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ORIGINAL PAPER

Did adaptation strategies work? High fatalities from tropical cyclones in the North Indian Ocean and future vulnerability under global warming

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Abstract This paper examines the fatalities from tropical cyclones (TC) generated in the Bay of Bengal and the Arabian Sea making landfall in India, Bangladesh, and neighboring countries. In these locations, the number of TC fatalities, on average, far outnumbers those found in the rest of the world. Applying negative binomial models, we find that TC fatalities are explained by high TC intensity, storm surge, and low income. A one unit increase in TC intensity (1 hpa) on TC fatality is commensurate with the effect of a one unit increase in income per capita (1000 INR). We also show that income growth reduces TC fatality, in part, because it increases adoption of information-based adaptation measures. Based on these results, future fatalities are projected based on forecasts from eight climate models and two income scenarios. A key result is the interplay between future increases in cyclone intensity versus income. If hurricane intensity were to increase, as predicted by three of the seven climate models, fatalities are predicted to increase dramatically in the low-income scenario. However, if income grows at a faster rate, hurricane fatality is predicted to fall in all scenarios. Therefore, economic development remains an important policy variable to mitigate future impacts from global warming.

Keywords Tropical cyclone · Storm surge · North Indian Ocean · Fatality · Adaptation

1 Introduction

Tropical cyclones in the North Indian Ocean lead the globe in deadly impacts. Since 1990, more than 2000 fatalities occur, on average, for each tropical cyclone landfall across India, Bangladesh, and Thailand (IMD 2014a, b). Individual storms have led to more than

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130,000 fatalities (Guha-Sapir et al. 2015). This is in a stark contrast to the TCs making landfall elsewhere in the world. In the USA and Australia, where fatalities average in the dozens per storm, only a single storm—Hurricane Katrina in 2005—has caused more than 1000 lives lost since 1970. A key factor in explaining these differential impacts is income. While hurricane fatalities depend, in part, on the physical forces of the storm as well as adaptation measures to protect valuable assets in harm's way, income level is a key driver of adaptation, as income determines the choices of adaptation measures economically available for protection (Seo 2015).

In addition to current TC risks, climate change, due primarily to anthropogenic activities (IPCC 2014a), is expected to impact tropical cyclones via atmospheric and oceanic warming (NCEI 2015; NHC 2014; IPCC 2014b). These impacts include increased frequency of severe hurricanes in a warmer world (Emanuel 2005, 2013; Elsner et al. 2008; Knutson et al. 2010; Camargo 2013; Tory et al. 2013). Given the highly nonlinear relationship between economic damages and storm intensity—with damages scaling by as much as the 9th power of maximum wind speed—increasing storm intensity could greatly exacerbate losses over the coming century (Pielke et al. 2008; Nordhaus 2010). However, changes in hurricane activities are predicted to vary across oceans, as are the predicted changes in economic damages (Mendelsohn et al. 2012; Emanuel 2013; Seo 2014). In addition, differential rates of economic development may increase a nation's ability to adapt. Therefore, conditions in the future world must be carefully studied to understand future vulnerabilities under a changing world.

This paper analyzes current and future vulnerability to tropical cyclone fatalities, with special attention to the role of adaptation strategies made possible by income growth in the North Indian Ocean. The authors begin by examining the history of observed TCs to quantify the roles that adaptation strategies, as well as TC and socioeconomic factors, play in determining the magnitude of human fatalities across the Bay of Bengal and the Arabian Sea from 1990 to 2012 (See Figs. 1, 2). An array of negative binomial models is run to explain hurricane fatalities by TC intensity, income level, and other variables (Seo 2015; Bakkensen and Mendelsohn 2016). Probit models are run to explain the choice of information-based adaptation measures such as TC trajectory projection methods, TC surge models, and TC advisories (Seo 2015). This paper then examines changes in tropical cyclone activities due to global warming and the consequences of such changes in the North Indian Ocean, where hurricane-related death tolls are especially high and, therefore, is the region of greatest concern globally (Bakkensen and Mendelsohn 2016; Seo 2015). Future TC projections under various scenarios of climatic changes are obtained from the Emanuel's work (Emanuel et al. 2008; Emanuel 2013). We simulate the changes in TC fatalities based on these TC projections downscaled from seven climate models and assuming both low-income and middle-income scenarios. The authors estimate how adaptation strategies can be enhanced to reduce vulnerability to future hurricanes in a warmer world.

We find that TC fatalities are explained by high TC intensity, storm surge, and low income. A one unit increase in TC intensity (1 hpa) on TC fatality is commensurate with the effect of a one unit increase in income per capita (1000 INR). We also find that income growth reduces TC fatality, in part, because it increases adoption of information-based adaptation measures. When making future projections, of key concern is the interplay between future increases in cyclone intensity versus income. If hurricane intensity were to increase, as predicted by three of the seven climate models, fatalities are predicted to increase dramatically in the low-income scenario. However, if income grows at a faster rate, hurricane fatality is predicted to fall in all scenarios. Therefore, economic development remains an important policy variable to mitigate future impacts from global warming.

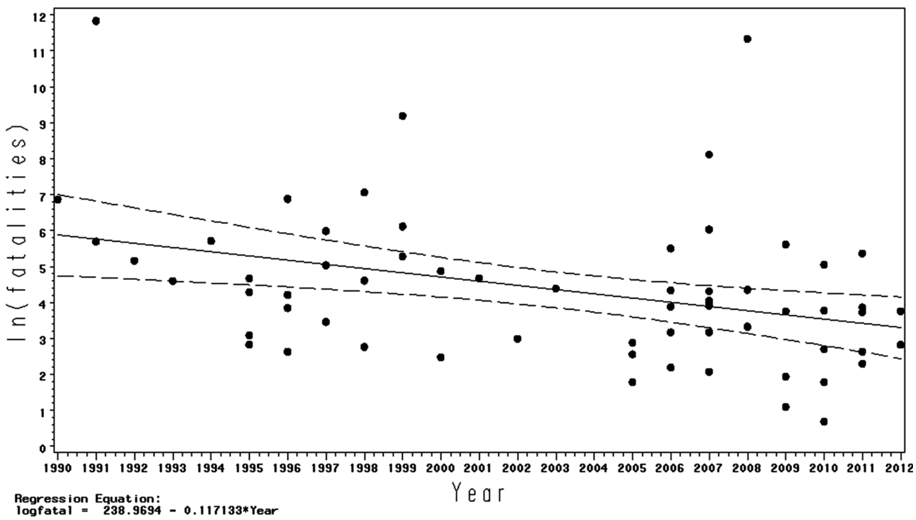

Fig. 1 Number of TC fatalities from 1990 to 2012

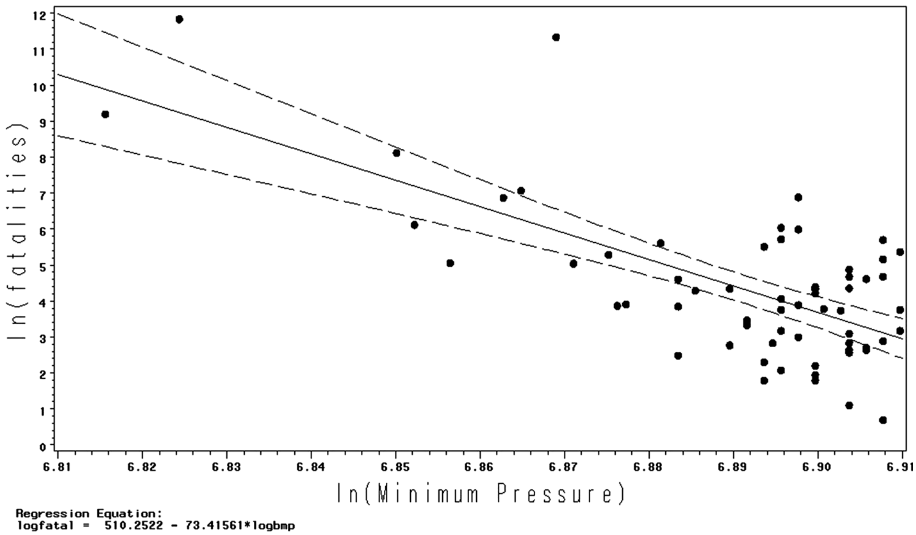

Fig. 2 Fatalities and minimum central pressure

The paper comprises the following sections. In the next section, we present a theory of TC fatalities. The third section explains our empirical approach and data. The fourth section explains empirical results from the applications of negative binomial models. The fifth section analyzes determinants of adaptation through probit models. The sixth section provides future simulations of TC fatalities based on the scientific projections of TC intensities and frequencies by the end of twenty-first century. We conclude the paper with a summary and discussion.

2 Tropical cyclone fatalities

Tropical cyclones (TC), also called hurricanes in the northern Atlantic and Eastern Pacific Oceans and typhoons in the western North Pacific Ocean, are giant heat engines fueled by the flux of heat from the ocean to the upper atmosphere (Seo 2015). TCs are driven by a positive feedback loop whereby stronger TC winds lead to lower sea surface pressure, thereby increasing surface heat flux and creating yet stronger winds. The Indian Meteorological Department classifies cyclones based on wind speed when a storm is over water and air pressure when a storm is over land. A cyclone is defined as a storm reaching a wind speed of at least 60 kmph (IMD 2015c).

Human fatality is one of the hurricane consequences most feared by affected individuals and government agencies. The number of fatalities from a hurricane depends upon the severity of a hurricane, commonly expressed in terms of maximum wind speeds and minimum central pressure (Seo 2015). It also depends on vulnerability factors including population, elevation, capital assets, and income of the region struck by a hurricane (Nordhaus 2010). Hurricanes also cause a temporary storm surge in the sea level. In low-lying areas of poor countries such as India and Bangladesh, hurricane-caused storm surge often is a primary driver of high fatality counts (Jelesnianski et al. 1992; Lin et al. 2012; IMD 2015b).

Growing literature exists on the relationship between TCs and climate. Emanuel first theorized the relationship between elevated CO_2 concentrations, due to the greenhouse effect, and increases in the destructive potential of hurricanes (Emanuel 1987). Previous research shows a clear upward trend in hurricane power, as defined by the Power Dissipation Index (PDI) which is a function of maximum wind speeds and frequency, in the latter half of the twentieth century in the North Atlantic and the western North Pacific Oceans (Emanuel 2005, 2008). Underlying the PDI trend are changes in hurricane intensity and frequency (Knutson et al. 2010). Work by Kossin et al. (2013) shows that the lifetime maximum intensity of the strongest storms has increased globally, although weakly, in the past few decades, in all oceans except the western North Pacific. Even after adjusting for potential missing storms in the historical record before the advent of satellite tracking, hurricane counts show distinct multi-decadal swings over time, but no long-term trend (Vecchi and Knutson 2011). Although historical data on hurricanes such as the HURDAT best track file in the USA—which form the basis of the above studies—are available from the 1850s, the satellite era of hurricane observations began only in the 1970s (McAdie et al. 2009; Landsea et al. 2009). Hurricane data during the pre-satellite era suffer from missed observations, imprecise measurements, and non-standardized recording procedures.

3 Empirical approach and data

To model the counts of hurricane fatality, we use the negative binomial (NB) distribution which can be derived from the Poisson distribution (Cameron and Trivedi 1986; Hilbe 2007). Assume y_i, a random variable, is of the number of fatality from a hurricane i whose distribution is a Poisson with parameter λ_i:

$$y_i \sim \text{Poisson}\ (\lambda_i). \tag{1}$$

We further assume that the parameter λ_i is a random variable with a Gamma distribution:

$$\lambda_i \sim \text{Gamma}\ (\alpha, \beta). \tag{2}$$

The unconditional distribution of y_i is the negative binomial distribution whose first two moments are:

$$\begin{aligned} E(y_i) &= \alpha\beta, \\ \text{Var}(y_i) &= \alpha\beta + \alpha\beta^2. \end{aligned} \tag{3}$$

Substituting in $\mu_i = \alpha\beta$ and $\kappa = {}^1/_{\alpha}$, the mean and variance of fatalities becomes:

$$\begin{aligned} &E(y_i) = \mu_i, \\ &Var(y_i) = \mu_i + \kappa\mu_i^2. \end{aligned} \tag{4}$$

The NB distribution is preferable to the Poisson distribution when overdispersion exists in count data. The variance in Eq. 4 captures overdispersion in the sample and increases in a quadratic (nonlinear) function of the mean (Lambert 1992; Hilbe 2007). In contrast, the variance in the Poisson distribution is equal to the size of the mean. We test for (and find) overdispersion in our sample.

The probability density function (PDF) of y_i is

$$f(y_i) = \frac{\Gamma(y_i + \kappa^{-1})}{\Gamma(y_i + 1)\Gamma(\kappa^{-1})}\left(\frac{\kappa^{-1}}{\kappa^{-1} + \mu_i}\right)^{\kappa^{-1}}\left(\frac{\mu_i}{\kappa^{-1} + \mu_i}\right)^{y_i}, \quad \text{for } y_i = 0, 1, 2, \ldots \tag{5}$$

where $\kappa > 0$ is the dispersion parameter.

Economic theory guides our understanding of hurricane fatalities, which are a function of hurricane characteristics, as well as human vulnerability and adaptation (Nordhaus 2010; Seo 2015; Bakkensen and Mendelsohn 2016). We therefore include the following variables in our empirical fatalities model: hurricane intensity and surge (to characterize the hurricane), income and population (to characterize vulnerability), and various endogenous and exogenous adaptation measures (to characterize adaptation).

We estimate our NB fatalities model using the following log link:

$$g(\mu_i) = \ln \mu_i = \alpha + \beta_1 \text{MCP}_i + \beta_2 \text{INC}_i + \gamma_1 \text{SUR}_i + \gamma_2 \text{POP}_i + \varphi \text{AD}_i \tag{6}$$

where MCP is the minimum central pressure, INC is income per capita, SUR is the level of storm surge, POP is population density, and AD is a vector of adaptation measures (Seo 2015).[1] The log link ensures that the over-dispersed data are adequately captured in the model and the estimated number of deaths does not become negative. The parameters are estimated using the maximum likelihood method and the Newton–Raphson technique for nonlinear optimization.[2]

Several tests of interest result from Eq. 6. First, through the estimated parameter γ_1, we test the hypothesis that the level of storm surge is a significant cause of high fatalities from

[1] Previous work has shown that MCP is a better measure of the destructiveness of a storm than maximum wind speed, due in part to better accuracy in historical measurement (Gray et al. 1991; Mendelsohn et al. 2012; Seo 2014; Bakkensen and Mendelsohn 2016). Our data indicate that there are missing records of wind speed for some cyclones and that the estimated model with wind speed is weaker in terms of significance of parameter estimates.

[2] An alternative specification is possible, although not preferred, by a log–log functional relationship. This is shown graphically in Fig. 2. A reviewer also suggests that a linear-in-the-logs model should be used. However, such a model is theoretically incorrect because it assumes a declining marginal effect of hurricane intensity on the number of fatalities as hurricane intensity becomes stronger.

hurricanes in low-lying tropical countries including India and Bangladesh. Second, adaptation measures, such as the development of tropical cyclone trajectory projection methods and availability of a storm surge modeling, TC advisories, and the Global Maritime Distress and Safety System (GMDSS), are tested through the significance of φ (Seo 2015).

Other estimated parameters are of interest. $\hat{\beta}_1$ estimates the relationship between cyclone intensity and fatalities. It is interpreted as the proportional change in the mean fatality in response to one unit increase in the intensity of a hurricane, i.e., minimum central pressure:

$$\hat{\beta}_1 = \frac{\mathrm{d}\ln\hat{\mu}_i}{\mathrm{d}\,\mathrm{MCP}_i} = \frac{\mathrm{d}\hat{\mu}_i/\hat{\mu}_i}{\mathrm{d}\,\mathrm{MCP}_i} \tag{7}$$

Similarly, the estimated parameter $\hat{\beta}_2$ estimates the relationship between income change and fatalities. It is interpreted as the proportional change in the mean fatality in response to one unit increase in income per capita:

$$\hat{\beta}_2 = \frac{\mathrm{d}\ \ln\ \hat{\mu}_i}{\mathrm{d}\ \mathrm{INC}_i} = \frac{\mathrm{d}\ \hat{\mu}_i/\hat{\mu}_i}{\mathrm{d}\ \mathrm{INC}_i}. \tag{8}$$

We hypothesize that a weaker (higher pressure) storm will lead to fewer fatalities ($\hat{\beta}_1 < 0$), while income growth will decrease the magnitude of lives lost ($\hat{\beta}_2 < 0$).

The impact of a change in hurricane intensity from MCP_0 to MCP_1, caused by a climatic shift, on the number of fatality is measured as follows:

$$\Delta = \hat{\mu}_i(\mathrm{MCP}_1) - \hat{\mu}_i(\mathrm{MCP}_0). \tag{9}$$

We construct an original dataset on tropical cyclones generated in the North Indian Ocean—the Bay of Bengal and the Arabian Sea—from 1990 to 2012, when detailed data on each cyclone is available from the Indian Meteorological Department (IMD 2015a, b). TCs primarily make landfall in India, but also impact South Asian countries including Bangladesh, Thailand, Sri Lanka, Burma, and Pakistan. A handful of cyclones made landfall in Africa and the Middle East but are excluded from the analysis due to data limitations.

We use both best track data and annual TC reports by the IMD. The best track database contains data on TC location, minimum central pressure, maximum wind speeds, and other information for each observation period throughout the lifetime of the storm. The annual TC reports describe each TC in detail and contain information on fatalities, financial damage, landfall locations, storm surge, trajectory projections, TC advisory, evacuation, GMDSS, and other variables. We collect data on five relevant adaptation measures: availability of a surge modeling as a forecasting tool, the TC observation interval, availability of TC advisory, application of the Global Maritime Disaster and Safety System (GMDSS), and availability of TC trajectory projection using the Limited Area Model (LAM).

Socioeconomic data are gathered from various sources including the World Bank Development Indicators and the Open Government Data Platform of India (World Bank 2015; OGDPI 2015). Income per capita and population density are available at the state level for India and at the country level for non-Indian countries. Using a World Bank Consumer Price Index, income data are adjusted to real 2006 prices.

Projections of hurricane activities by the end of this century are obtained from Emanuel (Emanuel et al. 2008; Emanuel 2013). Applying downscaling methods to the CMIP3 and CMIP5 (Climate Model Inter-comparison Project) models, Emanuel predicts changes in TC frequency and intensity by the end of twenty-first century across global oceans. This paper relies on his predictions for the North Indian Ocean. The downscaled hurricane predictions are generated from the following seven AOGCM climate models: CCSM3, CCNRM, CSIRO, ECHAM, GFDL, MIROC, and MRI.

4 What explains fatalities?

We begin by examining summary statistics from our dataset and then formally model the determinants of tropical cyclone fatalities. Table 1 presents descriptive statistics for variables in our dataset. To examine trends over time in our data, statistics are presented for the two periods: an early period (from 1990 to 2001) and a late period (from 2002 to 2012). Altogether, 64 TCs made landfall in the early period and 61 TCs made landfall in the late period.

While still high, the average number of TC fatalities declined from 2441 persons in the early period to 1469 persons in the late period. The minimum pressure, on the other hand, rose slightly from 986 to 989 hpa, which implies a decrease in average intensity, though not significant statistically (Evan et al. 2011). Average surge level declined from 0.59 to 0.48 m. These statistics tell us that the decline in the number of TC fatalities in the late period may be attributed to, *inter alia*, a decrease in TC intensity and storm surge. However, from the early period to the late period, income per capita and population density both increased.

The variable 'surge model' in Table 1, an indicator variable taking the value 1 if a surge model was present, was used in all TCs in the late period, but in none of the TCs in the early period. In addition, the time between official TC observations, when TC data are collected for a given event, has decreased, averaging 5.02 h between observations in the early period and 3.3 h between observations in the later period. All late period TCs were coupled with a TC advisory, the Global Maritime Disaster and Safety System (GMDSS), and the TC trajectory projection using the Limited Area Model (LAM). Given different development dates, these technologies and systems were not available for some TCs in the early period.

Given the observed records regarding TC characteristics, adaptation, and fatalities, we now examine the conditional relationships between fatalities and variables of interest through a set of regression analysis. In Table 2, we present the results from our six negative binomial models. According to the log-likelihood statistics and the scaled deviances close to one, all six models are significant at the 5 % level.

Model 1 is the most parsimonious model in which minimum central pressure, income per capita, and population density are entered as explanatory variables for the explanation of TC fatality. The error terms are assumed to be independent. The dispersion parameter is 8.3, which shows that the sample data are highly dispersed and the choice of the negative binomial model is appropriate. In this model, the estimate of minimum central pressure is significant, as is that of income per capita. The estimate for minimum pressure is −0.12, which implies that one unit decrease in minimum central pressure leads to 12 % increase in the number of fatality. The estimate for income per capita is −0.029, which implies that a one unit increase in income per capita (1000 INR which is approximately 17 USD) leads to

Table 1 Descriptive statistics

Variable	Early: 1990–2001		Late: 2002–2012	
	Mean	SD	Mean	SD
Fatalities (*N*)	2441.89	17399.52	1469.95	10751.70
Minimum central pressure (hpa)	986.05	21.40	989.10	12.94
Income per capita (INR)	11099.19	11605.34	25243.66	22239.88
Population density (ppl/km^2)	518.60	327.37	558.31	514.31
Observation interval (h)	5.02	1.01	3.32	0.68
Surge model (0/1)	0.00	0.00	1.00	0.00
Surge (m)	0.59	1.49	0.48	1.22
TC advisory (0/1)	0.02	0.13	1.00	0.00
Global Maritime Distress and Safety System (0/1)	0.02	0.13	1.00	0.00
Trajectory projection using Non-hydrostatic Meso-scale Model (NMM) (0/1)	0.00	0.00	0.72	0.45
Trajectory projection by Limited Area Model (LAM) (0/1)	0.61	0.49	1.00	0.00

2.9 % decrease in the number of fatalities. The estimate for population density is positive, as expected, but not significant.[3]

In India and South Asian countries, the number of death from a TC is strongly linked to the level of a storm surge due to many reasons including fragile houses, low-lying areas, and lack of shelters. In Model 2, we add the availability of a storm surge model and the level of surge. Data on the height of storm surge is available for all years but is missing for a handful of small storms. As expected, the surge level is a highly significant factor with parameter estimate of about 1. A one meter increase in a surge leads to a 100 % increase in TC fatality. The inclusion of the surge variables decreases the magnitude of the estimate of minimum central pressure. In Model 2, the estimate is −0.03, which is significant. This in turn shows that the high sensitivity of fatality to MCP is owing to a mis-specification of the model, i.e., omission of surge variables.

In Model 3, we add a dummy variable for the TC trajectory projection using the Limited Area Model (LAM). This is one of the first employed TC trajectory projection methods in India and continues to be used for every storm. It began to be systematically adopted in 1976. The estimated coefficient is positive, but not significant.

In Models 4 and 5, we use the same set up as Model 2, but change the error assumption to exchangeable error terms in Model 4 and unstructured error terms in Model 5 (Seo 2015). Model 4 assumes a fixed correlation parameter while Model 5 assumes no structure in correlation parameters between the error terms. There is no theoretical ground on which we can bound an error structure, which means that the unstructured error structure in Model 5 is preferable in our modeling. Changes in the assumption of the error terms, however, do not affect the results significantly.

[3] This may be due to very high population densities across all regions in the study. That is, unlike Australia and the USA where population density varies a great deal from one region to another, Indian coastal regions are all densely populated with little variation. In addition, it could be due to greater resilience in urban areas, relative to rural areas, such that fatalities do not scale proportionately with population.

Table 2 Negative binomial models of fatalities

	Model 1		Model 2		Model 3	
	Est.	*P* value	Est.	*P* value	Est.	*P* value
Intercept	124.213	<.0001	33.9403	<.0001	18.9908	0.0114
Minimum central pressure (hpa)	−0.1206	<.0001	−0.03	<.0001	−0.0159	0.04
Income per capita (1000 INR)	−0.0292	0.0006	−0.0292	0.0012	−0.0268	0.0021
Population density (ppl/km^2)	0.0002	0.8269	0.0001	0.8466	0.0002	0.7639
Surge (m)			1.0001	<.0001	1.1392	<.0001
Surge model			0.0642	0.9004	−0.3408	0.5154
Trajectory LAM					1.2	0.1839
Dispersion parameter	8.3742		7.6306		7.4726	
Likelihood ratio (*P* value)	<0.0001		<0.0001		<0.0001	
Scaled deviance (value/DF)	0.9702		0.9877		0.9967	
Assumption on the error terms	Independent		Independent		Independent	
	Model 4		Model 5		Model 6: estimated level of surge	
	Est.	*P* value	Est.	*P* value	Est.	*P* value
Intercept	33.9403	<.0001	33.9403	<.0001	133.5627	<.0001
Minimum central pressure (hpa)	−0.03	<.0001	−0.03	<.0001	−0.1295	<.0001
Income per capita (1000 INR)	−0.0292	0.0012	−0.0292	0.0012	−0.0359	0.0024
Population density (ppl/km^2)	0.0001	0.8466	0.0001	0.8466	0.0002	0.7329
Surge (m)	1.0001	<.0001	1.0001	<.0001	−0.354	0.1885
Surge model	0.0642	0.9004	0.0642	0.9004	0.4095	0.5705
Dispersion parameter	7.6306		7.6306		8.568	
Likelihood Ratio (*P* value)	<0.0001		<0.0001		<0.0001	
Scaled deviance (value/DF)	0.9877		0.9877		0.9765	
Assumption on the error terms	Exchangeable		Unstructured		Unstructured	

Adopting the specification in Model 5, we replace the surge level with an 'estimated' surge level in Model 6. Since surge level is not recorded for small TCs, the authors estimated the surge level using minimum central pressure, spatial location, and other variables and used it as one of the explanatory variables. The estimate is not significant implying that additional variables, such as bathymetry and coastal elevation gradients, are needed to model surge. However, the estimated coefficient of minimum central pressure returns to the magnitude in Model 1, which does not include the surge variable. This implies that the surge variable and the minimum central pressure are correlated to some degree (Jelesnianski et al. 1992; SURGEDAT 2015). When the level of surge is not accurately measured for each of the TCs in the dataset, the minimum central pressure measure of hurricane intensity is likely to absorb much of the impact of a higher storm surge.

What are the effects of non-information-based adaptation measures against storm surge including bunkers and shelters built on the hurricane-prone low-lying zones (Paul 2009)? The estimate of the minimum central pressure in Model 2 may capture the effects of such adaptation measures. In other words, the damage from a high-intensity hurricane occurs because of both high-speed winds and high sea surge. Individuals and public agencies will take adaptation measures, including building and evacuating into the bunkers and shelters, which will reduce the casualties from a TC due to hurricane intensity. In India and Bangladesh, a lack of shelters and bunkers as well as poor housing conditions of many residents in the low-lying areas are perceived to be a primary policy concern. These effects are captured in the large parameter estimate of storm surge: +100 % increase in hurricane fatality with an additional 1 meter increase in storm surge. On the other hand, income growth provides a large reduction in hurricane fatality, given hurricane intensity and storm surge, probably because higher income equips people with more sturdy housing and local communities with sufficient numbers of shelters. The relationship between income growth and adaptation innovation is an important area of future research.

5 Adoption of adaptation measures

We now turn to specific adaptation measures employed to protect against tropical cyclone impacts. We focus on information-based adaptation measures and leave physical protection options for future work. Through detailed TC reports from the Indian Meteorology Department, the authors recorded various adaptation measures that were used before and during TC events (IMD 2015b). In Table 3, adoption of each of these measures is modeled using the Probit choice model (Train 2003). The five measures are: availability of a surge model, a TC trajectory projection using the Limited Area Model (LAM), a TC trajectory projection using the Non-hydrostatic Meso-scale Model (NMM), a TC advisory, and the Global Maritime Distress Safety System (GMDSS). During this period, all TCs were observed by satellites.

Table 3 Probit models of adaptation strategies

	Surge model		Trajectory LAM		Trajectory NMM	
	Est.	*P* value	Est.	*P* value	Est.	*P* value
Intercept	−3.1995	0.6343	10.2061	0.2418	2.0382	0.765
Minimum central pressure	0.00274	0.6886	−0.0102	0.2518	−0.00316	0.648
Income per capita (1000 INR)	0.0295	0.0002	0.0292	0.0198	0.0264	0.0006
Population density (/km^2)	−0.00009	0.7916	0.000612	0.1721	0.0004	0.2599
Wald statistic	14.4178	0.0024	6.5128	0.0892	13.0136	0.0046

	TC advisory		GMDSS	
	Est.	*P* value	Est.	*P* value
Intercept	−4.0901	0.5452	−4.0901	0.5452
Minimum central pressure	0.00366	0.5933	0.00366	0.5933
Income per capita (1000 INR)	0.0295	0.0002	0.0295	0.0002
Population density (/km^2)	−0.0001	0.7745	−0.0001	0.7745
Wald statistic	14.5621	0.0022	14.5621	0.0022

Adoption of adaptation options phased in over time and the technologies continued to improve in accuracy after initial adoption. Storm surge models were first used in 2002 while TC advisories and the GMDSS began in 2001 (IMD 2015b). The NMM technology is a more recently adopted (in 2006) dynamical model. The LAM technology began to be systematically adopted in 1996. Before that, the CLIPER (Climatology and Persistence) model, a statistical model which was developed in 1972 by the National Hurricane Center in the USA, was used for TC trajectory projection (NHC 2009). These measures have been developed and adopted over time in response to the society's desire to better deal with the destructiveness of tropical cyclones.

In Table 3, adoption of each of these measures is explained by intensity, income per capita, and population density (Seo 2015). According to the Wald statistics, all the models are significant at the 5 % level except the choice of a TC trajectory projection using the LAM which is significant at the 9 % level. In all five models, income per capita is significant at the 5 % level. The positive estimate indicates that the adoption of these measures is more likely when a TC approaches a higher income region and/or occurred in a higher income year. The parameter estimate is quite steady across the five models at about +0.029. In addition, the technologies have become more sophisticated through the establishment of regional centers and international collaborations.

Adoption of these measures by Indian agencies is a public effort to reduce the number of fatalities caused by the hurricane. These measures improve the knowledge of local people who make decisions to avoid personal catastrophes. An individual may or may not decide to evacuate to a bunker or physically protect property, given this information. However, it is not apparent in the individual reports of these hurricanes whether these measures are adopted selectively only when certain regions, e.g., high-income regions are approached by a hurricane. The probit models nonetheless inform us that these measures are more likely to be adopted in areas or at times when incomes are higher.

Turning to the storm characteristics, the estimated coefficient on the intensity variable is not significant across the five adaptation measures. This implies that information-based adaptation measures are not adopted due to the intensity of a TC or specifically targeted to areas with intense storms. These measures are different from other adaptation measures such as evacuation and physical protection, which are primarily driven by the intensity of an approaching TC.

The results from the probit models also shed light on the results from the negative binomial models in Table 2. Adoption of information-based adaptation strategies, via increases in income, have reduced the number of fatalities from TCs. These results provide evidence that adaptation measures against TCs have been effective in India.

6 Future simulations

Based on the empirical results presented in the previous section, we simulate the impacts of climate change on TC fatality by the end of this century. From the six models presented in Table 2, we use the following three parameter estimates for our future projections: minimum central pressure = −0.03, income per capita = −0.029, and surge = +1.001.[4] These parameters are highly stable across Models 2 through 5. As there is no known scientific literature on the level of storm surge expected by the century's end in a warmer

[4] Alternatively, Model 6 could be used for future simulations with similar results presented in this section.

world (Jelesnianski et al. 1992; SURGEDAT 2015), we base our future simulations on changes in three measures: changes in TC intensity, TC frequency, and income.

As shown in Table 4, we employ sixteen future climate change scenarios detailing changes in TC intensity, TC frequency, and income per capita. The projections of the TC activities in the North Indian Ocean are drawn from Emanuel and coauthors (Emanuel et al. 2008). They base their projections on the seven AOGCM climate models under an A1B climate change scenario. The seven climate models are CCSM3, CNRM, CSIRO, ECHAM, GFDL, MIROC, and MRI. A final scenario is Emanuel's average of the seven models. For each of these scenarios, we simulate a low-income scenario and a middle-income scenario.

On average, the frequency of the TCs is predicted to decrease by 8.2 % and the intensity is predicted to increase by 3.7 % in the North Indian Ocean (Emanuel et al. 2008). However, a more recent study predicts a nonsignificant change in the hurricane frequency (Emanuel 2013). This is a major departure from the assessment by the Intergovernmental Panel on Climate Change (IPCC 2014a). The seven downscaled hurricane projections vary a great deal from one to another with regard to frequency prediction and intensity prediction.

For income changes, two scenarios are used: a low-income scenario and a middle-income scenario. In the low-income scenario, income per capita is predicted to grow more slowly at 2 % per year. In the middle-income scenario, the income per capita in the region is predicted to grow at 3 % per year. At the end of twentieth century, the income per capita was 17.8 thousand INR. A century of 3 % growth will lead to an income level of 324 thousand INR. These estimates are conservative, as India may grow at a higher growth rate than these scenarios. The Indian economy grew at about 7 % from 2005 to 2015 (World Bank 2015).

In Table 5, we simulate the changes in TC fatality by the end of twenty-first century assuming the sixteen scenarios described above. Average fatality in our sample data during the end of twentieth century was 10,670 persons per year. In a low-income scenario, the fatality increase has a wide range: more than 100,000 additional deaths per year in the MIROC scenario to a decrease in 10,670 deaths per year (total eradication of cyclone fatality) in the CNRM scenario. Increases in hurricane fatalities are observed in the MIROC, MRI, and CCSM3 scenarios due to a large increase in intensity predicted in these

Table 4 Future Scenarios

	TC frequency (%)	TC intensity (%)	Low-income scenario	Middle-income scenario
Current value	5.4 TCs per year	987 hpa	17.8 thousand INR	17.8 thousand INR
Future projections				
Emanuel scenario	0	+3.7	+111	+324
CCSM3	+6	+13	+111	+324
CNRM	−21	−15	+111	+324
CSIRO	−11	+8	+111	+324
ECHAM	−19	+2	+111	+324
GFDL	−13	−3	+111	+324
MIROC	−12	+20	+111	+324
MRI	+12	+2	+111	+324

Table 5 Projections of fatality by the end of twenty-first century

Current value	Low-income scenario 10,670 deaths per year	Middle-income scenario 10,670 deaths per year
Future projections		
Emanuel scenario	−10,470	−10,670
CCSM3	+8067	−10,643
CNRM	−10,670	−10,670
CSIRO	−7060	−10,670
ECHAM	−10,280	−10,670
GFDL	−10,573	−10,670
MIROC	+109,858	−10,472
MRI	+2438	−10,670

scenarios. A decrease in hurricane fatality occurs in the CNRM, CSIRO, ECHAM, GFDL, and the Emanuel average scenarios due to both a decrease in hurricane intensity and a decrease in hurricane frequency.

In the middle-income scenario, all eight scenarios lead to a large reduction in the number of fatalities from hurricanes. Regardless of changes in hurricane characteristics, the change in income dominates the outcomes.

For comparison, what would happen if the sensitivity of fatality to hurricane intensity is much larger than that on which these simulations are based, say, twice more destructive with the sensitivity parameter of −0.06? Our analysis shows that in the MIROC model, income growth of about 3.1 % would be sufficient to offset the increased number of fatalities due to increased intensity, given the doubled sensitivity parameter of −0.06. Therefore, the growth of income relative to hurricane intensity will be a critical factor in the determination of future fatalities and will be an important metric for policy.

7 Discussion

This paper examines fatalities from tropical cyclones generated in the Bay of Bengal and the Arabian Sea from 1990 to 2012, where the average number of TC fatalities far outnumbers those found in the USA, Australia, and the rest of the world (Seo 2015; Bakkensen and Mendelsohn 2016). The authors use negative binomial models to explain fatality count data by minimum central pressure, level of storm surge, income, population density, and adaptation measures. This paper finds that one unit increase in TC intensity (one millibar) has a similar impact on TC fatality as one unit increase in income per capita (1000 INR). One meter increase in storm surge is estimated to double the number of fatalities from a TC.

A unit of income growth reduces the TC fatality proportionally by 3 %. One mechanism by which income reduces TC fatality is through innovation and adoption of information-based adaptation measures. Historical measures include TC trajectory projections by various methods, storm surge models, TC advisories, and a global cooperative system such as the Global Maritime Distress and Safety System (GMDSS). Probit models show that adoption of these measures increases as income per capita grows.

Future simulations are made relying on the eight TC projections under CMIP3 and CMIP5 climate models and two income scenarios. In a low-income scenario in which the income per capita is predicted to grow at 2 % per year, hurricane fatality is determined by how destructive hurricanes would become. In the MIROC model in which hurricane intensity is predicted to increase by 20 %, hurricane fatality is predicted to increase by more than 100,000 persons per year. If hurricane intensity were to increase moderately or even decrease, hurricane fatality is predicted to fall by a great deal. In the middle-income scenario, hurricane fatality is predicted to fall in all scenarios regardless of changes in hurricane characteristics.

From a policy perspective, we synthesize our key results within the literature. First, overall hurricane fatalities are very high in the North Indian Ocean compared to those in high-income regions (Bakkensen and Mendelsohn 2016). Second, the paper indicates that the high fatalities are not ascribed largely to high hurricane intensity. The parameter estimate of minimum central pressure in the Indian Ocean context is −0.03, which is only one-half of the parameter estimate (−0.06) in Australian TCs (Seo 2015). Third, in addition to TC intensity, storm surge is highly dangerous in this region due likely to poor housing structures and a lack of appropriate shelters and bunkers (Paul 2009; Peduzzi et al. 2012). One additional meter of storm surge is predicted to double the number of fatalities. Fourth, adaptation measures employed in this region such as a surge model, TC trajectory projection, TC advisory, and the GMDSS have been effective. Adoptions of these strategies are largely a function of income growth. Finally, income growth and accompanying increases in adaptation facilities and capacities will, by and large, determine the severity of hurricane fatalities in India and its neighboring regions in the future under climatic changes (Seo 2015).

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