Dependence of tropical cyclone damage on maximum wind speed and socioeconomic factors

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Abstract

Tropical cyclones (TCs) have devastating impacts and are responsible for significant damage. Consequently, for TC-induced direct economic loss (DEL) attribution all factors associated with risk (i.e. hazard, exposure and vulnerability) must be examined. This research quantifies the relationship between TC-induced DELs and maximum wind speed, asset value and Gross Domestic Product (GDP) per capita using a regression model with TC records from 2000 to 2015 for China’s mainland area. The coefficient of the maximum wind speed term indicates that a doubling of the maximum wind speed increases DELs by 225\% [97\%, 435\%] when the other two variables are held constant. The coefficient of the asset value term indicates that a doubling of asset value exposed to TCs increases DELs by 79\% [58\%, 103\%]; thus, if hazard and vulnerability are assumed to be constant in the future, then a dramatic escalation in TC-induced DELs will occur given the increase in asset value, suggesting that TC-prone areas with rapid urbanization and wealth accumulation will inevitably be subject to higher risk. Reducing the asset value exposure via land-use planning, for example, is important for decreasing TC risk. The coefficient of GDP per capita term indicates that a doubling in GDP per capita could decrease DELs by 54\% [39\%, 66\%]. Because accumulated assets constantly increase people’s demand for improved security, stakeholders must invest in risk identification, early warning systems, emergency management and other effective prevention measures with increasing income to reduce vulnerability. This research aims to quantitatively connect TC risk (expected DELs, specifically) to physical and socioeconomic drivers and emphasizes how human dimensions could contribute to TC risk. Moreover, the model can be used to estimate TC risk under climate change and future socioeconomic development in the context of China.

1. Introduction

Tropical cyclones (TCs) were the costliest natural disasters in the world during the period 2000–2017; they led to estimated losses of 946 billion US dollars (USD) and were responsible for one-third of all natural hazard-induced damage (Munich 2018). Based on the well-established concept that TC risk is a function of three distinct determinants—hazards, exposure and vulnerability (IPCC 2014, Noy 2016), many studies have been conducted to examine the role that these three factors play in TC risk assessment (Schiermeier 2005, Mendelsohn et al 2012, Peduzzi et al 2012, Gettelman et al 2018, Nam et al 2018, Yonson et al 2018).

Regarding TC hazards, the majority of studies have used maximum wind speed to characterize TC intensity (Schmidt et al 2010, Murnane and Elsner 2012, Geiger et al 2016), whereas TC footprint size is another indicator (Zhai and Jiang 2014). Recently, TC-induced rainfall was found to be a significant loss determinant (Bakkensen et al 2018, Wen et al 2019). The impact of global warming on TC activities (such as occurrence frequency, intensity and
track migration) evokes considerable concern for the potential consequences of TCs. Recent studies have indicated the likelihood that the average frequency of TCs will decrease or remain constant and that the average intensity of TCs will increase worldwide, and large variations exist in different regions (Knutson et al 2010, IPCC 2013, Kang and Elsner 2015, Sobel et al 2016). In addition, observations have shown a poleward shift in TC genesis (Daloz and Camargo 2018) and lifetime-maximum wind speeds of TC tracks in the northwestern Pacific (Lin and Chan 2015, Kossin et al 2016). Changes in TC tracks and corresponding intensity and frequency will inevitably change the TC risk landscape under climate change.

Exposure to TCs is projected to increase under economic growth (Ye et al 2019). There are various choices of indicators of exposure, such as Gross Domestic Product (GDP) (Wen et al 2019), asset value (Wu et al 2018a), population (Peduzzi et al 2012) and residential built environment (Freeman and Ashley 2017). Since socioeconomic development has a great impact on TC damage, studies on the detection and attribution of TC damage have also focused on the role of socioeconomic factors (Changnon et al 2000, Pielke 2007, Schmidt et al 2009, 2010, Geiger et al 2016). Previous studies have applied shared socioeconomic pathways (SSPs) (O Neill et al 2014), representing a newly proposed approach, to depict socioeconomic conditions under various future scenarios and to assess the impact of climate change on TC losses in the future (Geiger et al 2016, Wen et al 2019).

Research on the vulnerability of specific exposure to TCs still lacks consistency of metrics and measurement techniques (Noy 2016); nevertheless, most researchers agree that vulnerability can be measured using income, population density, GDP per capita or poverty, physical environments and broad variables related to adaptive capacity (Mendelsohn et al 2012, Peduzzi et al 2012, Fricker et al 2017, Wu et al 2018b).

Recent studies have reviewed how the compounding effects of changes in the climate, socioeconomic growth and vulnerability will impact TC risk (Noy 2016). Variables indicating hazards, exposure and vulnerability as described above have been partially applied to the development of regression models (Fricker et al 2017, Elsner et al 2018, Wu et al 2019a) and to project the future losses of TCs under various climate change and socioeconomic development scenarios (Geiger et al 2016, Gettelman et al 2018, Wen et al 2019). However, quantifying the effects of climate change and socioeconomic growth on DELs from TCs remains challenging. Many early studies diagnosing the relationship between economic development and disaster risk (e.g. Kellenberg and Mobarak 2008) were based on yearly and country-level data and analyses, but not that of the TC event level. Fortunately, recent research also quantitatively investigates the statistical relationship of risk factors with disaster-induced DELs at the TC event level, especially because of improvements in geospatial data acquisition of hazard and exposure (e.g. (Pielke 2007, Park et al 2015, Bakkensen et al 2018). Despite these, empirical research on TC event-based DEL attribution in China is still lacking; therefore, an empirical study on the relationship between the three risk elements and TC-induced damage with TC records from China would be useful for TC risk assessment in this part of the world that is frequently affected by tropical cyclones and suffers huge losses.

The complexity of loss attribution makes it difficult to explore the interrelationship among disaster losses and risk factors by concentrating on hazards or human activity-related exposure and vulnerability in relative isolation (Huggel et al 2013). Therefore, we incorporate socioeconomic factors and physical hazards and develop an integrated model to quantify how the TC-induced DELs (L) respond to changes in TC-related hazards (H), economic exposure (E) and vulnerability (V), thereby providing a foundation for understanding TC loss attribution. Maximum wind speed (W), asset value exposure (K) and per capita GDP (I) are considered as risk determinants. The approach in this research is to express TC-induced DELs as a function of the maximum wind speed during the lifetime of a TC as well as the asset value and GDP per capita in the TC-affected areas. This research provides an empirical study on quantifying change in TC-induced DELs under the dynamic changes in the three elements of risk in China.

The section ‘Data and methods’ describes the necessary data used in this study and explains the quantitative analysis method and regression model that represents the assumed connection between TC-induced DELs and changes in maximum TC wind speed, asset value and GDP per capita. Statistical estimates (including uncertainties) of the regression model are presented in the ‘Results’ section. Quantifications are performed at the TC event level from 2000 to 2015 and exclusively focus on damage-producing TCs in China’s mainland area. In addition, the regression coefficients are further estimated using different subsets of TC records, and regression models with different variables are compared. This article also discusses the dynamic nature of exposure and vulnerability and then provides specific recommendations for and explores policy implications on risk prevention in the ‘Discussion’ section. The ‘Conclusions’ section summarizes the extent to which TC hazards and socioeconomic factors affect TC-related DELs and the prospect of applying our empirical model for future research.

2. Data and methods

We correlate the reported DELs with different TC-related physical and socioeconomic variables for 114
2.1. Tropical cyclone data and DEL records

The best TC track dataset over the Western North Pacific (WNP) (table 1) is frequently used when studying the TCs that have affected China (Ying et al 2014, Wen et al 2018). The dataset is readily available from the China Meteorological Administration (CMA) in a text file format (tcdata.typhoon.org.cn). The best track record of an individual TC includes locations of a TC every six hours from generation to extinction as well as the TC intensity category, minimum pressure and 2-minute mean maximum wind speed at the exact times of occurrence. We converted these records to a shapefile format, with each TC track depicted as a line between the initial point and end point with different wind speeds around the TC center (figure 1). In particular, maximum wind speed was observed during the lifetime of the TCs, and it is usually considered a better indicator of TC intensity.

Historical TC-induced DEL records at the provincial level (table S1) are recorded by the China Meteorological Administration (CMA 2015) and summed to the TC level. These DEL records are estimated by the replacement costs and adjusted with the price indices of investments in fixed assets in China to the 2015 price level (Chinese Yuan, CNY) to ensure that the inflation-adjusted data are comparable. Then, we converted the adjusted values of DELs into US dollars (USD) using the 2015 currency exchange rate (1 USD = 6.2284 CNY).

From 2000 to 2015, 114 TCs were linked to the total DELs of 130.1 billion USD in China's mainland area. The DELs caused by each TC ranged from 1 million USD to 10 billion USD (figure 2(a)). Overall, the 25 super typhoons resulted in the highest DELs, which was 46.2 billion USD, and closely followed by the 24 severe typhoons with DELs of 44.7 billion USD (table 2). The 17 tropical storms resulted in the lowest DELs of 0.9 billion USD. On average, a damage-producing tropical storm resulted in 0.1 billion USD in losses, and this figure increased to 0.6 and 1.0 billion USD for severe tropical storms and typhoons, respectively, and then increased to 1.9 billion USD and 1.8 billion USD for severe typhoons and super typhoons, respectively.

2.2. Asset value

In this study, asset value (or wealth capital stock) is used to represent economic exposure and includes buildings and non-building infrastructure, and it is more suitable for the assessment of DELs than GDP (Gunasekera et al 2015, UNISDR 2015, Wu et al 2018a, 2019b). The changes in asset value and size of TC footprints are necessary factors when evaluating the concept of exposure and its contribution to disasters (Freeman and Ashley 2017).

Asset value data were taken from Wu and colleagues (Wu et al 2014, 2018a), who performed the perpetual inventory method analysis at the county level (figure 1). We adjusted the asset value at current prices to the 2015 price level using price indices of investments in fixed assets in China and converted the values into USD. We referenced the methods used by Ye and colleagues (Ye et al 2019) and estimated TC event-level asset value exposure using the following steps.

| Table 1. Data sources. |
|------------------------|
| Data | Time period | Resolution | Source |
| Tropical cyclone track | 2000–2015 | Per TC event, 6 hourly | Shanghai Typhoon Institute (STI) of China Meteorological Administration (CMA, tadata.typhoon.org.cn) (Ying et al 2014) |
| TRMM Multi-satellite Precipitation Analysis (TMPA) | 2000–2015 | 0.25° × 0.25°, 3 hourly | https://disc.gsfc.nasa.gov/datacollection/TRMM_3B42RT_7.html (Huffman 2016) |
| TC-induced DELs | 2000–2015 | Provincial level | CMA (various years) (e.g. CMA 2015) |
| Asset value | 2000–2015 | County level | Wu and colleagues (Wu et al 2014; Wu et al 2018a) |
| GDP and population | 2000–2015 | County level | China Statistical Yearbooks Database (data.cnki.net) |
| Price indices of investment in fixed assets | 2000–2015 | Provincial level | China Statistical Yearbooks Database (data.cnki.net) |
| GDP deflator | 2000–2015 | China | World Bank (http://data.worldbank.org/data-catalog/world-development-indicators) |
First, we determined the affected extent of TCs by considering the wind field and the extent of TC-induced precipitation (Ye et al. 2019). Figure 3 shows an example of the affected extent of typhoon Usagi, which landed in Guangdong Province on September 22, 2013. The wind field of typhoon Usagi, which is represented by wind-speed radii for the wind-speed threshold 17.2 m s\(^{-1}\) (shown as the light gray areas in figure 3), was determined by the Holland wind field model (Holland 1980, Holland et al. 2010). The key parameters used in the Holland wind field model are central pressure, radius of maximum wind and the Holland B parameter. The daily precipitation synthesized by the TRMM data with 3-hour intervals is considered to be a determinant when defining the extent of the TC-induced precipitation within 500 km of a TC path (Zhang et al. 2018) (shown as the blue areas in figure 3).

Then, TC-affected counties for each TC can be extracted by counties where the wind field surpasses the threshold value of 17.2 m s\(^{-1}\) or daily rainfall surpasses the threshold value of 25 mm (Chen et al. 2011) within 500 km of the path of respective TC (shown as the brown diamonds in figure 3 for the example of typhoon Usagi).

Finally, for each TC, the aggregated asset value in TC-affected counties was used as the TC’s economic exposure. The density distribution of asset value exposed to TCs is shown in figure 2(c). The average and standard deviation of asset value exposure for a TC are 487.0 billion USD and 1254.2 billion USD, respectively. With respect to the TC intensity category, the average asset value exposed to TCs ranges from approximately 257.4 billion USD in the extent of a tropical storm to 1512.0 billion USD in the extent of a super typhoon (table 2).
Table 2. Statistics of the DELs, asset value, GDP per capita and maximum wind speed by TC intensity category.

| Intensity category      | DELs (billion USD) | Asset value exposure (billion USD) | GDP per capita (USD) | Maximum wind speed (m/s) |
|-------------------------|--------------------|-----------------------------------|----------------------|-------------------------|
|                         | Sum    | Average | Standard deviation | Average | Standard deviation | Average | Standard deviation |
| Tropical storm          | 0.95    | 0.06    | 0.09                | 257.39  | 462.63              | 5581.80 | 3277.06             | 20.94 | 2.14               |
| Severe tropical storm   | 12.45   | 0.59    | 1.46                | 546.45  | 405.41              | 5441.00 | 3512.27             | 28.00 | 2.12               |
| Typhoon                 | 25.75   | 0.95    | 1.48                | 773.13  | 911.97              | 4475.79 | 2024.07             | 37.07 | 2.92               |
| Severe typhoon          | 44.69   | 1.86    | 2.32                | 1487.29 | 1818.89             | 5364.18 | 3102.06             | 45.75 | 2.74               |
| Super typhoon           | 46.22   | 1.85    | 1.80                | 1512.03 | 1386.02             | 6269.95 | 3564.64             | 60.08 | 6.79               |
Figure 3. Affected extent of typhoon Usagi (no. 1319), which was assessed by determining the areas where the wind field exceeded the threshold value of 17.2 m s$^{-1}$ or the daily rainfall exceeded the threshold value of 25 mm within 500 km of this TC's path.

2.3. GDP per capita

Regarding the socioeconomic condition-related vulnerability factor, several studies have found that GDP per capita is a viable indicator for the characterization of economic vulnerability to disasters (Peduzzi et al 2012). A higher GDP per capita suggests a lower vulnerability (Hallegatte 2017, Wu et al 2018b). Thus, we used GDP per capita to measure the economic vulnerability to TC hazards, which was calculated by the average of all the GDP per capita in individual TC event-affected counties (table S1).

GDP and population data, which were used to calculate the GDP per capita at the county level in China’s mainland area from 2000 to 2015, were collected from the China Statistical Yearbooks Database (CSYD, data.cnki.net) (table 1). Similarly, we also adjusted the GDP per capita values to the 2015 price level using the GDP deflator in China and converted it into USD.

The GDP per capita density distribution is shown in figure 2(d). The average and standard deviation of GDP per capita for a TC are 4691.0 USD and 3111.4 USD, respectively. For the TC intensity category, the average GDP per capita varies from 4475.8 USD in the extent of a typhoon to 6269.9 USD in the extent of a super typhoon (table 2).

2.4. Negative binomial model

For the set of DEL-inducing TCs from 2000 to 2015, the mean and standard deviation of DELs were 1.14 billion USD and 1.77 billion USD, respectively, suggesting a negative binomial model for counts expressed by the following mathematical formula:

$$C \sim \text{NB} (\hat{\mu}, N)$$

$$\log(\hat{\mu}) = \hat{\alpha} + \hat{\beta}_1 \log(H) + \hat{\beta}_2 \log(E) + \hat{\beta}_3 \log(V)$$

where $\text{NB}(\hat{\mu}, N)$ indicates that the conditional counts of DELs are explained by a negative binomial distribution with a mean $\hat{\mu}$ and size N. The negative binomial distribution has been confirmed to be more reasonable than a normal distribution when quantitatively modeling tornado casualty counts (Fricker et al 2017, Elsner et al 2018) and earthquake DELs (Wu et al 2019a), which leads to non-normal residuals. The log of the loss rate ($\hat{\mu}$) is linearly correlated with the log of TC intensity ($H$), the log of economic exposure ($E$) and the log of vulnerability ($V$) in harm’s way. Specifically, the maximum wind speed ($W$) is an indicator of TC intensity, asset value ($K$) is an indicator of economic exposure, and GDP per capita ($I$) is an indicator of vulnerability conditions to TC hazards (Peduzzi et al 2012) in the TC-affected regions. The use of these indicators is referred to as the WKI model. The $\hat{\beta}_1$, $\hat{\beta}_2$ and $\hat{\beta}_3$ are the coefficients of maximum wind speed, asset value and per capita GDP, respectively, and $\hat{\alpha}$ is the intercept parameter.

The proposed model is an effective approach that simplifies the analysis and allows for comparison of changes in TC-induced DELs by concentrating on the ratios of the percentage changes in maximum wind speed, asset value and GDP per capita to the percentage changes in the DELs. The coefficient of maximum wind speed ($\hat{\beta}_1$) of TC-induced DELs
measures the change in DEL potential in response to a change in maximum wind speed holding asset value and GDP per capita constant, which indicates that a 1% increase in maximum wind speed leads to a $\beta_1$% increase in the rate of DELs (Fox 2015).

3. Results

3.1. Bivariate relationships

In figure 4(a), TC-induced DELs increase nonlinearly with maximum wind speed. Figure 4(b) shows that the DELs caused by an individual TC also increase with the asset value in harm’s way on a log-log scale, indicating that the highest DELs are more likely to occur over the most developed areas with dense asset values. Overall, the DELs are limited by a TC’s intensity and asset value, suggesting that with low hazard intensity or low asset values, only small DELs are expected to occur, whereas with high hazard intensity or dense assets, DELs are expected to be larger.

The two points labeled on the far right of figures 4(a) and (b) are typhoon Haiyan (no. 1330) and severe typhoon Matmo (no. 1410), respectively. However, the largest DELs (at the top of both scatter plots) were caused by typhoon Fitow (no. 1323), which had neither the largest intensity nor the densest asset value, suggesting the compound impact of TC hazard intensity and asset value on DELs. However, these factors are necessary but not sufficient to explain TC DELs. GDP per capita, which is a viable alternative for representing economic vulnerability, has the effect of amplifying or narrowing the DEL rate (here calculated by [DELs/asset value exposure × 100%]) and is further examined in figure 4(c). The DEL rate tends to decrease when the GDP per capita increases.

3.2. Regression model

The coefficient of determination ($R^2$) between the logarithm of DEL records and the logarithm of DELs estimated by the WKI model is 0.65 (table S2). The coefficient of the maximum wind speed term is 1.70 ([10.98, 2.42], 95% credible interval (CI)) (table 3), indicating that for a 100% increase in maximum wind speed (doubling), a 225% [97%, 435%] increase in DELs—calculated by $(2^{1.70} - 1) \times 100\%$, similarly hereafter—is expected. The asset value coefficient is 0.84 [0.66, 1.02], meaning that a doubling of the asset value exposure in the danger zone increases the DELs by 79% [58%, 103%]. The coefficient of per capita GDP is $-1.13$ [−1.55, −0.71], indicating that a doubling of the average per capita GDP decreases the DELs by 54% [39%, 66%]. As discussed in the theoretical framework for risk assessment, maximum wind speed, asset value exposure and per capita GDP, which represent the intensity of a TC hazard and the exposure and vulnerability components, respectively, are important in explaining TC-induced DELs.

3.3. Robustness tests

3.3.1. Sensitivity analysis of coefficients of the WKI model

We used different subsets of the data in table S1 for the sensitivity analysis of the WKI model (table 3). After refitting the model with only the TCs from 2006 to 2015, the coefficient values of maximum wind speed and asset value exposure increase to 229% [91%, 476%] and 92% [66%, 122%], respectively, while the coefficient of GDP per capita is constant (54%, [32%, 69%]). The results indicate that there is no large difference in coefficients when changing the study period to 2006 – 2015 compared to the whole study period from 2000 to 2015. Considering that TCs in 2013 caused the most DELs in China’s mainland area since 1990 (CMA 2013), we removed all TCs during that year and refitted the WKI model, which increased the coefficient of maximum wind speed and GDP per capita to 253% [119%, 475%] and 61% [47%, 71%], respectively, and slightly decreased the coefficient of asset value to 77% [57%, 99%]. These findings suggest that there is no single year dominating the regression coefficient values. Furthermore, we excluded the highest 5% of DELs and refitted the WKI model. The coefficients of maximum wind speed, asset value exposure and GDP per capita change to 278% [134%, 514%], 60% [40%, 82%] and 57% [44%, 68%], respectively.

3.3.2. Uncertainties using different regression models

We considered two other indicators, namely, minimum pressure ($P$) and proportion of non-steel-concrete residential buildings ($B$), to represent the TC intensity and vulnerability, respectively, and retained the asset value to represent economic exposure. We then compared the four regression models ($PKI, PKB, WKI$ and $WKB$) formed by different combinations of the five variables ($P, W, K, I$ and $B$) based on the residual deviance, Akaike Information Criterion (AIC) and coefficient of determination ($R^2$). The $R^2$ between the logarithm of the DEL records and the logarithm of the DELs estimated by the WKI model is 0.65, which is higher than those of the other three models ($R^2$ for $PKI, PKB$ and $WKB$ are 0.63, 0.55 and 0.58, respectively) (table S2), indicating a more credible fit of the proposed regression model to the available data. More information on the data and model comparison is provided in the supplementary information.

4. Discussion

4.1. Integrated model for TC loss attribution

We developed an integrated model to determine how disaster constituents (i.e. hazard, exposure and vulnerability) interrelate. The potential changes in TC-related wind speed represent an indicator of TC intensity that affects TC-induced DELs (Geiger...
et al 2016). The ‘expanding bull’s-eye effect’ indicates that greater exposure can amplify potential disaster effects (Ashley et al 2014, Strader and Ashley 2015). However, as presented in section 3.1, these two parts are necessary but not sufficient for determining TC-induced DELs. The vulnerability dimension, which is indicated by GDP per capita in this research, is another important factor impacting TC-induced DELs, where a higher GDP per capita means higher demands for safety, a higher capacity to take precautionary measures, and further decrease in DELs when facing disasters (Jongman et al 2015, Hallegatte 2017, Wu et al 2018b). Table S3 additionally presents the models with single variable (maximum wind speed only, asset value only, and GDP per capita only) and two variables (maximum wind speed-asset value, maximum wind speed-GDP per capita, and asset value-GDP per capita pairs). The results verify that our WKI model incorporating socioeconomic factors and physical hazard performs the best, and thus the three elements of risk all should be considered in TC risk analyses.

4.2. Human dimension contributes significantly to TC risk

The estimated results accentuate the human dimension (determined by exposure and vulnerability) as a significant driver underlying the escalating consequences of TC disaster. On the one hand, socioeconomic development had led to a major increase in asset values in areas exposed to TCs during our study period (Ye et al 2019). The coefficient of the asset value term suggests that a doubling of asset value in TC-prone areas increases the DELs by 79% [58%, 103%] when the hazard and vulnerability factors are held constant. The estimated results suggest that the wealth accumulation in TC-prone areas will inevitably lead to an increase in TC risk. Therefore, development planners should consider effective measures, such as land-use planning, to reduce exposure in disaster risk management (Ye et al 2019).

On the other hand, as some studies have indicated, economic growth (reflected by per capita GDP growth) has increased the demand for security and further prompted stakeholders to implement effective measures to reduce risk (Hallegatte 2017). Higher

Table 3. Sensitivity analysis of coefficients of the regression model of DELs and maximum wind speed \((W)\), asset value \((K)\) and GDP per capita \((I)\). Uncertainty is given by a 95% credible interval in parentheses.

| Coefficients | TCs from 2000 to 2015 | TCs from 2006 to 2015 | TCs from 2000 to 2015 excluding 2013 | TCs from 2000 to 2015 excluding the highest 5% of DELs |
|--------------|-----------------------|-----------------------|-------------------------------------|-----------------------------------------------------|
| Constant     | 18.52** (14.45, 22.62)| 17.62** (12.54, 22.69)| 19.99*** (15.98, 23.97)             | 19.33*** (15.26, 23.35)                              |
| \(\log(W)\)  | 1.70*** (0.98, 2.42)  | 1.72*** (0.93, 2.52)  | 1.82*** (1.13, 2.52)                | 1.92*** (1.23, 2.62)                                 |
| \(\log(K)\)  | 0.84*** (0.66, 1.02)  | 0.94*** (0.73, 1.15)  | 0.82*** (0.65, 0.99)                | 0.68*** (0.49, 0.87)                                 |
| \(\log(I)\)  | –1.13** (–1.55, 0.71) | –1.13** (–1.68, 0.57) | –1.35*** (–1.77, 0.92)             | –1.23*** (–1.64, 0.83)                               |
| Number of samples | 114              | 74                    | 101                                 | 108                                                 |

***Significant at the 0.001 level.
GDP per capita in richer regions increases the ability to invest in risk identification, early warning systems, emergency management and other prevention measures, such as enforcement of building codes and higher safety standards (Park et al 2015, Hallegatte et al 2016, Wu et al 2018b). From this perspective, an increase in GDP per capita enables governments and individuals to invest in precautionary measures to satisfy the safety demand and to reduce vulnerability (Toya and Skidmore 2007). Our results indicate that a doubling in GDP per capita could lead to a 54% decrease in TC-induced DELs.

Overall, socioeconomic development leads to a major escalation in asset value exposure to TCs in China (Ye et al 2019). The inevitable increase in wealth prompts stakeholders to consider reducing TC risk from the perspective of reducing exposure and vulnerability.

4.3. Possible future changes in TC-induced DELs in China

In the context of climate change, TC risks are inevitable and often exacerbated (Ghosh et al 2019). Research results differ regarding whether the number and proportion of very intense TCs will increase (Bacmeister et al 2018, Webster et al 2005, Vecchi and Soden 2007, Murakami et al 2012, Bhatia et al 2018, Patricola and Wehner 2018) or decrease (Yoshida et al 2017) globally in a warmer climate. Given the offsetting effect between TC intensity and frequency, Lin and Chan (2015) indicated that the destructive potential of a TC has decreased significantly and will decrease continuously under future climate scenarios. In other words, changes in TC hazard trends in the future still present great uncertainties.

Regarding the human dimensions, i.e. exposure and vulnerability, our results suggest that (1) even if TC activity is held constant at its current level, TC-induced DELs will increase because the asset values in TC-prone areas will more than likely continue to accumulate due to socioeconomic development (Leimbach et al 2017), and (2) appropriate adaptation measures under economic growth can reduce the economic vulnerability to TCs and narrow the extent of TC-related damage (Wu et al 2018b).

As such, the quantitative relationship should be investigated to provide deep insights for a proper understanding of TC risk under future scenarios and to propose possible effective adaptation solutions to minimize the risk (Ghosh et al 2019).

4.4. Limitations

There are still several limitations of this study. First, the results depend on the quality of the TC reports used in this study; however, there are no significant variations in the estimated regression coefficient values when taking into consideration different study periods. Second, potential biases may be introduced when determining TC-affected counties because the method overlooks the impact of distance from the center of the TC tracks. Additional factors that have not been considered in our model could also improve the model fit—including demographics, early warning, response capacity, and government efficiency (Brooks 2003, Peduzzi et al 2012, Logan and Xu 2015), although the macroeconomic indicator, i.e. GDP per capita, could partially reflect these socioeconomic factors.

5. Conclusions

How TC-induced DELs change with TC intensity, economic exposure and vulnerability within a risk framework remains a challenging question. In this study, we quantified the correlation between TC-induced DELs and three constituents in tandem at the TC event level based on a negative binomial regression model (WKI model) using China as a case study.

By constructing regression models with different indicators, we found that maximum wind speed, asset value exposure and per capita GDP are more suitable indicators when estimating TC-induced DELs. The coefficients of the three terms indicate that a doubling in maximum wind speed increases TC-induced DELs by 223% [97%, 435%], a doubling in asset value exposure increases TC-induced DELs by 79% [58%, 103%], and a doubling in per capita GDP leads to a 54% [39%, 66%] decrease in TC-induced DELs.

This research is an effort to connect TC disaster risk (expected DELs, specifically) with physical hazard and socioeconomic factors. Continuing economic development in the eastern coastal areas of China, which are prone to TC impacts, and the associated wealth accumulation will lead to greater DELs; thus, planners should incorporate risk management into development plans to reduce the exposure to TCs. Moreover, socioeconomic growth expands the demand for safety and enables stakeholders to invest in risk prevention measures to satisfy this demand and further reduce TC risk.

Overall, this study particularly emphasizes how the human dimensions could contribute to TC risk. The quantitative correlation between DELs and hazard intensity, exposure and vulnerability based on the empirical regression model can be used to predict subsequent TC-induced DELs in the context of global warming using general climate models under shared socioeconomic paths, and this method can be further applied to adaptive strategy creation to identify and reduce risks.

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