations to implement preemptive measures. Through an iterative research, application, and assessment process, these communities remain at the forefront of our collective response to climate change, ensuring that the knowledge they generate translates into action. We delineate the pivotal role of scientific research communities as the cornerstone of our global response to climate change.

6.5.2.3 Knowledge Processing Centres

At the intersection of raw data and human understanding, knowledge processing centers serve as pivotal nexuses where the complexities of climate science are distilled into digestible, accessible formats. These hubs of intellectual synthesis are not mere repositories of information but dynamic workshops where scientific findings are transformed into knowledge that informs, educates, and empowers the general public. Knowledge processing centers are tasked with a mission of paramount importance: to bridge the chasm between the intricate world of scientific research and the practical needs of society. They are the translators of scientific jargon, the demystifiers of data, converting the language of research into the vernacular of everyday life. Here, pedagogical expertise comes into play, adapting the climate science narrative to suit educational curricula that can reach a diverse audience (Chakravarty et al. 2023). The imperative for these centers is to create learning materials that resonate with people from all walks of life.

We have utilized the 3C framework to propose a similar environment where natural/community knowledge is transmitted through the scientific research community and then arrives at KPCs in *Stage 3*, where the climate information or pockets of useful knowledge are processed for the educators and learners. Within environmental and educational research, the Cooperative Institute for Research in Environmental Sciences (CIRES), a dynamic collective of over 500 researchers and scientists affiliated with the University of Colorado, USA, has developed a suite of K-12 educational materials. These resources encompass a range of critical environmental and climate-centric themes grounded in scientific research designed to enrich classroom instruction. CIRES aims to equip educators with the skills to craft engaging, research-driven curricula through workshops and webinars covering vital subjects such as climate change, pollution, polar ecosystems, forest vitality, wildfires, and global warming (Griffith et al. 2021). We have utilized the CIRES Data puzzle workshop resources in research and found it well received by educators and learners of rural India.

They produce a wide array of resources such as in the case of UN CC Learn, from textbooks that explain the science of climate change to interactive online platforms that track its impacts in real time. They also develop training programs for educators, equipping them with the tools to effectively engage students with the subject matter. Internationally recognized bodies such as UNESCO play a central role in this endeavor through their Education for Sustainable Development (ESD) program. They collaborate with institutions around the globe to ensure that educational content is not only scientifically accurate but also culturally sensitive and regionally relevant. This tailored approach helps communities understand how global climate trends affect them locally, fostering a sense of connection and urgency. Institutions like the National Center for Atmospheric Research (NCAR) and the Hadley Centre for Climate Prediction and Research also contribute to this effort, providing valuable data and insights that fuel the content produced by knowledge processing centers. These centers are essential in crafting the narrative of climate change, shaping it into a story that is informative and motivational, spurring individuals to take action. The role of knowledge processing centers extends beyond the production of educational content; they are also active participants in public discourse. Through public lectures, workshops, and media engagement, they facilitate a broader conversation about climate change, inviting the public to ask questions, seek clarification, and voice concerns. However, the challenge these centers face is not insignificant. Climate science is a field that is constantly evolving, with new findings emerging at a rapid pace. Knowledge processing centers must remain agile, updating their materials to reflect the latest research while maintaining clarity and consistency in their messaging. Furthermore, in an era of rampant misinformation, these centers take on the added responsibility of fact-checking and debunking myths about climate change.

6.5.2.4 Educational Institutions

Educational institutions are responsible for shaping future generations' minds and attitudes towards climate change. Their mandate extends beyond disseminating facts and figures; they are tasked with weaving climate education into the rich tapestry of students' cultural identities and lived experiences. This duty involves crafting curricula that are not sterile abstracts of data but are vibrant, engaging narratives that reflect the diverse realities of the learners' communities. These institutions act as crucibles for forging an informed citizenry, equipped with the critical thinking skills necessary to navigate the complex issue of climate change. They are the stages upon which students grapple with the nuances of climate science and the implications of environmental stewardship within their cultural and geographical contexts. We suggest that in *Stage 4*, by integrating traditional subjects with climate education, institutions ensure that environmental awareness and action become intrinsic to the educational journey. The challenge for educational institutions is twofold. Firstly, they must ensure that their climate education initiatives are scientifically robust, reflecting the latest research and understanding of climate dynamics. Therefore their reliance on KPCs (*Stage 3*), scientific research communities (*Stage 2*) and natural/community knowledge (*Stage 1*) is a necessity. Secondly, they must contextualize this information, tailoring it to the learners local environment and cultural setting. This dual approach ensures that climate education is not just a theoretical exercise but a practical, relatable aspect of the student's education. Institutions must also foster an environment where dialogue and debate on climate issues are encouraged. Classrooms should be arenas for active engagement, where students can discuss and dissect the impacts of climate change on their communities, propose solutions, and debate policy. This open discourse is vital for students to appreciate the multifaceted nature of climate challenges and understand their role in addressing them. Moreover, educational institutions are uniquely positioned to foster partnerships with local communities, government bodies, and industry to provide students with real-world learning experiences. Through field studies, community projects, and internships, students can see the practical application of their learning and the tangible effects of climate change on their surroundings. The role of educational institutions is not just to prepare students for future careers but to empower them as active participants in creating a sustainable future. By instilling a sense of responsibility and providing the tools for environmental advocacy, institutions help cultivate a generation of leaders ready to tackle the climate crisis head-on. In this light, the curriculum developed by educational institutions should be dynamic, evolving with the changing landscape of climate science and policy. It should also be inclusive, ensuring that all students, regardless of background, have access to quality climate education. Such an inclusive approach not only enriches the learning experience for all but also ensures that diverse perspectives are brought to bear on the issue of climate change.

6.5.2.5 Facilitators: Community, Researchers, Educators, and Learners

In the tapestry of climate resilience, the threads that bind the fabric of knowledge to action are the facilitators—the community leaders, researchers, educators, and learners as final (*Stage 5*). The learners, imbued with information that is scientifically rigorous and culturally resonant, stand at the vanguard of change. They are the ultimate recipients of climate education, and through their informed actions, the theories of resilience translate into the praxis of sustainability in their respective locales. Facilitators in this context are the drivers of climate knowledge whereas we believe stakeholders are people with an interest in their local climate issues but may not necessarily contribute to implementing and disseminating climate information. This convergence of knowledge and application underscores the imperative for climate information to be contextually relevant. It must echo the local dialect of weather patterns, resonate with the cadence of regional ecosystems, and align with the cultural narratives that define each community. This localized approach ensures that learners are not passive recipients of information but active agents capable of understanding and engaging with climate issues relevant to their own backyards. Researchers play a pivotal role in this educational ecosystem, providing the foundational knowledge upon which curricula are built. They bring the latest scientific findings to the table, ensuring that the information disseminated is current, credible, and actionable. Their continuous quest for understanding and innovation seeds the learning content with fresh insights and emerging concepts, keeping the discourse on climate change dynamic and forward-looking. Educators, for their part, serve as the critical intermediaries in this knowledge exchange. They are the translators of complex scientific data, the storytellers who bring to life the narrative of climate change in a language that resonates with their audience. Their pedagogical strategies are key in fostering an environment of inquiry and critical thinking, enabling learners to probe, question, and challenge the information presented. The learners, from young students to adult community members, are the central figures in this narrative. Their engagement with climate education is not a passive absorption of facts; but an active, participatory journey. They are encouraged to connect the dots between global trends and local impacts to weave their understanding of climate science with the knowledge of their communities' historical interactions with the environment. This synthesis of information empowers them to make informed decisions, advocate for sustainable practices, and become stewards of their environment. The journey towards a climate-resilient future is collective and collaborative, with learners at its core, educators as its compass, researchers as its chart, and community as the terrain. It is a journey marked by the transfer and transformation of knowledge into actionable wisdom. At the heart of this transformative process are the teachers, whose influence shapes not only the minds of the learners but also the prospects of a sustainable future. They nurture the seeds of knowledge that grow into the actions defining humanity's response to the climate crisis. As such, the onus lies on educational institutions, policymakers, and communities to support and invest in these educators, for they hold the key to unlocking the full potential of our collective climate resilience.

6.6 Implementation Case Study: Climate Education in India

In January 2024, a significant stride was made in Hyderabad, India, where the 3C Model was piloted in a high school setting. This initiative marked a crucial step in demonstrating the model's capacity for fostering collaborative adaptation and resilience on a community scale. To tailor the program material to align with local climatic conditions, we adapted teaching and learning material supplied by the CIRES research group from the University of Colorado. CIRES' work is grounded in the fact that they not only provide open-access datasets for researchers but also provide educational material for anyone to use as-is or adapt according to their teaching and learning contexts. Key to the program's success was the adaptation of teaching and learning materials provided by the CIRES research group from the University of Colorado. CIRES, known for its open-access datasets and educational resources, has a history of contributing significantly to climate science and education. This was evident in several notable studies: Rajesh & Goswami's examination of sea surface temperature (Rajesh and Goswami 2020), Mokhov et al.'s analysis of sea-level pressure (Mokhov et al. 2021), Saha et al.'s study using daily pressure level air temperature data (Saha et al. 2023), Wilson-Lopez et al.'s use of CIRES curriculum in outlining pedagogical principles for high school engineering curricula (Wilson-Lopez et al. 2022), and Collier et al.'s (2015) assessment of their K-12 curriculum on air quality program based on guidelines developed by CIRES. Similarly, our adaptation of CIRES' teaching material to the local Indian context was crucial in ensuring the curriculum's relevance and effectiveness.

6.6.1 *The 3C Model Pilot at Hyderabad, India*

Serving as a vital testbed, the Hyderabad, India pilot has been a rich source of feedback and insights. By integrating locally-sourced information from public data repositories and tailoring it to the Indian context with the help of school science teaching staff, we created a curriculum that resonates deeply with the students. The use of WhatsApp instant messaging app, as a communication tool proved effective in facilitating information dissemination and gathering participant feedback, complemented by in-person workshop activities for kids (Gattupalli et al. 2023). This blend of digital and traditional learning methods significantly enriched the students' understanding and active participation in community knowledge building. While not totally hurricane related, this workshop focused on other high- priority climatic events which affected community members at the time of our workshop. Our approach was intentional and purpose-built, so kids can relate what they see on a daily basis around them with our teachings.

Following the workshop, a competition was conducted in which students engaged in the analysis of climate data. This task involved identifying patterns and

responding to inquiries formulated with assistance from educators. The data, provided in an Excel format, required participants to apply fundamental data science methodologies to discern climatic trends. The competition saw the participation of 26 high school students from 2 schools, who coordinated and communicated their findings through the WhatsApp platform. The event was organized with the objective of enhancing knowledge regarding local weather and climate trends, as well as understanding the effects of climate change on regional microclimates. Following the training, students were tasked with analyzing weather patterns, identifying trends, and examining localized meteorological conditions. This exercise aimed to deepen their comprehension of the microclimate specific to each respective “*Mandal*” (province). Through such targeted educational initiatives, awareness of climate-related issues is effectively elevated at the local level.

This 3C case study has been instrumental in providing us with a wealth of feedback and insights. The rich repository of data, experiences, and lessons learned are not only a testament to the program’s initial success but also a critical asset in refining our approaches for future implementations. Future iterations of the program allow us to tailor our initiatives more precisely, adapting to evolving educational needs and environmental conditions. As we look forward to expanding our reach and impact, the lessons learned from this testbed will guide our strategies, ensuring that our educational interventions remain dynamic, context-sensitive, and increasingly effective in promoting climate literacy and resilience. Following the success of pilot studies in Hyderabad, similar initiatives are now being carried out in Patna, India, and on various online platforms in an educational context. Technology-enabled participation has enabled participation from individuals across the country, expanding the reach and impact of the 3C model in practice.

6.6.2 *Community Engagement Initiatives*

One crucial element of the 3C Model’s implementation has been its focus on community engagement. In India, where the first author is originally from, due to the proximity of village “*panchayats*,” who are public-elected leaders for the rural community, our next initiative involves engagement activities like dialogues with village heads and local leaders about climate change and its mitigation strategies. Such interactions are vital for ensuring that climate education is not just theoretical but grounded in the realities and needs of local communities. The village leaders interact with farmers, and other stakeholders in their village vicinities, and we believe our engagement activities will allow for a smooth flow of information in such rural areas.

As a part of the 3C Model implementation, climate resilience dialogues are being conducted in Jharkhand, India, an area noted for its significant Indigenous population, including the Santhal, Munda, and Ho tribes. These dialogues engage village leaders, notably the *Sarpanch*, *Pahan*, or *Manjhi* (local names for the village heads), in a reciprocal learning process. The aim is to provide training on contemporary

climate resilience strategies while gaining insights into their traditional practices. This approach facilitates the development of sustainable and resilient methodologies tailored to the specific impacts of climate change in their localities.

Furthermore, the 3C Model has been applied to developing holistic strategies for hurricane readiness. This involves establishing open-access knowledge banks focused on hurricane risk and resilience for specific regions. These repositories combine insights from Indigenous communities, scientific research, knowledge centers, and government bodies, ensuring a comprehensive understanding of climate crises.

6.6.3 Future Directions and Ongoing Efforts

The 3C Model is set to expand its scope and influence. Plans include enhancing the knowledge banks with more localized data, scaling up community engagement programs, and developing more targeted educational materials for diverse audiences—and making all learned knowledge available through the Open Science Foundation repositories. The model serves as a guiding framework for the participatory development of disaster resilience solutions, advocating for a synthesizing diverse ways of knowing and empowering vulnerable communities.

By mapping out the key components and applying its core principles of inclusive knowledge co-production and multilateral collaboration, the 3C Model stands as a beacon for global efforts in enhancing climate literacy and resilience. Its application in India serves as a testament to its adaptability and effectiveness in diverse cultural and geographic contexts.

6.7 Cost Benefit Overview for the 3C Model Implementation

While a detailed cost-benefit analysis for the implementation of the 3C (*Climate Communication Channels*) model in hurricane studies hasn't been thoroughly conducted due to case-to-case variability, we can broadly estimate potential costs and savings. This variability arises from the differing regional needs, resources available, and unique challenges in each location. Yet, we can identify common areas where costs might arise and where savings are likely, particularly with the benefit of international collaboration.

A significant expense in the 3C model implementation involves developing and distributing educational materials, such as training modules, communication tools, and data collection systems. This cost, however, can be effectively reduced through global collaboration. Sharing educational resources and technological tools, and pooling expertise from various regions can lessen the financial burden on individual

areas. Such collaboration also provides opportunities for exchanging best practices and insights, enhancing the 3C model's effectiveness across different environments. This international cooperation not only facilitates cost reduction but also helps to forge a stronger and more unified global strategy in addressing the ramifications of climate change and natural disasters. Precise quantification of these cost savings might be challenging without a comprehensive analysis, but pooling international resources offers significant promise in making the 3C model more attainable and effective worldwide.

In terms of direct impact, the initial costs associated with the 3C model include setting up technology for communication channels and training community members and scientists. These upfront investments are anticipated to bring long-term benefits like enhanced knowledge sharing and improved understanding of local conditions. Involving AI in data collection and analysis could entail considerable funding for data processing and system maintenance. Still, this investment is justified by the benefits of more accurate predictions and the ability to adapt swiftly to changing scenarios, which are key in preventing major damage and enhancing disaster response.

Community engagement, integral to the 3C model, involves organizing workshops and meetings, which require resources. Nevertheless, this investment is crucial for fostering stronger community involvement and resilience, leading to sustainable and culturally aligned solutions. The ongoing research and development for long-term resilience building might incur costs, but these are offset by the reduced expenses from future disasters, thanks to the development of localized resilience strategies and increased community self-sufficiency. Through the integration of AI and traditional knowledge, the 3C model seeks to improve predictive capabilities and encourage a proactive stance in disaster management, with the initial costs being outweighed by considerable long-term benefits (Table 6.4).

6.8 Conclusion

The intensification of tropical cyclones and hurricanes driven by climate change poses grave threats to vulnerable communities worldwide. As this work elucidates, Indigenous knowledge systems hold profound lessons for building resilience and adapting to escalating hurricane risks. Holistic worldviews fostering acute environmental awareness equip communities to understand and predict local storm patterns through generations of place-based observations. Traditional practices for protective infrastructure, resource management, and forecasting offer time-tested strategies for survival as empirical research continues to validate. However, realizing the full potential of Indigenous knowledges requires confronting systemic biases that marginalize native ways of knowing. Collaborative hurricane readiness can be strengthened worldwide through inclusive partnerships elevating Indigenous voices. Blending community insights with advanced computing capabilities demonstrates particular promise for enhancing forecasting and response. Ultimately, this synthesis

Table 6.4 Cost-benefit overview for 3C model implementation

Aspect	Benefits	Costs	Net impact
Initial setup and training	Enhanced knowledge sharing	Training costs for local communities and scientists	Long-term savings in disaster response
	Improved understanding of local conditions	Technology setup for communication channels	Better-prepared communities
Data collection and analysis	More accurate predictions using combined knowledge	Costs for data collection and processing	Prevention of major damages
	Real-time adaptation to changing scenarios	Maintenance of AI systems and databases	Improved disaster response efficiency
Community engagement	Stronger community involvement and resilience	Resources for community workshops and meetings	Sustainable and culturally appropriate solutions
Technology utilization	AI-driven analysis for quick decision-making	Investments in AI technology and updates	Enhanced predictive capabilities
Long-term resilience building	Development of localized resilience strategies	Ongoing research and development costs	Reduced costs from future disasters
	Empowerment of local communities	Continuous engagement efforts	Increased self-sufficiency and reduced dependency on external aid

of ancient wisdom and modern technology underscores the vital role of Indigenous knowledges in navigating the uncertainties of our climate future. Facilitating open knowledge exchange and participatory adaptation can create resilient and just solutions to mounting threats can arise.

The escalation of tropical cyclones driven by anthropogenic climate change constitutes one of the most urgent challenges at the intersection of environmental and social justice today. Vulnerable Indigenous communities face disproportionate risks, yet their ITK systems hold profound lessons for global climate resilience. As this research explores case studies worldwide, generations of Indigenous observations, cultural practices, governance, and adaptation strategies offer invaluable resources for hurricane preparedness that Western policies have often overlooked. Realizing the potential of this knowledge requires confronting enduring legacies of marginalization to genuinely integrate Indigenous perspectives into disaster management and climate policymaking. Partnerships for knowledge co-production, elevating native voices, reconciling bureaucracies with traditional governance, and blending indigenous insights with new technologies like AI offer pathways for empowering local actors. This synthesis of ancient wisdom and modern capabilities can forge solutions to the shared challenges of a rapidly changing climate. But progress demands seismic shifts toward just, participatory processes that center Indigenous sovereignty, expertise, and leadership. Through such inclusive

collaboration, we can navigate uncertain futures by learning from those with the deepest wisdom cultivated over centuries of adapting to their lands and waters. This chapter provides a compass pointing toward the transformations in awareness, justice, and governance needed to harness diverse ways of knowing for the greater, collective good in facing intensifying hurricane threats worldwide.

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Chapter 7

Navigating Storms: Understanding the Complexities of School Interruptions Post-Hurricane María



Eileen Segarra-Alméstica, Yolanda Cordero-Nieves,
Indira Luciano-Montalvo, Sylvia Martínez-Mejías,
and Hilda Rivera-Rodríguez

Abstract This chapter explores the intricate aftermath of Hurricane María in Puerto Rico, investigating the correlation between educational disruptions and climate-change-induced hurricanes through Urie Bronfenbrenner's ecological model. The analysis reveals the complex governance structure's challenges and the delayed federal response, emphasizing municipal governments' role in disaster management despite disparities in planning capacities. School interruptions' ramifications on communities, families, and children are explored, emphasizing the interconnectedness of local neighborhoods and schools as crucial support systems. Social capital's significance in community resilience post-disaster is highlighted, with proactive schools strengthening community ties for effective support during disruptions.

The disruptions resulted in prolonged school closures, loss of class time, and adverse academic consequences, particularly for vulnerable student groups. Standardized test scores declined, dropout rates increased for some groups, and recovery challenges in the education system surfaced. Beyond academics, the chapter delves into the physical and emotional implications of school interruptions, emphasizing the need for addressing mental health and well-being.

E. Segarra-Alméstica (✉) · I. Luciano-Montalvo
Department of Economics, University of Puerto Rico at Río Piedras, San Juan, Puerto Rico
e-mail: eileen.segarra@upr.edu; Indira.luciano@upr.edu

Y. Cordero-Nieves
School of Public Administration, University of Puerto Rico at Río Piedras,
San Juan, Puerto Rico
e-mail: ycordero.nieves@upr.edu

S. Martínez-Mejías
Department of Psychology, University of Puerto Rico at Río Piedras, San Juan, Puerto Rico
e-mail: sylvia.martinez@upr.edu

H. Rivera-Rodríguez
Graduate School of Social Work, University of Puerto Rico at Río Piedras,
San Juan, Puerto Rico
e-mail: hilda.rivera2@upr.edu

The analysis advocates for improved planning to address Puerto Rico's infrastructure vulnerabilities and government response to hurricanes, particularly post-Hurricane María. It recognizes geographical factors and government shortcomings as vulnerabilities but emphasizes community cooperation, municipal efforts, and alliances as strengths facilitating recovery. Social capital and community resilience are underscored, guiding the recovery focus toward minimizing school interruptions, prioritizing academic and emotional recovery, and fostering collaboration between government entities, schools, and community organizations. The section concludes by stressing the need for a comprehensive and collaborative approach to effectively address the complexity of climate change's impact on education and communities.

Keywords Educational disruptions · Puerto Rico · Hurricane María · School community resilience

7.1 Introduction

The impact of anthropogenic climate change has intensified notably since the mid-twentieth century, causing a range of phenomena, including alterations in temperature, precipitation patterns, rising sea levels, and heightened frequency and intensity of extreme weather events. Among the regions significantly affected by these occurrences, the Atlantic basin stands out, exerting substantial repercussions on Puerto Rico, particularly its young population.

The literature asserts natural disasters' profound emotional, behavioral, and academic consequences on children (Pane et al. 2008; Gibbs et al. 2019; Gomez and Yoshikawa 2017). Given the ongoing development of cognitive, emotional, and physical capacities during childhood, this demographic group is particularly susceptible to the perils associated with adverse situations. However, not all children experience the same degree of vulnerability. The level of vulnerability is shaped by factors such as age, mental health, disability, socioeconomic status, exposure to violence, immigrant status, availability of adult support structures, and familial circumstances (OECD 2019; Clarke et al. 2019). In that sense, Ruppel-Schlichting et al. (2013) contend that an effective response to disasters concerning children necessitates an assessment of their vulnerabilities and capabilities and an acknowledgment of their participatory environments.

Undoubtedly, one such environment crucial to children's development is the school environment. It serves as an educational hub and offers essential nutrition and psychosocial services, occupying a central role in the social fabric of school-aged populations. In the short term, disruptions to schooling due to socio-natural disasters can deprive children of crucial services. Over the long term, these interruptions can lead to enduring effects, manifesting as academic deficiencies, physical and mental health challenges, constraints in social skill development, or limited formation of social capital. Hence, it is imperative to consider the ramifications of school disruptions caused by hurricanes on children and their surroundings.

The empirical evidence presented herein draws upon prior studies conducted by the authors on the impact of Hurricane María on children and youth in Puerto Rico. The initial study (Study 1) was commissioned by the Youth Development Institute, with its principal findings summarized in Enchautegui et al. (2018). The subsequent study (Study 2) is part of research subsidized by the Natural Hazard Center through the Quick Response Research Award Program, Special Call for Quick Response Research in U.S. Territories.¹

Through interviews and focal groups, these studies gathered insights from diverse community members, including school personnel and high school students. This chapter focuses on school service interruptions caused by hurricanes and their effects on children and youth. With this idea in mind, the chapter aims to address the following research questions:

- How do interruptions in the educational process correlate with the heightened intensity and frequency of hurricanes due to climate change and the institutional backdrop in which they occur?
- What are the implications of disruptions in the educational process on academic, social, and health dimensions?
- What were the observed strengths facilitating the resumption of the educational process or mitigating the effects of the disruption, and what deficiencies and vulnerabilities accentuated them?

The analysis is framed within Urie Bronfenbrenner's ecological model, which offers a comprehensive lens to study individuals' relationships with their environment. While high-intensity hurricanes are projected to persist, comprehensive responses can mitigate adverse impacts on people's lives. The ecological model facilitates the comprehension of interactions between individuals and their environments (Bronfenbrenner and Evans 2000), making it a valuable tool for analyzing and comprehending a hurricane's impact on the educational process of children and youth alongside the systems that could support them. This model identifies five interconnected systems (microsystem, mesosystem, exosystem, macrosystem, and chronosystem), enabling the identification of actors, actions, and relationships with children and youth that either amplify or mitigate their capacities to confront the impact of a hurricane.

The microsystem encompasses the children and their immediate surroundings, while an analysis of the mesosystem reveals how individual responses to climate change intertwine with collective actions seeking solutions. Adaptation and resilience emerge as pivotal factors for survival and overall well-being.

Conversely, the exosystem delves into the impact of external factors, such as government policies and available resources. Political decisions concerning the environment, energy, and sustainability directly influence communities' ability to

¹The Quick Response Research Award Program, Special Call for Quick Response Research in U.S. Territories, supported by the National Science Foundation (NSF Award #1635593), and supplementary funds from the Centers for Disease Control and Prevention (CDC).

confront climate change. Insufficient resources or the implementation of inadequate policies can exacerbate the negative impact of the phenomenon. At the macrosystem level, the analysis focuses on how a society's cultural and ethical values influence the stance taken regarding climate change. A culture's valuation and respect for the environment affect individual and collective decisions and behaviors. Environmental consciousness and ecological ethics become crucial in responding to climate change. These two systems are fundamental to the institutional context where school disruptions occur. Lastly, the chronosystem examines how climate change evolves as a global phenomenon. The acceleration of extreme weather events and long-term changes necessitate strategies for adapting to the future. The capacity to anticipate and prepare for forthcoming changes is critical in ensuring sustainability and survival.

Also, this model furnishes a valuable conceptual framework for comprehending the intricate interconnections among diverse factors and actors amidst climate change, particularly the impact of major hurricanes on the population. From direct effects on daily life to broader political and cultural influences, each system in the model underscores the imperative need for comprehensive and collaborative approaches to grasp the phenomenon's complexity and devise effective and sustainable strategies. The ecological approach encourages introspection on adapting, collaborating, and redefining our values and behaviors to construct a sustainable future in a changing world.

We hope this conceptual framework will help to comprehend the alterations and interactions in diverse environments affecting children and how the interruption of services in one such environment, namely the school, profoundly impacts them. From an ecological standpoint, schools hold a pivotal role in furnishing emotional support services and networks of social interaction (Peek et al. 2018). Moreover, schools function as connectors within and for the broader community. Guided by our primary inquiries, we have delineated the systems of Bronfenbrenner's model, considering environments particularly pertinent to children, especially in hurricane response processes. Figure 7.1 encompasses the definitions of each identified system relevant to our specific objective. The microsystem comprises children, their families, and their communities, constituting their primary environment. The mesosystem considers the interrelationships between family, neighbors, and the school community. At the exosystem level are external institutions, including governmental entities. These systems intertwine within the framework of prevalent culture and the pressures arising from climate change.

7.2 Interruptions to the Educational Process: Climate Change and Institutional Context

The continuity or disruption of school services directly impacts children, making it crucial to comprehend how hurricanes and their disruptions affect various aspects of their lives. This section explores how climate change contributes to more frequent

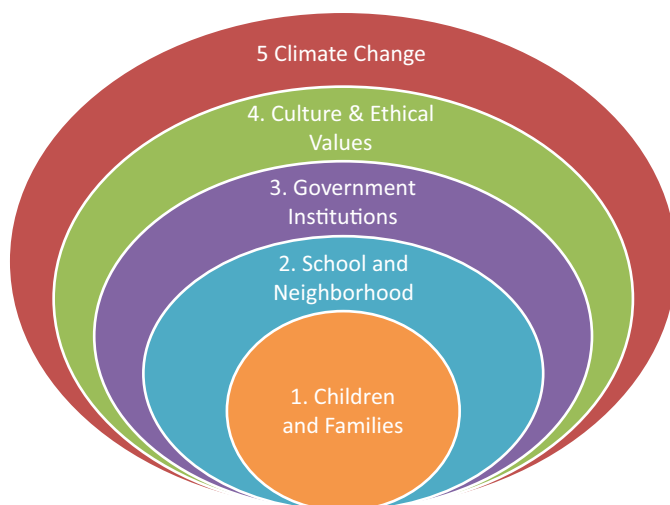


Fig. 7.1 Ecological model applied to the effect of climate change and Hurricanes on children

emergencies and how institutional responses can promote or prevent these emergencies from interrupting school services. The discussion is contextualized within the aftermath of Hurricane María in Puerto Rico.

Hurricane Irma, a Category 5 hurricane, passed near Puerto Rico's northeast region and the municipal islands of Vieques and Culebra on September 6, 2017. Two weeks later, on September 20, 2017, Hurricane María directly struck the island, causing significant devastation, numerous fatalities, a complete electrical outage, and severe damage to the telecommunications infrastructure (FEMA 2018). Consequently, school activities were disrupted across the education system. While some public schools resumed classes by the end of October 2017, the majority recommenced between November and December and, in some cases, as late as January to March 2018. Notably, twenty-two schools did not reopen.

7.2.1 Climate Change as an Accelerator of School Interruptions

It is essential to consider human behavior to grasp the connection between climate change, hurricanes, their impact on the Caribbean region, and the educational process in Puerto Rico. NASA defines climate change as a prolonged alteration in average climate patterns that traditionally define Earth's local, regional, and global climates (Biferno et al. 2023). However, akin to the Intergovernmental Panel on Climate Change (IPCC) and the United Nations Framework Convention on Climate Change (UNFCCC), it is acknowledged that human behavior has significantly contributed to climate deterioration since the mid-twentieth century.

According to the IPCC (2018), climate change denotes climate variations identified by changes in its properties' mean or variability, persisting for extended periods. It encompasses alterations attributable to both natural variability and human activities. Conversely, the UNFCCC (2011) attributes climate change entirely to human behavior, defining it as a direct or indirect result of human activity altering the global atmosphere's composition, augmenting observed natural climate variability over similar periods.

NASA, as IPCC (2013) and an extensive literature (Knutson et al. 2021; Trenberth et al. 2014, 2018; USGCRP 2017; Von Schuckmann et al. 2016), affirm that climate change encompasses various phenomena, including shifts in temperature, precipitation patterns, rising sea levels, and heightened frequency and intensity of extreme weather events. Human activities like fossil fuel combustion, deforestation, and industrial processes have escalated greenhouse gas concentrations, contributing to global warming.

The repercussions of global warming correlate with hurricane pattern modifications primarily because storms occur in warmer, more humid environments (Emanuel 2017; Knutson et al. 2021; Trenberth 2005; Trenberth and Fasullo 2007). Warmer seas and oceans intensify hurricanes, which, upon arrival, cool down, leading to increased water evaporation, making hurricanes wetter and more torrential (Trenberth et al. 2018). In addition to causing more intense rainfall, hurricanes have intensified and prolonged with slower translation speeds (Holland and Bruyere 2014). Moreover, in the last two decades, the probability of developing more intense hurricanes increased by 15%, while the translation speed between 1949 and 2016 decreased by 10% (Kossin 2018; Kossin et al. 2020).

The National Oceanic and Atmospheric Administration (NOAA 2023) notes that for the Atlantic basin (including the Atlantic Ocean, Caribbean Sea, and Gulf of Mexico), the hurricane season spans from June 1 to November 30, peaking between mid-August and mid-October. Over a 30-year climatic period (1991 to 2020), the Atlantic experiences an average of 14 storms, seven hurricanes, and three major hurricanes (category 3, 4, or 5 on the Saffir-Simpson hurricane wind scale). Bhatia et al. (2019) reported significant intensification rate increases in tropical cyclones in the region between 1982 and 2009, attributed to anthropogenic warming. Knutson et al. (2021) corroborate these results by synthesizing findings from over 90 scientific articles on the impact of climate change on hurricanes. Additionally, the authors predict an approximate 5% intensity increase for the region under a global warming scenario of +2 °C. Notably, there has been a global redistribution of hurricane occurrence frequency since 1980, with heightened occurrences in the Atlantic region (Murakami et al. 2020).

Moreover, the Central and East Atlantic regions witnessed substantial increases in hurricane intensity changes within 24-hour periods (Balaguru et al. 2018). Puerto Rico faces this reality, being an archipelago in the Atlantic basin. According to the United States Environmental Protection Agency (E.P.A. 2016), Puerto Rico's temperature has risen by over one degree Fahrenheit since the mid-twentieth century, while the surrounding waters warmed by nearly two additional degrees since 1901.

These increases contribute to severe storms, a situation anticipated to worsen in the coming decades.

Hurricane María stands as Puerto Rico's most intense hurricane since Hurricane San Felipe in 1928, inflicting catastrophic infrastructure damage, extensive casualties, and profound impacts on the economy and population's emotional well-being. This hurricane brought the largest maximum precipitation event since 1956 (38 inches) and recorded the highest total average precipitation among the 129 storms impacting the island since then (Keellings and Hernández 2019; Pasch et al. 2023). According to Trenberth et al. (2018), 2017 witnessed an unusually active Atlantic hurricane season with 17 storms and ten hurricanes, six of which were major hurricanes.

7.2.2 Government Management and School Interruptions

Governments grapple with significant challenges in addressing the impacts of climate change. They represent the institution with the most consolidated resources to aid a population during a disaster. Therefore, effective, timely responses by governmental bodies to emergencies, such as major hurricanes, are expected to reduce losses and suffering for their constituents. It also enables a quicker resumption of daily activities. However, how responsibilities are shared and coordinated among levels of government is essential in disaster response.

Puerto Rico has remained an unincorporated territory of the United States since the early twentieth century, organized into three branches of government: Judicial, Legislative, and Executive.² The Executive Branch is responsible for providing essential services encompassing education, security, housing, and health. In 2017, when Hurricane María struck, Puerto Rico was amidst an economic crisis that commenced in 2006. The extended financial crisis led the government to enter bankruptcy negotiations. Since 2016, Puerto Rico's government finances have been overseen by a board appointed by the U.S. Congress.

The country also has a municipal level of government, dividing the island into 78 municipalities. However, municipal governments possess limited powers and fiscal resources, mainly from taxes on business volume (patents), property, and sales and use taxes. The bulk of taxes collected by the state remains centralized. Nonetheless, municipal administrations primarily focus on providing services such as managing solid waste, debris, landscaping, and emergency response (López Rodríguez et al. 2019).

²In 1917, Puerto Ricans and their descendants became citizens of the United States, and in 1950, the U.S. Congress granted the island the power to choose its governor and structure its internal government. However, Congress retained powers related to postal service, international trade, migration, military affairs, monetary policy, customs, and certain criminal offenses. It also did not grant the right to vote for the president or representation in Congress, except in the House of Representatives, where Puerto Rico elects a representative with a voice but without a vote.

Post-Hurricane María, the U.S. government dispatched National Guard personnel and officials from the Federal Emergency Management Agency (FEMA) to Puerto Rico. The Department of Housing and Urban Development (H.U.D.) evaluated home damages to assist in their reconstruction. However, the federal government's response has faced intense criticism due to its perceived slowness, inefficiency, and politicization.

...a year after the emergency, Puerto Rico's government was still making its case to the U.S. Government. Eventually, Congress approved around \$63 billion to be disbursed through the Federal executive agencies. However, the Trump administration delayed access to those funds by imposing insurmountable bureaucratic requirements. The Office of the Inspector General for Housing and Urban Development (H.U.D.) found an intentional effort to slow down the disbursement for Puerto Rico and the U.S. Virgin Islands (OIG-HUD 2021, p.42). In the same line, Wilson et al. (2019, p.1) concluded that "the U.S. federal government responded unequally to the three hurricanes [Harvey, Irma, and María] (Colón-Morera and Cordero-Nieves 2022, p. 396).

The complex political relations with the United States and the precarious fiscal situation of the central and municipal governments have posed significant challenges to the population's quality of life. Likewise, the bureaucratization of government agencies, the corruption, and the inability or irresponsibility of political leaders to lead the country have exacerbated precarity and reduced institutional responsiveness to emergencies or natural disasters (Metro 2018; Quintero 2018; Sosa-Pascial and Mazzei 2017).

Regarding corruption, Tormos-Aponte et al. (2022) emphasize how clientelism in resource and aid distribution slows down recovery efforts after disasters and worsens existing inequalities. They also caution against seeing privatization as the solution, as it can facilitate corrupt activities. Meanwhile, García-López (2022) highlights the complex web of private actors and institutions involved in environmental corruption in Puerto Rico, driven by colonial politics and a neoliberal economic outlook. This corruption is not just related to bribery and illegal practices but also to legalizing wrongdoing through deregulation. The post-Hurricane Maria reconstruction efforts and the deregulatory stance of the congress-appointed control board have further entrenched these corrupt practices.

Just as the central government could not respond to the emergency quickly and effectively, municipal governments were the ones that, to a greater extent, provided the first response to their citizens. Unlike the central government, several municipalities had a greater capacity to plan and organize their response after Hurricane María. Their actions contributed to saving lives by reducing the time families in mountainous areas were isolated and cut off. In contrast, in other municipalities where planning was scarce, the population in rural areas experienced distress and isolation for several days. In those cases, community organizations reopened access and distributed water and food (Enchautegui et al. 2018). It's important to highlight that many municipal governments faced financial strain even before Maria. This problem has worsened due to the gradual reduction of transfers from the central government to municipalities, along with other austerity measures. Additionally, an outdated property tax system and diminished revenue collection after Maria have

compounded the issue. Furthermore, FEMA's reimbursement-based payment policy, the erosion of institutional memory caused by municipal workforce attrition, and technical capacity limitations further restrict disaster response capabilities (López Rodríguez et al. 2019; Fischbach et al. 2020).

The school closure after Hurricane María and the demonstrated inability of the central government to reopen them at a reasonable time exacerbated an already challenging situation for parents and students. At the same time, it significantly delayed the return to normalcy for communities because, as students had no classes, parents who worked outside the home could not return to their jobs, causing a domino effect as commercial and economic activity was also affected.

What prevented the government from reopening public schools? Indeed, some schools suffered significant damage. Nevertheless, most of them seemed ready to reopen 2 weeks after the hurricane passed. The justifications offered to keep them closed changed over the weeks. Initially, it was argued that the schools needed to be conditioned; consequently, parents, school staff, and neighbors organized to collect debris and clean the schools. However, the Puerto Rico Department of Education later argued that expert staff had to certify that the school could reopen (Virella 2017). It was also mentioned that they were waiting for the Federal Emergency Management Agency (FEMA) to reimburse the government for the task. Later, the central government argued that the schools had no water or electricity and could not function (Correa Velázquez 2017). However, municipal governments were willing to provide water to the schools (Enchautegui et al. 2018).³ The schools ready to reopen within a week after the hurricane were forced to remain closed for about 2 months, awaiting authorization from the central government.

7.3 Implications of School Interruptions for Communities, Families, and Children

7.3.1 *Effects on the Local Neighborhood and the School Community*

Students navigate through two vital environments: their local community and the school environment, serving as crucial support systems during emergencies. However, it is essential to recognize that in the aftermath of a major hurricane, all local support networks involve individuals who have also been impacted. Also, these contexts are not isolated since a significant interconnection exists between the school and its geographical community.

Following Hurricane María, the neighborhood emerged as a primary support system, second only to immediate family. Neighbors were the initial responders,

³ After Hurricane María, the complete restoration of electric power and water services in Puerto Rico took many months.

offering aid due to their proximity, as shared by two high school students who participated in Study 1.⁴

It impacted me because my neighbors live far from my house, which is in a rural area. So, it moved me that everyone came to help, which rarely [happened] because I could go two years without seeing my neighbors.

In the first week or two, we were making really big meals. Because one of my neighbors owns a restaurant, he distributed [food] to the whole street to prevent it from going rancid.

The ability to foster support within a community hinge on its pre-established social capital. Putnam (1994) defines social capital as the networks, norms, and trusting relationships that enable coordination and cooperation within groups, encouraging joint efforts toward common goals. Numerous authors underscore the crucial role of social capital in disaster response and resilience building. Aldrich (2010) highlights how recovery occurs faster in areas with higher social capital, while Munasinghe (2007) highlights the pivotal role played by local communities and civil society in orchestrating the recovery process post-2004 tsunami in Sri Lanka. Similarly, Abunywaha et al. (2023) pinpoint collective social capital as a significant determinant of community resilience.

In the aftermath of Hurricane María in Puerto Rico, civil society, community organizations, and non-governmental bodies formed a vital support network. Accounts detailing the recovery phase post-Hurricane María attest to a profound sense of community and belonging within Puerto Rico's neighborhoods, enabling the activation of robust and efficient support networks in an organic manner.

Furthermore, these accounts highlight a cyclical process where pre-existing relationships foster solidarity and mutual aid within the neighborhood community and reinforce these bonds through the aid processes, as revealed by other participants in Study 1.

The unity we formed with my neighbors during the hurricane lasted. We visit each other's houses as if they were our own. . .

I have a brother who is autistic, and before [the hurricane]. . . he never left my house; he was constantly glued in front of the television. And when María happened, he met my neighbors, and now he always wants to visit. My neighbors love him. . .

The feelings of reciprocity that prevailed in the community also allowed students to develop their capacity for solidarity. Participants in Study 1 mentioned their voluntary work in the recovery process, clearing paths, distributing food, assisting in elderly centers, or simply roaming the neighborhood in search of anyone needing help.

Before the hurricane, I didn't get along with almost [everyone]. After the hurricane, I went to all the houses, helped my neighbors. . . my friends. . .

⁴ All the verbatim quotes capturing participants' narratives in the qualitative studies are originally in Spanish and have been translated and edited by the authors.

The importance of community support is also underscored by Quiñones-Domínguez (2019). The author illustrates how, following Hurricane Maria, communities organized themselves to address their needs amidst precarious conditions and a sense of abandonment. Credibility played a crucial role, highlighting the significant contributions of women in the organizational processes. Similarly, Roque (2023) emphasize the significance of networks in facilitating access to water within communities, whether through neighbors, family members, friends, or coworkers. They also highlight the existence of extensive networks, particularly among women.

At the school community level, experiences varied. While students mentioned receiving some support upon returning to school, the delayed resumption of classes often diminished the effectiveness of that support. This delay also hindered the development of stronger relationships between students and school staff, unlike the scenario observed in the neighborhood community. Instead, there was a notable enhancement of social capital among school staff members who returned to their schools shortly after the hurricane, even in the absence of students. The account provided by a social worker participating in Study 1 exemplifies it.

Well, we became more humane. Because most of the time, we were coworkers, each doing their job.

In terms of fostering connections between the school and its neighboring community, experiences varied. During that period, there was no specific institutional school policy outlining the role of schools beyond instructing school staff to report to their respective schools. However, the schools could not receive students until they were certified suitable by the Puerto Rico Department of Education, prolonging the school disruption. Nevertheless, certain schools demonstrated proactive behavior. For instance, some school staff members visited students to assess their conditions, while others transformed the school into a community service center, providing food and clothing. The level of proactivity among school staff seemed tied to the strength of existing ties between the school and its neighborhood community and the leadership vision within the school.

These proactive schools took the initiative to offer essential services to their communities and formed partnerships with other institutions, including faith-based organizations. In such cases, the interruption in teaching services did not necessarily result in decreased social capital between the school and the community. Instead, the schools utilized the break in teaching to serve the community directly, thus reinforcing trusting relationships and networks that foster emotional bonds between the school and its surroundings.

Social work professionals interviewed in Study 1 underscored the significance of a communal sense in reopening schools post-hurricane devastation. They witnessed a unified effort among parents, students, and other community members to prepare and reopen the schools. The narratives of these social workers highlighted this unity.

Parents gathered, and a parents' committee was formed; volunteers helped us clean the school premises because they had initially indicated that we all had to return to school. But since the school was not suitable for the return of students, a group of parents, who have always been fully committed to our school, helped us rise again and put our school in a position to receive our students.

They also narrated the role that schools play as sources of support to the community after the hurricane.

We started it from the moment when the event happened because the school principal communicated with the corresponding staff. We have always been at the school, working and providing services to students and families because we reached out to the community.

And we kept going to school. . . Rather than teaching students, it was to provide support. We found people who brought us hotspots so students could have internet and communicate with their loved ones since they couldn't find a way to do it [at home]. Collaboration was managed and channeled to help those in the community who needed it the most.

However, in cases where school staff followed orders from the central government and passively awaited the start of classes, students were left to their means. Consequently, they had limited access to daily meals, social services, counseling, and school services. It also eliminated the possibility of enhancing social capital between the school and the community.

7.3.1.1 Migration as a Consequence and Its Impact on the Community

The interruption of educational services also promoted emigration from Puerto Rico to the United States. The uncertainty about the return date to school and the anxiety it caused encouraged families with children to relocate after the hurricane.

The rise in migration disrupted the local neighborhood ties and the academic community. For the students who remained, it resulted in watching the departure of neighbors, friends, and even family members, summing up the losses they were experiencing. Study 1 participants expressed this sentiment.

Before the hurricane, my parents planned to move us there (U.S.) because my father had already found a job. . . He was supposed to return, but he stayed there. My mom then decided to go with him in January (after hurricane María). My sister had to stay here as a university student, and I chose to stay with her. Now my parents live there, and I live with my sister and grandmother.

For students who emigrate, it was a complete shift in their neighborhood surroundings. The challenges encountered in their new settings are evident as students and school staff note that many of those who migrated eventually returned. In recounting their experiences, students express their difficulties adapting to a different environment. One focus group participant vividly described the drastic change she and her brother faced upon moving to a strange setting, with a lifestyle that felt unfamiliar, especially in a place with fewer Hispanic residents. She also highlighted the challenge of attending classes in a different language.⁵

The post-hurricane migration significantly reduced the student population in many schools, further intensifying the impact of school closures that had commenced in Puerto Rico before the hurricane and escalated afterward. Following

⁵In Puerto Rico, Spanish is the common language.

Hurricane María, 22 schools that had begun the academic year did not reopen. For students from these schools, returning to classes meant transitioning to a different and sometimes challenging school environment. It also created disruptions for school staff whose schools closed. Under challenging circumstances (no clean water nor power), they had to travel to new and sometimes faraway schools.

7.3.2 Impact on Children and Families

Hurricanes, as devastating natural disasters, not only cause physical destruction but also severely disrupt crucial aspects like educational progress and the emotional well-being of the affected population. Given that education serves as the bedrock for intellectual, social, and economic development, its disruption creates significant instability, especially among vulnerable groups such as children and youth from lower socioeconomic backgrounds. The resulting physical and emotional devastation can also have a detrimental impact on family structures.

Renowned theorists and researchers in the field of development, including Piaget (1983), Vygotsky (1979a), Rodríguez (1999), and Lejarraaga (2004), have highlighted the intrinsic link between the educational journey of children and youth and their emotional development. Due to hurricanes, interruptions in their educational path can induce stress and anxiety, negatively affecting their learning. Disruption of the school routine and exposure to emergencies can emotionally impact them, instilling fear, insecurity, and a sense of instability.

Since education is not solely an individual process, it plays a vital role in fostering social relationships and skills (Vygotsky 1979b). Disruptions in the educational process caused by hurricanes isolate children and youth from their peers and the social structure provided by the school, impacting social connections and their sense of community belonging. Consequently, this adversely affects their learning process. In this context, young participants in Study 1 expressed the following sentiments.

I was most worried about my friends, not Facebook or those things; I [wanted to know] that they were okay.

I missed my friends from school... About four days later, I saw them because I went to their houses, knew they were okay, and spent time with them.

These statements highlight the association between the school campus and peer relationships. The school represents more than the physical place for receiving formal education; it is a place to generate knowledge through social exchanges.

School interruptions caused by hurricanes pose a significant challenge for families. Concerns for the safety and well-being of children and youth during a hurricane deepen their financial and logistical stress. The necessity to temporarily relocate or rebuild homes can profoundly impact the emotional and financial stability of the family, directly affecting their capacity to support their educational journey. Additionally, educational institutions serve a social role by providing stability amid family conflicts. As long as schools remain closed, children and youth miss out on

the opportunity to build relationships with teachers and authority figures that are part of their safety net.

In this regard, school social workers stress that after Hurricane María, students strongly needed to discuss their experiences and express their emotions. Hence, activities that foster camaraderie and support among students within the school environment proved crucial. A psychologist in Study 2 shares her experience regarding these kinds of activities.

I think it was an effective dynamic because they could vent their feelings, feel liberated, and calmer, and they said so. . . . In large open community activities, even the parents expressed that they felt calmer [and] thanked us for doing it because other schools didn't. In our experience, I think it was very satisfactory and well-channeled.

Interdisciplinary interventions for students and their families' emotional and social development are vital after catastrophic events like hurricanes. The narrative of another social worker emphasizes the importance of "working with sensitivity, empathy, and solidarity in the face of socioeconomic and emotional situations that students and their families may face, which could affect their performance and academic achievement."

In this context, minimizing school interruptions is crucial as it enables various professionals, such as social workers and psychologists, to employ problem-solving techniques in addressing home situations that might impact students' academic performance following catastrophic events. This involves conducting home and community visits to assess the student's circumstances, devising intervention plans, and ensuring ongoing support and counseling services. Therefore, fostering collaboration with government and community agencies becomes essential to ensure accessibility to services and comprehensive therapeutic interventions.

7.3.2.1 Academic Impact

The literature highlights that socio-natural disasters adversely affect students' academic performance (Crespo Cuaresma 2010; Gibbs et al. 2019; Nguyen and Pham 2018). In wealthier nations, educational disruption is directly attributed to the interruption in schooling. Conversely, in less affluent countries, an increase in child labor often follows the loss of resources at home (Kousky 2016). These repercussions are heightened for students with functional diversity due to their increased vulnerability. McAdams Ducey and Stough (2011) underscore the impact of interruptions to medical and other support services on this population, which may lead to the loss of vital equipment and academic, social, and independent living skills. They, along with La Brocquem et al. (2017), emphasize the crucial role of teachers in providing stability and security to students, restoring routines, and identifying those who require additional professional help and support services.

Prolonged interruptions in education significantly affect the academic performance of children and youth. Although the education system might propose alternative methods to cover missed educational content, we have discussed how the

learning process is much more than that. It involves an integrated approach, linking concepts with personal experiences to facilitate understanding. The absence of classroom time directly impacts students' capacity for creative thinking and learning; aspects fostered through social interaction (Vygotsky 1979b). Additionally, prolonged absence from school affects academic performance and impedes social development, as schools play a pivotal role in nurturing interpersonal skills crucial for community life.

According to Segarra-Alméstica et al. (2021), students in public schools in Puerto Rico showed extremely high levels of vulnerability.⁶ Nearly 80% of students in public schools lived in families with incomes below the poverty level, and almost 30% reported at least one disability affecting their learning. Twenty-five percent of students reported both vulnerability conditions.

Segarra-Alméstica et al. (2022) analyzed data from Puerto Rico's Department of Education student information system to gauge Hurricane María's impact on academic performance in the public elementary and secondary school system. They assessed the hurricane's effect on standardized test scores using a panel data model with adjustments to mitigate potential biases from student migration. Students were categorized based on the hurricane's impact level in their municipality within three groups: highly affected, moderately impacted, and least affected. While there was a downward trend in standardized test scores across the public school system, students in the most affected areas exhibited an additional 3% reduction compared to those in less-affected regions. Among students with disabilities or from households below the poverty line, there was an additional estimated 3 to 4% decrease in standardized test scores. However, even after adjusting for missing school days, a significant adverse effect persisted, suggesting the presence of other factors influencing academic performance.

Insights gathered directly from school communities help clarify these findings. Hurricane María made landfall in Puerto Rico on September 20, 2017. A survey of public-school principals, part of Study 2, revealed that by October 2017, only 17% of schools had reopened, and one-third began to receive students in November of that year. The remaining schools reopened between December and February of the following year. Schools that served as shelters were the last to reopen. Among school principals interviewed during our studies, only one unauthorizedly received students on October 16, 2017. However, the students' return to school was on a limited schedule due to water and electricity shortages. For most, the number of missed school days for the 2017–18 academic year was substantial, consistent with findings from youth focus groups in Study 1.

The school I was in started in early December, and we were there from 7:30 to 11:30 [in the morning] until May, and the electricity was reestablished when classes ended.

⁶In addition to children's innate vulnerability, the concept also relates to the hurricane's impact level, poverty level, and presence of a disability.

As a result of the length of school disruption, there was little time to catch up with grade-level requirements. Interviewed teachers pointed out that this meant prioritizing essential skills and knowledge required for standardized tests. Nevertheless, they believed it was not possible to prepare the students adequately. These gaps in fundamental knowledge lingered into the 2018–2019 academic year. Students felt they did not recover academically and had a backlog that made advanced-grade material more challenging. Their perception of being left behind might affect their future performance in school, higher education, and the workplace. Student narratives account for how their academic performance was affected.

Nowadays, it feels much more challenging because I need the knowledge they didn't offer me.

The workload piled up brutally because they wanted to compensate for all the time lost . . . they started giving a lot of homework, and I think some people even lowered their grades.

Yes, (speaking about academic lag) in mathematics because our math teacher arrived in March [seven months later].

School staff highlighted several factors beyond the loss of class time that influenced academic performance. Among those, they mentioned the absence of technology caused by power outages at school and home. They also stressed the emotional toll of the hurricane on students and the inadequate living conditions for those whose homes were damaged. Social workers and teachers who participated in our studies emphasized these crucial aspects.

. . . many class days were lost. So, when classes were finally being held, there were practically no resources, power, printed material, or anything. There were not even notebooks for the kids because many had lost their school supplies. . .

Unfortunately, the material that was supposed to be covered couldn't be fulfilled; adjustments had to be made. We had to shorten the chapters and focus on the most critical parts of each module, and each student had to work on it at home . . . We were careful with this since they didn't have electricity . . . we didn't assigned excessive work.

Students living in relatives' homes faced other hurdles; they didn't have study areas, and sometimes [they moved] far from schools or moved to grandparents' or uncles' houses.

The teacher mentioned that the absence of schooling and the post-disaster economic situation might have encouraged high school students to prioritize work over school, dedicating less time to their studies.

. . . We encountered many students who chose to go to work and pay less attention to their studies. It's a family issue if the parent allows it. It is mainly the 12th graders who have chosen to do that, and we see how it affects the grades . . .

The Puerto Rico Department of Education's decision to adjust the curriculum to incorporate real-life experiences into the teaching-learning process had a positive impact in many cases. Hurricane María presented an opportunity for students to comprehend natural events, climate change, and their effects on human, animal, and plant life. During the same academic year post-Hurricane María, the Department of Education introduced project-based learning (P.B.L.). This approach involved students engaging in projects that merged various subjects. Interviews conducted with

teachers and students suggested the effectiveness of these projects when they were directly related to the hurricane and other natural phenomena. However, if topics were unrelated to the students' immediate experiences, they were seen as an added burden, being less effective as perceived by teachers and students.

Contrary to expectations, despite declining academic achievement, Segarra-Alméstica et al. (2022) discovered that school dropout rates did not surge in the most affected areas. The study assessed Hurricane María's impact on dropout rates among eighth and tenth-grade students after the hurricane struck. Surprisingly, eighth-grade students in areas moderately impacted by the hurricane were 18% more likely to drop out than those in low-impact zones. Conversely, among tenth-grade students, those in areas most affected by the hurricane were less likely to drop out of school. Our qualitative research yields two explanations for this trend. One factor was the proactive efforts in certain schools in those severely affected areas to reach out to their students, offering personalized support and direct attention, as illustrated by a social worker participating in Study 2.

The counselor and I identified those students and listed those who were academically behind by grade. Then, we took those students and guided them. After that, we had a parents' meeting because there had to be a connection between school and home. We gathered the parents, presented the situation, and provided guidance, offering help strategies so that they could work with their children. . .

We inferred that another influential factor could have been the school's role in becoming a safe haven and a source of normalcy. Schools whose leaders actively engaged with students, parents, and other community members solidified the attachment to the school as a social environment, providing a respite from the aftermath of the hurricane and the ensuing pressures of daily life when there was no power or clean water. In the narratives of all interviewed individuals, the sense of community, solidarity, and mutual support after the hurricane stood out. They attributed students' increased motivation and hopefulness to this environment. Despite the losses and trauma caused by the hurricane, they found solace in being able to physically help each other—a stark contrast to the distancing and isolation experienced during the COVID-19 pandemic.

7.3.2.2 Physical and Emotional Implications of School Interruption

The disruption of education due to hurricanes does not just impact academics; it also affects children's and youth's physical and emotional well-being. As mentioned earlier, educational institutions play a crucial social role by providing services to their student community. Schools ensure access to updated medical services and at least one meal per day for children and youth. However, during school interruptions caused by events like hurricanes, when there is limited food availability and a lack of access to therapeutic services, among others, if schools remain closed, a relief opportunity is lost.

Limited access to healthcare during and after the disaster, along with exposure to unsanitary conditions in temporary shelters, increases the risk of diseases. The survey conducted among school principals in Study 2 revealed that over 70% of their schools provided screening and prevention services for physical and mental health conditions after Hurricane María once they opened, underscoring the school's vital role in health service provision (Segarra-Alméstica 2023). However, these services cannot be offered until students return to the school premises. Moreover, the interruption of school meal programs can impact the adequate nutrition of children and youth, potentially affecting their growth and development. The following excerpt sheds light on the impact of these deficiencies as reported by participants in our Studies.

It was desperate, sleeping without power, and we had no water at home. There was a shortage of food. We had to get up early to go here and there looking for them.

Emotional health is also affected—sadness, uncertainty, and confusion cause difficulties in dealing effectively with sudden change. When a family structure is dealing with feelings of instability, both physical and emotional, it cannot serve as a foundation to promote learning in children and youth. To the extent that children and adolescents are confronting mental health issues, their learning capacity is affected (Baraldi 2002). The narrative of a young person revealed the following:

My home felt sad because my dad had to stay with my grandfather and couldn't come back home for two weeks[after the Hurricane] because there was no access. . . and we were cut off because there was no phone signal. And when he arrived, there were a lot of emotions because on the radio they had been saying there were dead people.

School social workers who served students during these phenomena testify to how emotionally affected they are. They emphasized that, in the face of reactions from their parents or guardians, who were dealing with their extreme living conditions, students express anger, tension, fear, and sadness, among other emotions. The ravages of the hurricane leave traces that are still difficult for some students to overcome. The narrative of a social worker revealed the following:

They expressed much about that storm event, the noise it made, and [that] the wind sounded like a bull running. They told us that their houses flooded with the windows closed. They could not understand where the water was coming from. . . and everything got wet and damaged. Sometimes, they played with the water, but at the same time, when they saw things getting lost and saw their parents crying, they said they cried too. They got nervous as they climbed on their beds, scared, and huddled in a corner. . . they expressed a lot of tension, fear, and anger.

Some studies have found that, in children and youth, the emotional effect can last up to 6 months after the experience of a hurricane, manifesting in nightmares, anxiety, loss of interest in previously enjoyed activities, irritability, and difficulty concentrating (Murray 2011, as cited in Enchautegui et al. 2018). The teachers participating in Study 2 emphasized that working on students' emotions was necessary before addressing the academic aspect. A teacher stated,

Although I tried to do a lot, it was going to be a bit impossible to cover everything required because students didn't always come in the right mood. Sometimes, they were a bit sadder, and at that moment, for me as a teacher, it was much more important to be able to reach that emotional part and make sure that the kid, when leaving my classroom, felt a little calmer or in a better mood, rather than making sure he learned to write a paragraph correctly.

Similarly, school social workers have agreed that there is a great need to focus on strategies to promote effective communication and emotion management. The narrative of a social worker emphasizes this point by specifying her experience:

As a school social worker, I focused on effective communication and emotional management. After a natural disaster like Hurricane María, many of our students and parents were emotionally affected, and work was done there. Also, with referrals to various agencies so that they could provide psychological services.

The emotional impact is not confined to students alone; it also manifests in signs of anxiety and trauma symptoms among parents or guardians confronted with unexpected and distressing conditions. Parents experience multifaceted effects across socioeconomic dimensions, impacting their physical and mental health post-hurricane. A social worker noted that the anxiety and distress observed in students' parents or guardians directly affected the classroom environment.

Students are also emotionally affected by the critical situation in which their families and communities find themselves due to the loss of their homes and the lack of essential resources for an extended period. Children and youth experiencing school interruption due to hurricanes may experience post-traumatic stress, anxiety, and depression. Uncertainty, the loss of routine, and exposure to traumatic events contribute to mental health problems that can persist in the long term if not addressed adequately. The school provides a social and emotional support environment. Verbal expressions from a group of young people reveal that the only time they had for themselves was in school, where they found the activities relaxing.

I wanted to go back [to school] to talk and share. The school was the time of normality. There was no electricity at home; it was hard to get food. . .

As a social institution, the school provides a safe space for forming bonds, socioemotional development, and leadership skills. Prolonged interruption jeopardizes not only the stability and development opportunities of children and adolescents but also the school community.

In affective terms, the separation from friends and teachers, the loss of the school structure, and the adaptation to new circumstances can affect the emotional health of children and youth, impacting the overall family structure. Consider, for example, the impact of migration on families following the hurricane. Many families separated in search of better options for their members, causing instability and unease. The following segments highlight the impact of migration on families and emotional well-being:

The atmosphere felt strange; many of our friends told us they were going to the U.S. because their homes had been destroyed. In my class, we were 25, and now we are 17.

I spent the whole year there, finished my 11th grade in a school in Orlando, and spent nine months with my dad, getting to know him because I didn't have very good communication or relationship with him before. I had to go there without knowing. . . . It was tough because my mom has been with me forever, and going there without her was very difficult.

The impact of hurricanes often leads to significant shifts in family dynamics, with children sometimes cared for by grandparents or other relatives, adults taking responsibility for older family members, and separations among couples, among other changes. The lack of social support prompts individuals to seek opportunities outside the country to sustain their families. The despair and loss of hope in the aftermath of Hurricane Maria's devastation, coupled with the inadequate government response, drove emigration, displacing numerous Puerto Rican families from their homes and undermining their sense of belonging. (Blackwell et al. 2021). Aranda et al. (2023) show that families who migrated from Puerto Rico faced tough economic situations, difficulties accessing educational services, and social interaction challenges. The emergence of the COVID-19 pandemic worsened these issues.

In discussions with social workers regarding the post-Hurricane María school community experiences, the issue of migration emerged repeatedly. Frequently, parents would depart, leaving their children with relatives in Puerto Rico, or they would remain while sending their children to the United States. Unfortunately, social workers mentioned distressing accounts of children facing mistreatment or abuse during these transitions.

Many went to the United States because their houses were lost, and they had nowhere to live. The family was divided. Some stayed in Puerto Rico, others didn't. There were many changes, and students, unfortunately, were greatly affected. That separation from parents to live with a relative and living traumatic events with some relatives. . .

The population with disabilities faces even more significant challenges during situations like hurricanes. Their specific needs make them particularly vulnerable when dealing with the aftermath of such natural disasters. School closures disrupt their education and interrupt related services vital for their well-being. Children with disabilities rely on specialized support, often provided through the school system, and the discontinuation of these services can lead to a worsening in their condition.

The interruption of schooling due to hurricanes does not just result in academic setbacks; it profoundly affects children's and young people's physical and emotional health. Recognizing and addressing these implications is crucial for facilitating recovery and developing protective strategies against future events. Investment in mental health services, access to medical care, and community support programs can significantly impact the ability of children and young people to cope with the challenges stemming from school interruptions caused by natural disasters.

7.3.2.3 Implications for Human Capital Formation

The prolonged negative impact of school interruptions on academic performance and health signifies a decline in human capital development among affected students. It is essential to delve into the theoretical underpinnings of social capital formation to evaluate how it is affected by school disruptions. The concept of human capital, originating from the works of Schultz (1959) and further developed by Becker (1983), defines it as the productive capabilities acquired through the accumulation of knowledge, whether general or specific (Luciano et al. 2021). Becker (1975) associates school education and health as activities contributing to human capital formation. This perspective considers human capital as a production factor, with investments yielding individual and macroeconomic returns. Further advancements in this theory emphasize that investing in human capital leads to higher future incomes, social mobility, poverty reduction, cultural enrichment, individual and social capacity development, and economic growth (Briceño 2011; Eicher 1988; Mincer 1974; Sen 1997; Thurow 1978).

Drawing from this theoretical framework, the closure of public schools following Hurricane María negatively impacted students' human capital formation. This impact manifests directly through the interruption of the educational process and indirectly through its effects on students' physical and emotional health. In the short and medium term, this disruption can affect students' academic performance upon their return to school and in subsequent grades. In the long term, it may influence their income generation and social mobility.

7.3.2.4 Economic Impact

From an economic standpoint, hurricanes have an economic impact even before their arrival, as communities incur expenses to prepare for the event. Post-landfall, the recovery process becomes economically complex as communities grapple with family members, infrastructure, services, employment, and income losses. Impoverished households face more challenges in preparing for and recovering from these natural disasters.

As per Segarra-Alméstica (2018), Hurricane María's passage was anticipated to escalate losses of physical assets and infrastructure and a contraction in economic activity in Puerto Rico due to prolonged power outages, potentially raising the country's poverty rate. Additionally, analyzing the financial implications of interrupted public-school services is crucial. Communities hosting these schools experience declining economic activity due to decreased demand for local products and services. Moreover, these interruptions limit parents' ability to work and earn income while their children are home.

The most vulnerable individuals, including the impoverished, elderly, children, those with critical health conditions, and marginalized populations, bear the most significant impact (Segarra-Alméstica 2018). Public school students in Puerto Rico

face heightened vulnerability due to the interplay of childhood with poverty, compounded by other challenging conditions and circumstances.

7.4 Learned Lessons

Recent climatic events in the region have highlighted the essential need for better planning to face hurricanes of unprecedented intensity. Puerto Rico's current situation is one of significant vulnerability, as its electrical, road, and transportation infrastructure remains fragile after Hurricane María, and the government has not made the necessary adjustments to confront the impacts of climate change successfully. According to the E.P.A. (2016), cities, roads, and ports in Puerto Rico are vulnerable to the effects of winds and water during storms. Furthermore, homes and coastal infrastructure will likely experience more frequent flooding as sea levels rise because cyclonic surges will also increase. The experience after Hurricane María demonstrated that the ability to respond to these events primarily comes from communities, municipal governments, and non-profit organizations (Cordero-Nieves 2018; Enchautegui et al. 2018; Observatorio de la Educación Pública 2023; Segarra-Alméstica 2018). During and after a hurricane, the lack of resources and the required time to fulfill a household's basic needs can make it difficult for children and young people to get the attention they need. The lack of school counseling services and the discontinuity in providing mental health and related services —exacerbated by school interruption— are additional challenges facing families and communities. Simultaneously, systemic vulnerabilities in federal and state government agencies to coordinate necessary services with the school community aggravate the problem.

On the other hand, it is essential to highlight the strengths that most municipal governments, public schools, families, and their communities exhibit, even in times of uncertainty and distress. Here, we summarize some of those vulnerabilities and strengths. Some vulnerabilities accentuated by the interruption of the educational process in Puerto Rico after Hurricane María can be classified into two categories: those associated with the geographical context and those associated with the response capacity. Regarding the regional context, the archipelago of Puerto Rico is in the Atlantic Region, making it more vulnerable to the effects of hurricanes, as previously mentioned. Higher-intensity events cause a more significant impact, leading to more prolonged closures. However, this cannot be separated from the response capacity of federal and state governments, which have been criticized for their slowness, inefficiency, and politicization in managing the emergency. Other elements that have contributed to affecting the response capacity and, therefore, prolonging school interruptions include the fiscal crisis of the central and municipal governments, the bureaucratization of government agencies, corruption, centralized policies at the Department of Education, the fragility of electrical, road, and transportation infrastructure, and the use of schools as community shelters.

Centralized decision-making kept schools closed longer than necessary. In this sense, centralized decisions during the emergency were misguided. In cases where school staff passively awaited the start of classes without participating in community recovery processes, the return to learning was delayed further. It exacerbated the impact of the lack of services.

Nevertheless, we observe several strengths from various instances that contributed to efforts to start the reconstruction period and reopen schools. The sense of cooperation and commitment demonstrated through the actions of municipal government brigades and community-based organizations to restore communication routes and streamline the distribution of food, water, and other supplies must be emphasized. An important lesson was the essential role of maintaining alliances with the community, local businesses, and municipal governments. Schools that maintained closer relationships with their surroundings could clean up quickly and became spaces for collecting and distributing food, water, and clothing. These actions helped mitigate the impact of losses suffered by numerous families.

Historically, in Puerto Rico, the strong sense of community, mutual support, and solidarity among neighbors have shone brightly during the most challenging times, as evidenced in the aftermath of the hurricane. Fueled by social capital, this community unity was pivotal in navigating the situation as effectively as possible. School staff often actively engaged in these community initiatives, showcasing adaptability, empathy, and expertise in identifying and addressing various emotional, social, and academic needs. Undoubtedly, it is essential to highlight the integrity, resilience, and courage displayed by students and their families, demonstrating their ability to rise above and confront new challenges with hope, aiming to progress forward.

7.5 Towards Recovery: Prioritizing Education and Support Systems After Disasters

The passage of Hurricane María across Puerto Rico in 2017 laid bare vulnerabilities in infrastructure, government response, and the lack of proactive climate change planning. It underscored communities, municipal governments, and non-profit organizations' crucial role in immediate response efforts.

The complex impact of hurricane-induced interruptions on the educational process extends to children and their families. Adaptability during these challenging times relies not just on individual family members but also on the societal support system. Effective governmental responses must prioritize academic recovery, emotional well-being, and social stability of children, youths, and their families. Recognizing the magnitude of these challenges, we can pursue solutions that enhance resilience and facilitate comprehensive recovery across educational and emotional domains. The solutions should involve enhancing municipal governments' financial and technical capabilities to respond to disasters and improving utilities' infrastructure.

The information presented in this chapter highlights schools as vital support systems for students and the wider community post-disaster. Hence, minimizing school interruptions due to hurricanes should be a primary focus.

Prompt resumption of school activities can benefit from emergency and disaster management protocols centered on teamwork. These protocols should ensure effective communication among decision-making entities and empower school communities to make decisions based on their unique circumstances. Protocols should also facilitate collaboration and integration of services within the school's multidisciplinary teams, supporting students and families. Strengthening ties with government agencies is crucial for swift and effective emergency communication. Promoting social cohesion within the school community and the broader geographical community is equally essential. Formalizing connections with non-profit organizations, known for their rapid disaster response, is of the essence.

The education system should position schools as hubs for comprehensive training, providing diverse educational, social, and emotional services before, during, and after disasters. These activities should be tailored, considering each school population's strengths, risks, and specific characteristics. Priority should be given to the needs of the most vulnerable students disproportionately affected by disasters.

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Chapter 8

College Students and Hurricane Preparedness: Cluster Analysis of Factors Affecting Vulnerability and Coping Capacity



Saige Hill, Juita-Elena (Wie) Yusuf, and Meagan M. Jordan

Abstract College students are especially vulnerable when faced with hazards and disasters. Adequate preparation and response are necessary to mitigate the effects. The present research addresses the following question: How does hurricane evacuation preparedness vary among college students? This chapter includes an analysis of factors that lead to student hurricane vulnerability and preparedness, an overview of the utilized conceptual framework, discussion of the methodology, and finally, an examination of the results and conclusion. Two hundred five students at Old Dominion University, a 4-year public university in Coastal Virginia, were studied. The Person-relative-to-Event theory of coping was using as the foundation of the conceptual framework, and four clusters emerged from the analysis: cluster 1—students who are somewhat prepared with adequate knowledge and resources ($n = 35$); cluster 2—students with no preparation, but significant knowledge and resources ($n = 67$); cluster 3—students with high preparation and planning, but with knowledge and resource gaps ($n = 31$); and cluster 4—students who are prepared, planned, knowledgeable, and resourced ($n = 72$). Factors such as full-time enrollment, level of study, race, and marital status had little effect on hurricane preparedness, while employment, income, access to information and resources, experiencing severe hurricanes, and being relied on by others were statistically significant.

Keywords Evacuation · Higher education · Hurricane preparedness · Risk · Vulnerability

S. Hill (✉) · J.-E. Yusuf · M. M. Jordan
Old Dominion University, Norfolk, VA, USA
e-mail: shill@odu.edu

8.1 Introduction and Overview

Vulnerable populations have unique needs or require specific accommodations to ensure they receive adequate information regarding risks and to prepare and respond effectively (Burger et al. 2019; Eisenman et al. 2007; He et al. 2007; Maldonado et al. 2016). College or university students are a specific vulnerable population compared to the general population due to their young age, lack of experience, and limited support and access to resources (Hill 2023). This chapter focuses on how college or university students plan for and are prepared to evacuate ahead of a hurricane. Throughout the remainder of this chapter, we use the term “college students” to apply to students attending colleges or universities in the U.S.

This chapter addresses the question: How does hurricane evacuation preparedness vary among college students? We answer this question by exploring differences in hurricane evacuation preparedness of college students enrolled at Old Dominion University, located along the U.S. Atlantic coast in southeastern Virginia. Cluster analysis is used as an exploratory tool to determine if college students fall into different categories in terms of their preparedness for hurricane evacuation. Comparison of the resulting clusters allows examination of how groups of students are prepared to evacuate ahead of a hurricane and how their vulnerability profiles vary.

This chapter begins with a review of the critical issues regarding college students’ vulnerability and preparedness for hurricanes. This discussion of the literature is followed by a description of the conceptual framework that underpins our expectations of different categories or clusters of college students’ preparedness for hurricane evacuation, emphasizing three dimensions: preparedness and planning, knowledge about evacuation, and resources for evacuation. The next section provides an overview of the student survey used to collect data and reviews the clustering algorithm used to conduct the analysis. The cluster analysis methodology resulted in four clusters representing four combinations of preparedness and planning with different levels of knowledge and resources. These clusters are examined, validated, and interpreted regarding how they conform to the literature and conceptual framework. The chapter concludes with a review of the findings, limitations, and implications for research and practice.

8.2 Literature

8.2.1 Hurricane Evacuation Preparedness

Effective evacuation is essential to hurricane response and results from preparedness at multiple levels and across various sectors. “Preparedness functions not only to decrease risk and increase people’s ability to cope, adapt and recover when disaster strikes, but also contributes to curtailing the ballooning costs of hazard events” (Paton 2019, p. 327). While state and local governments are responsible for ordering

evacuation and ensuring evacuation operations, nonprofit organizations, such as the American Red Cross, may support evacuation efforts, and residents must prepare for and take action to evacuate. At the most basic level, individual-level evacuation hinges on individual preparedness. Research has consistently found a positive relationship between preparedness, such as having an evacuation plan, and evacuation behavior (Tanim et al. 2022).

Essentially, preparedness refers to the knowledge and capacity to effectively anticipate, respond to, and recover from the impacts of disasters (United Nations International Strategy for Disaster Reduction 2016). People prepare by acquiring knowledge and resources to respond and developing the capacity to apply this knowledge and resources through having an active and up-to-date hurricane evacuation plan (Burnside 2006; Mozumder and Vásquez 2018; Paton 2019). Preparedness activities include having a household emergency plan that outlines where to go and what to do, setting aside supplies, being familiar with community-based disaster preparedness systems, and participating in emergency-based training programs (Federal Emergency Management Agency 2009).

However, decisions driving evacuation behavior, such as whether to prepare and the level of preparedness, are multidimensional (Hasan et al. 2011; Yusuf et al. 2023). Factors contributing to hurricane evacuation behavior can be organized into two primary categories that drive vulnerability: risk perceptions and resources. Risk perception forms after disaster experiences. “Personal experience has a powerful impact on risk perception. Prior personal hazard experience, a form of knowing, is widely thought to have an impact on self-protective behavior” (Mishra and Mazumdar 2015). Lacking prior experience with a potential disaster and having little knowledge of associated risks can lead to low risk perception and diminish the importance of preparedness (Hill 2023). Experiences with past hazards such as Hurricane Sandy (Burger et al. 2019) and Hurricane Katrina (Zhang et al. 2007) influenced decision-making and preparedness. Furthermore, older individuals have more experience than younger ones and are likely to perceive a hazard risk and prepare for a disaster (Mishra and Mazumdar 2015).

The resource category includes factors related to economic resources and enabling factors for, or barriers to, evacuation (Tanim et al. 2022; Yusuf et al. 2023). Disaster losses can be significant, and actions to reduce vulnerability can be expensive. Access to resources enables people to better prepare for future contingencies, invest in resource enhancement, and take action to minimize risk. On the other hand, people who lack appropriate resources may be challenged to invest in protective measures (Schönpflug 2021). The latter’s resource limitations may prompt them to cope reactively instead of investing resources in proactively coping (Hobfoll 1988, 2001). Having access to transportation resources to evacuate also factors into decisions about evacuation behavior (Lazo et al. 2010; Rosenkoetter et al. 2007). Furthermore, compounding hazards—for example, surges in COVID-19 during hurricane season, can inhibit response, especially for those dependent on shelters as based on a 2021 survey, three-fourths of participants viewed risk of COVID-19 exposure as a greater threat than hurricanes (Collins et al. 2021).

8.2.2 College Student Vulnerability to and Preparedness for Hurricane Hazards

There are several reasons for focusing on college students and the extent to which they are prepared to evacuate ahead of a hurricane. Due to factors such as age, inexperience, limited income and financial resources, lack of transportation, lack of knowledge or guidance, and reliance on others, college students are especially vulnerable when faced with hazards (He et al. 2007; Sattler et al. 2014; Tanner and Doberstein 2015). Furthermore, the needs of college students are often overlooked during hazards, thus calling for special attention to be paid to this population (He et al. 2007; Tkachuck et al. 2018). They “are a distinctive population in the sense that they are transient, marginally aware of their vulnerabilities, and do very little to prepare for disasters” (Lovekamp and Tate 2008, p. 86).

In general, “people differ in their level of preparedness; a minority prepare comprehensively, but the majority either adopt a few (easily adopted) measures or do not prepare” (Paton 2019, p. 330). Research shows a similar lack of preparedness among college students. For example, Tanner and Doberstein (2015) found that less than a third of college students have emergency kits, and any emergency preparedness supplies students may possess were also not readily available for everyday use. Claborn (2010) found that over half of college students had a 3-day supply of food and a first aid kit, but less than a third of students had a radio, generator, or extra supply of medication. Over a third of college students in a study by Lovekamp and Tate (2008) had completed preparedness planning actions such as establishing plans and discussing with others what to do in the event of a disaster. Simms et al. (2013) found more significant deficits in emergency preparedness among college students—only 2% of students were able to identify the nearest emergency shelter location and only 8% reported having emergency supplies, while more than 70% did not have an evacuation plan. College students, particularly international students, lacked effective evacuation plans despite efforts by universities to educate the international student population on hazards and associated risks (Abukhalaf et al. 2022; He et al. 2007). Recent research found that more than three-fourths of international students knew the location of hurricane shelters on campus, but very few had complete emergency kits (Abukhalaf and von Meding 2021). More than half of international students had a plan for what to do in the case of a hurricane (Abukhalaf et al. 2022).

Vulnerability lies in the lack of preparedness of populations. Many of the same vulnerabilities in the general population apply to college students, reflecting different perceptions of risks given experiences with and awareness of hurricane threats, and coping capacity resulting from the availability of transportation and financial resources, and access to information. In addition to college students as a whole being vulnerable, there are groups within the population with overlapping vulnerabilities, such as students with disabilities, those speaking English as a second language, and low-income students (Hill 2023). International and out-of-state students, particularly, are subject to several additional factors that increase vulnerability

to hazards, such as limited disaster experience, financial burdens, lack of education, interrupted social networks, language barriers, and cultural differences (Abukhalaf and von Meding 2021; Abukhalaf et al. 2022; He et al. 2007; Thorup-Binger and Charania 2019).

Traditional-age college students generally lack life experience and have only been responsible for making decisions for themselves for a relatively short period. Many college students live away from their families for the first time and must make hazard-relevant decisions with limited guidance (Hill 2023). Having left the confines of their caretakers' protection, these students are transitioning to developing their preparedness approaches.

Students, especially those attending college in new locations, may be susceptible to different risks than in their previous environments and lack of prior experience impacts risk perceptions and preparedness (He et al. 2007; Lovekamp and Tate 2008; Tkachuck et al. 2018). Ponstingel et al. (2019) found that students' previous experiences increased their risk perceptions.

In terms of resources, Mulilis et al. (2000) found that compared to the general population, college students were the least prepared, likely due to limited resources. Assessment of sufficient resources related to the perceived severity of the threat leads to greater preparedness (Duval and Mulilis 1999; Mulilis and Duval 1995). Family and friends can provide much-needed support in emergencies. Many college students live away from home and are disconnected from previously established social networks while attending college. This disconnection can cause distress when students cannot easily communicate with family and friends, whom they may need to rely on for assistance; additionally, having family or friends to stay with while evacuating can influence preparedness (Hill 2023). Furthermore, as people tend to evacuate to homes of friends and family, college students who have places to evacuate to are better prepared.

8.2.3 Conceptual Framework

We use cluster analysis as an exploratory tool for determining the multiple ways that college students are prepared for hurricane evacuation. As an exploratory tool, cluster analysis is useful for classifying observations when based on a theoretical or conceptual framework (Hair et al. 2010). The conceptual framework underpinning our exploratory analysis centers on preparedness as a combination of proactive preparation and planning to guide action, knowledge to decide that action needs to be taken, and resources that may be utilized to take action.

Underpinning the conceptual framework is the Person-relative-to-Event (PrE) theory of coping, where an individual approaches preparedness as self-protective behavior that results from an evaluation of the threat and the sufficiency of resources to address the threat (Duval and Mulilis 1999; Mulilis and Duval 1995). When individuals perceive they possess resources such as appropriate knowledge of the actions that can be taken to protect against a threat, they can engage in preparedness

behavior (Levac et al. 2012). Through “problem-focused coping” (Duval and Mulilis 1999; Mulilis and Duval 1995), individuals can prepare for threats by developing plans and undertaking annual preparation activities.

Applying the PrE theory to our conceptual framework for explaining different approaches to college students’ preparedness for evacuation given the threat of a hurricane, the cluster analysis differentiates college students according to their hurricane preparation and planning activities, knowledge about when and how to evacuate, and availability of resources to support evacuation such as money, transportation, and a place to which to evacuate. These differentiating action-related variables will be used in conducting the cluster analysis. However, because of the exploratory nature of the cluster analysis methodology, it is important to use the conceptual framework to validate the resulting clusters and ensure practical significance. Specifically, the conceptual framework outlines a nomological network of constructs and variables expected to differ across the four clusters of college student hurricane evacuation preparedness constructs and variables that we expect to be invariant regardless of hurricane evacuation behavior (see Fig. 8.1). This network allows for assessing criterion or predictive validity for the cluster results.

According to the PrE theory of coping, preparedness results from recognition of the threat and its consequences. If people are to engage in preparedness, they need to “first anticipate both what could occur and what that means for what they need to do to reduce their risk and increase their capacity to respond when hazard events occur” (Paton 2019). They need to perceive risk and understand what to do to prepare as a way to mitigate risks and their impact and increase capacity to respond. Therefore, in applying the conceptual framework to our cluster analysis of college student hurricane preparedness, we expect resulting clusters to have different vulnerability profiles reflecting differing perceptions of the hurricane threat and coping capacity to respond to the threat.

Vulnerability refers to the probability that, extent to which, and factors that contribute to how that an individual will be exposed to and adversely impacted by a hurricane. Vulnerability is a function of risk and the ability to respond. The literature identified several factors related to hurricane risk. These include age and experience with hurricanes (Koskan et al. 2012; Midtbust et al. 2018; Norris and Murrell 1984; Tanner and Doberstein 2015). Two additional factors related to vulnerability—having a disability and being relied on by others during a disaster (Hill 2023)—are also expected to vary across the clusters with different preparedness.

Knowledge and resources are critical elements of a college student’s ability to respond. Knowledge about the hazard or actions to decrease the effects of the hazard can contribute to mitigating potential impacts (Mishra and Mazumdar 2015). This knowledge, coming from various sources, can be about the threat itself or about protective actions. We expect clusters representing higher levels of preparedness would also be comprised of students with greater knowledge. These clusters should have more students who know where to access information about an upcoming hurricane or where to go for community resources to assist with evacuation.

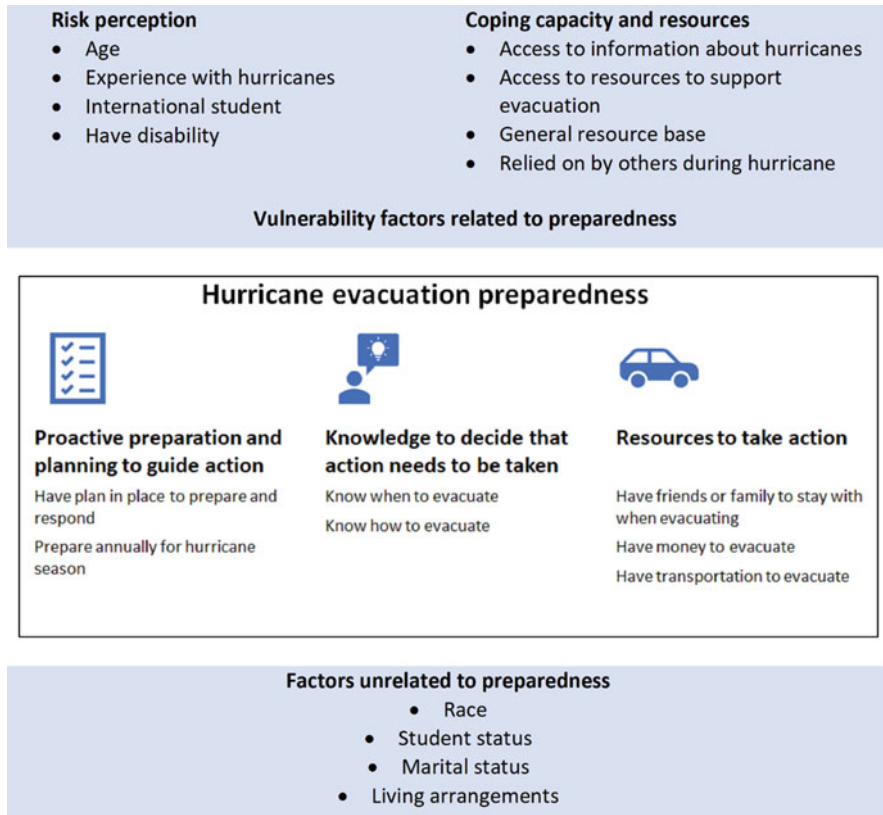


Fig. 8.1 Differentiating variables for categorizing college students' hurricane evacuation preparedness and expected variations in vulnerability profiles

Resource access can be a barrier to evacuation (Yusuf et al. 2023) and hold college students back from evacuation preparedness. College students who are employed full-time or have higher household incomes will likely have more liquid assets that, while not specific to evacuation, can facilitate students to undertake preparedness activities. Hobfoll (1988), for example, suggests that people seek to retain and protect their resources. Those with more resources are motivated to prepare and plan for evacuation to protect their assets; furthermore, due to their income, they are more likely to have the financial capability of doing so.

Finally, the conceptual model also includes constructs and variables that are not expected to vary across clusters with different levels of hurricane evacuation preparedness. Specifically, we do not expect clusters with different hurricane evacuation preparedness levels to change according to student status, such as enrollment status as full-time or part-time and student level (undergraduate or graduate student), and characteristics such as race, marital status, and living arrangements.

As shown in the conceptual framework summarized in Fig. 8.1, we expect significant differences across groups of college students according to how much they proactively prepare and plan, their knowledge about when and how to evacuate, and their access to resources that allow evacuation. Furthermore, based on the literature, we expect these clusters to be different in terms of their vulnerability profiles. However, several demographic and student status factors are expected to be similar across the clusters, as these should be unrelated to hurricane evacuation preparedness.

8.3 Survey of College Students in Coastal Virginia

Our examination of college student hurricane preparedness relies on data from a survey of undergraduate and graduate students focused on understanding their experiences with and preparedness for coastal hazards. Students enrolled at Old Dominion University, located in coastal Norfolk, Virginia, were the target population for the survey. More information about Old Dominion University and the student population is provided in Fig. 8.2. Responses were collected from January to March 2023. Relevant survey questions used in operationalizing variables reflecting hurricane evacuation preparedness and vulnerability are included in Table 8.1. Regarding Table 8.1 and vulnerability variables, severity was not explicitly defined due to the survey being based on student perception of risk. Rather, the survey stated, “The following questions are based on your own perception of mild versus severe storms, hurricanes, and flooding” which allowed participants to respond to questions on their experiences using their personal judgements and perceptions of risk. The Institutional Review Board of Old Dominion University reviewed the survey protocol and determined it was human subjects research exempt.

Students were recruited through various methods, including emails and flyers sent to faculty and student organizations such as the International Student Advisory Board and the Graduate Student Advisory Board. Invitations were also posted in the university-wide student announcement and on university-affiliated social media. Participants who completed the survey were entered into a raffle to win one of twenty \$10 gift cards.

The sample for analysis comprised 205 college students. Characteristics of the sample are provided in Table 8.2. Undergraduate students made up 61% of participants, and 38% were graduate students. A total of 79% of students were attending the University full-time, 45% identified as male, and 53% as female. Over half were 24 years old and younger, and the mean age was 26.75 years. White students made up the majority at 71%, 18% identified as Black or African American, and less than 4% identifying as other racial minorities. A majority (96%) were US citizens. In terms of employment, 35% and 48% were employed full-time and part-time, respectively, while 17% were unemployed. Over half of the participants had incomes of less than \$25,000 per year. Almost two thirds (63%) of participants were single, with

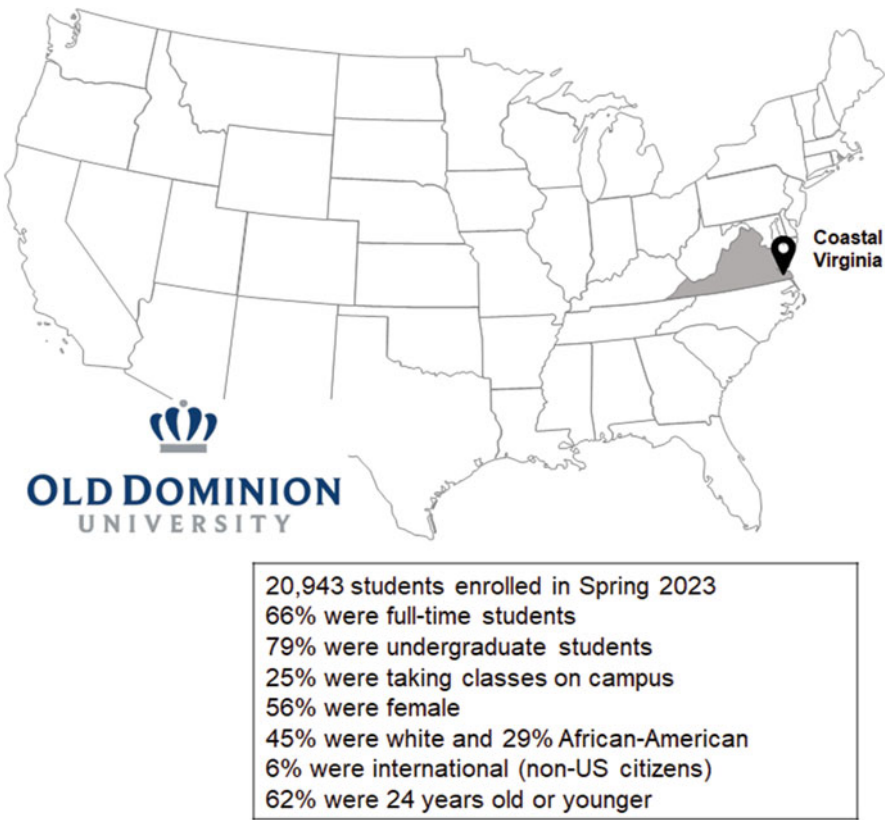


Fig. 8.2 Information about Old Dominion University
Source: ODU Factbook (<https://www1.odu.edu/about/facts-and-figures/factbook>).

an additional 20% married and 15% in long-term relationships. Regarding living arrangements, 18% lived alone and 33% lived with roommate(s). The remaining live with parents (20%), a partner/spouse (14%), or with a partner/spouse and/or children (16%). Almost a third resided on campus and 47% lived off campus in the local area.

Table 8.3 provides the means and standard deviations for the dichotomous variables reflecting different hurricane preparedness activities for college students in the sample. In terms of preparation and planning for hurricane evacuation, 63% of college students agreed or strongly agreed with the statement, “I have a plan in place to prepare and respond during storms, hurricanes, and flooding” and 52% agreed or strongly agreed with the statement, “I prepare annually for hurricane season.” Much larger percentages of college students had knowledge about when and how to evacuate and had more resources to evacuate: 84% and 82% of students indicated knowing when and how to evacuate, respectively, and 87%, 84%, and 79% have friends or family who would welcome them in evacuation, have transportation to evacuate, and have money to evacuate, respectively. Regarding general resources,

Table 8.1 Variable definition and operationalization

Variable	Survey question and operationalization	Coding
Variables reflecting hurricane evacuation preparedness		
Preparation and planning		
Have plan	I have a plan in place to prepare and respond during storms, hurricanes, and flooding.	0 = strongly disagree, disagree, or neutral 1 = agree or strongly agree
Prepare annually	I prepare annually for hurricane season.	
Evacuation knowledge		
Know when to evacuate	I know when to evacuate during storms, hurricanes, and flooding.	0 = strongly disagree, disagree, or neutral 1 = agree or strongly agree
Know how to evacuate	I know how to evacuate during storms, hurricanes, and flooding.	
Resources to evacuate		
Have friends or family to stay with	I have friends or family to stay with when evacuating.	0 = strongly disagree, disagree, or neutral 1 = agree or strongly agree
Have money	I have money to evacuate during storms, hurricanes, and flooding.	
Have transportation	I have transportation to evacuate during storms, hurricanes, and flooding.	
Vulnerability variables related to preparedness		
Experience with hurricanes		
Own experience with mild hurricanes	I have experience dealing with mild hurricanes.	0 = strongly disagree, disagree, or neutral 1 = agree or strongly agree
Own experience with severe hurricanes	I have experience dealing with severe hurricanes.	
Others' experience with mild hurricanes	I have seen or heard of others' experiences dealing with what I consider mild hurricanes.	0 = strongly disagree, disagree, or neutral 1 = agree or strongly agree
Others' experience with severe hurricanes	I have seen or heard of others' experiences dealing with what I consider severe hurricanes.	
Access to information and resources about hurricanes and/or evacuation		
Access to information	I know where to access information on storms, hurricanes, and flooding.	0 = strongly disagree, disagree, or neutral 1 = agree or strongly agree
Access to resources	I am aware of school and community resources to assist with sheltering and evacuation during storms, hurricanes, and flooding.	
Other vulnerability factors		
Have resources on hand	I have 72 h' worth of resources on hand in case of storms, hurricanes, and flooding.	0 = strongly disagree, disagree, or neutral 1 = agree or strongly agree
Have disability that hinders evacuation	I have no disability that would hinder sheltering or evacuation during storms, hurricanes, and flooding.	
Relied on by others during hurricane	No one relies on me for assistance during storms, hurricanes, and flooding.	0 = strongly agree, agree, or neutral 1 = disagree or strongly disagree

Table 8.2 Characteristics of college students in the sample (N = 205)

Student level	
Undergraduate students	60.98%
Graduate students	37.56%
Non-degree seeking	1.46%
Gender	
Male	44.88%
Female	53.17%
Nonbinary	1.95%
Age	Mean: 26.751 Std dev: 8.573
Race	
White	70.73%
Black or African American	18.05%
American Indian or Alaska native	1.46%
Asian	1.95%
Native Hawaiian or Pacific islander	0.49%
Two or more races	5.37%
Other	1.95%
International student status	
Domestic	95.61%
International	4.39%
Student status	
Full-time student	79.02%
Part-time student	20.98%
Employment status	
Full-time	34.63%
Part-time	48.29%
Unemployed	16.59%
Retired	0.49%
Annual income	
Less than \$10,000	28.29%
\$10,000–\$24,999	24.88%
\$25,000–\$49,999	21.46%
\$50,000–\$74,999	9.27%
\$75,000–\$99,999	8.78%
\$100,000 or more	7.32%
Marital status	
Single	62.93%
In long-term relationship	15.12%
Married	19.51%
Divorced or widowed	2.44%
Living arrangement	
Living alone	17.56%
Living with roommate(s)	32.68%
Living with parent(s)	20.00%
Living with partner/spouse	13.66%
Living with partner/spouse and/or child(ren)	15.61%
Other	0.49%
Living arrangement	
On campus	32.20%
Off-campus in the local area	47.32%
Off-campus outside of the local area	20.49%
Length of residency in the local area	Mean: 8.227 Std dev: 9.481

Table 8.3 Descriptive statistics for variables related to hurricane evacuation

	Mean	Std Dev
Variables reflecting hurricane evacuation preparedness		
Preparation and planning		
Have plan	0.634	0.483
Prepare annually	0.517	0.501
Evacuation knowledge		
Know when to evacuate	0.839	0.368
Know how to evacuate	0.824	0.381
Resources to evacuate		
Have friends or family to stay with	0.873	0.334
Have money	0.790	0.408
Have transportation	0.844	0.364
Vulnerability variables related to preparedness		
Experience with hurricanes		
Own experience with mild hurricanes	0.698	0.460
Own experience with severe hurricanes	0.395	0.490
Others' experience with mild hurricanes	0.800	0.401
Others' experience with severe hurricanes	0.698	0.460
Access to information and resources about hurricanes and/or evacuation		
Access to information	0.907	0.291
Access to resources	0.678	0.468
Other vulnerability factors		
Have resources on hand	0.654	0.477
Have disability that hinders evacuation	0.049	0.216
Relied on by others during hurricane	0.420	0.495

65% of college students in the sample agreed or strongly agreed that they have 72 h' worth of resources on hand in case of storms, hurricanes, and flooding. Only 5% reported having any disability that may hinder evacuation or sheltering. Additionally, 42% of college students reported having others, such as children, elderly relatives, or a spouse, rely on them for assistance during storms, hurricanes, and flooding, which may be a potential challenge for evacuation. Students in the sample reported more experience with what they perceived as mild hurricanes (70% reporting first-hand experience and 80% reporting second-hand experience) compared to severe hurricanes (40% and 70% for own and others' experience, respectively). Most students know where to access information on storms, hurricanes, and flooding (91%) but fewer are aware of school and community resources to assist with sheltering and evacuation (68%).

8.4 Cluster Analysis

The cluster analysis was based on the seven clustering variables reflecting hurricane evacuation preparedness, shown in the middle portion of Fig. 8.1. All clustering variables are dichotomous and are not standardized because they are on the same scale. We utilized a clustering algorithm that combines both hierarchical and non-hierarchical clustering methods, leveraging the strengths of the hierarchical method while complementing the rigidity of this hierarchical method with the ability of the nonhierarchical method to fine-tune the clusters (Hair et al. 2010).

First, a hierarchical clustering technique was used to identify the optimal number of clusters, derive the initial clusters, and obtain a preliminary profile of the cluster centers (centroids). This used the complete-linkage method with the Euclidean distance measure of similarity. The complete-linkage approach avoids problems with “chaining” of observations and can lead to more coherent and meaningful clusters (Hair et al. 2010).

This algorithm groups observations based on the maximum distance between the two most dissimilar members of that cluster, thus maximizing inter-cluster differences. This produces the most compact and distinct clustering solution as a preliminary profile that can serve as better seeds for the subsequent non-hierarchical cluster analysis. Furthermore, the complete-linkage method is generally appropriate for a wide range of clustering applications and is robust to noise and outliers (Hair et al. 2010).

The Euclidean distance measure is the most commonly recognized and used distance measure (Hair et al. 2010). While our clustering variables were dichotomous variables that typically require association measures of similarity rather than distance measures of similarity, we follow Dolnicar’s (2002) suggestion that the Euclidean distance can be used for dichotomous variables. The Duda and Hart Index stopping rule, one of the top-performing stopping rules for cluster analysis (Milligan and Cooper 1985), was used to determine the optimal number of clusters. The Duda and Hart stopping rule indicated four clusters. With the specification of three clusters, the hierarchical cluster analysis provided the initial clusters and their respective cluster seeds.

Second, partition or non-hierarchical cluster analysis was utilized based on the optimal number of clusters and using the centroids identified from the previous step as initial seed points. The non-hierarchical cluster analysis utilized the K-means algorithm to partition the observations based on the Euclidean distance measure. For the resulting clusters, we created profiles of the cluster solution to explain how they differ in the seven hurricane evacuation preparedness activities. A predictive validity assessment was also conducted based on the expected relationships outlined in the conceptual framework.

8.5 Results

The cluster analysis resulted in four clusters ranging in size from 31 students to 72 students. Table 8.4 summarizes how these four clusters vary according to the seven differentiating variables reflecting various aspects of preparedness. We created a preparedness score as the sum of the seven preparedness variables. This variable ranged from a minimum of zero (no preparedness) to a maximum of seven (all preparedness elements are present). Table 8.4 presents the means for the preparedness score for the four clusters. The clusters are numbered in order of increasing levels of hurricane evacuation preparedness. These clusters are also labeled according to the extent to which students in the respective clusters exhibit the three dimensions of hurricane evacuation preparedness: preparation and planning, evacuation knowledge, and resources to evacuate.

Table 8.4 Four evacuation preparedness clusters

	Cluster 1 N = 35	Cluster2 N = 67	Cluster 3 N = 31	Cluster 4 N = 72
Label	Somewhat prepared with adequate knowledge and resources	No preparation and planning, but with significant knowledge and resources	High preparation and planning but with knowledge and resource gaps	Prepared, planned, knowledgeable, and resourced
Have plan	0.457	0.254	0.806	1
Prepare annually	0.171	0	0.903	1
Know when to evacuate	0.657	0.761	0.839	1
Know how to evacuate	0.657	0.704	0.871	1
Have family and friends to stay with	0.406	0.821	0.774	1
Have money	0	1.000	0.742	1
Have transportation	0.743	0.925	0.419	1
Preparedness score	3.091	4.465	5.354	7
Description	Have a plan and somewhat prepared, adequate knowledge and some resources.	Unplanned reactive response driven by high levels of knowledge and significant resources to support evacuation.	Proactive planning that can be executed based on substantial levels of knowledge and moderately supported by available resources.	Proactive planning supported by high levels of knowledge and resources.

Note: Across the four clusters, these variables were statistically significant ($p < 0.05$) different according to the Kruskal-Wallis rank-sum test

Cluster 1, with 35 students, had the lowest level of preparedness, with a mean preparedness score of 3.091. We labeled this cluster as including college students who are somewhat prepared and have adequate knowledge and resources. These students are prepared in terms of having a plan, knowledge about evacuation, transportation, and family and friends who would welcome them in evacuation. However, while 74% of college students in this cluster have transportation, none have sufficient money to evacuate. While this group of students might have a plan to prepare and respond, it was also less likely to undertake annual preparation for hurricane season.

Cluster 2, with 67 students, contained individual who are slightly more prepared than cluster 1, with an average preparedness score of 4.465. Fewer students in this group have undertaken proactive planning and annual preparation, as only 25% of the college students have a plan and none reported having prepared annually for hurricanes. Despite the lack of a proactive approach to preparing for hurricanes, this group of college students had a strong knowledge and resource base. For example, every student in this cluster indicated having money to evacuate and 93% indicated having transportation to evacuate. As such, we label cluster 2 as encompassing graduate students with almost nonexistent preparation and planning but having significant knowledge and resources for hurricane evacuation. The high levels of knowledge and significant resources to support evacuation allow this cluster of students to approach hurricane evacuation in an unplanned, reactive, and resource-driven manner.

Cluster 3, the smallest cluster with 31 students, had a mean preparedness score of 5.354. Compared to clusters 1 and 2, a larger percentage of students in this cluster have undertaken planning and preparation and have higher levels of knowledge about when and how to evacuate. However, compared to cluster 2, these college students have fewer resources to evacuate. We label this cluster as one with high levels of preparation, planning, and knowledge to direct action but with some resource gaps for evacuating. In this cluster, 77% of college students in this have family and friends they could go to during evacuation and 74% have money to cover evacuation costs, but only 42% had transportation to evacuate.

Finally, cluster 4 encompassed college students who were prepared, planned, knowledgeable, and resourced. All 72 students in this cluster have proactively planned and prepared to respond to a hurricane, know when and how to evacuate, and have needed resources to evacuate.

Our conceptual framework suggests that differences in preparedness are associated with greater vulnerability, reflected in different risk perceptions and resource access. Table 8.5 shows the vulnerability profiles for the four clusters and how these clusters differ in terms of risk perceptions and resource base. The only vulnerability factor that was not statistically significantly different across the clusters was having a disability that hindered evacuation. The prepared, planned, knowledgeable, and resourced cluster (cluster 4) reflected the most extensive experience with hurricanes. In this cluster, 82% had first-hand experience with mild hurricanes, 67% had experience with severe hurricanes, 86% knew or had heard of others who had experienced mild hurricanes, and 75% knew or had heard of others who had

Table 8.5 Experience, information, resources, and other factors expected to vary with preparedness for hurricane evacuation

	Cluster 1 N = 35	Cluster 2 N = 67	Cluster 3 N = 31	Cluster 4 N = 72	Kruskal Wallis χ^2_{3df}
Cluster label	Somewhat prepared with adequate knowledge and resources	No preparation and planning, but with significant knowledge and resources	High preparation and planning but with knowledge and resource gaps	Prepared, planned, knowledgeable, and resourced	
Risk perceptions	Experience with hurricanes				
	Own experience with mild hurricanes	0.571 (0.502)	0.612 (0.491)	0.742 (0.445)	0.819 (0.387)
	Own experience with severe hurricanes	0.286 (0.458)	0.224 (0.410)	0.258 (0.445)	0.667 (0.475)
	Others' experience with mild hurricanes	0.686 (0.471)	0.821 (0.716)	0.742 (0.445)	0.861 (0.348)
	Others' experience with severe hurricanes	0.714 (0.458)	0.716 (0.454)	0.516 (0.508)	0.750 (0.436)
	Age	24.543 (8.480)	26.776 (9.570)	24.645 (4.644)	28.708 (8.618)
	US citizen	0.857 (0.355)	0.955 (0.208)	0.968 (0.180)	1.000 (0.000)
	Have disability that hinders evacuation	0.114 (0.323)	0.045 (0.208)	0.065 (0.250)	0.014 (0.118)
					5.288 (p = 0.152)

Coping capacity and resources	Access to information and resources about hurricanes and/or evacuation					
	Access to information	0.771 (0.426)	0.881 (0.327)	0.903 (0.301)	1.000 (0.000)	15.539 (p = 0.001)
	Access to resources	0.400 (0.497)	0.463 (0.502)	0.839 (0.374)	0.944 (0.231)	53.441 (p < 0.001)
	Relied on by others during hurricane	0.514 (0.507)	0.507 (0.504)	0.419 (0.502)	0.292 (0.458)	8.211 (p = 0.042)
	General resource base					
	Have resources on hand	0.343 (0.482)	0.478 (0.503)	0.677 (0.475)	0.958 (0.201)	53.444 (p < 0.001)
	Annual income					
	Less than \$10,000	48.57%	40.30%	38.71%	13.89%	11.440 (p = 0.010)
	\$10,000–\$24,999	28.57%	19.40%	32.26%	22.22%	
	\$25,000–\$49,999	8.57%	19.40%	9.8%	25.00%	
	\$50,000–\$74,999	11.43%	7.46%	6.45%	9.72%	
	\$75,000–\$99,999	2.86%	5.97%	12.90%	15.28%	
	\$100,000 or more		7.46%		13.89%	
	Employed full-time	0.200 (0.406)	0.239 (0.430)	0.419 (0.502)	0.486 (0.503)	13.610 (p = 0.004)

experienced severe hurricanes. This group also had the highest knowledge about where to access information and resources related to hurricanes and evacuation. Consistent with having evacuation-specific resources, college students in this cluster also have a strong general resource base. For example, across the four groups, cluster 4 had the highest proportion of college students who reported having 72 h' worth of resources on hand in the event of a hurricane and the highest proportion of students who are employed full-time.

At the opposite end of the preparedness spectrum, cluster 1 was characterized by college students with the lowest knowledge about where to access information and resources. In this cluster, 77% of students in knew where to find information about the hurricane threat, and 40% knew where to find community resources for evacuation. More international students fall into this cluster compared to others. Regarding the general resource base of college students, only 20% of students in this category are employed full-time, and 34% have access to resources to support 72 h of evacuation in case of a hurricane.

Other notable differences across the clusters regarding firsthand experiences with severe hurricanes exist. For the cluster representing the highest preparedness levels (cluster 4), two-thirds of the students had experienced severe hurricanes. However, for the remaining clusters, between 22% and 29% of the students have had such personal experiences. Direct experience with mild and severe hurricanes seems to predispose college students to be in clusters with greater levels of preparedness. The same trends can be seen regarding knowledge of how to access information and resources, with increasing proportions of more knowledgeable students as the clusters reflect increasing levels of preparedness. Similarly, fewer international students comprise the high preparedness clusters. The highest preparedness cluster consists of college students who are all US citizens, with the proportion decreasing as the level of preparedness decreases. US citizens made up 86% of college students in the least prepared cluster (cluster 1).

College students who must assist others in the event of a hurricane make up a larger proportion of clusters that reflect less preparedness. While only 29% of students in cluster 4 (prepared, planned, knowledgeable, and resourced) indicated that others rely on them for assistance during a storm, hurricane, or flooding event, this percentage increased to 42% for cluster 3 and 51% for the two clusters with the lowest preparedness levels (clusters 3 and 4). This finding is troubling as it suggests that not only does lack of preparedness result from greater vulnerability, but also that this lack of preparedness can have ripple effects on those who rely on the college student during a disaster.

Finally, consistent with the conceptual framework, the clusters were not statistically different ($p < 0.01$) in terms of student characteristics such as full-time student status, undergraduate student status, race, marital status, and living arrangement. This points to support for predictive validity and conformance to the nomological network suggested by the conceptual framework.

8.6 Conclusion

Four clusters emerged from the analysis of the student surveys. Cluster 1 ($n = 35$) was comprised of students who are somewhat prepared for hurricanes and possess adequate knowledge and resources. Cluster 2 ($n = 67$) included students who were not prepared for hurricanes but possessed significant knowledge and resources. Cluster 3 ($n = 31$), the smallest cluster, included students with high hurricane preparation and planning, but with knowledge and resource gaps. Cluster 4 ($n = 72$) proved to be the largest group, and was comprised of students who are prepared, planned, knowledgeable, and resourced. Mean preparedness scores, ranging from 1 (least prepared) to 7 (most prepared) were 3.091, 4.465, 5.354, and 7 respectively, indicating that Cluster 1 was minimally prepared, and therefore, vulnerable while Cluster 4 reported being highly prepared to respond when faced with the threat of a hurricane. Factors such as full-time enrollment, level of study, race, and marital status had little effect on hurricane preparedness, while employment, income, access to information and resources, firsthand experience with severe hurricanes, and being relied on by others were statistically significant.

Two primary limitations are present in the research. Only 205 participant responses were studied. Additional responses were received, but deemed non-viable due to being incomplete, student enrollment at another university, or being flagged by Qualtrics as “spam.” Another limitation is that only students at Old Dominion University were included. Incorporating other institutions would allow an analysis across institutions, potentially highlighting similarities and differences that span universities. A greater number of responses and the inclusion of more universities would have provided more insights into student vulnerabilities and coping capacities.

Considering these limitations, opportunities for future research include using additional data collected through the survey to conduct more analyses. Follow up research can also be conducted to get a better understanding of the factors that affect student vulnerability and coping such as a study to determine the presence of subclusters within each of the four clusters. Another opportunity for future research is to study other academic institutions, either locally or other coastal universities, to determine whether findings are consistent across student bodies and what factors contribute to them. Moreover, studying populations outside of college students in the future will help determine if the findings apply outside of the academic setting.

This research studies a vulnerable population with varying degrees of knowledge and resources. College students are often overlooked during disaster planning and preparation, and this study explores the factors that contribute to their vulnerability and how they respond during hurricanes in light of them. The research addresses a gap in current emergency management literature and further, opens the door for future research. This research has the potential to benefit both higher education and emergency management by allowing officials to develop and implement evidence-informed policies with a better understanding of how students react when responding to hurricanes and why. Finally, by providing field practitioners, school

administrators, and students with crucial findings, they will be better prepared to execute informed decision-making when faced with hurricanes in the future.

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Chapter 9

Effective Risk Communication for Disaster Response During Extreme Weather Events in a Changing Climate: The Puerto Rican Experience



Federico Subervi-Vélez, Mirelsa Modestti-González, Sandra M. Fábregas, and Gary L. Kreps

Abstract Puerto Rico's geographic location in the Caribbean renders it prone to hurricane threats every year. Over the past centuries, dozens of such natural phenomena have afflicted the archipelago causing devastation of its infrastructure, agriculture, housing, and economy, not to mention the people who have lost property, health, and even their lives. This chapter addresses the importance of effective risk communication for disaster response during extreme weather events, which in a changing climate, are expected to become even greater threats to larger numbers of people and places. As a preamble to recommendations to improve information gathering, dissemination and exchange during disasters, the chapter also brings attention to the long history of hurricanes that have afflicted Puerto Rico. Recommendations—such as including fostering trust and engaging with vulnerable populations, integrating emergency risk communication into health and emergency response systems, and the actual practice of strategic risk communication—are especially important given the foreseeable challenges stemming from climate changes in the Caribbean region.

Keywords Puerto Rico · Health-risk emergency communication

F. Subervi-Vélez (✉)

University of Wisconsin–Madison, Madison, WI, USA

M. Modestti-González · S. M. Fábregas

Latino Center for Bioethics and Humanities, San Juan, PR, USA

G. L. Kreps

George Mason University, Fairfax, VA, USA

9.1 Introduction

Weather events, like hurricanes, are certainly natural events. They cannot be prevented, eliminated, or even diverted. Their disaster potential, however, can and needs to be addressed, since their intensity is probably increasing every year due to warmer waters in the mid-Atlantic Ocean (Knutson et al. 2021; Méndez-Tejeda and Hernández-Ayala 2023). Global climate models predict hurricanes will likely increase in intensity and the potential for more rainfall and stronger winds, thus increase coastal flooding risks due to higher storm surges (Colbert 2022). Recent research suggests that damaging hurricanes are three times more frequent than one hundred years ago, and that the proportion of major hurricanes (Category 3 or above) in the Atlantic Ocean has doubled since 1980. The literature reviewed by Knutson also suggests there is strong evidence that climate change is affecting the frequency, strength, and rapid intensification of weather phenomena. Rising sea level and global warming are projected to increase in the destructive potential and rapid intensification of storms (Knutson 2023). Climate change may, in turn, impact local construction, energy, and economic practices. Meanwhile, the negative impact of the changing climate is increased by unrestricted coastal constructions, which are rapidly destroying natural barriers against storm surges (Hernández-Delgado et al. 2012). Governments have the responsibility for revising construction permits in coastal areas and enforcing laws that protect maritime-terrestrial zones. Inland construction codes also need to be revised and enforced. A recent study in Puerto Rico found that over one third of the Puerto Rican population lives in areas of high to extreme landslide risk zones, and many homes do not meet established construction safety codes (West et al. 2023).

Puerto Rico’s geographic location in the Caribbean makes it particularly prone to hurricane threats. Over the past six centuries, dozens of such natural phenomena have afflicted the coasts as well as mountains of this archipelago of approximately 3435 square miles (see Table 9.1 and Appendix 9.1). As explained in more detail later in this chapter, those hurricanes have caused devastation of the infrastructure, agriculture, housing, and economy, not to mention the people who have lost property, health, and even their lives. Hurricane María, on September 20, 2017, was the most devastating of all. It revealed, among other things, the fragility of the Island’s structures and infrastructures. It also exposed the limited capabilities of the government and news media (among other entities) to prepare for and respond to foreseeable risk and health communication needs of the population. This was

Table 9.1 Summary of major Hurricanes impacting Puerto Rico 1508–2022

Centuries	Number of Hurricanes
1508–1575	6
1615–1657	4
1713–1788	17
1804–1899	25
1901–1999	32
2000–2022	19

especially true pertaining to the most vulnerable people during environmental crises. Five years later, Hurricane Fiona directly hit Puerto Rico on September 17, 2022. The force of its winds, as well as the intensity of its heavy, persistent, and widespread downpours (Ramos-Scharrón et al. 2022), contributed to devastations like those caused by Hurricane María. Once again it exposed many persistent limitations by the government and the news media in preparing for and responding to the population's risk and health communication needs during these crises.

Given the recurring and foreseeable continued severe weather threats, this chapter addresses the imperative of risk and health communication in Puerto Rico. It is an issue that scholars have addressed only recently (e.g., Modestti-González 2018; Nieves-Pizarro et al. 2019; Rosario-Albert and Takahashi 2021; Takahashi et al. 2019, 2022; Takahashi and Zhang 2023). Special emphasis is given to hurricanes María and Fiona, as the authors have explored lessons learned from the former, and carried out research on risk and health communication policies and practices about the latter, and both events have been considered among the worst weather-related disasters in Puerto Rican history. The chapter then closes with recommendations that are especially important given the anticipated challenges stemming from climate changes in the Caribbean region. These include building trust and engaging community leaders from at-risk populations, integrating emergency risk communication into health and emergency response systems, and the actual practice of strategic risk communication. Recommendations for news media, such as better training of staff that covers emergencies, are also offered. Altogether, this work emphasizes the importance of effective communication in disaster mitigation before, during and after extreme weather events which, as climate keeps changing, are expected to become even greater threats to larger numbers of people and places.

9.2 The Imperative of Risk and Health Communication

Risk communication integrates emergency management, public policy, communication, and public health, among other fields. It is interdisciplinary in nature and intertwined with health communication as both have common objectives and aim to improve outcomes by influencing, engaging, and reaching out to different at-risk audiences with timely and appropriate information. As MacIntyre et al. (2019) note, risk communication is an important step for reducing community vulnerability, particularly when dealing with extreme weather and climate change. According to Berg et al. (2021), trust, engagement, and tailored communication are fundamental for risk communication and health communication; absence of either one could hinder effective communication.

In terms of risk communication, the World Health Organization (WHO), as well as the Centers for Disease Control and Prevention (CDC) have issued specific guidelines. For example, WHO has established that effective emergency risk communication is developed in three phases: building trust and engaging with

at-risk populations, integrating emergency risk communication into health and emergency response systems, and emergency risk communication practice. According to WHO guidelines, to effectively build trust with the public and the different stakeholders, “risk communication interventions should be linked to functioning and accessible services, be transparent, timely, easy-to-understand, acknowledge uncertainty, address affected populations, linked to self-efficacy, and be disseminated using multiple platforms, methods and channels” (WHO 2017). Moreover, overcoming uncertainty is especially important in weather events that can suddenly change because it will directly impact risk perception, which is one of the determinant factors in the decisions people make when confronting a potential emergency (Adjei et. al. 2022). This is why NHC advisories have different alert levels, and they are given at different stages of imminent weather events.

Risk communication for prevention, mitigation and recovery from disasters should also be culturally sensitive and relevant, as well as catered to the social realities of the target population. For example, as Thompson (2014) points out, people with limited second-language skills may not accurately understand risk messages that are offered only in that language and not the recipients’ primary language. Even a message delivered in a language that is understood might be unsuccessful in achieving the desired outcomes if it does not address the literacy and health literacy levels of the intended audience. Another cultural factor to ponder is if the messages consider the physical ability and financial capacity of target audiences to undertake the recommended actions. In essence, risk-related messages must be sensitive to the realities and potential constraints of target audiences if they are to succeed (Campbell et al. 2020; Thompson 2014).

Community engagement is another pressing issue for appropriate risk communication. According to WHO guidelines, risk communication officials must identify community leaders and people that the community trusts and build relationships with them. WHO recommends that these leaders be involved in decision-making to ensure interventions are collaborative, contextually appropriate and that communication is community centered, which implies that the focus of the messages is based on the reality of the locality. This is especially important for vulnerable and underserved populations who do not have access to the Internet or, at times, even to traditional media.

Another important challenge regarding risk communication during extreme weather events is the content of the information, particularly pertaining to hurricanes. At present, the Saffir-Simpson Hurricane Scale is being used in communicating the potential strength of a hurricane to the public. Although this scale is very useful to meteorologists and emergency management personnel, it raises questions as to its efficacy in risk communication to the public because what is conveyed to the public is primarily the category of hurricanes in terms of the strength of its winds in a scale from 1–5. While the amount of rain a hurricane may generate may be part of what meteorologist gather and report, less emphasis is given to potential flood outcomes. During environmental crises, such as hurricanes, there is a tremendous demand for government officials and media representatives to provide the public

with timely, accurate, and relevant risk information about winds as well as about rain and floods in order to help them to make effective decisions to avoid danger and promote their wellbeing (Kreps et al. 2005; Kim and Kreps 2020). To meet the health and risk communication needs of the people during extreme weather events it is essential to engage in strategic communication that is designed—based upon evidence—to meet not only their unique audience information needs, but also their communication competencies and preferences (Kreps 2021). Strategic risk communication involves careful situational analysis of the affected audiences to provide them with more precise risk information in ways that are appropriate to their unique levels of health literacy, as well as their ability to access available communication channels (Kreps et al. 2019).

The literature on health and risk communication also addresses issues related to different modes of communication used by authorities in times of crises, such as during a pandemic, which are certainly different from weather related challenges. In either case, common themes include the importance of establishing trust, the dissemination through multiple channels, the framing and narratives used in the communication efforts, the value of stressing self-efficacy, the avoidance of jargon, and the challenges of misinformation and disinformation, among others (Berg et al. 2021). Regarding the use of multiple communication channels, two points are important to bear in mind: First, people are not passive and instead seek and obtain information from different sources—formal or informal—including social media (Kington et al. 2021). Second, there can be major challenges stemming from multiple sources, especially social media, when there is inconsistency of the information disseminated by different authorities and voices (see Bui 2019). Exposure to multiple sources is valuable when it contributes to clarity, credibility, and elicits informed decision-making, but it can be challenging for people to navigate through the infodemic on the Internet, since most social media platforms do not differentiate information from trusted sources from misinformation or disinformation (Berg et al. 2021).

Particularly for the field of health communication, Kreps (2001) proposed that there are two major interdependent branches of inquiry: health promotion and healthcare delivery. Both are crucial to reducing risk. The first, by helping prepare for and prevent health challenges at any time, including about impending extreme weather conditions such as those related to climate change. The second, by mitigating and helping to recover from extreme weather conditions and the impact of drastic climate change on living conditions. Kreps (2023) also addresses elements of the field of bioethics that relate to social challenges with health as well as risk communication. The challenges stem, on the one hand, from failures to meaningfully gather, disseminate, translate, and implement advanced health risk knowledge that can help guide informed decisions about risk prevention and response. On the other hand, they also stem from the complexities to clearly explain risk information, especially emerging health risks such as pandemics, and the intricacies of communicating current knowledge about responding to these health issues when attempting to interact effectively with diverse and vulnerable populations (Kreps 2023).

Applying the first challenge to risk communication related to storms, it is known that the National Weather Service offers the most up to date information about inclement weather, including hurricanes. But how that information is translated and disseminated to the Puerto Rican public, and how the public receives and interprets it, has not been subject of systematic analyses. There is also lack of research about gathering, interpretation and dissemination of information available from other providers of risk data, such as available from SLIDES-PR (dedicated to landslide hazard science and risk communication in Puerto Rico, <https://sites.google.com/uprm.edu/slidespr/home>), the Caribbean Integrated Ocean Observing System (CARICOOS.com), and the United States Geological Survey (<https://www.usgs.gov>).

Related to the above, an article by Afolabi (2018) brings attention to ethical issues in the arena of disaster ethical inquiry, such as: human rights, vulnerabilities, conflicting ethical options, limited resources, and justice. He also points out that ethical compromise will be inevitable when dealing with the quandaries and challenges posed by disasters. Risk communication efforts must adapt to the unique demands faced by vulnerable populations during environmental crises to help them overcome the many health, safety, and social justice challenges they are facing (Kreps and Neuhauser 2015).

Risk as well as health communication should take into consideration elements of bioethics that relate to emergencies and could be applied to decision-making, policy formulation and other emergency communication and emergency management activities during extreme weather events. These elements, which are part of UNESCO's Declaration of Ethical Principles in relation to climate change, include preclusion of harm, precautionary approach, justice and equity, sustainable development, solidarity, scientific knowledge, and integrity in decision making (UNESCO 2017).

9.3 Risk Communication Challenges in Puerto Rico

Although in Puerto Rico there are many more risk and health communication challenges than we can address in these pages, a few stand out and are integrally related to the literature reviewed: cultural aspects, media operational patterns, limited education and research, and government constrictions and proclivities.

One of the cultural characteristics pertains to Puerto Ricans' perceptions of risk, which are significantly lowered every time there is a "false alarm."¹ This happens whenever a storm that has been announced to strike the Island changes its course before landfall and does not arrive. Most Puerto Ricans will then be skeptical and refuse to prepare or evacuate if another storm is announced in the same hurricane

¹ While there is no empirical (survey-based) data related to these perceptions of risk, opinions such as these were often repeated during our interviews with emergency management personnel in 2023 (see below regarding our study after Hurricane Fiona).

season, even when the NHC issues a warning, which is typically 36 h before the weather event is expected to arrive. Many of Puerto Rico's weather-related disasters have occurred because of this. Such was the case with Hurricane María, which passed barely 2 weeks after Hurricane Irma had been expected to pass over the entire Island, but passed just north of it, and only affected part of the population. Perceptions about María's imminent and more devastating threat were lower for many people, including government officials responsible for emergency matters. This has proven detrimental, especially in an era of so much misinformation and disinformation. Many have grown skeptical and unbelieving of risk information, even when given through official channels.

A study by Dookie and Spence-Hemmings (2022) recorded storm awareness in 14 Caribbean countries from 1995 to 2015 and found that Puerto Rico was the country with more storm "false alarms" (14), followed by Jamaica (12), and Dominica (11). Although false alarms would normally be considered "good news", they present a greater risk if another weather event approaches the island on the same hurricane season.

This lower and incorrect perception of risk was also painfully observed during Fiona's approach, which was advised as "just" a Category 1 hurricane. Most people did not feel the need to take any protective measures. The same phrase could be heard repeatedly: "It's just a Category 1 hurricane. If we survived María, which was Category 5, we can do this..." But it wasn't only about the winds. As mentioned earlier, it was the extreme rainfall in an already saturated soil that was responsible for the catastrophe.²

In contrast, but related to the above, is the hyper-preparation of some people for what, sometimes, turns out to be a "false alarm". After the food and water shortage experienced in Hurricane María, any potential storm—even news about a distant low-pressure system—triggers unnecessary preparations in terms of stocking food, water, and other supplies, and worse yet, causes public apprehension and even panic. However, this panic-ridden food and water stocking "preparation" does not necessarily translate to home safety preparations. Most Puerto Rican will wait until the very last minute to install home safety devices, like shutters, and bring patio furniture or potted plants inside. If the potential danger passes, the next warnings could incorrectly be ignored with a false sense of being prepared.

The underestimation of a hurricane warning and the unnecessary over-preparation for it are both challenges for risk and for health communication efforts that aim to properly prepare people for actual weather threats and climate change. Of course, these cultural traits related to risk perception are certainly not unique to Puerto Ricans. They are common patterns, possible across many population groups, and can be seen in other Latin American, specifically, Caribbean, countries. The challenge in Puerto Rico stems from the frequent false alarms every year during hurricane season, between June and November—a period during which dozens of low-pressure systems develop in the mid-Atlantic region but do not turn into deadly storms or hurricanes that afflict the archipelago.

²Interpersonal conversations with friends and family members.

Contrary to Puerto Rico, where weather information begins to be disseminated 28.4 h before a storm arrives, on average, other Caribbean countries are aware of impending threats within 24 h of impact, on average, and one country, Grenada, receives information within 9 h of impact on average (Dookie and Spence-Hemmings 2022). On weekends, information is slower to reach the public, which could increase disaster potential even for less dangerous storms. Heavy rainfall events that occur on Mondays affect more people compared to events on any other day of the week (Dookie 2020).

The media operational patterns related to those weather conditions are a second line of challenge for risk and health communication. Even though Puerto Rico has over 135 AM and FM radio stations, numerous TV stations, a few daily newspapers plus many print and online periodicals (Subervi-Vélez et al. 2018, 2022), not all operate the same way with respect to informing the public about potentially hazardous weather conditions. Most lack personnel trained to properly inform about weather threats. In fact, many radio and TV stations don't even have news personnel assigned to weather-related emergencies or don't carry live up-to-date news at all. People whose media diet stems primarily from stations that don't broadcast news (such as most cable outlets), are at a loss for being informed about potential weather threats unless their media input includes outlets that do inform on such matters (Subervi Vélez et al. 2023).

The media operational patterns challenge is even greater regarding vulnerable populations. In Puerto Rico, these include economically disadvantaged communities, many of them in inaccessible places, people with chronic conditions, functional diversity and mental health conditions, people who live in unsafe structures in coastal communities, and homeless individuals, among others. Communicating risk to these populations has proved to be extremely challenging. In some mountainous and isolated rural areas of the Island, access to TV and even to radio options can be very limited—if not with respect to reception of a broadcast station or two, certainly in the number of radio or TV channels available to them. The same applies to access to newspapers, which do not circulate—at least not frequently—in the most isolated areas, and, more so with respect to the Internet, which is certainly not available in many populated, yet remote mountain communities. In such media and news deserts, access to reliable and updated weather information represents a major challenge for much needed risk communication in times of threats due to inclement weather or other emergencies. That challenge is more pronounced for hearing and/or visually impaired populations for whom there are no easily accessible news and information outlets. Those populations most isolated from traditional media outlets must therefore rely on neighbors and family members (who may or may not be fully or adequately informed about impending risks), or rely on municipal emergency management personnel, which, as we have learned, can delay in reaching those remote areas.³ While accurate and official information may be

³Based on interviews with directors of municipal emergency management officers. Study in progress at this writing.

delayed, rumors, especially via text and social media may quickly reach many people, be they isolated or not (Bui 2019).

Although in 2023 Puerto Rico's Department of Health published a health guide for emergencies and disasters (Departamento de Salud de Puerto Rico 2023a), and an operational plan for health and medical services during emergencies (Departamento de Salud de Puerto Rico 2023b), neither of these documents address news media access problems or health and risk communication policies and practices for reaching those most isolated and vulnerable populations. Exactly how many vulnerable people are in such precarious communication conditions and their exact location is unknown. That stated, during our research about Hurricane Fiona (Subervi Vélez et al. 2023) we learned that after Hurricane María, efforts have been made, at least at municipal level, to survey and contact community-based organizations to help disseminate emergency risk communications to the populations at large.

One reason for that lack of more precise data about communicating with vulnerable populations stems from the third challenge: limited education and research *primarily on health and risk communication*. Certainly, there are scholars in natural sciences, such as geology, geography, and oceanography, coastal dynamics, marine sciences, and in engineering, planning and medical sciences, all of whom, in their own fields, teach and conduct research that overlap with weather and climate change problems and/or risks. However, to the best of our knowledge, none are primarily dedicated to risk or health communication sciences or practices. Also, at the Schools of Pharmacy and Public Health of the University of Puerto Rico's Medical Sciences Campus, only occasional elective courses address risk or health communication sciences or practices (Fábregas and Vega 2011).⁴ At the time of this writing, we know of only one program at the Catholic University, in Ponce, which might offer an academic concentration specifically dedicated to emergency management (Vaello-Calderón 2023). How much of that curriculum will address health or risk communication is unknown.

Most of the Island's journalism programs lack courses to train future news professionals on how to cover major emergencies or how to offer news and information that would most efficiently contribute to the preparation, mitigation, and recovery from hurricanes and other weather-related events. Also, none of Puerto Rico's journalism programs has established ongoing courses or developed an integrated research agenda that would help assess news media coverage or stories about health, weather events or climate change.⁵ Nevertheless, professional media organizations and some major media outlets occasionally offer workshops or in-house training on such matters.

⁴While this source is dated, the fact remains and has been corroborated by the first author of that work, who retains close professional ties with UPR's Schools of Pharmacy and Public Health.

⁵Numerous U.S. universities offer undergraduate and graduate degrees in emergency management and communication. Currently, no such curriculum has been adopted at any university if Puerto Rico.

The scenarios summarized in the third challenge are undoubtedly related to the fourth challenge: government constrictions and *modus operandi*. To this date, the development of academic and research agendas to address health and risk communication have not been a priority or even in the radar of government decision-makers, who could have worked with local higher education institutions to establish such programs, promote and fund much needed research on these matters so vital for Puerto Rico. However, during our research about Hurricane Fiona, we learned of a developing initiative from the Department of Health regarding the adoption of risk communication practices to communicate better during health emergencies like the COVID pandemic (see Subervi Vélez et al. 2023).⁶ Yet government constrictions and *modus operandi*, as well as their information exchange with official weather services also affect policies and practices on how information is gathered and disseminated during times of emergencies. As Dookie (2020, p. 26) noted:

“There is a process of information transfer between the NHC [National Hurricane Center] and local government authorities and agencies, which may or may not be in the affected island, before such forecasts are made publicly available. This process may delay or have other consequences on the transfer and real-time availability of forecast information.”

An example alluded to during the study's round tables was that often, during press conferences by Puerto Rico's emergency management officials to address an ongoing emergency, politicians would take over and there would be too many government officials delivering information (sometimes contradictory) and thus causing confusion with the most crucial messaging. A more recent and most revealing example of government constrictions was made evident during the public hearings to establish policies to prepare for the challenges stemming from impending climate change (Guillama Capella 2023a, b, c, d). According to Guillama Capella—a journalist covering those hearings—some public participants criticized the short-sightedness of some of the proposals, particularly that the plans had not included the populations most certain to be affected by climate change, such as coastal residents.⁷ Also, none of the twelve thematic sections of the draft proposal specifically and explicitly mentioned risk communication plans for the public, much less the isolated or most vulnerable populations.⁸ Another shortcoming of the draft plan is that it considered fines and penalties for government agencies that violate the land preservation regulations, but no penalties for private entities (Guillama Capella 2023d). Moreover, an in-depth study by Center for Investigative Journalism regarding the historical lack of government oversight and attention to coastal concerns raises concerns about effective action and remedies related to the challenges of climate change (Méndez González 2023).

⁶Interview with government official, April 2023.

⁷The draft plan can be accessed at <https://www.drna.pr.gov/wp-content/uploads/2022/03/Borrador-de-Bosquejo-del-Plan.pdf>

⁸The 12 thematic sections are: energy, infrastructure, transportation and mobility, waste, health, agriculture and livestock, water, marine systems and coastal zones, forestry, tourism, education, and climate justice.

While the constrictions and *modus operandi* summarized above are about the Puerto Rican government, others are outcomes of the U.S. federal government's policies for dealing with the archipelago's emergencies. One prime concern is the slow and extremely bureaucratic ways that FEMA and other federal agencies respond to the Puerto Rican needs and emergencies. The following excerpt from an article by Larnerd, Ballard & Kurtzer (2022, paragraph 6) titled "Humanitarian response and climate change in Puerto Rico" exemplifies this most poignantly:

"Although Congress quickly approved \$20 billion of assistance following María, severe restrictions imposed by the Department of Housing and Urban Development (HUD) prevented Puerto Rico from accessing most of the funds. Under the Trump administration, the Office of Management and Budget obstructed the disbursement of disaster funds, mandating complex interagency review processes for approving recovery grants. In March 2019 congressional concerns over the delays of aid led to a probe by the HUD Office of Inspector General. During the investigation, HUD officials admitted the department had failed to "comply with the law" in meeting a congressionally mandated deadline to unlock federal recovery funds for Puerto Rico. Former HUD secretary Ben Carson defended the agency's actions by blaming corruption and questioning "Puerto Rico's capacity to manage these funds. Despite the findings of this investigation, the Trump administration continued to oppose disaster funding for Puerto Rico. By April 2021, Puerto Rico had received less than 1 percent of allocated funding."

Puerto Rico's colonial and subordinate position relative to the U.S. (Subervi-Vélez et al. 2018, 2022) is a fundamental factor that contributes to these and other federal governments' constrictions and proclivities regarding if and how Puerto Ricans can deal with and overcome current and future health, risk and climate change challenges. Recommendations to address preparedness and disaster mitigation undoubtedly need to take into consideration this reality, and all other challenges summarized above.

9.4 Lessons Learned in Emergency Risk Communication

In the United States, during the seventies, an Incident Command System (ICS) called FIREScope was developed in Southern California to manage wildland fires. There was also a Multiagency Coordination System (Stambler and Barbera 2011). These systems evolved and gave way to what is today called the National Incident Management System (NIMS), which, in turn, develops procedures and defines responsibilities and operations of Joint Information Centers (JICs). The JICs are the coordination hub for all public information operations during emergencies. These centers include Public Information Officers (PIOs) from all agencies and organizations that participate in "incident management operations" to ensure multi-agency and multi-jurisdiction coordination of all messages provided to the public.

JICs carefully train their personnel and work in direct coordination with federal, state and city emergency management agencies (U.S. Department of Homeland Security n.d.). The problem is that they are geared more toward national and local

security threats like active shooter incidents, terrorist threats, hostage situations, and other emergencies like landslides, fires, or earthquakes, and aircraft trains or multiple vehicle accidents. Emergencies due to extreme weather events are managed by local emergency management agencies and federal weather agencies, like NWS, NHC, NOAA, etc., and the recovery efforts are mostly managed by FEMA, Red Cross, and disaster recovery organizations. Emergency risk communication needs to have a more prominent role in disaster prevention and mitigation and needs to be managed centrally for the communication efforts to be integrated. As the U.S. Department of Homeland Security' document points out regarding virtual JICs, risk communication, in general, is best when it is not created *ad hoc*. Research, education, careful planning, and a solid communication infrastructure must be designed and in place before weather-related and other emergencies are imminent.

In 2017, a community-based communication pilot study and plan was commissioned in the north coast town of Loíza, Focus group sessions, meetings, and surveys were conducted to examine risk, perception and government disaster, mitigation, and prevention actions (PRCCC 2022). Participants demonstrated knowledge about climate change and how it could affect their community. However, they expressed concerns that federal authorities relied on social media for most of their communications, and that they were exclusively in English. In this particular town, most residents are in the low-income range, do not have access to Internet or manage digital platforms, and 90% of them are not fluent in English (PRCCC 2022).

The issue of cultural relevance cannot be stressed enough. The same words may have different meanings to different populations and not only the message might not pass through, but some messages might be received with disbelief, discomfort or even resistance (West et al. 2021). If effective risk communication is to be achieved in places like Puerto Rico and cities with high concentrations of culturally diverse communities, it is imperative that risk communication protocols be revised with a focus on cultural differences, language barriers and communities' social realities.

And if additional evidence were needed regarding the imperative of risk and health communication, the following summary of hurricane history, experiences and lessons learned in Puerto Rico—particularly after the most recent Hurricanes María and Fiona—should more than suffice.

9.5 Hurricane History and Experiences in Puerto Rico

Long before the Spanish colonization of the Puerto Rican archipelago, which started in 1493, the native Taíno populations used the word “Juracán” (*Hur-uh-kaan*) to refer to an evil god, most certainly one that would bring destruction with its winds and intense rains even back then (Vacas 2023). The early sailors took the word back to Spain as *huracán* and their recorded history has numerous mentions of recurring ravaging storms during summer and autumn months. Vacas (2023) suggests that the natives of Bareque (the island later named Hispaniola, which now includes the

Dominican Republic and Haiti) warned Cristopher Columbus about a potential hurricane, thus safeguarding his fourth return voyage from the “new world.”

The first documented and named hurricane to directly hit Puerto Rico was San Roque, which made landfall on August 16, 1508.⁹ This was noted by Juan Ponce de León as his caravel left Santo Domingo. Shortly after, another unnamed storm after it came ashore in Guayanilla and mainly affected the southwest coast of the Island. Since then, many other hurricanes that have passed over or close enough to Puerto Rico to cause significant damage have been documented.¹⁰

As shown in Table 9.1 (see also Appendix 9.1), the number of hurricanes impacting Puerto Rico has increased over time. Although during the 16th–17th centuries documentation of such natural phenomena was probably less rigorous and thus some records of such storms might have been lost over time—which means the numbers may have been higher—the trend has been rising steadily. What is not included in the table (or appendix) is the number of tropical storms that have also caused great havoc, if not as much because of extremely strong winds, certainly as a consequence of their substantial and extended periods of downpours.

One of the significant facts that analyses of the dates show is that in any given year, multiple hurricanes and tropical have affected the Island. In 1530, there were three hurricanes withing a few weeks of each other. Two devastating storms also hit Puerto Rico in each of the following years: 1738, 1766, 1772, 1780, 1813, 1901, 1966, 1995, 1999, 2007, 2009, 2013, 2015, 2017, 2019, 2022. After the 1530 trio, the triple hits happened again in 2008, 2011, 2012, 2014, 2020 (Puerto Rico Hurricane Center, *n.d.*). Still more notable where the five storms that afflicted Puerto Rico between July and August of 2010. Even though record-keeping might not have been as accurate in previous years, data undeniably show that the twentieth century had an exponential increase in multiple hurricanes and storms afflicting Puerto Rico—and for certain other parts of the Caribbean and mid-Atlantic regions of the globe Schwartz’s (2015).¹¹ Here it is important to note that the hurricanes afflicting Puerto Rico in just the first 22 years of the twenty-first century account for 61% of extreme weather events, in comparison to those of the twentieth century, and 73% in comparison to all hurricanes during the nineteenth century (see Table 9.1). Some of the most noteworthy examples of these recurring natural phenomena impacting Puerto Rico merit mention, especially the recent ones due to the massive losses in human lives, agriculture and the structural damages they have caused.

At the end of the twentieth century, hurricane activity started to increase possibly already due to climate changes. In September 1995, Hurricanes Luis, and Marilyn, only 10 days apart from each other, and Tropical Storm Sebastian, 10 days after

⁹Quiñones’ (1992) history of hurricanes in Puerto Rico includes an unnamed one in 1502, and other unnamed tempests during the 16th to 19th centuries. Thus, count of hurricanes differs slightly from those used for Table 9.1 and Appendix 9.1.

¹⁰See Wikipedia (https://en.wikipedia.org/wiki/List_of_Puerto_Rico_hurricanes) for the most up to date list of the hurricanes that afflicted Puerto Rico and sources and notes on damages they have caused.

¹¹Schwartz’ book offers a panoramic social history of hurricanes in the Caribbean.

Marilyn wreaked havoc on the island. In September 1998, Hurricane Georges made landfall, causing \$2 billion in damages and flooding, and five fatalities.

Then, as predicted by climate change experts, the twenty-first century brought significantly more hurricane activity and hurricanes have caused more extensive flooding and thus greater damages due to the intensity of their rains. One notable example was Hurricane Jeanne, which made landfall on September 15, 2004, near Maunabo, as a strong tropical storm with sustained winds of 70 mph and heavy rains. Close to 50% of people in the Island spent 3 days without running water, and 70% had no power. Damages were estimated at \$169.5 million and 200,000 people were left homeless (National Oceanographic and Atmospheric Administration [n.d.](#)). Another devastating example was Hurricane Hanna, which although passed 350 north of Puerto Rico in late August-early September, produced 10–12 inches of rainfall in a 24-h period, causing many rivers to flood, as well as multiple landslides. In September that same year, Hurricane Kyle produced record-breaking rainfall, reaching totals as high as 30.47 inches, with subsequent flash-floods and mudslides. Losses were estimated at \$48 million; \$25 million of structural damages, and \$23 million of agricultural damages.

As alluded to above, the year 2010 stands out for its multiple hurricane activity afflicting Puerto Rico. Most notable was that from August 29 to September 4, Category 4 Hurricane Earl produced heavy rains as it slowly passed north of Puerto Rico. Nearly 187,000 people were left without power, and 60,000 more were left without running water. Also, in early October, Hurricane Otto, still a tropical storm, brought rain to Puerto Rico during 6 days, peaking at 17.86 inches in Ponce. More than 40 roads were closed and other 295 were damaged. Overall damage to the road system was estimated at \$6.5 million. An additional \$1.5 million was estimated in damages to agriculture in Ponce. At least 134 people had to take refuge from the storm, while an estimated 45,000 people lost access to drinking water.

The years 2011–2016 continued to bring even more major weather events to Puerto Rico. Altogether, the strong winds, extraordinary downpours and floods from the storms and hurricanes those years ended dozens lives, while scores of people were injured, had their health impacted, lost homes, property, businesses, crops and/or livestock. The losses were in the millions, as were the recurrent destructions of infrastructure, leading to massive shortages of running water, electric power, access to healthcare, and educational facilities.

Undoubtedly, 2017 was the deadliest year in Puerto Rico's recent hurricane history. First, on September 5–7, Category 5 Hurricane Irma passed northeast of Puerto Rico the Island, producing tropical storm force winds across much of the archipelago. At least 362,000 people lost access to water services, and approximately 1.1 million of the Puerto Rico Electric Power Authority's 1.5 million customers lost power. The hurricane caused \$1 billion in damages, and the NHC attributed three fatalities to Irma in Puerto Rico, though four other deaths were related to that storm. Then, 2 weeks later, on September 19, Category 4 Hurricane María made landfall entering in the southeast town of Yabucoa, and crossing diagonally before it exited the northwestern town of Isabel. Rains totals as high as 37.9 inches were reported, which caused landslides (Bessette-Kirton et al. [2019](#);

Hughes et al. 2019; Ramos-Scharrón et al. 2022), significant flooding, and high wave surges all of which, in turn, caused catastrophic damage to crops, livestock, infrastructures and homes. In addition, the Island's entire power grid was destroyed, and 95% of cellular and communication networks were inoperable. Five days after the hurricane, 95% of the Island still had no power or cell service, and 44 of the population had no tap water. Even five months after that hurricane, 45% of power customers still had no electricity in their homes, and 14% had no tap water. Hurricane María also caused an estimated \$80 billion in all types of damages and losses. Moreover, it was also the main cause of 4645 deaths, thus becoming the deadliest hurricane since the 1899 San Ciriaco.

Other recent storms to afflict Puerto Rico were Hurricane Dorian on August 28, 2019, Tropical Storm Karen on September 23–25, 2019, then in 2020 Tropical Storms Isaiás on July 29, Laura on August 22, followed by Hurricane Teddy on September 18. All continued to cause havoc on people, property and land, including significant major coastal erosions. The most recent impacting storm to date was Hurricane Fiona on September 17–19, 2022. It made landfall in the southern municipality of Lajas and then turned into a very slow-moving Category 1 hurricane that brought heavy rains, which caused extreme flooding over the whole Island. Damage to crop, cattle, and infrastructure was estimated at over 10 billion dollars, making it one of the costliest hurricanes in Puerto Rican history (Fig. 9.1).

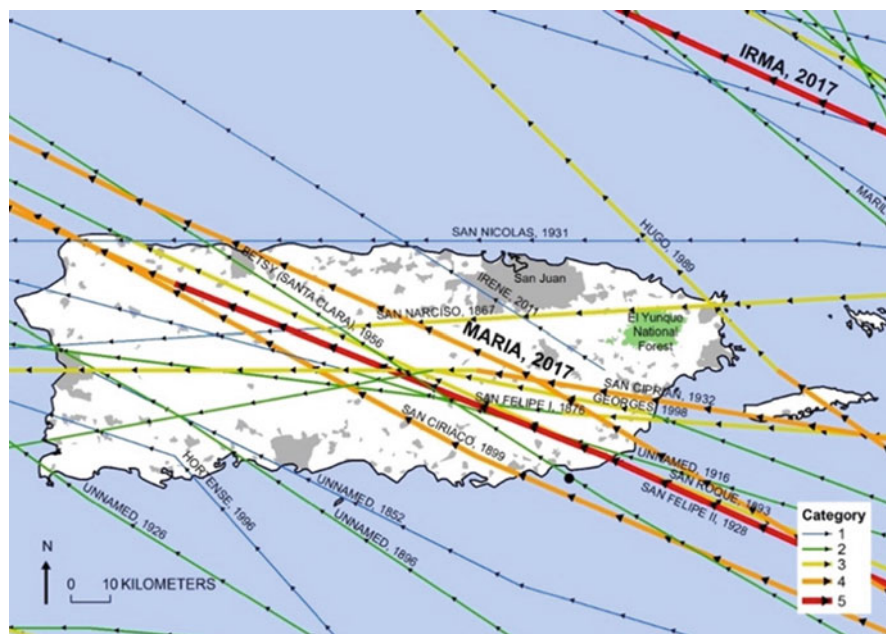


Fig. 9.1 Puerto Rico Hurricane Map, partial record

Source: US Geological Survey (2017) <https://www.usgs.gov/media/images/puerto-rico-hurricanes-map>

9.6 Hurricane María: A Before and After for Puerto Rico

As mentioned earlier, Hurricane María was the biggest catastrophe in Puerto Rico's recent history. On September 20th, 2017, Puerto Ricans on the island experienced a weather event that would forever change their lives. At approximately 6:15 AM AST, Hurricane María made landfall in the southeastern municipality of Yabucoa, as a strong Category 4 hurricane, bearing maximum sustained winds of 155 mph. For most of the day, the fury of the winds destroyed the Island's tropical foliage and crops, killed cattle, wrecked houses, tore apart roads and bridges, shattered buildings, smashed cars, and brought down the entire power grid and communications infrastructure of the Island. Incalculable losses were also caused by María's extreme rainfall (Keellings and Hernández Ayala 2019; Ramos-Scharrón and Arima 2019). The hurricane crossed diagonally, from the southeast to the northwest coast, during several hours and emerged into the Atlantic around 1800 UTC 20 September. According to a National Hurricane Center (NHC) report on Hurricane María, "The combined effect of the surge and tide produced maximum inundation levels of 6 to 9 ft. above ground level to the north of María's landfall along the coasts of Humacao, Naguabo, and Ceiba municipalities in Puerto Rico" (Pasch et al. 2023a).

By the end of the day, only silence and disbelief could be felt in the air. The next morning, people woke up to a new Puerto Rico with no electric power and no running water. Stores, banks, government offices, schools and restaurants were all closed. There was no road access to most communities, no television, no Internet and only two radio stations were transmitting (Rodríguez Cotto 2018). Since all power and communications were down, people had not realized how bad things were across the whole Island. Puerto Ricans on the mainland saw the images on national television and tried to contact their relatives on the Island, but Puerto Rico itself was practically unreachable (Modestti-González 2018). Three weeks before, Hurricane Irma had wreaked havoc on the power grid and agriculture. Peak wind gust speeds were recorded over 120 mph, and 28 inches of rainfall were registered. Over a million residents lost power and many houses were severely damaged (FEMA 2022). Many residents were still without electric power from Irma when María struck and claimed 4645 lives (Kishore et al. 2018). It has been dubbed the third costliest hurricane in US history (National Hurricane Center 2018).

It took residents of Puerto Rico a few weeks to realize how bad the situation really was. Lacking access to news media or power to connect via Internet or cell phones, most people thought it was bad for them, but did not realize the whole archipelago had been destroyed. People who could find access to radio stations and wanted to let their relatives know that they were safe, would go to the available radio stations' studios and give their names (Nieves-Pizarro et al. 2019; Rodríguez Cotto 2018). Announcers kept reciting on air the lists of names and the respective towns or neighborhoods of these people, hoping that their relatives would hear the names and know that they were safe. Since the banking system was down, banks could not allow transactions of over \$200. Ships were not entering the ports, which had no

electricity to operate, so the supermarkets and pharmacies did not have enough inventory to supply demand. Perishables had to be discarded, and they could only sell canned or dried goods. Supermarkets, pharmacies, and gas stations opened only a few hours per day and had to limit quantities. Ice was a rare commodity. People spent hours in line to buy gasoline, bottled water, and basic everyday products and, sometimes, even after hours in line to enter the supermarkets, they would only find empty shelves. Stores, theaters, schools, restaurants, hotels and many other businesses remained closed for weeks, some for months; others never reopened. Three weeks after the hurricane, only 392 miles of Puerto Rico's 5073 miles of roads were open for transit (Dapena et al. 2017). By January 2018, four months after the hurricane, over 300,000 people had left Puerto Rico (Negrón-Muntaner 2019). In April, Puerto Rico's Department of Education announced that 283 of its approximately 1110 public schools were being closed because of the out-migration of 38,762 students (Artiga et al. 2018).

María destroyed hundreds of thousands of residences across the Island. Federal Emergency Management Agency (FEMA) distributed 125,000 blue roof awnings to people who had lost their roof to the hurricane and the US Army Corps of Engineers distributed some 60,000 sheet roofs. These awnings and sheets were to be used as a temporary shelter from rain and sun damage for up to 30 days. But a year later, over 30,000 families still had a blue tarp over their homes (Florida 2023). Six years later, some 3000 blue tarps are estimated by the government to still be in place, although other estimates of unrepaired roofs damaged by María rise to 15,000. Recovery has been uphill for many reasons. Access to economic assistance to fix or rebuild homes has been very difficult. One of the problems is that, for decades, many Puerto Rican families have built homes on family-owned land and do not have property titles in their names. An article published in the American Bar Association Journal, stated that 1,118,862 homeowners applied for FEMA's Individuals and Households Program (IHP) to help rebuild their homes. According to Ron Roth, a FEMA spokesperson, the number of approved applications totaled 452,290. In turn, 335,748 denied. "This means that about 40% of those who self-identified as being in need were not awarded assistance" (García 2021).

Another issue that increased damages to homes and buildings was coastal erosion and constructions in coastal zones. Coastal erosion, inland flooding, and coral loss results in increased hazards to natural and populated shorelines, putting critical infrastructure at risk (USGS, n. d.). A study on the impact of Hurricane María on beach erosion stated that "Hurricane María caused immediate beach loss of 3 to 5 m in Puerto Rico, with very large local disparities" (Pérez-Valentín and Müller 2020). The study also found up to 40 m of coastal erosion at some beaches. Mangroves, reefs, sand dunes and wetlands all provide natural barriers that protect coastal life and communities from rising sea levels. But accelerated coastal construction and mangrove deforestation weakens these natural barriers exposing coastal ecosystems and communities. Due to the large amount of carbon stored in mangroves, it is crucial to prevent future potential CO₂ emissions and to conserve remaining

mangroves (Leal and Spalding 2022). Mangroves are especially important to protect coastal communities and ecosystems. As explained by Joanna Ellison in her 2015 study, “Degradation and loss of these coastal buffering systems due to climate change and direct human impacts negates the coastal protection they provide during extreme events and increases their vulnerability, with significant environmental, economic and social consequences for coastal people” (Ellison 2015). According to the Centro de Periodismo Investigativo, a local independent journalism organization, “Puerto Rico’s coastal wetland and marsh areas are regulated by the 1899 Harbors and Bays Act and the Federal Clean Water Act (CWA), as well as by the US Corps of Engineers and the federal Environmental Protection Agency regulations. However, these provisions appear to be a dead letter for the economic model followed in Puerto Rico” (Rodríguez-Velázquez 2022).

But María’s disaster cannot be reviewed out of context. A series of events that spanned over more than a decade put Puerto Rico in a position of extreme vulnerability in case of an extreme atmospheric or geologic event. The decade before Hurricane María was a very difficult period for Puerto Rico’s economy. In 2005, after a grace period, section 936 of the US Tax Code, which granted U.S. corporations a tax exemption from income originated at U.S. territories was eliminated (Greenberg and Ekins 2015). Without this exemption, Puerto Rican subsidiaries of U.S. corporations would be subject to the same worldwide corporate income tax as other foreign subsidiaries. This prompted an exodus of pharmaceutical, manufacture and other companies, leading to massive unemployment and a deep recession, from which Puerto Rico never fully recovered. Massive migration of Puerto Ricans towards the mainland, especially young professionals with their families, created a somber economic landscape.

One of the Island’s infrastructure components severely affected by this economic decline was the Puerto Rican Electric Power Authority (PREPA). To stay functional, it needed to increase the electricity rates (which were already very high), stop paying bondholders or abandon the maintenance of its plants and infrastructure. PREPA management chose this last option, leading to the shutdown of several of its electricity generating plants. The system now had limited surge capacity and less ability to restore the power after the hurricane (Guerra Velázquez 2022). This proved to be disastrous when Hurricane María struck. Poor maintenance made the grid more vulnerable, and the shutting down of several power plants led to a significantly lower capacity. The reconstruction meant building up a new power grid and distribution lines almost from scratch, which was not economically viable. As a result, 2 months after the hurricane, 51 of Puerto Rican homes were still in the dark. After 3 months, 35% still had no power. It took a whole year to bring power to 99% of the Island, and 6 years after the hurricane, the system is so unstable that power outages are regular throughout the Island. At present, the grid does not have the stability and infrastructure to meet the electrical power demand of the Island. Similarly, the telecommunication infrastructure collapsed completely. Many radio and television stations simply could not afford to reconstruct their towers and satellites and had to relinquish their licenses to operate (Modestti-González 2018). The main cable tv service

took over a year to recover enough to offer its service. The cellular grid recovered partially, but with a much weaker grid, phone service is still unreliable.

Other services and the Island's infrastructure faced similar problems. Water processing plants and many other essential services depend on electrical power to properly function. Thus, many communities, especially those in the mountain regions endured weeks or even months without running water, and the problem has not found a permanent solution. The reconstruction of roads and bridges that had been destroyed is yet to be completed.

After the hurricane, access to water was minimal. Water treatment plants and pumping stations were out. Two weeks later, less than 50% of homes had water service. Two months after the hurricane, 91% of the population had access to water, but still, about 300,000 people had no water in their pipes (Michaud and Kates 2017). People without access to safe water were getting it from natural fresh water sources such as ponds, lakes, and streams, but these were contaminated with debris and dead animals. To further complicate matters, 20 of the Island's 51 sewage treatment plants were still out of service 1 month into the aftermath, due mainly to lack of power. As a result, sewage was identified as a possible contaminating source in drinking water. This, of course was the perfect breeding ground for several disease outbreaks. In the 6 weeks following the hurricane, for example, Puerto Rico had already reported 121 cases and 4 confirmed deaths from leptospirosis, compared to about 60 cases in total for a regular year (Michaud and Kates 2017). Many of the lives lost to María were patients of chronic and catastrophic illnesses, most of whom had little or no access to diagnostic and therapeutic procedures, like dialysis, chemotherapy or to medication, like insulin, hypertension medication, etc. Countless patients lacked not only their maintenance medications, but also any record of the medications they needed. Many of those patients went first to their usual community pharmacy (if it was open) or the closest open community pharmacy, not only for prescriptions for their chronic diseases, but also general health care consultations and first aid supplies. Especially in the rural areas of Puerto Rico, community pharmacists are often the first healthcare providers with which many patients interact, based on a long tradition of patient-pharmacist trust and increased accessibility (Melin and Rodríguez-Díaz 2018).

Although health centers in Puerto Rico are providing services, the lack of power remains a critical problem for many. A Medicaid study states that "while improvements have been made in restoring power, approximately 1 in 10 (11%) of the permanent health center sites on the Island have limited or no grid power. Three of these health centers have intermittent grid power and rely on generators as a backup source of power, while five remain without grid power and rely solely on generators" (Medicaid Report 2018). These strenuous working conditions, along with the economic hardship that prevents healthcare professionals to earn a reasonable income have prompted a massive out-migration of physicians, nurses, and other health professionals, producing a colossal health services crisis.

The day after the Hurricane María, Puerto Rico's Federal Communications Commission (FCC) prepared a report stating that 95.2% of cell towers were out of

service, that all counties in Puerto Rico had greater than 75% of their cell towers out of service, and that 48 out of the 78 counties in Puerto Rico have 100% of their cell sites out of service (FCC 2017a). It also reported that most consumers were without either cable or wireline services, and that most television and radio stations were out, and had not even been able to report their status to the FCC. On the December 8 report, 7 weeks into recovery efforts, it was noted that 23.1% of the cell sites were out of service, and that 11 municipalities still had more than 50% of their cell sites out of service (FCC 2017b). Wireless companies had to open roaming on the Island so that they could, collectively, serve the maximum population of the archipelago with the available coverage. In terms of broadcast status, 7 weeks after the hurricane, five TV stations were confirmed operational (WKAQ, WIPR, WNJX, WTIN, WORO) 2 TV stations were suspected to be out of service (WIPM, WELU), 70 TV stations had been issued Special Temporary Authority to be offline, and 30 TV stations had unconfirmed status. This presented an enormous challenge because without television, radio, or Internet signals, communicating to the public was virtually impossible. According to Puerto Rico's Telecommunication Regulatory Board, the most affected part of the communication infrastructure of the Island was the optic fiber network.

During the hours in which Hurricane María was over the Island, 57.92% of the population reported being completely uncommunicated (Modestti-González 2018). This means that they had no way of knowing if the storm was beginning or passing, they had no way of communicating their emergencies, and the government and media could not properly inform the public about the emergency. Landline telephones worked throughout the emergency, but since the proliferation of cellular phones and Internet devices, 82% of Puerto Ricans had cancelled their landline telephone accounts and depended exclusively on digital technology for their communication activities (Modestti-González 2018).

In essence, Hurricane María revealed the fragility of Puerto Rico's communication infrastructure (Modestti-González 2018; Nieves-Pizarro et al. 2019; Rosario-Albert and Takahashi 2021; Takahashi et al. 2019; Takahashi et al. 2022). Interruption of energy service, as well as the collapse of radio, television, and cell phone service isolated thousands of families (Modestti-González 2018). Failures of communication infrastructure led to a public policy law (Act #5, 2018) declaring Telecommunications as an essential service on equal standing with electrical power and potable water.

Precisely because Hurricane María was so devastating in health and life matters, in 2018 a group of national and international bioethics experts, government officials and academics gathered in Puerto Rico to discuss and analyze the diverse situations and causes that resulted in loss of lives and infrastructure and that especially affected the most vulnerable populations (Centro Latino de Bioética y Humanidades and Federación Latinoamericana y del Caribe de Instituciones de Bioética 2018). Consequently, an international Congress of Bioethics celebrated in Puerto Rico in 2019 adopted "communication as an important tool in Bioethics" as the main topic for

discussion during that gathering (Subervi-Vélez and Fábregas-Troche 2020; Fábregas and Rodríguez 2023). Consequently, the Declaration of San Juan was crafted and in one of the first articles emphasized the importance of on-going communication that was reliable in situations in which the values of life and health were compromised. This reminder seems to be in line with some of the statements that 2 years earlier had been made in the *Declaration of Ethical Principles in relation to Climate Change* promulgated by UNESCO (2017). In different sections of such a highly morally binding document at the international level, several pages refer to elements of risk communication.

9.7 Lessons from Hurricane Fiona

In September 2022, Hurricane Fiona arrived in the Caribbean moving somewhat erratically, but maintaining peak winds of 58 mph. On September 18, the storm turned toward the west-northwest and strengthened while approaching the southern coast of Puerto Rico. The system became a hurricane and made landfall later that day over the southwestern part of the Island, around 19:20 UTC, with peak sustained winds of approximately 86 mph and producing 1 to 3 ft. of storm surge inundation above ground level (AGL) along the southern coast (Pasch et al. 2023b). Although it was a Category 1 hurricane on the Saffir-Simpson scale, it has been recorded as the costliest hurricane to have struck the Island. The reasons merit discussion.

Prior to Fiona, the passage of Earl to the north of Puerto Rico in early September resulted in heavy rainfall. Although it didn't cause significant damage, it saturated the soil and brought rivers near or above normal levels (Pasch et al. 2023b). This set the stage for the catastrophic flooding across Puerto Rico brought by Fiona.

During that hurricane's passage, many locations in Puerto Rico received 8–16 inches of rainfall, with even higher totals reported over the southern and eastern portions of the Island (Pasch et al. 2023b). There were numerous observations of over 2 feet of rainfall, and a storm-total maximum of 32.40 inches was reported by the United States Geological Survey rain gauge near Ponce. This extreme rainfall resulted in significant flash flooding and landslides across the Island. The National Hurricane Center report on Hurricane Fiona (Pasch et al. 2023b, p. 8) stated:

“There were thousands of water rescues performed in more than 25 municipalities across Puerto Rico, including over 400 in Salinas where a flash flood emergency was issued. Widespread river flooding occurred, especially in the central and eastern portions of the island. Almost half of the USGS river gauges rose above flood stage, and over a dozen locations crested above major flood stage including along the Río Cibuco, Río Grande de Arecibo, Río Grande de Loiza, Río Grande de Manatí, and Río Guanajibo. Some river gauges reached crests that surpassed record levels from Hurricane María in 2017. Overall, the National Weather Service office in San Juan issued about 50 Flash Flood Warnings and 30 Flood Warnings between 18–20 September.”

More than one million Puerto Ricans were left without power and more than 35% of homes had no running water because the severe flooding impacted filtration plants. On September 20, 2022, Governor Pedro Pierluisi requested an expedited major disaster declaration. The next day, President Biden declared the Island as a major disaster zone. This declaration made individual assistance requested by the Governor available to affected families in 55 of the archipelago's 78 municipalities.

After Hurricane Fiona, our research team set out to assess the emergency communication policies and practices followed by Puerto Rico's government and the news media. Based on structured online surveys and interviews via Zoom with key government communication officials and media managers, we learned that the communication exchanges within and across government personnel and media staff faced fewer technical difficulties in comparison to how they been during Hurricane María in 2017 when the power grid and communication infrastructure were devastated (Subervi Vélez et al. 2023). We also found that—again in comparison to the aftermath of Hurricane María—risk communication efforts by Puerto Rico emergency management agencies took place with fewer technological or logistic complications, that key staff interviewed was knowledgeable about risk communication practices, and that they had credibility among the public.

Nevertheless, our interviews also revealed that turnovers in news media staff and assigning of crises stories to inexperienced journalists limits effective coverage of emergency developments. In addition, government staff turnover and the practice of political appointments contribute to newcomers not having the appropriate knowledge or skills to handle emergency communication tasks. We also learned that during press conferences, politicians would take over and, at times, there were too many government officials delivering (sometimes contradictory) information causing confusion with the most crucial messaging. Another finding of our study was that existing health and social disparities in Puerto Rico—combined with governance issues and financial constraints placed on the territory, which are quite different when compared to the continental United States—lead to an increased vulnerability for residents living in the archipelago, many of whom had to leave Puerto Rico to then face new but similar challenges in Florida and elsewhere.

Based on our findings, our report's recommendations included, among other things, that media coverage strategies and government information policies should be reformulated to address the challenges emerging from major changes in news staff or government personnel turnover of officials in charge of risk communication. Another important recommendation from that study was that, when communicating risk to the public in an extreme weather event, an alternative natural hazard risk evaluation system should be used or created in order to offer the public not just hurricane categories based on wind speeds, but also significant risk factors such as intensity of rain and flood potential.

9.8 Conclusions

Puerto Rico is undeniably subject to recurring devastating tempests with disaster potential. Given the fact that hurricanes and tropical storms have caused so much damage during so many years, and that other weather events are expected to continue to afflict the archipelago in the future, more safeguards are need to protect the populations at risk, especially the most vulnerable. Extreme weather events are a part of nature, but disasters are social phenomena. In other words, “there is no such thing as a natural disaster” (Peek et al. 2021). Social scientists have been studying the root causes and consequences of emergency situations and have pointed out to a common denominator in emergencies and disasters: social vulnerability and poor planning. Previous sections of this chapter have addressed the role of effective risk communication in disaster mitigation and also discussed how the Puerto Rican experience communicating risk and responding to extreme weather events can contribute to help mitigate disasters in a changing climate. The following conclusions and recommendations are now presented.

As documented in this chapter, the recorded history of hurricanes afflicting the Puerto Rican archipelago is long and replete with innumerable losses of property, agriculture, infrastructure, as well as prolonged consequences on peoples’ health and lives. For decades to come, hurricanes will not only continue to afflict Puerto Rico and the Caribbean Region, but due to the impending climate change, probably be more frequent, intense, and potentially destructive. Therefore, it is crucial for government officials, all forms of news and social media, community organizations and the public to dedicate more efforts to prepare for (and, when needed, mitigate, and recover from) the impacts of hurricanes and all types of inclement weather hazards. Improving risk—as well as health—communication policies and practices is crucial to better manage those times of crises.

There is ample literature to offer guidance on such matters, including the important role played by bioethics. Recurring risk and health communication challenges in Puerto Rico are already known and require prompt attention with the implementation of policies and practices that are certain to reduce the losses to property and lives. Weather events cannot be controlled by human activities, but their impact can be significantly diminished by well-directed and implemented prevention and mitigation efforts that include integrated, well-planned, culturally relevant, and accessible risk communication.

The Puerto Rican experiences, especially with hurricanes María and Fiona, offered valuable lessons in disaster mitigation and prevention. Emergency management institutions have certainly taken steps to mitigate disasters like them. It remains to be seen whether these measures properly address the needs and challenges of the most vulnerable and will be sufficient to prevent disasters of great magnitude in the future. Education, research, and constant self-evaluation by government agencies need to be a continuous effort to achieve effectiveness and efficacy in risk communication. Our recommendations to such ends are summarized below.

9.9 Recommendations: Preparedness and Disaster Mitigation Through Education and Persuasive Risk Communication

A starting point is the application of the three phases that World Health Organization (WHO), as well as the Centers for Disease Control and Prevention (CDC) recommend for effective emergency risk communication: fostering trust and engaging with affected populations, integrating emergency risk communication into health and emergency response systems, and the actual practice of emergency risk communication. For the application of each of these activities, the corresponding Puerto Rico government entities (i.e., central and municipal emergency management and health departments and their officials) should focus particularly on vulnerable and underserved populations: those who are most isolated, live in high-risk areas, have limited access to news and information sources, or have special needs due physical or mental conditions.

To assist with communication and related outreach activities, it falls upon the corresponding Puerto Rico government entities to develop and maintain in good working conditions the appropriate infrastructure, policies, and procedures for sharing relevant information about health threats and other risks, such as potential landslides, river, and coastal flooding. While some of the vulnerability maps and other data are available in multiple reports and documents, central and municipal staff need training not only to access, properly interpret and learn from those resources, but also how to communicate them in culturally accessible ways to their diverse community members. Regular testing of the working conditions of their plans and policies, procedures and of their communication efforts are also needed. This implies regular assessments of their implementation with rigorous evaluations of the policies and processes, as well as surveys of the target populations. These assessments may require developing and testing new communication strategies, models, and tools. It is not sufficient to assume, without rigorous regular evaluations, that the established protocols and risk communication outreach and messages are appropriate for all types of situations and diverse populations. It is also necessary to assess that the targeted populations actually receive, understand and trust those messages.

Two areas of risk communication assessments merit special attention. First, research, to analyze if and how information is reaching key audiences in a timely matter. This is especially needed to assure that the most vulnerable populations are being reached and are receiving the information that is most relevant for them as promptly as they will need it for prevention and recovery. Second, community feedback to check for the appropriate persuasiveness of the information so that it is acted upon according to the risk at hand. The Puerto Rico Climate Change Council could be a good model for this, since it has a special commission on Communication and Outreach and have developed community engagement communication initiatives.

To achieve those goals, university-level risk and health communication education and research programs are crucial. In Puerto Rico, these are underdeveloped and should not be disregarded any longer. Programs that teach and conduct research about risk and health communication, and more so about the impending impacts of climate change, could open new paths to guide the government and the public to prepare for, mitigate and recover from the impacts of hurricanes and all types of inclement weather hazards. These programs could also play central roles in developing the most appropriate persuasive messages for diverse populations.

As previously discussed, the Saffir-Simpson scale being used to estimate hurricane disaster potential is based, primarily, on wind force. Another instrument should be developed, either to complement or to substitute the Saffir-Simpson scale, which not only assesses the threat due to the force of the winds, but also addresses the rainfall and flood potential of a weather event, to communicate risk more accurately, not only due to the winds, but also to the rain. While most of the aforementioned recommendations fall upon the corresponding government entities, other suggestions apply to traditional media (radio, television, and press) as well as to websites and social media channels. A prime directive should be that journalist who report—and others who post on social media—about weather, health and risk concerns be fully trained on how and where to gather accurate and reliable information about inclement weather conditions and hazards, as well as other types of emergency situations. To assist with that directive, university-level risk and health journalism education and research needs to be prioritized. Meanwhile, professional news media organizations should offer more workshops on risk and health communication, and also *regularly assess* (i.e., constructively critique) news reports about these matters. These forms of journalism education and training could ideally improve how risk and health news are reported. Improvements could also emerge from research that regularly and systematically assesses the outcome of such reporting as well as its effects on different sectors of the audience. To complement the above, state and local municipal emergency staff should be trained to communicate most effectively with journalists and media personnel as to policies and procedures regarding prevention, mitigation, and recovery efforts, as well as risk communication, to ensure proper coverage and dissemination of news and information about emergency situations.

The common denominator of these recommendations is that preparedness and disaster mitigation, especially in the Caribbean and other areas that experience recurrent weather-related threats, are possible through education and persuasive risk communication. Moreover, educational and research programs are crucial building blocks for guiding and strengthening risk communication. For sure, as West et al. (2021) have asserted, culturally relevant and effective risk communication must begin long before any weather related or other type of potential hazard is imminent.

Appendix 9.1 Partial list of Hurricanes impacting Puerto Rico 1508–2022 Excludes devastating tropical storms, except when noted

Dates	Names	Impact notes.
Aug. 16, 1508	San Roque	Unknown in history records
1508, unknown day	Unnamed	Southwest area affected
Oct. 4–5, 1526	San Francisco	Violent storm, hit most of San Juan
Three in 1530	S. Ana, S. Hipólito	
	& S. Ramón	Each caused great destructions & poverty
Sept. 7, 1545	Unnamed	
Aug. 24–25, 1568	San Bartolomé	Widespread
Sept. 12, 1575	San Mateo	Widespread
<i>Century's total: 6</i>		
Sept. 12, 1615	San Leoncio	Widespread, damaged cathedral, ships
Sept. 15, 1626	San Nicomedes	Widespread, sank ships in San Juan Bay
Sept. 1642	Unnamed	Widespread
Aug. 1657	Unnamed	Widespread
<i>Century's total: 4</i>		
Sept. 6, 1713	San Zacarías	Surges in southwestern coast
Sept. 7, 1718	Santa Regina	Damaged San Juan
Aug. 30, 1738	Santa Rosa	Crossed, damaged entire island
11 between 1740–75	Various saints	Multiple areas affected, great damage
June 13, 1780	San Antonio	Major damage and losses
Oct. 14, 1780	San Calixto*	>200 mph winds, >20,000 deaths in Caribbean area
2 between 1785–88	S. Lupo, S. Roque	Multiple areas affected, damaged
<i>Century's total: 17</i>		
2 between 1804–06	S. Rosalía, S. Vicente	Widespread
Aug 17–19, 1807	San Jacinto	Stationary path for 2 days; widespread damage
21 between 1813–71, 1878–96	Various saints	All damaged agriculture-based economy
Sept. 13, 1876	San Felipe I*	Very deadly
Aug. 8, 1899	San Ciriaco*	Cat. 4; 28 consecutive days of rain; >3365 deaths
<i>Century's total: 26</i>		
7 between 1901–26	Various saints	Multiple areas affected, damaged
Sept. 13, 1928	San Felipe II**	Cat. 5, >200 mph winds, crossed S.East-N. West
Sept. 10–11, 1931	San Nicolás	
Sept. 26–27, 1932	San Ciprián	>120 mph winds
2 between 1943–49	S. Calixto, S. Mateo	
Aug. 12, 1956	Betsy (Santa Clara)	>\$40,000 in damages, typhoid fever outbreak
Sept. 5–6, 1960	Donna	>100 deaths, thousands of homes impacted

(continued)

Appendix 9.1 (continued)

Dates	Names	Impact notes.
5 between 1963–67	Various names	
Oct., 1970	Azores	Intense rain activity, massive agricultural losses
5 between 1975–81	Various names	
Sept. 18, 1989	Hugo	Cat. 3, 125 mph winds; major damage to rainforest
Oct. 8, 1990	Klaus	Floods
Sept. 1995	Luis, Marilyn	Extreme flooding and damage
July, Sept., 1996	Bertha, Hortense	More flooding and major damages
Sept. 21–22, 1998	Georges	Mass flooding, \$2 billion in damages
Nov. 17, 1999	Lenny	
<i>Century's total: 31</i>		
Aug. 22, 2000	Debby	
Sept. 15, 2004	Jeanne	Major loss of water, power; \$169.5 million in losses
Aug. 25–27, 2006	Ernesto	
Aug. 18, 2007	Dean	
Aug.–Sept. 2008	Hanna	
Sept. 20–24, 2008	Kyle	Record breaking rainfalls, flashfloods, mudslides
Oct. 13–16, 2008	Omar	
Aug.–Sept. 4, 2010	Earl	Major loss of power, water
Sept. 17, 2010	Igor	Extensive flooding
Aug. 21–24, 2011	Irene	
Oct. 14–15, 2014	Gonzalo	
Aug. 25, 2015	Danny	
Sept. 5–7, 2017	Irma	Cat. 5, major devastation in northeast
Sept. 19–21, 2017	María	Cat. 4 crossed whole island; major devastation
July 9–10, 2018	Beryl	
Aug. 28–29, 2019	Dorian	
Sept. 18, 2020	Teddy	
Sept. 17–19, 2022	Fiona	Prolonged, extensive & devastating rain
Nov. 4–6, 2022	Nicole	
<i>Running total in just the first 22 years: 19 excluding various devastating tropical storms</i>		

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Chapter 10

Reconsidering the Saffir-Simpson Scale: A Qualitative Investigation of Public Understanding and Alternative Frameworks



Leilani D. Paxton, Jennifer Collins, and Laura Myers

Abstract Traditional hurricane communication, often reliant on simple wind-based categories like those given in the Saffir-Simpson Hurricane Wind Scale, fails to capture the multifaceted anxieties and decision-making processes of individuals facing these complex storms. This paper, based on focus group data, reveals a spectrum of emotions and concerns, including anxieties about flooding, tornadoes, and storm surge. It proposes a shift towards audience-centered communication strategies with separate rating systems for wind, surge, and rainfall, tailored to diverse information needs and preferences. Acknowledging the subjective nature of risk perception, the research emphasizes the importance of accessible visuals, transparent calculations, and personalized information delivery. By empowering individuals with accurate and actionable information, this approach can potentially lead to improved preparedness and better decision-making, ultimately saving lives during these powerful natural events.

Keywords Hurricane communication · Hurricane preparedness · Public perception of risk · Risk communication strategies · Hurricane scales · Disaster communication · Focus groups · Micro-Interlocuter Approach · Qualitative data analysis · Participant demographics · Public engagement · Disaster preparedness · Decision-making · User experience

L. D. Paxton · J. Collins (✉)

School of Geosciences, NES 107, University of South Florida, Tampa, FL, USA

e-mail: collinsjm@usf.edu

L. Myers

University of Alabama, Tuscaloosa, AL, USA

10.1 Introduction

The persistent threat of tropical cyclones looms over coastal communities worldwide, exacting a grim toll on human lives and property. In the United States alone, these formidable storms claimed 6593 lives between 1980 and 2020, highlighting the critical need for effective preparedness and evacuation strategies (NOAA 2021). While advancements in weather forecasting have enhanced our ability to predict the arrival and intensity of these destructive systems, the crux of mitigating their impact often hinges on the timely evacuation of vulnerable populations.

However, understanding the cognitive processes and decision-making factors that underpin individual evacuation behavior remains a complex and multifaceted challenge. This research embarks on an investigation into this critical domain, employing focus group methodology to unravel the intricate relationship between public perceptions of hurricane intensity scales and evacuation decision-making.

The Saffir-Simpson Hurricane Wind Scale (SSHWS), implemented in 1974 (Iacovelli 1999), has become a widely recognized tool for communicating hurricane intensity. Categorizing storms solely based on their maximum sustained wind speeds, the SSHWS provides crucial decision-making cues for individuals residing in potential hurricane impact zones. However, the scale's limitations have come under increasing scrutiny, as several notable hurricanes have highlighted its shortcomings.

For example, Hurricane Floyd, though it made landfall in North Carolina in 1999 as a Category 2 storm, produced significant storm surge exceeding 4.6 m (15 feet), spawned numerous tornadoes, and dumped 250–500 millimeters (10–20 inches) of rain across seven states (National Weather Service 1999). Similarly, Hurricane Katrina, despite being classified as a Category 3 on the SSHWS during its devastating 2005 landfall, unleashed catastrophic storm surge and inland flooding, phenomena not explicitly captured by the scale (Pierce 2009). More recently, Hurricane Sandy, a post-tropical storm upon landfall in 2012, exhibited the potential for Category 1 storms to produce significant storm surge, reaching up to 3.9 meters (13 feet) in this instance (Blake et al. 2013). Similarly, Hurricane Florence, despite making landfall in South Carolina as a Category 1 storm in 2018, caused devastating freshwater flooding across the southeastern United States, resulting in 55 fatalities (Stewart and Berg 2019).

The scale's limitations can lead to dangerous situations, as people use the category to decide whether to evacuate and finalize hurricane preparations. (Morss and Hayden 2010). Polen et al. (2023) noted that, of those surveyed about their thoughts on hurricanes generally, 75.5% of the sample stated that the category influenced their decision to evacuate. Of this group, Polen et al. (2023, p. 548) further note that “35.3% stated that the lowest category they would evacuate for is Category 3, whereas 4.9% selected Category 1, 10.8% selected Category 2, 16.7% selected Category 4, and 7.8% selected Category 5.” The Category 3 designation has been a trigger point for evacuation decisions because Category 3 storms are the starting category for major hurricanes. Recent hurricanes like Hurricane Michael in

2018 have rapidly intensified to Category 4 and 5, leaving people at risk who thought they would have time to evacuate “if” the storm strengthened. Senkbeil et al. (2020) note that with Hurricane Michael, which made landfall in October 2018 as only the third SSHWS Category 5 storm to hit Florida, 61% of residents did not evacuate, and approximately 80% either underestimated the intensity, misinterpreted or did not believe the forecast, or realized the danger too late to evacuate. Of those who did not evacuate, many of them had evacuated for Category 3 Hurricane Opal in 1995 and were not allowed to reenter in a timely manner. Even though they had a good understanding of the SSHWS and found it helpful to their planning, other factors such as the uncommon month of the hurricane season, landfall location, and the impacts of previous storms also factored into their evacuation decisions. While the SSHWS was useful, it did not address those concerns.

Other researchers have shown the public’s dissatisfaction with the SSHWS in relation to specific hurricanes. For example, Morss and Hayden (2010) interviewed Texas residents after the impact of Hurricane Ike (2008). Many residents reported that since many people decided to stay in their homes rather than adhere to a mandatory evacuation order due to their perceptions of the SSHWS, they believed the SSHWS did an inadequate job communicating the risk and potential for damage caused by a Category 2 hurricane, which included storm-surge flooding.

These examples highlight the limitations of the SSHWS in comprehensively conveying a hurricane’s potential dangers. Even Robert Simpson, co-creator of the scale, acknowledged its shortcomings in fully capturing the totality of a hurricane’s potential impact (Iacovelli 1999). The limitations of wind speed as the sole metric have sparked calls for reform. Some researchers advocate for developing more comprehensive metrics encompassing storm surge, rainfall potential, and inland flooding risks, while others propose expanding the Saffir-Simpson Hurricane Wind Scale (SSHWS) by adding categories to account for the increasing intensity of storms anticipated with climate change (Kantha 2006; Powell and Reinhold 2007; Song et al. 2020; Camelo and Mayo 2021; Wehner and Kossin 2024).

Despite a burgeoning pool of proposed alternative scales that incorporate additional parameters such as storm surge and potential rainfall, a dearth of empirical research exists to assess their relative effectiveness in influencing evacuation decisions. This paper addresses this critical gap in knowledge by conducting a series of focus groups designed to explore the public’s interpretation of hurricane scales and the impact of those interpretations on evacuation decisions. By presenting participants with simulated hurricane scenarios using a variety of intensity scales, this research aims to elucidate the cognitive processes underlying their interpretation and subsequent evacuation decision-making. The findings hold the potential to not only inform the development of more effective hurricane communication strategies but also contribute to a deeper understanding of human behavior in the face of extreme weather events.

In the context of a projected increase in the frequency and intensity of severe hurricanes due to climate change (Knutson et al. 2020), the quest to optimize hurricane communication and evacuation decision-making assumes even greater urgency. While the National Hurricane Center’s hurricane cone graphic has

undergone a recent revision (National Hurricane Center 2024), the Saffir-Simpson Hurricane Wind Scale (SSHWS) remains ripe for modernization. This research delves into this area, aiming to inform the development of enhanced and more informative hurricane scales, potentially leading to improved public protection through better decision-making.

10.2 Literature Review

Evacuation decisions in the face of approaching hurricanes depend critically on how people perceive the storm's risk (Irish et al. 2008). This perception, in turn, is significantly influenced by the storm's intensity, communicated primarily through the Saffir-Simpson Hurricane Wind Scale (SSHWS) (Simpson 1974). Developed in the late 1960s as the Saffir-Simpson Hurricane Scale (SSHS), it assigned categories (1–5) based on maximum sustained wind speeds, later incorporating estimated surface pressure, storm surge, and descriptions of potential property damage (Simpson 1974). However, political pressure led to its premature release before planned refinements to storm surge and surface pressure calculations were implemented (Iacovelli 1999).

The aftermath of Hurricane Katrina in 2005 exposed the SSHS's limitations in effectively communicating risks (Irish et al. 2008). In response, the predicted storm surge and flooding information was removed in 2009, and the scale was renamed the Saffir-Simpson Hurricane Wind Scale (SSHWS) (Pierce 2009). Numerous researchers have critiqued the SSHWS's inadequacy in conveying the full spectrum of hurricane hazards (Powell and Reinhold 2007; Kantha 2008), prompting the development of several alternative intensity scales, as shown in Table 10.1.

Kantha (2006) proposes two continuous scales: the Hurricane Intensity Index (HII) and the Hurricane Hazard Index (HHI). The HII, ranging from 0.1 to 5, focuses on wind speed, while the HHI incorporates wind speed, wind radius, and forward speed to deliver a broader risk picture. Powell and Reinhold (2007) suggest two parallel continuous scales (0.1–5.9) based on calculated kinetic energy to represent wind and storm surge/wave destruction potentials. Kantha (2008) has called into question their methodology, saying that the destruction potential of a hurricane is not dictated by its integrated kinetic energy. Irish and Resio (2010) present a surge-focused scale (SS) (0.1–3.5) derived from calculations considering intensity, size, forward speed, and regional bathymetry. Pilkington and Mahmoud (2017) utilize an artificial neural network to create a discrete 1–5 scale for classifying hurricanes based on their potential economic damage. Klotzbach et al. (2020) advocate for a discrete scale (1–5) based on surface pressure instead of wind speed. Most recently, Bloemendaal et al. (2021) developed the Tropical Cyclone Severity Scale (TCSS) (1–6), incorporating wind, storm surge, and rainfall for a more holistic risk assessment.

Table 10.1 Overview of proposed alternative hurricane scales. (Adapted from Bloemendaal et al. (2021))

Tropical cyclone classification method	Tropical Cyclone Hazard (s) reflected by scale			Applicability	Continuous/ Discrete	Reference
	Wind	Storm surge	Precipitation			
Saffir-Simpson Hurricane Wind scale	Yes	No	No	Pre-landfall	Discrete	Simpson (1974)
Hurricane Severity Index	Yes	No	No	Pre-landfall	Discrete	Hebert et al. (2010)
Hurricane Hazard Index	Yes	No	No	Pre-landfall	Continuous	Kantha (2006)
Hurricane Intensity Index	Yes	No	No	Pre-landfall	Continuous	Kantha (2006)
Integrated Kinetic Energy	Yes	No	No	Pre-landfall	Continuous	Powell and Reinhold (2007)
Hurricane Classification System	Yes	Yes	Yes	Post-landfall	Discrete	Senkbeil and Sheridan (2006)
Surge scale	No	Yes	No	Pre-landfall	Continuous	Irish and Resio (2010)
Hurricane Surge Index	No	Yes	No	Pre-landfall	Continuous	Kantha (2008)
Multihazard Hurricane Index	Yes	No	Yes	Pre-landfall	Continuous	Song et al. (2020)
Tropical Cyclone Severity Scale	Yes	Yes	Yes	Pre-landfall	Discrete	Bloemendaal et al. (2021)

10.3 Methodology

10.3.1 Selection of Alternative Survey Scales

This study aimed to assess the effectiveness of three alternative hurricane scales in conveying storm severity, particularly considering the potential for changing climate patterns (Bloemendaal et al. 2021; Wehner and Kossin 2024). Each of these scales employed a unique approach to communicating various aspects of hurricane impact.

One of the evaluated scales, the Tropical Cyclone Severity Scale (TCSS), builds upon the familiarity of the existing SSHWS by utilizing a 1–5 rating system for separate wind, storm surge, and rainfall factors (Bloemendaal et al. 2021). This approach retains a similar format to the current public standard while acknowledging the potential for combined extreme weather hazards by introducing an additional “Category 6” to represent their cumulative severity. Appendix IV provides more information on how the aggregate storm categories are calculated. The rationale

behind this addition stems from the growing concerns regarding the potential increase in such multifaceted storms due to climate change (Bloemendaal et al. 2021). Further research is needed to explore public perception and understanding of the TCSS approach, particularly concerning its use of specific threat categories within a familiar 1–5 framework.

The Hurricane Hazard Index (HHI) departs from the wind-focused approach of the SSHWS by incorporating additional factors into its calculations. These factors include storm intensity (wind speed), size (radius of maximum sustained winds), and forward speed (Kantha 2006). This results in an unbounded scale with decimal points, potentially offering a more detailed representation of the overall hurricane threat compared to the five-category system of the SSHWS. However, this increased detail comes at a potential cost. The HHI's unfamiliar structure and reliance on complex calculations, as opposed to the single factor of wind speed used by the SSHWS, may present challenges for public comprehension. Unlike the readily understandable 1–5 format of the SSHWS, the HHI's unfamiliar framework and intricate calculations might create a barrier for the public to grasp its full meaning and implications.

Finally, the Wind and Surge Potential Destruction Ratings (WSPDR) bridge the gap between the two by leveraging the simplicity and familiarity of the 1–5 format from the SSHWS while incorporating a more comprehensive assessment of the threat. This is achieved by utilizing integrated kinetic energy, a metric that considers both wind speed and storm size within a familiar framework (Powell and Reinhold 2007). Additionally, the WSPDR offers separate wind and surge ratings, catering to specific concerns and potentially facilitating targeted risk mitigation strategies. This approach strives to achieve a balance between detail and accessibility, providing a potentially more specific and actionable understanding of the diverse threats posed by hurricanes to the public. However, further research is needed to evaluate the effectiveness of the WSPDR in practice, particularly regarding public comprehension and its integration into existing communication strategies.

10.3.2 Participant Recruitment

This study employed a purposive sampling strategy to recruit a total of 19 participants residing in Florida. Florida was selected because its residents are more likely to have first-hand experience with hurricanes than other coastal states. Social media platforms, specifically Facebook and Reddit, served as the recruitment channels. Advertisements outlining the study's purpose, eligibility requirements (including Florida residency and being over 18 years old), and compensation (a \$20 gift card) were posted on these platforms (Appendix I, A). Individuals interested in participating responded via email, prompting the distribution of a short online questionnaire. This questionnaire aimed to verify eligibility by collecting the following information: date of birth, zip code (used to confirm Florida residency), availability for focus groups, and preferred gift card type.

Concerns regarding participant eligibility arose during the fourth focus group. Inconsistencies were observed in participants' self-reported knowledge of Florida, and concerns of potential misuse of Amazon gift cards overseas arose. To address these concerns and enhance data integrity, recruitment was temporarily paused. Subsequent participants underwent residency verification through Qualtrics, a secure online platform, prior to their inclusion in the focus groups. Amazon Gift Cards were no longer offered, and instead, only gift cards were provided that could not be easily used overseas.

10.3.3 Participant Demographics

A total of 19 individuals participated in this study. Participants were recruited from various locations across Florida, with 17 residing in the central region and two residing in the southeast region (Fig. 10.1). Their ages ranged from 21 to 75 years old, with an average age of 37.5 years.

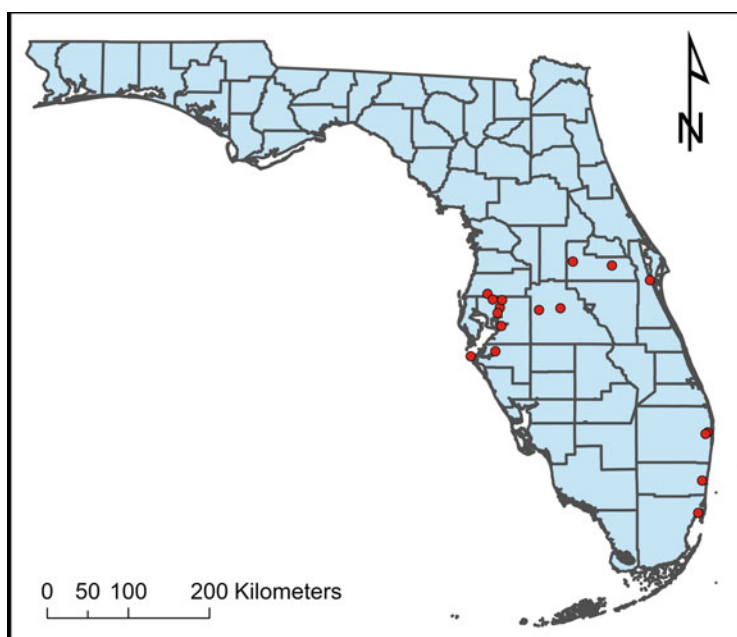


Fig. 10.1 Distribution of participants: Red dots indicate participant zip codes

10.3.4 Focus Group Procedures

Data collection occurred between September 2022 and October 2023 through five virtual focus groups conducted using the Google Meet platform. Each session lasted approximately 45–75 minutes and involved 2–6 participants residing in Florida, resulting in a total of 19 participants. After obtaining informed consent, documented through verbal recording, participants engaged in a semi-structured discussion guided by a PowerPoint presentation (Appendix I, B-I).

The focus group discussion began with a foundational overview of tropical cyclones, encompassing hurricanes, tropical storms, and their associated impacts (Appendix I, B). This was followed by an explanation of the SSHWS (Appendix I, C). To assess participants’ pre-existing knowledge and experiences, 18 semi-structured questions were posed (script available in Appendix II). These questions explored a range of topics, including personal feelings towards hurricanes, past evacuation behavior, encountered property damage, and preferred information sources. Throughout the discussion, each question remained visible on the screen to maintain focus. Subsequently, six additional questions delved specifically into hurricane categories, evaluating participants’ understanding of category meanings, their perceived evacuation thresholds, and any additional factors influencing their perception of hurricane severity.

The third section focused on the SSHWS. Participants viewed a slide summarizing the scale (Fig. 10.2), followed by a series of questions that explored their existing knowledge and perceptions. These questions delved into their familiarity with the SSHWS, their prior exposure to similar visuals, their assessment of the usefulness of the scale’s categories, their perception of the information’s adequacy, and any additional considerations they believed should be incorporated into the scale.

The Saffir-Simpson Hurricane Wind Scale		
The scale that is currently used is called the Saffir-Simpson Hurricane Wind Scale.		
It categorizes hurricanes from 1-5 based on their maximum wind speed.		
Category	Wind Speed	Type of Damage
1	74-95 mph	Some Damage
2	96-110 mph	Extensive Damage
3	111-129 mph	Devastating Damage
4	130-156 mph	Catastrophic Damage
5	157 mph and above	Catastrophic Damage

Fig. 10.2 Saffir-Simpson Hurricane Wind Scale (SSHWS): Slide presented to participants explaining the scale’s categories and wind speed thresholds

Section four introduced the concept of alternative hurricane scales to the participants (Appendix I, E). Throughout the following sections, the moderator ensured clarity by addressing any questions participants raised about the operation of the proposed scales.

Following the introduction of alternative hurricane scales in Section Four, participants were presented with detailed overviews of three specific scales using slide decks, as shown in Fig. 10.3. Each presentation (TCSS in Section Five, HHI in Section Six, and WSPDR in Section Six) clearly outlined each scale's structure and categories, along with a relatable example of how Hurricane Katrina would be categorized, leveraging its familiarity for participants (Appendix I, E-H). Focused group discussions followed each presentation, exploring participants' perceptions of the respective scales. The moderator used targeted questions to probe understanding, gather opinions on individual categories, identify any concerns, and gauge overall usefulness for public communication. Question slides accompanying the discussions further enhanced clarity by including graphic representations of each scale.

The focus group discussions concluded with six final questions designed to prompt reflection on the presented alternative scales. Each question was accompanied by a brief description of the presented alternative scales on the screen (Appendix I, I) to aid recall. The first question asked participants to compare the alternative scales to the SSHWS, specifically inquiring whether any felt like an improvement and prompting them to articulate their reasoning. Subsequent questions invited participants to identify the scale they found most useful for public communication and the one they perceived as offering the most comprehensive information. This repetition, using slightly different phrasing, aimed to capture any subtle nuances in their assessments, particularly regarding the scales' perceived effectiveness in informing evacuation decisions.

Leveraging their exploration of various hurricane scales, participants were then presented with an open-ended question: "Which information do you think should be included in a hurricane scale?" This question aimed to assess any shifts in their initial perspectives on hurricane scale design after encountering different approaches to risk representation. Finally, participants were asked about their perceptions of using decimal places within hurricane categories, a feature incorporated in some of the previously discussed scales.

10.3.5 Data Analysis

Following the completion of the focus group sessions, the audiovisual recordings were transcribed verbatim using Otter.ai software. These rich qualitative data were then analyzed using a Micro-Interlocuter Approach (Onwuegbuzie et al. 2009). This method prioritizes a detailed examination of both individual and collective responses within the focus group discussions. It goes beyond simply capturing the spoken word by incorporating the analysis of nonverbal cues, group dynamics, and the identification of recurring themes, key arguments, and nuanced perspectives.

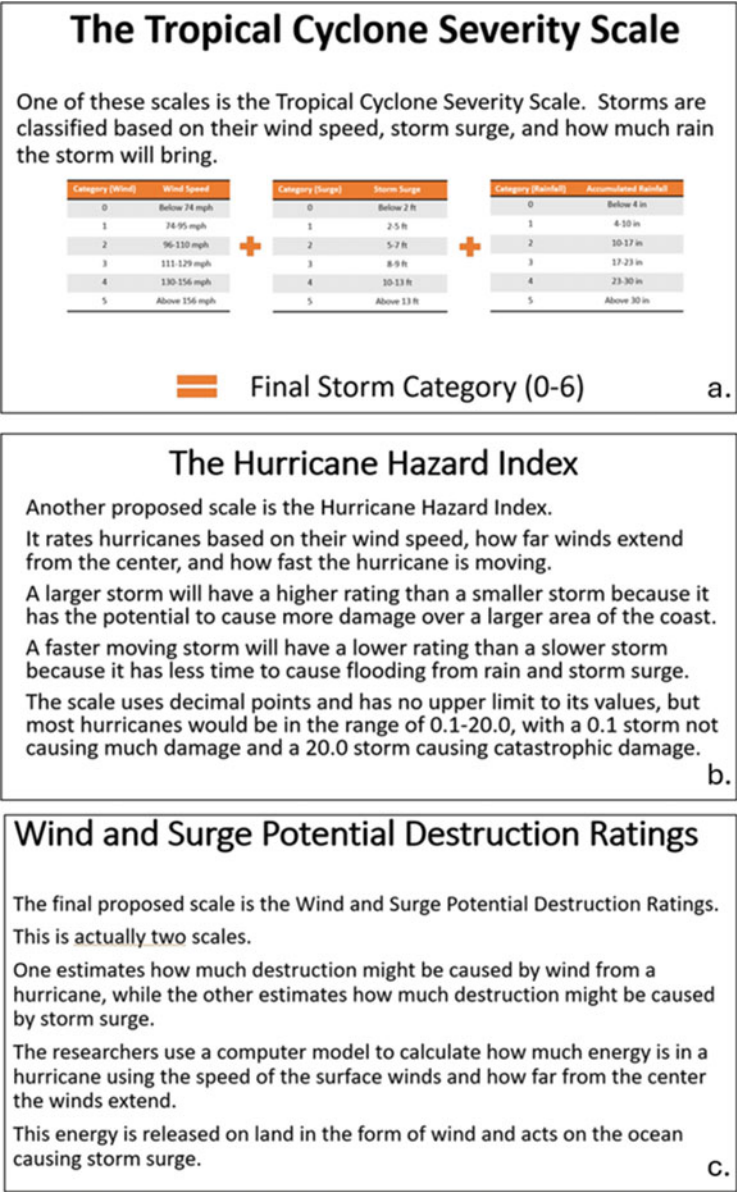


Fig. 10.3 Slides presented during the focus groups, introducing three alternative hurricane intensity scales: (a) TCSS, (b) HHI, and (c) WSPDR

To facilitate in-depth analysis, individual responses to each question were systematically organized within a spreadsheet (Appendix III provides a summary of the results). This facilitated efficient coding of responses (where applicable) as positive,

negative, or neutral. Additionally, the discussions were analyzed to identify recurring themes and document their frequency. This multi-layered approach to data analysis ensured a comprehensive understanding of the participants' experiences, opinions, and perspectives.

10.4 Results

10.4.1 *General Hurricane Experiences*

Drawing on data from all five focus groups, this study explored the experiences and perceptions of hurricanes among 19 participants residing in Florida. All participants had prior exposure to hurricanes, but their emotional responses varied significantly. While a substantial portion expressed fear, anxiety, or even terror, others reported emotions like excitement or exhilaration. This diversity underscores the subjective nature of individual hurricane perception.

Concerns regarding specific hurricane effects also diverged among participants. While some expressed minimal concern or prioritized specific threats like storm surge, wind, property damage, or individual hazards like flooding, tornadoes, or falling trees, a noteworthy portion resided in flood zones. This variation highlights the influence of geographical location and individual risk factors on shaping personal anxieties related to hurricanes.

Past experiences further emphasized the variability in hurricane perception. Some participants had encountered flooding during previous hurricanes, while others had not. Similarly, concerns about flooding at their current location varied based on personal experience. These findings suggest that personal encounters with specific hurricane impacts can significantly shape risk perception and associated concerns.

Information recall from the last experienced hurricane showed disparity. Some participants recalled the storm's category or path, while others mentioned spaghetti plots, but only one remembered details about storm surge and wind effects. This discrepancy may be attributed to the salience and visual nature of trajectory and spaghetti plots compared to text-based information (Ally and Budson 2007), a potential media focus on visuals, the varying individual relevance of specific hurricane effects, the technical complexity of surge and wind information, and inherent differences in information processing among participants.

Local news emerged as the primary source of information for many participants during the last hurricane they experienced. This was followed by news websites, The Weather Channel, and government websites. Interestingly, individual sources like local officials, friends, and even social media played a secondary role. This finding highlights the public's reliance on both official and informal channels for hurricane information. Overall, while most participants felt sufficiently informed during the last hurricane, there were still gaps in communication. Requests for additional information primarily focused on the aftermath, tornado threats, and real-time

updates. These insights offer valuable clues regarding areas for improvement in existing communication practices.

10.4.2 General Hurricane Knowledge

While all participants acknowledged the five-category hurricane scale, their understanding and personal application varied. Most participants admitted needing to reference wind speeds associated with those categories, suggesting that the scale's numerical aspect is not always readily internalized. This finding highlights the importance of consistently educating and reminding the public of the wind speeds associated with each category, both preseason and during the days prior to the landfall of a hurricane.

Concerns about hurricane categories also differed among participants. While a significant portion prioritized Category 3 storms (hurricanes are considered major at Category 3), others expressed worry about less intense or more severe categories. This highlights the subjective nature of risk perception and the individual factors influencing it. Evacuation decisions reflected this variability. Some expressed willingness to consider evacuation based on the hurricane's characteristics, while others indicated a resolute stance against evacuation in any circumstance. One participant remained undecided regarding their evacuation decision. The conditions triggering evacuation also revealed diverse thresholds. Some relied solely on mandatory evacuation orders, while others responded to specific threats or impacts like flooding, a particular storm category, or a high category in general. This suggests that the storm category alone might not be the sole driver of evacuation decisions. One participant stated, "For me, evacuation is based on flooding. It can be a Category 6 or 7. I mean, whatever it is, as long as there's not flooding, I don't see myself leaving the area."

Similarly, the perceived importance of the category scale itself was inconsistent. Most deemed it important or very important, while others saw it as less significant. This inconsistency suggests that other factors, like evacuation feasibility, personal vulnerability, or trust in official guidance, might play a more prominent role in individual decision-making. Beyond these factors, participants mentioned additional factors influencing their evacuation choices, including traffic concerns, flooded roads, family considerations, and the fear of losing life, property, and family. These varied considerations emerged as potential deterrents or motivators for evacuation. One participant stated, "Everybody's thinking about evacuating. So now you're stuck on I-4, you know, you may not have enough gas to get somewhere. So you know, sometimes it's better to just stay where you are and roll the dice." Additionally, one participant highlighted the storm's trajectory as important, underscoring the role of spatial factors in individual risk perception.

10.4.3 Saffir-Simpson Hurricane Wind Scale

Drawing on data from all 19 participants across all five of the focus groups, the study revealed that while all participants were familiar with the SSHWS, their level of engagement and perceived usefulness varied. One participant admitted to the belief that the scale was logarithmic, highlighting the potential for confusion. Notably, this same participant had not seen a chart displaying the categories and wind speeds, suggesting that visual aids might be crucial for a clear understanding. Another participant stated, “I just wanted to say that I honestly look it up every single time if five is the highest wind speed or one is the highest wind speed. So that’s just me like, colors might be better.”

The participants expressed diverse perceptions of the SSHWS and its usefulness. While a portion of participants valued the SSHWS, appreciating its ability to compare storm intensities with past experiences, others expressed reservations about its limitations. Some participants emphasized the importance of considering context when interpreting the scale, while others cautioned against drawing “false equivalences” across different storms. This highlights the subjective nature of interpreting the SSHWS categories and the potential drawbacks of using wind speed as the sole indicator of overall hurricane risk.

The majority of participants felt the SSHWS lacked sufficient information, criticizing its vague descriptions of potential damage. This highlights the limitation of solely focusing on wind speed, as it fails to capture the complete spectrum of risks associated with hurricanes. Participants proposed various additional pieces of information they deemed beneficial, including details regarding storm surge, trajectory, rainfall, local wind estimates, air temperature, and high tide. This diverse range of suggestions underscores the need for more comprehensive communication strategies that address the multifaceted nature of hurricane threats. This also suggests that the SSHWS is still a valuable tool but must be accompanied with education and outreach that connects these other factors in decision-making.

10.4.4 Alternative Scales

Tropical Cyclone Severity Scale Drawing on data from all 19 participants, the study examined public perceptions of the TCSS. While some participants considered the TCSS easy or somewhat easy to understand, others expressed concerns about its accessibility for the public. This highlights the potential challenge of introducing a new and complex scale, even with separate metrics for wind, surge, and rainfall. The separate risk categories received a more positive response, with a significant portion approving, some remaining neutral, and only one offering a negative view. However, even among those who found the individual metrics helpful, concerns emerged. Some participants disliked the aggregation into a final score (see Appendix IV), fearing it would overshadow specific threats and necessitate substantial public

education for effective interpretation. Some even expressed concern about the public taking years to acclimate to the new system

Despite these reservations, the TCSSS garnered support for its comprehensiveness. Several participants appreciated the expanded information compared to the SSHWS, with each threat receiving its own dedicated metric. This suggests that while the scale's complexity might pose challenges, its potential for a more nuanced understanding of hurricane risks also holds value. Ultimately, opinions on the TCSSS's usefulness were divided. Some participants found it beneficial, while others offered a neutral or negative response. This underscores the need for further research and communication strategies to refine the scale's presentation and ensure its accessibility for the public.

Hurricane Hazard Index The Hurricane Hazard Index (HHI) elicited a predominantly negative reception among participants. While a small portion found it potentially useful, the majority perceived it as difficult for the public to understand. This stark disparity underlines a potential communication gap between the design team and the intended audience. A key criticism focused on the HHI's lack of boundaries. Several participants expressed confusion about comparing various threat levels without a familiar reference point, like the traditional 1–5 scale. Additionally, a significant portion found the HHI excessively complex, implying a need for extensive public education or suggesting its suitability for scientific analysis rather than public information dissemination. One said, "... not only do I not know the difference between point one and 20, I don't even know the difference between 19.3 and 20. So this seems great for researchers or people who are really into the information. But I imagine this would cause a lot of debate in in households, and you're just like, I'm only evacuating at 17.2, and my husband's like, I'm evacuating at 16.9. I think that creates a lot of conflicts."

Despite the overwhelmingly negative reception, some aspects of the Hurricane Hazard Index (HHI) garnered support. A few participants valued its potential for research, while others appreciated its inclusion of rainfall, storm size, and the possibility of increased attention for higher values. One even welcomed the openness of the unbounded scale. These limited positive responses suggest potential value in specific features of the HHI, even if its overall presentation may require substantial revision. Ultimately, the HHI's usefulness remained a subject of debate, with only a few of the participants endorsing it and an equal portion rejecting it entirely. This inconclusive stance underscores the need for further refinement and public engagement before such a complex scale could be effectively adopted for broader public communication.

Wind and Surge Potential Destruction Ratings The WSPDR elicited a mixed response. A majority found it easy to understand, while a significant minority expressed concerns about its accessibility to the public. This highlights the challenge of balancing detailed information with simplicity for a broad audience. While its separate categories for wind and surge were praised, specific aspects received criticism. Some disliked the decimal points, suggesting a simplified presentation

with fewer numbers. One participant suggested applying a multiplier to shift the scale to a 10-point format for easier public comprehension. In reference to the WSPDR, one participant explained, “I have an issue with the numbers that, like to go to 5.9. Our brains aren’t wired like that. Like, have you ever encountered anything else that random 5.9? But there are ways to manipulate these, right? So I feel like it needs like you multiply everything by like, one 1.8 or something like that would get you on a 10 point scale. And I think that would be much easier for the general public to understand.” Interestingly, another participant preferred even more detail, desiring numerical values alongside the color-coded map.

Colorblindness was also raised as a concern, highlighting the need for inclusive design considerations. A few participants felt the two-number format was confusing, suggesting a preference for the storm surge rating to instead use lettered categories. Another concern pertained to the scale’s limitations in providing precise local information. Interestingly, despite the visual nature of the map, one participant argued for the inclusion of numerical values for specific locations. The omission of tides was also flagged as a potential drawback. Despite these concerns, many participants found the WSPDR useful, while several remained unconvinced. This overall positive trend, despite specific criticisms, points to the scale’s potential effectiveness, with the potential for further refinement and customization based on user feedback.

10.4.5 Concluding Questions

While the SSHWS remained familiar and comfortable for some, a clear majority embraced new approaches to hurricane communication. Many participants saw the TCSS as an improvement, valuing its separate ratings for wind, surge, and rain. Some favored the WSPDR, appreciating its visual map and distinct wind and surge categories. Notably, only one participant opted for the established SSHWS, highlighting potential limitations in its ability to address diverse information needs.

Interestingly, opinions on simplicity diverged. Some found the SSHWS easiest to understand due to its familiarity, while others found the WSPDR’s visuals more intuitive or preferred the TCSS’s separate categories. This demonstrates that simplicity is subjective and depends on individual preferences and prior knowledge. Similarly, perceptions of information depth varied. Some found the TCSS most informative due to its comprehensive breakdown, while others favored the WSPDR’s visuals, suggesting visual communication might not always compete with detailed text. When it came to immediate usefulness, the WSPDR appealed to some participants due to its actionable guidance, while others valued the TCSS’s informational detail. This suggests that immediacy and clear action steps can outweigh comprehensive information for some people during crucial decision-making.

The ideal hurricane scale information revealed further diversity. Surge was the most frequently mentioned priority, followed by rainfall or inland flooding, wind, and storm forward speed. Interestingly, some participants suggested color-coding categories for accessibility and emphasized the importance of including tornado threats. This wide range underscores the need for comprehensive communication strategies that cater to diverse risk priorities and concerns. Finally, opinions on decimal points were split. Many disliked them, potentially finding them unnecessary or confusing, while a few embraced them for perceived precision. Interestingly, some found them suggestive of a logarithmic scale, highlighting potential misunderstandings and the importance of clear explanations.

10.5 Discussion

10.5.1 *Subjectivity in Hurricane Perception*

This study unveils a compelling heterogeneity in human emotional responses to the threat of hurricanes, transcending the conventional emphasis on fear and anxiety. While negative emotions undoubtedly dominated, participants also reported positive reactions like excitement or exhilaration. This finding challenges the limitations of cognitive risk models, exemplified by Slovic et al. (2004), which solely focus on risk assessment through severity-probability calculations. Loewenstein et al. (2001) underscore the significant influence of visceral reactions, particularly fear, on decision-making in risky situations, aligning with our own empirical observations. Notably, the two participants expressing excitement towards hurricanes were the only ones who categorically rejected evacuation and exhibited low confidence in weather forecasts. This suggests a potential link between positive emotions, risk perception, and decision-making in high-impact scenarios.

Furthermore, focusing solely on storm categories fails to address the varied anxieties of individuals facing hurricanes. Our study found that most participants prioritized threats beyond wind, with concerns about flooding, tornadoes, and storm surge dominating their anxieties. Overreliance on wind speed as the primary risk indicator overlooks the multifaceted nature of these events, leaving individuals with specific concerns feeling uninformed and unprepared. This highlights the need for communication strategies that move beyond category labels and provide comprehensive, localized information addressing the diverse spectrum of hurricane threats and individual risk perception.

Additionally, individuals with extensive hurricane experience, as documented by Dow and Cutter (2000) and Taylor et al. (2009), often leverage their personal knowledge and past encounters to inform their evacuation decisions. This was evident in our study, where participants' confidence in weather forecasts influenced their responses to evacuation recommendations. The two participants who rejected evacuation expressed low trust in forecasts, potentially indicating a reliance on their own accumulated knowledge as the primary decision-making factor.

10.5.2 Understanding and Application of the Saffir-Simpson Hurricane Wind Scale

The SSHWS, intended as an informative guide, can unintentionally act as an anchor, influencing how individuals perceive hurricane severity and potential damage. This anchoring effect (Tversky and Kahneman 1974) was evident in our study, where participants' narratives revealed how past hurricane experiences across various categories significantly shaped their risk perception and subsequent actions.

Despite ongoing efforts to educate coastal residents about multifaceted hurricane threats, the SSHWS category often remains the dominant factor in risk perception, potentially leading to dangerous oversimplification (Camelo and Mayo 2021). This study, however, highlights a potential solution: diversifying risk indicators. Participants expressed positive responses to separate rating systems for both storm surge and rainfall/inland flooding, suggesting that such familiar formats could resonate with existing risk frameworks and bridge the gap between scientific information and public interpretation.

This research underscores the need for communication strategies that move beyond the sole reliance on the SSHWS. While separate flood warnings and products exist, they often fail to effectively engage the public during major storms (Carr et al. 2016). Utilizing familiar formats like separate ratings could enhance engagement and information retention, ultimately prompting preparedness actions tailored to specific threats beyond wind speed. By acknowledging the anchoring effects of the SSHWS and tailoring communication to resonate with existing risk frameworks, we can equip coastal communities with a more nuanced understanding of hurricane threats, leading to improved preparedness and resilience.

10.5.3 Public Reception of Alternative Scales

The efficacy of hurricane communication tools hinges on a delicate equilibrium between simplicity and comprehensiveness. The familiar SSHWS exemplifies this tension, offering readily accessible information while potentially underrepresenting diverse threats. Conversely, the TCSS provides a nuanced breakdown of individual risks like wind, surge, and rainfall, but its complexity raises concerns about accessibility for a broader audience. These contrasting reactions illuminate the need for hurricane communication tools tailored to various knowledge levels and information needs.

Further complicating the issue is the subjective nature of simplicity itself. While some participants lauded the HHI's straightforward 1–5 scale, others criticized its lack of clear reference points and unbounded nature. In contrast, the WSPDR's visual map and distinct wind/surge categories resonated with many, yet its decimal points and limitations in local information drew criticism. These diverse preferences necessitate an acknowledgement that “one size fits all” does not apply to hurricane

communication; effective tools must consider individual learning styles and prior knowledge.

Similar heterogeneity emerges in preferences for informational depth. Some participants valued the TCSS's comprehensive breakdown of threats, while others prioritized the WSPDR's focus on actionable guidance, such as evacuation zones. This suggests that individuals prioritize information differently depending on their risk perception and decision-making needs. During critical moments, some may prioritize easily digestible steps for immediate action, while others may crave a deeper understanding of the evolving threat landscape.

Beyond wind speed, participants' ideal hurricane scale information revealed a broader spectrum of concerns. Surge, rainfall, and even tornado risks ranked high on the list, highlighting a need for communication strategies that acknowledge the multifaceted nature of these storms. Additionally, suggestions for color-coding and clear explanations for complex concepts demonstrate a desire for accessibility and inclusivity in risk communication.

10.5.4 Overall Public Understanding of Hurricane Risks

The focus group participants demonstrated a high level of understanding of the SSHWS. They had a broad understanding of how the scale works, the windspeeds the categories represent, and they are able to apply their past experiences with hurricanes to understand the damage that may be caused by future storms. However, the dynamic nature of hurricane threats means that experience with a past storm may not apply to future storms.

10.5.5 Evaluation of Alternative Scales

The alternative scales introduced to the participants all had their strengths and weaknesses. Participants liked the separate metrics for wind, storm surge, and rainfall used by the TCSS, but they did not like that these metrics were combined into a single score, instead preferring that the individual ratings be presented separately. They also felt that the TCSS may be too confusing for the general public. However, the participants, as members of the general public, seemed to understand the scales presented and may be underestimating the intelligence of others. One participant, referring to the TCSS, said, "I like this scale. I think it's fantastic. I wish they would have been done sooner. But when you ask the question, is it easy for the general public or the public easy to understand, and sadly have to say, no, I don't trust the public."

When presented with the HHI, the participants did not like that most hurricanes fell in the range of 0.1 to 20.0. This indicates that the complex nature of the

calculation used to create this scale makes it difficult for the participants to visualize the damage it may cause.

When presented with the WSPDR, the participants liked the intensity map and the separate scales for wind and storm surge. However, some indicated frustration with the decimal points used by the scale.

10.5.6 Implications for Hurricane Communication

Focus group participants highlighted several key factors for effective hurricane communication. They expressed a strong preference for separate, easily interpretable metrics for wind, storm surge, and rainfall rather than a single scale that could lead to information overload. This aligns with research demonstrating that information overload can hinder decision-making under stress, potentially exacerbating risks during hurricanes (Phillips-Wren and Adya 2020). Familiar scales like 1–5, 1–10, or alphabetical systems were favored over numerical scales with decimal points, which were often misinterpreted as logarithmic. Color coding was suggested as a means to remember the order of the scale. Participants also sought transparency in the calculations used to construct hurricane scales, as understanding the underlying metrics is crucial for assessing the severity of threats. Finally, visual representations of storms, highlighting areas of peak threat, were highly appreciated, suggesting the value of using maps, charts, or other visual aids to enhance risk perception and facilitate decision-making.

These findings underscore the importance of audience-centered strategies in hurricane communication. Implementing separate metrics for wind, surge, and rainfall can mitigate information overload and provide clear, actionable information. Prioritizing familiar scales and transparent scale calculations can foster trust and understanding among diverse audiences. Utilizing visual representations of storm threats can make complex information more accessible and intuitive, empowering individuals to make informed decisions based on a comprehensive understanding of the risks they face.

10.5.7 Limitations and Future Research

While this study offers valuable insights into how the public perceives hurricane scales and communication strategies, it is important to acknowledge potential limitations that can guide future research directions. Firstly, the study examined only three of the various proposed hurricane scales. While this selection facilitated a thorough examination of various features and their influence on participants' understanding, exploring a broader range of available scales could provide a deeper understanding of public preferences and challenges related to hurricane scales. However, it is crucial to balance the number of scales presented with potential

participant overload and fatigue, which can hinder both data quality and participant recruitment.

One key limitation lies in the potential for sampling bias. While efforts were made to recruit participants residing in Florida, the possibility remains that some individuals in earlier focus groups may have come from outside the state. This introduces a geographic bias, as local risk perceptions and concerns might not be adequately captured. Additionally, relying on social media for recruitment likely excluded individuals with limited technological access. Furthermore, reposts by prominent meteorologists may have attracted participants with more specialized knowledge than the general public, introducing bias towards those with a pre-existing understanding of weather forecasting. Finally, self-selection bias is a possibility, as those who have experienced hurricanes firsthand or have a keen interest in the weather might have been more likely to participate despite efforts to recruit a diverse sample.

The inherent vulnerability of focus groups to groupthink (Cyr 2017) was also observed in this study. For instance, the two participants who expressed reluctance to evacuate came from the same group, potentially indicating influence and shared opinions. Additionally, some homogeneity within responses within other groups suggests further exploration of factors contributing to group dynamics and their impact on data interpretation.

Looking ahead, several promising avenues for future research emerge. One priority could be further refining hurricane scale design. Conducting targeted usability testing with diverse participants could inform the development of scales tailored to specific needs and preferences, ultimately enhancing clarity, accessibility, and effectiveness. Additionally, based on the insights gleaned from this study, developing, and testing a new hurricane scale format could provide valuable feedback and help identify optimal communication strategies. This could involve piloting different scale designs with representative samples to assess their impact on risk perception and decision-making.

Furthermore, investigating the cognitive and psychological factors influencing individuals' interpretation of hurricane information, alongside cultural and regional variations, could offer further insights into effective communication strategies. Finally, combining focus group findings with complementary data sources such as surveys, interviews with emergency response personnel, and analyses of social media data can provide a more comprehensive understanding of public perception and communication effectiveness.

By acknowledging these limitations and proposing these future research directions, we can strengthen the overall research contribution and encourage further exploration of public engagement and improved hurricane communication strategies. Ultimately, this can lead to more effective communication of risk during these potentially devastating events, enhancing preparedness and potentially saving lives.

10.6 Conclusions

Human responses to hurricane threats extend far beyond the simplistic models typically employed in risk assessment. This research demonstrates the complex interplay of emotions and cognitive factors shaping evacuation decisions. Moving beyond fear and anxiety, a spectrum of emotions, including excitement, exhilaration, and even curiosity, influences how individuals respond to hurricane threats.

The Saffir-Simpson Hurricane Wind Scale (SSHWS), while widely recognized, presents a narrow view of hurricane risks by focusing solely on wind speed. Our research reveals that individuals prioritize a broader range of threats, including flooding, tornadoes, and storm surge directly impacting their evacuation decisions. This emphasizes the need for communication strategies that move beyond wind-based categories and provide comprehensive information reflecting the diverse threat landscape individuals face. Separate rating systems for wind, surge, and rainfall, offering familiar formats and bridging the gap between scientific data and public comprehension, hold promise in fostering informed evacuation choices.

Effective hurricane communication faces the challenge of balancing simplicity and comprehensiveness. While readily accessible information is crucial, oversimplification can be misleading. Our research identifies diverse reactions to various scales, from appreciation for detailed breakdowns of individual threats to discomfort with unbounded complexity. This indicates the need for a varied toolkit of communication tools tailored to different knowledge levels and information needs. Similarly, preferences for informational depth vary, ranging from immediate action steps to a deeper understanding of evolving threats. Recognizing this heterogeneity demands communication strategies that adapt to individual risk perception and decision-making styles, ensuring everyone receives relevant information in a readily understandable format.

This research advocates for audience-centered hurricane communication strategies. Empowering individuals with separate, interpretable metrics for wind, surge, and rainfall combats information overload and equips them with actionable knowledge. Familiar scales, transparent calculations, and intuitive visual representations of storm threats can foster trust, understanding, and informed decision-making. Acknowledging the inherent subjectivity of risk perception necessitates diverse communication tools and personalized information delivery, ensuring everyone feels heard, understood, and prepared.

While this study sheds light on the complexities of human responses to hurricanes, it also recognizes its limitations. Potential sampling bias, groupthink within focus groups, and the need for further investigation into cognitive and cultural influences on risk perception point towards promising avenues for future research. Refining hurricane scale design, conducting targeted usability testing, and piloting new communication formats can pave the way for more effective outreach strategies. Combining focus group findings with complementary data sources can further enrich our understanding of public perception and communication effectiveness.

By acknowledging limitations and embracing the potential for new knowledge, this research aims to be a catalyst for ongoing research and refinement of hurricane communication strategies. Through this collaborative effort, we can empower individuals, enhance preparedness, and ultimately save lives in the face of these powerful natural hazards.

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Appendix

Appendix I Materials Presented to Participants

A. Focus Group Flyer Distributed Via Social Media

**Virtual Focus Group Volunteers Needed
for a Research Study Entitled**

**An Investigation of Alternative
Hurricane Intensity Scales**

We Need Your Opinion We are looking for Florida residents who are over 18 to give their opinions on hurricane awareness. We are trying to gauge the effectiveness of information given to the public when a hurricane is approaching.	What Will Happen? You will participate in a 45-60 minute meeting via google meet. You will be asked to share your experiences with previous hurricanes and asked to evaluate new hurricane scales. There are no right or wrong answers to the questions asked.	What's in It for me? We are offering a \$20 digital Walmart, Target, or Publix gift card as compensation for your time. Interested? Please email hurricaneresearchstudy@gmail.com for more information.

USF Study Number 003858



UNIVERSITY of
SOUTH FLORIDA

B. Slide: Understanding Tropical Cyclones**Hurricanes**

The purpose of this focus group is to discuss hurricane scales that relate to hurricane strength and related damage potential. A hurricane is a large storm that can impact millions of people with winds above 74 mph. The winds push ocean waters that create a storm surge that could reach 30 feet above normal water levels as a storm moves onshore. Hurricanes also dump rain that could add up to over 30 inches during the several days event. Tropical storms are like hurricanes but have lower wind speeds.

C. Slide: Explaining the SSHWS**The Saffir Simpson Hurricane Wind Scale**

When a hurricane is approaching, forecasters assign it a number using the Saffir-Simpson Hurricane Wind Scale. These numbers go from category 1 through 5 and are meant to help you understand how dangerous a storm might be. You have probably seen these numbers used on the news. A tropical cyclone is a generic name, used around the world, for a hurricane or the weaker tropical storm.

D. Slide: Clarifying the SSHWS

The Saffir-Simpson Hurricane Wind Scale

The scale that is currently used is called the Saffir-Simpson Hurricane Wind Scale.

It categorizes hurricanes from 1-5 based on their maximum wind speed.

Category	Wind Speed	Type of Damage
1	74-95 mph	Some Damage
2	96-110 mph	Extensive Damage
3	111-129 mph	Devastating Damage
4	130-156 mph	Catastrophic Damage
5	157 mph and above	Catastrophic Damage

E. Slide: Explaining the Concept of Alternative Hurricane Scales

Information About Alternate Scales

Some researchers have concerns that the Saffir-Simpson scale that is used now does not provide enough information about hurricanes.

Some hurricanes have low Saffir-Simpson categories, but they can still cause a lot of damage and deaths because of flooding from rainfall and storm surge.

Storm surge is water pushed onto the coast from a hurricane.

These researchers have come up with their own scales that take these other factors into account.

F. Slides: Introducing the TCSS

The Tropical Cyclone Severity Scale

One of these scales is the Tropical Cyclone Severity Scale. Storms are classified based on their wind speed, storm surge, and how much rain the storm will bring.

Category (Wind)	Wind Speed
0	Below 24 mph
1	24-95 mph
2	96-110 mph
3	111-129 mph
4	130-156 mph
5	Above 156 mph

+

Category (Surge)	Storm Surge
0	Below 2 ft
1	2-5 ft
2	5-7 ft
3	8-9 ft
4	10-11 ft
5	Above 11 ft

+

Category (Rainfall)	Accumulated Rainfall
0	Below 4 in
1	4-10 in
2	10-17 in
3	17-23 in
4	23-30 in
5	Above 30 in

Final Storm Category (0-6)

The Tropical Cyclone Severity Scale

Each of the storm hazards have their own category. These are combined using a special formula into a final category for the storm that can go from 0-6.

Category (Wind)	Wind Speed
0	Below 24 mph
1	24-95 mph
2	96-110 mph
3	111-129 mph
4	130-156 mph
5	Above 156 mph

+

Category (Surge)	Storm Surge
0	Below 2 ft
1	2-5 ft
2	5-7 ft
3	8-9 ft
4	10-11 ft
5	Above 11 ft

+

Category (Rainfall)	Accumulated Rainfall
0	Below 4 in
1	4-10 in
2	10-17 in
3	17-23 in
4	23-30 in
5	Above 30 in

Final Storm Category (0-6)

The Tropical Cyclone Severity Scale

For example, Hurricane Katrina was a category 3 storm using the Saffir-Simpson scale when it hit New Orleans, but the storm surge accompanying the storm caused a lot of damage and many people died in the floods. Using the Tropical Cyclone Severity Scale, Katrina would have been rated a 3 for wind, a 5 for storm surge, and a 2 for rainfall, with a final rating of a Category 5.

Category Number	Wind Speed
0	Below 15 mph
1	16-30 mph
2	31-50 mph
3	51-70 mph
4	71-90 mph
5	Above 90 mph

Category Number	Storm Surge
0	Below 2 ft
1	2-3 ft
2	3-5 ft
3	6-8 ft
4	10-14 ft
5	Above 14 ft

Category Number	Rainfall Amount
0	Below 4 in
1	4-10 in
2	10-15 in
3	15-25 in
4	25-30 in
5	Above 30 in

Final Storm Category (0-6)

G. Introducing the HHI

The Hurricane Hazard Index

Another proposed scale is the Hurricane Hazard Index. It rates hurricanes based on their wind speed, how far winds extend from the center, and how fast the hurricane is moving. A larger storm will have a higher rating than a smaller storm because it has the potential to cause more damage over a larger area of the coast. A faster moving storm will have a lower rating than a slower storm because it has less time to cause flooding from rain and storm surge. The scale uses decimal points and has no upper limit to its values, but most hurricanes would be in the range of 0.1-20.0, with a 0.1 storm not causing much damage and a 20.0 storm causing catastrophic damage.

The Hurricane Hazard Index

Using the same example as before, Hurricane Katrina was a category 3 storm when it hit New Orleans using the Saffir Simpson Scale; but was rated a 19.3 at landfall using the Hurricane Hazard Index.

H. Introducing the WSPDR

Wind and Surge Potential Destruction Ratings

The final proposed scale is the Wind and Surge Potential Destruction Ratings. This is actually two scales.

One estimates how much destruction might be caused by wind from a hurricane, while the other estimates how much destruction might be caused by storm surge.

The researchers use a computer model to calculate how much energy is in a hurricane using the speed of the surface winds and how far from the center the winds extend.

This energy is released on land in the form of wind and acts on the ocean causing storm surge.

Wind and Surge Potential Destruction Ratings

This is a map of Hurricane Katrina's wind field.

To calculate the energy of the storm, the researchers draw a grid over the storm, calculate the energy in each cell, then calculate how much structural damage or storm surge might occur from that energy.

This provides a sort of map of potential destruction from each part of the storm as it approaches and passes over the coast.

The numbers for the whole storm are then added up and then rated from 0.1 to 5.9 for both wind damage and the wave and storm surge impacts.

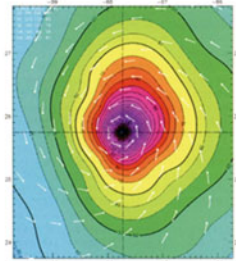
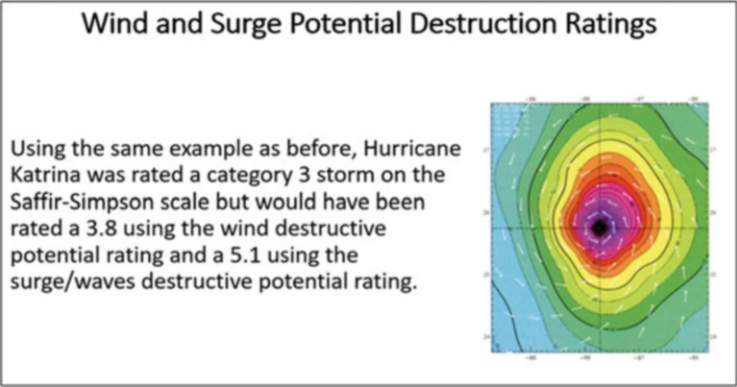


Image: Powell, M. D., & Reinhold, T. A. (2007). Tropical Cyclone Destructive Potential by Integrated Kinetic Energy. Bulletin of the American Meteorological Society, 88(4), 513–526. <https://doi.org/10.1175/BAMS-88-4-513> © American Meteorological Society. Used with permission.



I. Example of a Question Slide Used During Questions Comparing the Different Scales

Concluding Questions

1. Do you think any of these new scales is an improvement over the Saffir-Simpson Hurricane Scale?

Saffir Simpson Hurricane Wind Scale (currently in use)

Category	Wind Speed	Type of Damage
1	74-95 mph	Some Damage
2	96-110 mph	Extensive Damage
3	111-129 mph	Devastating Damage
4	130-156 mph	Catastrophic Damage
5	157 mph and above	Catastrophic Damage

Hurricane Hazard Index

- Uses speed of storm
- Scale from 0.1 – 20.0+

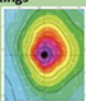
Tropical Cyclone Severity Scale

Category	Wind Speed	Category	Wind Speed	Category	Wind Speed
1	74-95 mph	2	96-110 mph	3	111-129 mph
4	130-156 mph	5	157-179 mph	6	180-210 mph

Final Storm Category (0-6)

Wind and Surge Potential Destruction Ratings

- Two separate scales for wind and storm surge
- Each scale ranges from 0.1 to 5.9



Appendix II Focus Group Script

The purpose of this focus group is to discuss hurricane scales that relate to hurricane strength and related damage potential. A hurricane is a large storm that can impact millions of people with winds above 74 mph. The winds push ocean waters that create a storm surge that could reach 30 feet above normal water levels as a storm moves onshore. Hurricanes also dump rain that could add up to over 30 inches during the several days event. Tropical storms are like hurricanes but have lower

wind speeds. When a hurricane is approaching, forecasters assign it a number using the Saffir-Simpson Hurricane Wind Scale. These numbers go from category 1 through 5 and are meant to help you understand how dangerous a storm might be. You have probably seen these numbers used on the news. A tropical cyclone is a generic name, used around the world, for a hurricane or the weaker tropical storm.

Prior Experiences with Hurricanes/Tropical Storms

1. What are your experiences with tropical storms or hurricanes?
 - (a) What city did you (or your friend/family member) live in when you had that experience?
2. How do tropical storms and hurricanes make you feel?
3. What effects of a hurricane or tropical storm most concern you?
4. Do you live in a flood zone?
5. Has your home ever flooded?
6. Are you concerned that your house might be flooded in the future?
7. Have you ever had any property damage from a tropical storm or hurricane?
8. Have you ever evacuated because of a tropical storm or hurricane?
9. How do you prepare for a hurricane?
10. Have any of your friends or family experienced tropical storms or hurricanes?
11. Do you know anyone who has evacuated from a hurricane or tropical storm?
12. Think back to the last tropical storm or hurricane you can remember. What information did you receive about the storm?
13. Where do you look to receive information about a hurricane or tropical storm?
14. Do you feel like you had enough information about the storm and how it would affect you?
15. Did you evacuate or stay at home during the storm?
16. Did the information you received influence your evacuation decision for this storm?
17. What additional information would have been helpful?
18. Do you trust weather forecasting?

Prior Knowledge of Hurricanes/Tropical Storms

1. What can you tell me about hurricane categories?
2. What category does a hurricane need to be before you become concerned about it?
3. Would you evacuate if a hurricane or tropical storm was heading towards your area?
4. What conditions need to be met in order for you to consider evacuation?
5. How important is the official category of the storm when you are considering evacuation?
6. What other factors do you consider when deciding whether or not to evacuate?

The Saffir-Simpson Hurricane Wind Scale

The scale that is currently used is called the Saffir-Simpson Hurricane Wind Scale. It categorizes hurricanes from 1–5 based on their maximum wind speed.

Show graphic:

Category	Wind Speed	Type of Damage
1	74-95 mph	Some Damage
2	96-110 mph	Extensive Damage
3	111-129 mph	Devastating Damage
4	130-156 mph	Catastrophic Damage
5	157 mph and above	Catastrophic Damage

1. How familiar are you with the Saffir-Simpson Hurricane Wind Scale?
2. Have you ever seen a chart similar to this one?
3. How useful do you find these categories?
4. Do you think this scale gives you enough information?
5. What other information do you think a hurricane scale should take into account?

Information About Alternate Scales

Some researchers have concerns that the Saffir-Simpson scale that is used now does not provide enough information about hurricanes. Some hurricanes have low Saffir-Simpson categories, but they can still cause a lot of damage and deaths because of flooding from rainfall and storm surge. Storm surge is water pushed onto the coast from a hurricane. These researchers have come up with their own scales that take these other factors into account.

The Tropical Cyclone Severity Scale

One of these scales is the Tropical Cyclone Severity Scale. Storms are classified based on their wind speed, storm surge, and how much rain the storm will bring.

Show graphic:



Each of the storm hazards have their own category. These are combined using a special formula into a final category for the storm that can go from 0–6.

For example, Hurricane Katrina was a category 3 storm using the Saffir-Simpson scale when it hit New Orleans, but the storm surge accompanying the storm caused a lot of damage and many people died in the floods. Using the Tropical Cyclone Severity Scale, Katrina would have been rated a 3 for wind, a 5 for storm surge, and a 2 for rainfall, with a final rating of a Category 5.

1. Do you think this scale is easy for the public to understand?
2. How do you feel about having different categories for wind, storm surge, and rainfall?
3. Do you have any concerns about this scale?
4. What do you like about this scale?
5. How useful do you think this scale would be?

The Hurricane Hazard Index

Another proposed scale is the Hurricane Hazard Index. It rates hurricanes based on their wind speed, how far winds extend from the center, and how fast the hurricane is moving. A larger storm will have a higher rating than a smaller storm because it has the potential to cause more damage over a larger area of the coast. A faster moving storm will have a lower rating than a slower storm because it has less time to cause flooding from rain and storm surge. The scale uses decimal points and has no upper limit to its values, but most hurricanes would be in the range of 0.1–20.0, with a 0.1 storm not causing much damage and a 20.0 storm causing catastrophic damage.

Using the same example as before, Hurricane Katrina was a category 3 storm when it hit New Orleans using the Saffir Simpson Scale; but was rated a 19.3 at landfall using the Hurricane Hazard Index.

1. Do you think this scale is easy for the public to understand?
2. Do you have any concerns about this scale?
3. What do you like about this scale?
4. How useful do you think this scale would be?

Wind and Surge Potential Destruction Ratings.

The final proposed scale is the Wind and Surge Potential Destruction Ratings. This is actually two scales. One estimates how much destruction might be caused by wind from a hurricane, while the other estimates how much destruction might be caused by storm surge. The researchers use a computer model to calculate how much energy is in a hurricane using the speed of the surface winds and how far from the center the winds extend. This energy is released on land in the form of wind and acts on the ocean causing storm surge.

Show graphic:

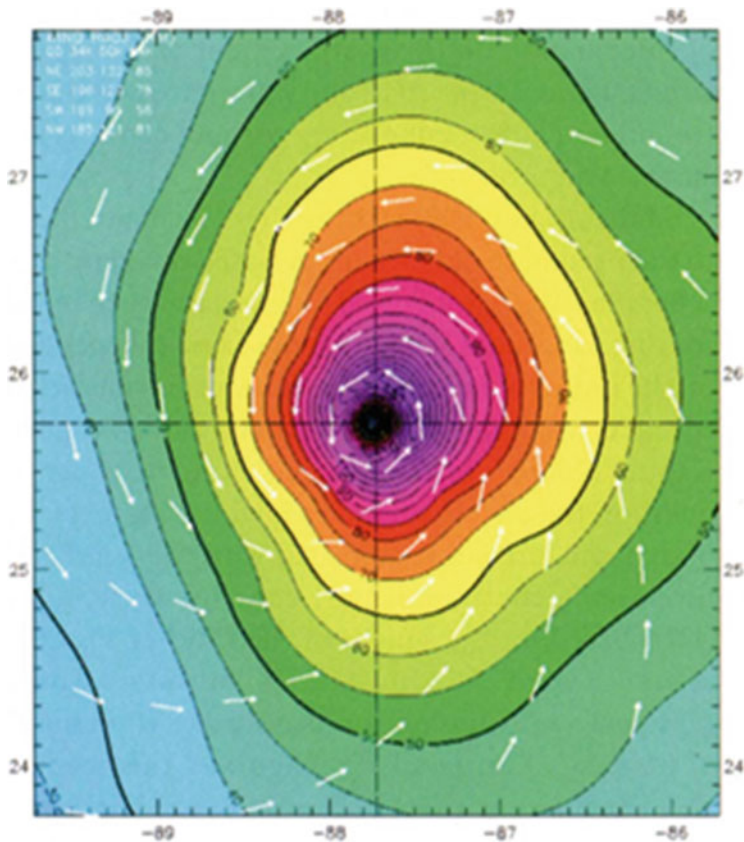


Image: Powell, M. D., & Reinhold, T. A. (2007). Tropical Cyclone Destructive Potential by Integrated Kinetic Energy. *Bulletin of the American Meteorological Society*, 88(4), 513–526. <https://doi.org/10.1175/BAMS-88-4-513> © American Meteorological Society. Used with permission.

This is a map of Hurricane Katrina’s wind field. To calculate the energy of the storm, the researchers draw a grid over the storm, calculate the energy in each cell, then calculate how much structural damage or storm surge might occur from that energy. This provides a sort of map of potential destruction from each part of the storm as it approaches and passes over the coast. The numbers for the whole storm are then added up and then rated from 0.1 to 5.9 for both wind damage and the wave and storm surge impacts.

Using the same example as before, Hurricane Katrina was rated a category 3 storm on the Saffir-Simpson scale but would have been rated a 3.8 using the wind destructive potential rating and a 5.1 using the surge/waves destructive potential rating.

1. Do you think this scale is easy for the public to understand?
2. Do you have any concerns about this scale?

3. What do you like about this scale?
4. How useful do you think this scale would be?

Concluding Questions

1. Do you think any of these new scales is an improvement over the Saffir-Simpson Hurricane Scale?
2. Which scale do you think is the easiest to understand?
3. Which scale do you think provides the most information?
4. Which scale do you find the most useful?
5. What other information should be included in a hurricane scale?
6. Some of these scales use decimal points. What are your thoughts on these scales that use decimal points versus scales that use whole numbers?

Appendix III Coded Answers to Focus Group Questions

TC Effects that most concern you	Wind	3
	Surge	3
	Property damage	2
	Falling trees	1
	Loss of power	1
	Flooding	2
	Tornadoes	1
How do TCs make you feel	Scared	8
	Excited	3
	Anxious	2
In flood zone currently	Yes	5
	No	9
Experienced flooding in past	Yes	4
	No	10
Property Damage	Yes	6
	No	3
Evacuated in the past	Yes	6
	No	6
Info Received Last TC	Category	4
	Spaghetti plots	2
	Path	3
	Speed	1
	Windspeed	3
	Amount of rain	1
	Storm surge	2
	Cone of uncertainty	1
	Flooding	1
	Tornado threat	1

(continued)

Information Sources	Internet	4
	Local news	9
	Friends	1
	NOAA/NWS website	2
	Weather app	1
	Social media	2
	Local government website	2
	Weather channel	2
Did you have enough information during the last TC?	Yes	9
	No	1
Do you trust weather forecasting?	Yes	14
	No	2
	Maybe	2
Category when I become concerned	category 3	7
	category 1	1
	1 or 2	1
	category 2	1
	2 or 3	1
What conditions need to be met for you to evacuate	Mandatory evacuation order	3
	Risk of home flooding	1
	Category 3	1
	Category 4	1
	High category	1
	Direct hit of major hurricane	1
	Will never evacuate	5
Other factors considered before evacuating	Ground already wet, flooding	1
	Pets	2
	Family worried	1
	Traffic	2
	Enough time before landfall	1
	Afraid of losing property/life/family	1
	Trajectory of the storm	1
SSHWS	Familiar with SSHWS Scale/has seen chart of windspeeds	18
	Not familiar with SSHWS Scale/has not seen chart	1
	Can compare future hurricanes with past experiences based on the scale	2
What else should be included in SSHWS scale	rainfall	2
	high tide	1
	storm surge	3
	temperature	1
	how close storm is to next category	1
	better damage descriptions	1
	nothing	1

(continued)

TCSS	Requires too much education/too difficult to understand	6
	Should report only the individual ratings for wind, surge, rainfall	5
	Likes separate ratings	7
TCSS: Easy to understand	Yes	3
	Somewhat	3
	No	5
TCSS: What do you think about the separate categories	Likes	7
	Neutral	3
	Dislikes	1
HHI	Too complicated/difficult to understand	10
	Dislike the scale (1–20)	6
	Higher numbers would get more attention	2
	Useful for researchers	2
HHI: Easy to understand	Yes	2
	Somewhat	1
	No	9
WSPDR	Two numbers are confusing, should use a letter and a number	1
	Likes separate wind and surge ratings	9
	Do not like decimals	2
	Likes decimals, tell you if it is close to the next higher category	1
WSPDR: easy to understand	Yes	4
	Maybe	1
	No	11
Other info that should be included	speed of the storm	1
	location specific surge/wind/rainfall risk	2
	color coding of categories (i.e. red for 5)	1
	rainfall and inland flooding	2
	tornado threat	1
	storm surge	2
	Information after the storm (i.e. when it is safe to go back, the level of damage in neighborhoods)	1
Decimal points in general	Like	2
	Dislike	9
	Makes them think it's logarithmic	3
Are any of these scales an improvement over SS?	TCSS	7
	WSPDR	3
	HHI	1
Which of these scales is the easiest to understand?	TCSS	1
	SS	6
	WSPDR	2

(continued)

Which provides the most information/is most useful?	TCSS	4
	WSPDR	4
What other information should be included in a hurricane scale? (second asking)	wind	1
	rain	2
	surge	3
	forward speed of storm	1
	color coding of categories	1
	tornado	1

Appendix IV TCSS Final Storm Rating Adapted from Bloemendaal et al. 2021

The TCSS aggregates its scores for wind, rain, and surge into one overall category for a given hurricane. To come up with this final category, the following process is followed:

- 1. **Categoryization:** Each hazard (wind, storm surge, precipitation) is assigned a category based on its intensity using a specific scale (e.g., Category 1 wind, Category 3 surge).
- 2. **Weighting:** These categories are then weighted to account for the varying impacts of different hazards.
- 3. **Score Aggregation:** The weighted values for each hazard are added together.
- 4. **Final Category:** Based on the total score, a final storm category is assigned using a predetermined scale.

Table IV.1 TCSS Rescaling Values. Adapted from Bloemendaal et al. 2021.

Category of hazard	Rescaling value
5	40
4	20
3	9
2	2.5
1	0.5
0	0

Table IV.2 TCSS final category determination. Adapted from Bloemendaal et al. 2021

Final category	Sum of rescaling values
6	≥ 80
5	40–80
4	18–39
3	9–17

(continued)

Final category	Sum of rescaling values
2	2.5–8
1	0.5–2.4
0	< 0.5

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Chapter 11

A Climate Change Paradigm and Its Effects on Emergency Operations Center Decision-Making Process



Kesley J. Richardson

Abstract The correlation between climate change and its impacts on hurricane risk has also impacted the decision-making process of emergency managers, Emergency Operations Centers (EOCs), and elected officials at every level of government. This correlation between meteorologists, for example, and multi-jurisdictional cooperation at all levels of government drives decision-making for all within the context of hurricane risk. This paradigm has been reflected in case studies and training to enhance the capability of professionals using emergency decision-making processes with ever-developing disasters while maintaining working capability under mental distress. The findings in this chapter are intended to identify hurricane risk through the lens of climate change and introduce its impacts on emergency management professionals and managers operating in the ever-evolving disaster management space. This understanding of the complexities of disaster and emergency decision-making not only has to improve for the practitioner continuously but also be translatable and understood by the elected officials who grant delegation of authority (DOA), that provide resources and personnel and finally impacts the ability and capability of Emergency Management Departments (EMDs) and organizations within their jurisdiction. Improving the decision-making process and supporting the whole community and its stakeholders promotes safety, reduces loss of life, and enhances EOC operations at various levels.

Keywords Climate Change · Decision-Making · Hurricane · Emergency Management

K. J. Richardson (✉)

School for Continuing and Professional Studies, Loyola University of Chicago,
Chicago, IL, USA

e-mail: Krichardson8@luc.edu

11.1 Introduction

Within Emergency Management (EM), often at the local, state, and federal levels, a disaster or incident is managed within an Emergency Operations Center (EOC). The EOC is a central location from which government at all levels can provide interagency collaboration, coordination, and communication with the support of executive decision-making entities (FEMA 2021, p.5). This type of location as a planning and operational hub can vary from a Departmental Operational Center (DOC) to a State Emergency Operational Center (SEOC), amongst other terms, but serving the same purposes. Within these operational centers, decision-making occurs in one of two methods: directly from executive leadership or by Delegation of Authority (DOA). The EOC is traditionally a community's EM organization for core operational locations where identified EM staff would work in operational periods to support the community through planned events, incidents, and disasters. Due to the impact of climate change, stronger storms, more frequent flooding, and compound effects have developed, which are not only by-products of climate change but also inadvertently impact emergency decision-making. The EOC shares a variety of capabilities dependent on the community or jurisdiction upon which the facility and organization are located. As a standard, this facility is where elected officials collaborate to decide on resources and actions to deal with various hazards and threats to their community that are larger than a single department. The local emergency management team and director advise these elected officials on the current situation with as much relevant data that can be consolidated from subject matter experts (SMEs). From here, actions are issued to mitigate property damage, preserve life, and stabilize the incident. EOC preventative actions in the preparedness and prevention phases can aid in lessening the stress on decision-making processes in an emergency. They can also be revisited in the mitigation phase of the emergency management process. However, preemptive or preventative actions are supported, compared to reactionary response actions during emergency decision-making (Raikes and McBean 2016). This is based on the premise that EOCs operate with the same resources, experienced personnel, and capacity, which is rarely the reality faced by EOCs.

Within the EOC, decisions are being made from evacuation for jurisdictions to preventative actions and operational decisions at various levels of activations. Decisions from activation to how to inform the public and what collective efforts to take based on the specific hazard have a variety of decision points that would occur within the EOC. These decisions have various processes and paths that significantly impact or gravitate to the decision-making process and high-stake consequences. Some of these processes are based on existing decision-making practices in other disciplines, such as law enforcement or fire, and can be applied to emergency management scenarios. Within emergency management, there has been research on emergency decision-making (EDM) and its potential effectiveness in the natural disaster field (Zhou et al. 2018). EDM can be a possible approach to the adjustments required to keep up with the increased frequency of storms and damage

from storms manifested by extreme weather associated with climate change. With the increased frequency of disasters such as floods and hurricanes, climate change continues to impact the correlation of disaster growth, which leads to more significant impactful events and higher pressure in the decision-making process. The impacts of time-sensitive decisions depend on the type of disaster, population density, and critical infrastructure in its path. The decision-making process can extend to 120 h in the case of a hurricane or minutes to hours in the case of flash flooding. Regardless of the time and decision-making process, it is influenced by the induced stress of the impending incident in an emergency (Kowalski-Trakofler et al. 2003).

The Gap in research to be addressed by this chapter is the decision-making process within the EOC. This is not limited to the effects of the stress of disasters and incidents faced by decision-makers within the EOC. This is relevant because there are bodies of work around decision-making and its science and even research within first responders for on-scene incidents. Still, more needs to be found within emergency management, EOCs, and the impacts of decision-making with the developing complexities of climate change. The gap between what is described as a theory-driven and research-driven approach by Gooden mentioned a 5-point logic model viewing the planned work and the intended results (Gooden and Berry-James 2018). This difference can be associated with the work and literature expansion on hurricane risk and the impacts on emergency management, particularly EOCs and decision-makers.

11.2 Materials and Methods

This methodological literature review or systematic secondary research will summarize current and state-of-the-art practices and information in climate change, decision-making, and emergency management. This approach was chosen to leverage the existing work on decision-making and emergency management within the context of hurricanes, climate change, and the developing impacts. By systematically reviewing established work and summarizing the current practices to support the developing implications of climate change on disasters (hurricanes) while incorporating the managers of disasters operating within an Emergency Operations Center (EOC). The data comprised literature reviews of emergency management doctrine, training manuals, and existing literature on emergency decision-making, EOCs, and management principles. Within the context of climate change, a focus on the chronological effects of climate change and its intersection with increasing natural disasters was a literary focus. The final area of observation and investigation was the connections in emergency organizational decision-making. This review aimed for practical inductive identifiers to the impacts of climate change on EOC decision-making by grounding in existing deductive methods.

11.3 The Impact of Climate Change on Hurricanes

Through the chronological development of hurricanes, their destructive power has been observed to have increased. The Environmental Defense Fund has noted some of these changes linked to hurricanes and their deadly force from the correlation of how warmer oceans fuel storms by increased evaporation, pulling in more vapor and heat (How Climate Change Makes Hurricanes More Destructive – Environmental Defense Fund [n.d.](#)). This is also not limited to the recorded sea level rise and its correlation to enhancing storm surges, as the sea level has already risen by half a foot since the early 1900s and nearly an additional four inches since 1970. These are just two examples of the cascading effects of climate change and the power it has given to hurricanes, increasing their risk, especially in areas that are prone to hurricanes, including but not limited to Florida, North Carolina, Alabama, Mississippi, and Louisiana (10 U.S. States Where Hurricanes Hit Most Often [2023](#)). Storms' strength and frequency impact communities faster than communities can recover from a previous storm. The best-case scenario is taking as long as 14 months for some form of recovery but can carry on to the length of 10–15 years (Build Fax Property History [2017](#)). This time frame, with the more frequent and consistent occurrences of stronger hurricanes every 12–14 months, often with more than one storm contacting a state at a time, can lead to more damage and longer recovery times. These impacts can become compounded and lead to families and lives being uprooted with no sign of normalcy returning before the next storm makes contact, increasing the risk associated with hurricanes in the southeast of the United States. The National and Central Pacific Hurricane Center has recorded the hurricane strikes on the United States by decade. This data shows forty-three major storms (category 3-5) between 1901 and 1970 and twenty-seven from 1971 to 2022 (U.S. Hurricane Strikes by Decade [n.d.](#)). This shows there are fewer major storms, but upon closer review of the data by the Department of Atmospheric Science during their tropical meteorology project located at Colorado State University, that between 2000 and 2022, in all categories within the data, there were more named storms (73), named storm days (252), hurricanes (8), hurricane days (7.75), major hurricanes (20), major hurricane days (70.25), and accumulated cyclone energy (461.1) in comparison to the collected data from 1970 to 1999 (North Atlantic Ocean Statistics Compared with Climatology [n.d.](#)).

Climate change as a natural climate variability is one of the largest sources of uncertainty within a risk context for climate projections (Terando et al. [2020](#)). This data is depicted in Figure one to show the growth of influence climate change is associated with hurricane activity (Hostetler [n.d.](#)). These variables impact meteorologists, the geoscience community, and all professions that leverage the accuracy of this information for taking preventative measures in mitigation and preparedness projects (Fig. [11.1](#)).

Graphs comparing modeled changes (orange line in panel A and blue line in panel B) and three independent estimates of observed changes (teal, red, and black lines in both panels) in the global annual mean air temperature since 1880. All the time series are presented relative

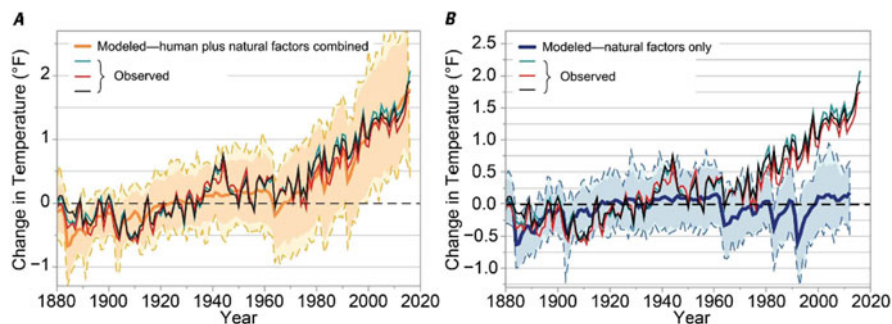


Fig. 11.1 Global mean temperature change from GyClimate.org

to the average temperature (in degrees Fahrenheit, °F) from 1901 through 1960. The temperature changes in panel A are from models that include both anthropogenic climate drivers (for example, greenhouse gases [GHGs], ground-level ozone, land use change) and natural climate drivers (for example, solar output, orbital variability, observed volcanic eruptions). In contrast, modeled temperatures in panel B include only the natural climate drivers. The thick orange and yellow curve (panel A) and thick blue curve (panel B) represent the mean across dozens of climate model simulations obtained from the coupled. Model Intercomparison Project Phase 5 (CMIP5; Lawrence et al. Laboratory, 2008). The shading indicates the standard deviation of all simulations. The outer dashed lines depict the absolute range of temperature differences across all simulations. Panel B shows that after about 1970, the observed global temperatures (green, orange, and black lines) diverged from the temperature simulated by the climate models, considering only natural factors (blue line). The consistency between the trajectory shape and magnitude of the modeled temperature changes and those of the observed temperature changes in panel A shows that the observed warming since 1970 is attributable primarily to anthropogenic factors. This modeled response of temperature to GHGs was produced by the earliest versions of climate models that were applied in the 1970s and continue to be built as the models have undergone significant refinements over the years by adding many more natural and anthropogenic drivers. Figures were adapted from the U.S. Geological Survey report field (Terando et al. 2020, p.5).

The increases in global temperature cause ice caps to melt at an accelerated rate, as well as warmer winds and warmer waters, which have been shown to correlate to increasing storm activity and strength scientifically. The details on hurricane strength will be reviewed in the next section to expand on the current storm risk classification.

11.4 Hurricanes and Their Increasing Impacts

As described by the Naval Air Station in northeast Florida, hurricanes serve as the largest installation in the Navy Region Southeast and identify five hurricane categories (Hurricane Categories n.d.). These categories range from one to five; the first category is winds from 74 to 95 miles per hour (mph). Category one storms can primarily damage shrubbery, tree life, and lightly constructed items such as

unanchored mobile homes. Category two contains 96 to 110 mph winds that can blow down trees, cause significant damage to lightly built items, and include storm surges of 6–8 feet above average sea level. The second category can also cause damage to piers and marinas in seaside or communities located around bodies of water where evacuations of some shoreline residences are recommended and required. Category three and up storms are identified as major hurricanes with winds from 111 to 130 mph, which can do more damage than category one and two storms, leading to destroyed mobile homes and structural damage to small buildings. Category three storms can produce a 9 to 12-foot storm surge with severe flooding on the coast, cutting off low-lying routes within nine to 10 h before the hurricane's arrival (Tropical Cyclone Climatology [n.d.](#)). This storm category can lead to major erosion of beaches and has recommended and required massive evacuation to all residents within five hundred yards of beaches and large bodies of water to two miles from shores. Category four major hurricane storms contain winds from 131 to 155 mph with extensive damage to roofing, windows, and doors and storm surges from 13 to 17 feet above normal sea levels. There can be major damage to lower floors near shores, debris accumulation, and chasing rising water 11 to 12 h before hurricane landfall.

Category five storms are the highest category of recorded major storms with winds greater than 155 mph, complete failure of structures, use of extensive sheltering, and storm surge larger than 18 feet with far greater evacuation recommendations at the exposure to 11–12 h before hurricane landfall. Figure 11.2 displays data collected between 1944 and 2020 on Atlantic hurricane activity, and Fig. 11.3 identifies Pacific basin hurricane activity from 1971 to 2020, presented by NOAA data and graphs. Finally, there has been news and conversation about establishing a category six storm with even larger identifiers, as recorded by The Palm Beach Post

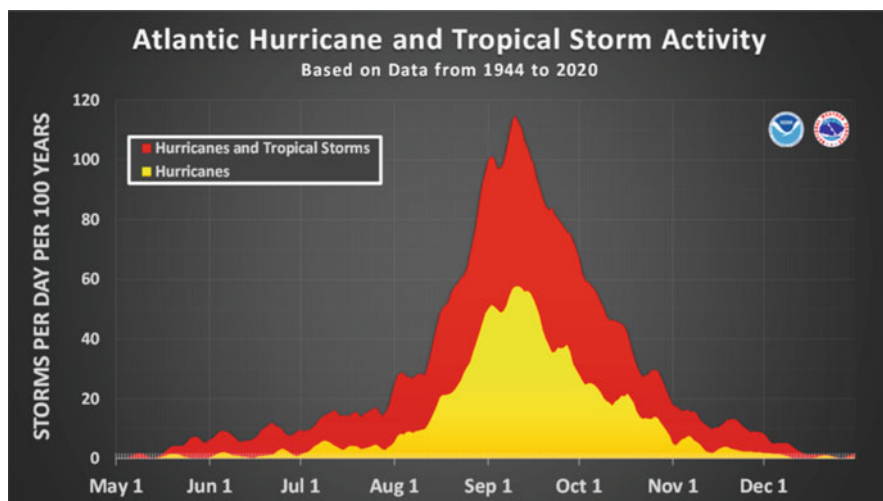


Fig. 11.2 Atlantic Hurricane and Tropical Storm Activity

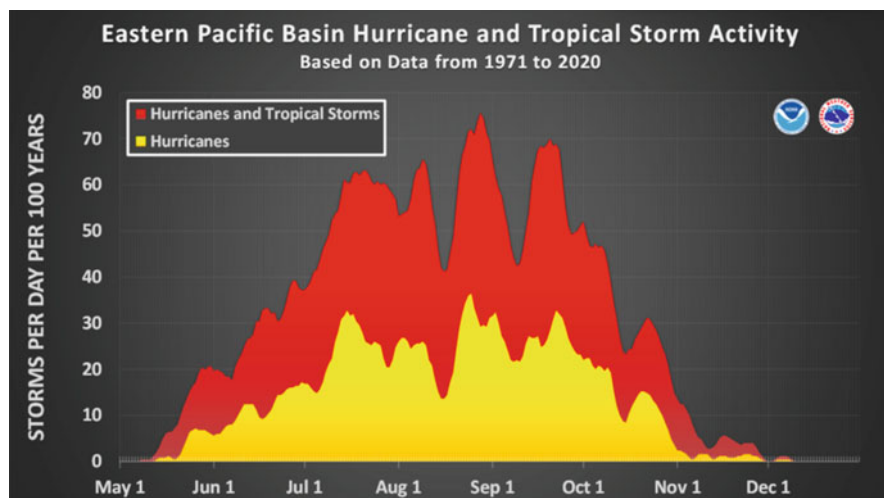


Fig. 11.3 Eastern Pacific Basin Hurricane and Tropical Storm Activity

of winds recorded at 180 mph to the Saffir-Simpson scale (Bridges 2023, p. 6). With the increased impacts of hurricanes throughout the United States and neighboring countries, the conversation of updating a wind scale created in the early 1970s could be one aspect of adapting existing tools to largely support a modern world with the cascading effects of climate change on disaster and hurricane risk. This is one of the various conversations that have implications for the capability of emergency management organizations, including but not limited to EOCs and decision-making processes in the face of hurricane risk. Hurricane Categories can affect decision-making based on the increasing climate change to hurricane impacts. This can be reflected when a category three storm has a more substantial effect, devastation, and damage to the affected community.

The increasing impacts of hurricanes from the frequency of named storms increases recorded damage.

11.5 Cascading After Effects of Hurricane and Storm-Based Impacts

After a hurricane or storm-based impact, there are after-effects and correlations to the presence of the storm within a given community. The National Hurricane Center describes such effects as storm surge, inland flooding, destructive winds, tornados, and high surf or riptides that can be associated with incoming hurricanes affecting a community (Hurricane Preparedness – Hazards n.d.). Storm surge is commonly associated with hurricanes and their impacts on coastal communities. However, even with this reality, the influence of connection to hurricanes and their surrounding

collective effects on storm surge is still up for debate and discussion in the literature (Camelo et al. 2020). Storm surge can range from 3 to 25 feet, and the inland encroachment varies based on location topography. This current data, in correlation with climate change factors, indicates that not only will there be more significant impacts by storms, but it will also lead to higher storm surge elevations as climate change continues to impact global temperatures (Snaiki et al. 2020). Storm surge is not the only cascading impact of hurricanes and storms; this can also include but is not limited to inland flooding, which impacts all communities at various levels depending on topography, mitigation efforts, drought, community vegetation, and inches of rainfall. Inland flooding can also impact EOC decision-making, like storm surges or any other identified after-effects of hurricanes and storm-based events.

Even with tools like HURREVAC (the most widely used decision-making support system for emergency managers), uncertainty about inland flooding can change with climate change and the implications of continued development into a community (Yang et al. 2019). The last of the water-based correlated impacts of hurricanes and storm-related events would be rip tides and high surf, which can lead to overtaking dunes and contributing to inland flooding. The conditions of rip tides and high surf can negatively impact individuals inclined to engage in water-related activities onshore and beachlines before storm landfall. As the documented average records indicate, the sea-level rise ranges from 1.2 to 1.7 mm per year over much of the twentieth century, with the anticipated continuation of sea-level rise with current climate change applications that can further impact communities in hurricane-prone and potential emergencies. (Griggs and Reguero 2021).

When the cascading effects are not water-related but wind-related, some impacts are associated with hurricane and storm-based natural disasters. Destructive winds by storms and hurricanes destroyed doors, windows, and forestry, moved cars, and threw boats from the water. This can be seen in association with increasing impacts from hurricanes, as depicted in the Journal of Structural Safety, where the dollar figure in connection with wind damage has increased. Between 1950 and 1989, the US averaged \$1.6 billion annually in damages, which increased between 1989 and 1995 to 6 billion dollars in hurricane damage and continues to rise (Bjarnadottir et al. 2011). Even with the increasing damages within the United States, there is a continued expectation for increases between climate change and coastal developments that can only be mitigated by reducing global emissions and exposure vulnerability to exposed communities (Dinan 2017).

From storm events and hurricanes, there is a phenomenon upon which individual storm clouds can spawn tornadoes as hurricanes make landfall and sometimes can occur several days after landfall. With the unpredictability of tornados, the approach to studying them to capture baseline information is challenging. Also, it extends to predicting tornados and their locations of impact concerning storm events and hurricanes. As research continues to expand and evolve with the increases in technology and research methods, more information on hurricane risk and the expanding cascading events that impact communities is available. Due to the effects of increasing climate-related disasters, agencies are encouraged to routinely adapt and update mitigation measures to counter the increasing risk. As the rising risk

complexity unfolds, the ability to mitigate the damage to life, property, and community is becoming a growing concern for researchers and practitioners alike. Whether water-based or wind-based, events and damage mitigation measures are constantly being proposed to lessen the unpredictable damage to life, infrastructure, and communities; as these methods and approaches continue to support communities and jurisdictions, the continued expansion of the interconnections between sciences and departments becomes more critical to the overall governance and networks needed to help people who live in locations with a high probability of risk.

11.6 Decision-Making Within the Emergency Operations Center (EOC)

Decision-making processes within the EOC during a variation of activation levels can differ based on the timeline associated with a particular hazard or disaster (flood, hurricane, tornado, unplanned event). Some disasters allow more intentional pre-planning, like hurricanes, in which notification can be monitored for around 48–120 h, but this does not apply to all disasters and hazards. For example, there can be anticipation for flooding based on historical data and rain estimation or shorter timelines like tornados where there is an area of contact, but less data on where, how severe the damage can be, and the duration of contact due to its unpredictable nature. One example of decision-making models within EOCs and emergency management within the developing profession is Emergency Decision Making (EDM). This model contains a general process, as seen in Fig. 11.4, previously shown in Tongji University’s work field (Su et al. 2022).

It allows for information to leave the EOC at various points in the decision process and for feedback modifications before, during, and after a hazard or incident. As data is collected and the problem definition and goal-setting process begins, the EOC is often aware of the probability of hazards taking place and affecting their community. Any particular project is isolated to the disaster at hand and applicable actions that would either prepare for, respond to, or assist in recovery. Or have the intentions to mitigate the loss of life, damage of property, and ability to stabilize an

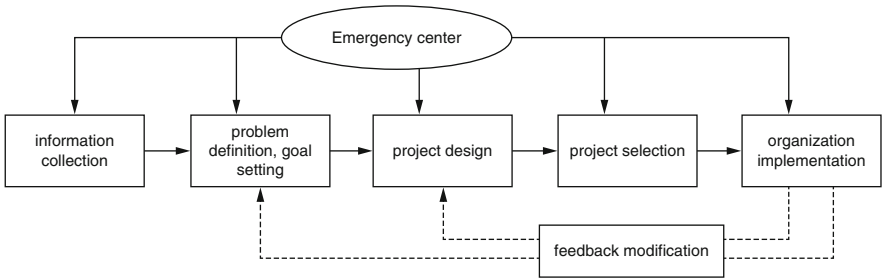


Fig. 11.4 General process of EDM

incident as effectively as possible under the circumstances. Upon implementation, methods of the set project or actions would follow the organization's existing implantation process across multiple departments, leveraging social networks and governance practice if there is a previous process or procedure to follow. The account of something unexpected that has never been seen before must also be taken into consideration as it will create new processes to adapt and adjust, as seen during the COVID-19 global pandemic or the conversations of potential scaling of a category six hurricane, which may include more extensive preparation or evacuation measures. At any point in the implantation process, feedback looks to project design or goal setting to the correct size, which is possible under the scope of available resources, structures, and personnel. At any point in the process, there is a desire for more information from the situation unit, which operates as a competent planning section within the EOC's operational framework to enhance the EDM process further. This is done by collecting and verifying information used in reports and briefs to leadership and key decision-makers.

Decision-making within the EOC can and is often at the liberty of the policy group or Multiagency Coordination Groups (MAC Groups), mostly comprised of agency administrators, executives, and elected officials. EOCs can also have a variation in makeup by being organized by the Incident Command System, Incident Support Model, Emergency Support Functions, Departmental Structure Model, Multiagency Coordination Group Model, Hybrid or Like Models. Based on the model utilized within an EOC can impact the decision-making process and influence the time taken to make a decision. Various decision pathways have been used within these groups as a policy-level body and source of multi-agency decision-making. One example is the phased decision-making employed by Lee County, Florida, which leverages a time-delineating schedule (Santier 1998) before the work by Wenxin Sue noted previously.

Please note that an in-person EOC or a virtual EOC operation can also affect the model, EOC Structure, or processes. This approach was identified to support an essential element of preserving life and property of the local jurisdiction by leveraging the ability to warn those in danger in time to carry out practical actions. Even though documented in 1998, this process is still a tactic Lee County EOC utilizes. This process is critical to appropriately taking emergency responses according to the community's hazards. This model was developed in 1982 by the Lee County Disaster Agency staff members and was initially designed for long-term risks such as hurricanes (Santier 1998). This decision-making model was identified as beneficial in any EOC and holds eight phases: awareness, stand-by, decision, preparation, evaluation, storm or disaster event, evaluation, and recovery. Within these eight phases, the decision-making process is in constant flux and impacted significantly by the amount of available and verifiable information at any given point and time. Also, within each of the phases, multiple points of information collection and decision-making processes move from one stage to the next or may also exist within more than one phase, as response and recovery actions can overlap based on the emergency management process and processes for any given EOC and government jurisdiction.

Along with this process, there are stressors to EOCs that drive decision-making, like time of the incident, duration of the incident, potential or received damage, life safety, and property preservation, all of which can have an impact on decision-making within an EOC and impact every engaged emergency manager. Many individual, organizational, and situational factors can influence this process, adding additional stressors to the EOC's ability to make effective decisions. One example of this can be reflected in the recovery phase of emergency management processes that begin at the onset of a disaster or incident but can continue for years post-disaster. It further broke down recovery into three functions: immediate emergency, restoration, and reconstruction phase, which now mirrors the recovery continuum shown in Fig. 11.5 below. These three functions are the cornerstone of the American approach to disaster recovery. Even though there is no in-depth breakdown of each phase, for this example, actions are associated with each phase and processes that can range from months to years for recovery for an impacted community. More on this continuum can be seen in the FEMA training course G-205 (One of many FEMA-based training courses that teach emergency managers the recovery process and areas of growth to support their organization's recovery approach) and the National Disaster Recovery Framework (Dept. of Homeland Security 2016, p.5).

Consequence management is a vital part of the decision-making process within an EOC and for Emergency Managers at every level of government. As there is values-driven decision-making, the five-step analytical approach process (identify the problem, explore alternatives, select an option, implement the solution, evaluate the situation), or understanding the impact of timing decisions and the processes need to be understood by all stakeholders to support productive and practical actions to maintain life safety, property management, and incident stabilization (FEMA 2021). The components are all being taken into consideration by the upper leadership within an EOC as every incident or disaster develops within their area of operation, and all impacted areas must be taken into consideration, even if they are extending across jurisdictional lines. In these cases, they are leveraging systems like

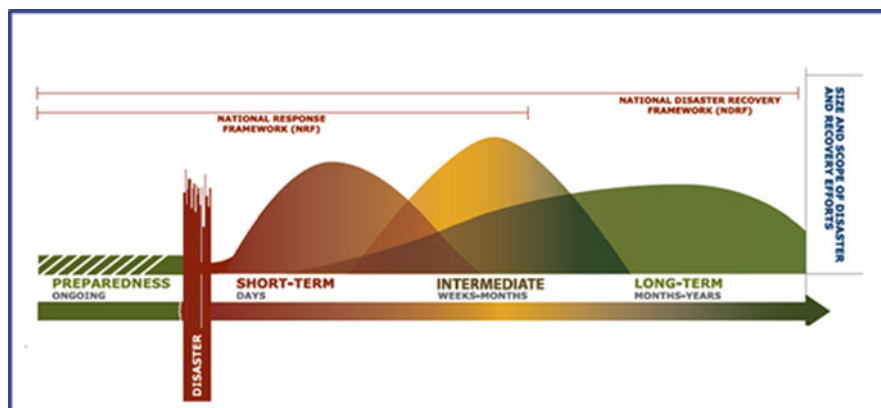


Fig. 11.5 National disaster recovery framework

Unified Command (UC) to operate and continue the same process, considering multiple governments collaborating, communicating, and coordinating emergency decision-making processes to support the safety of the affected areas. This must accurately capture the implications of each of the five steps regarding FEMA's analytical decision-making approach. The problem identification phase, like the goal-setting phase within the EDM, is where the decision process often begins within the emergency management conceptual framework. This framework can be impacted by political factors, shortages in resource funding, and, overall, by the jurisdiction's leadership the EOC is intended to serve.

As the exploration of alternatives occurs, the consequences and expected results are weighted to determine the most impactful solution. Based on the option selected, the implantation process takes time, funding, and personnel. The approaches within the previously mentioned EDM and the implementation and political implications associated with the recommended actions. A challenge within the emergency management and public administration community is this last part of the solution evaluation, where proper and accurate feedback for improvements and enhancements rarely leaves draft form to apply to organizations due to cascading political, job-associated, and organizational repercussions for performing anything other than exceptional. With the overwhelming number of factors from climate change impacts, organizational factors, political inputs, and the rising cost of disasters, attention to climate change in association with hurricane risk must be taken seriously.

11.7 Conclusion

Understanding not only the geological sciences between climate change and its implications for hurricane risk is essential, but it is also critical to consider the cascading stressors and implications for organizations that support communities by mitigating hurricane risk. This can be impacted by individual decision-making (from elected officials to community members) and community decision-making (considering sheltering versus evacuation, for example). The most critical aspect of a decision-making process is acquiring verified and factual data, including information that has perceived value to professionals and community members alike. This can be impacted by a variation of factors from the historical application of public administration organizations and their capability to deal with social, racial, economic, and administrative issues before the hurricane risk during hurricanes and after a hurricane to support the recovery of the prior normal or the new normal after storm implications. The complexities of communities are only expounded by the risk of hurricanes and other natural disasters that stress communities and organizations to their max with little opportunity to recover completely. This community and organization overlap at the EOC and its operation as most Emergency Managers operate and live within the community they serve. With there being studies on continued hurricane exposure and PTSD in communities like in Puerto Rico Field (Hodges et al. 2023) and that of first responders, there is room within the literature to

investigate the impacts of EOC or emergency manager decision-making post-continued exposure to disaster decision-making.

Throughout the research in this chapter, there are gaps and limitations to the literature, which revolves around concentrated research within the decision-making process and its evaluation for areas of improvement practically in the cross-section of emergency management and decision-making. This is limited to the first responders and community research on disaster impacts on decision-making and stressors, which has bodies of work to lend to this conversation, but not in particular to this intersection at length. Even with there being research in the space of decision-making as seen in the reflection of severe weather (Baumgart et al. 2008) and natural disasters, a recommendation to further research with a more direct review through the paradigm of emergency management. Hurricane risk is an impending issue in high-probability areas such as the coastal and southeastern United States, with the EOCs within these high-probability areas having more exposure to the impacts of evolving hurricane and landfall contact. This would be an area for continued research and exploration to further connect the concepts of hurricane risk, emergency management implications, and the connected areas of impact as an inter-connected organizational network upon which actions and collaborations are leveraged to mitigate hurricane risk throughout the US.

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