Does Economic Growth Increase or Decrease Economic Losses and Deaths from Storm Surge Disasters in China? An Empirical Analysis from The Aspect of Hazard Exposure

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Abstract. Storm surge disaster is the major threat to coastal residents' lives and property in China, which could steal away development gains in a short time. Therefore, the storm surge disaster loss reduction is an indispensable part of socio-economic development. However, the relationship between economic growth and the loss of storm surge disasters remains unclear. Herein, we explored the relationship between economic growth and the losses caused by storm surge disasters in China's coastal zones from 1978 to 2020. We established an empirical model through the indicators of direct economic loss and death toll using negative binomial estimate and tobit estimate models. To ensure the accuracy of the model, multiple socio-economic factors were also included in the models. The results revealed that there is an "inverted U-shaped" relationship between GDP per capita and the losses from storm surges. Furthermore, we used the entropy method to establish the storm surge hazard exposure index of China's coastal zone from 2000 to 2020, considering disaster intensity, population density and other factors. When considering hazard exposure level, the role of economic growth may be diminished. In other words, at the same economic level, higher hazard exposure leads to greater disaster losses. We argue that economic growth and disaster resilience are not identical goals. Thus, the government needs sufficient information support when formulating disaster prevention and reduction plans.

1 Introduction

Natural disasters are destructive phenomena that harm human existence or damage the living environment of human beings [1]. They often have devastating impacts on society and economic development. From the 1980s to the 2020s, more than 14000 natural disasters have been recorded worldwide, causing over 5.3 trillion US dollars in economic losses and approximately 2.7 million deaths [2]. In extreme cases, natural disasters can slow even

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reverse the economic development, especially in developing countries [3]. Accordingly, the disaster risk reduction has become a hot issue and received constant attention worldwide in recent years. Of the 17 Sustainable Development Goals (SDGs), 25 targets in 10 goals are related to natural disasters. Among them, the fifth target of Goal 11 is Sustainable Cities and Communities, which explicitly addresses reducing the adverse effects of natural disasters. Therefore, it is necessary to explore the relationship between natural disaster-related losses and the social economy, which will help the government and decision-makers formulate and implement policies to deal with natural disasters, thereby reducing the relevant losses.

In the past research on natural disasters and social economy, researchers generally focus on natural disaster impacts on the economic system [4–7]. Less attention is paid to the impact of economic level on natural disaster losses. However, the role of natural hazards in a society largely depends on the social development level. The loss of the natural disaster is determined both by the natural hazards and the attributes of human society and economy. Therefore, when studying the loss of natural disasters, we should focus on the impact of different levels of development on natural disasters. The main finding on the impact of economic growth on disaster losses was that death and damage from natural disasters declined with economic growth [8]. The main argument for these studies is that economic development can better mitigate and manage disaster risk. However, recent empirical studies have raised an interesting point, that is, the relationship between economic growth and natural disaster losses is non-linear, and they tend to increase first and then decrease [3,9–12]. Moreover, the pattern of "loss-development" relationship depends on the type of disaster, which poses a challenge for policymakers: they have to make a trade-off between economic growth and reducing disaster damage.

As a land-sea interface, coastal zones face an increased variety of natural disasters [13]. Among them, storm surge is one of the most significant threats to human lives and property during hurricanes and storms. Meanwhile, the coastal zone is the most densely populated area around the globe, and it contributes important resources and human endowments to global economic development. Therefore, natural disasters can cause serious damage to coastal areas and even other inland areas. In China, the main categories of marine disasters are storm surge, sea ice, severe waves, and coastal erosion [14]. Particularly, storm surge disasters caused by tropical cyclones and extratropical cyclones have caused the most severe damage to coastal areas [5,15–17]. From 2011 to 2020, China suffered economic losses from storm surge disasters exceeding 80 billion CNY, accounting for more than 95% of all marine disaster-related losses [14]. Storm surge disasters seriously affect coastal residents' daily life activities, and may threaten the safety of lives and property. There are many studies on the economic impacts of storm surges whereas the impacts of socioeconomic factors on storm surge damage have received limited attention. We may wonder how different regional development levels affect storm surge disaster losses. Although there is evidence that higher levels of economic development in coastal areas increase the magnitude and duration of storm surge damage [18], the empirical evidence exits different results. It seems that there is no simple linear relationship between the damage caused by storm surges in developed and less-developed areas and the level of local economic development, that is, the damage in developed areas is not necessarily higher than that in less-developed areas. This shows that we still lack a clear understanding of the regional influencing factors of storm surge disasters in China. Therefore, we put forward the following questions: (1) What are storm surge losses in China? (2) Do economic growth and social development increase or reduce storm surge losses? What is the relationship between them? (3) How is hazard exposure to storm surges distributed in China's coastal zone? And how does hazard exposure affect the loss-development relationship?

The main scientific contributions of this study are: (1) This study explored the pattern between economic growth and the loss of storm surge disaster at the regional level using multiple loss indicators, considering disaster intensity, geographical features, population and other socioeconomic factors; (2) A time series hazard exposure index of storm surge disaster in China was constructed using entropy method; (3) We investigated the role of hazard exposure in the loss-development relationship. Several policy recommendations have been made based on the analysis of socioeconomic factors and storm surge losses. These have positive significance for reducing storm surge losses and improving residents' well-being in China's coastal areas and can provide a general insight into the sustainable development of coastal zones in other countries and regions, especially in developing countries, which have the most vulnerable populations affected first and worst by natural disasters.

2 Literature review

Natural disasters can bring negative macroeconomic impacts, including per capita GDP, per capita income levels, GDP growth [19], and foreign trade [3]. A severe natural disaster usually has a terrible impact on the macro-economy of a region or even a country, especially in some underdeveloped regions. Furthermore, for individuals, disasters affect their income, employment, health, and migration decisions in the short-term influences of such events. These changes in individual behavior brought by natural disasters are likely to affect the level of regional economy further, thus bringing more serious consequences, such as labor loss. These are the secondary disaster effects caused by natural disasters [10]. On the other hand, some studies argued that natural disasters might bring long-term economic growth [7,16,17,20–24], which can be explained by the fact that despite the destruction of capital, newer and more advanced technologies will be adopted to rebuild the disaster-suffered areas [8]. This can improve total factor productivity and the return on human capital [8]. However, while the above empirical evidence offers the possibility of regional economic recovery after natural disasters, low-income countries tend not to use more advanced capital or technology to compensate for the damage after disasters. This is because extra time is often needed to invest in new technologies. They are more likely to restore their previous level of productivity as quickly as possible by constantly replacing damaged capital with capital similar to that before the disaster [25]. This limits the potential for future productivity gains and thus reduces the likelihood of long-term economic growth [3,25]. As one of the most severe natural disasters of marine disasters, storm surges have serious impacts on livelihoods in coastal zones, including infrastructure destruction, farmland inundation, aquaculture damage, landscape damage and coastal tourism [17,18]. Many studies have assessed the social-economic impacts of storm surges [5,26,27]; these results indicate that the impact of storm surge disaster on a region will affect non-coastal zones through modern production patterns such as trade, export and re-export. The above studies show that natural disasters, including storm surge disasters, will have great negative effects on the regional socio-economy.

The development level also determines the impact of natural disasters. When countries or regions are at a low development level, they usually do not have enough investment to resist natural disasters, which often cause heavy losses. With the development of the economy, capital and labor will be concentrated in this area. This makes the damage of natural disasters more severe, which shows an "increase in development, increase in loss" pattern. At the same time, corrupt political systems, weak insurance systems and other problems will also make low-development countries or regions more vulnerable to natural disasters [28]. Only when the economy has developed beyond a certain level can a country succeed in addressing weak institutions, creating better insurance markets, requiring stricter building standards, reducing corruption, and establishing more advanced early warning and emergency response systems. Several kinds of policies can be implemented to reduce the negative effects of natural disasters with economic growth. Firstly, technological upgrades can reduce losses. For example, levees and seawalls can alleviate damage from floods and tsunamis [29–36].

Furthermore, the investment in disaster prevention engineering or infrastructures will also bring development for the local economy [25,37]. The investment of funds can compensate for the loss of income due to natural disasters, thus can promote long-term growth [38]. The second important area for policy formulation is establishing a complete insurance market [3]. Individuals tend to underestimate the probability of disasters; hence they have a high discount rate for future compensation for damage from disasters [39]. Also, incomplete information is an important factor leading to the low willingness of individuals to purchase insurance [40]. However, the implementation of compulsory insurance policies in areas with high disaster risk may lead to inefficiency [41]. Therefore, establishing a well-structured insurance market is crucial for disaster prevention and mitigation, especially in developing countries [42,43]. The third kind of policy instrument is to encourage high-risk households to move out of high-risk areas [3]. Studies have shown that although low-income high-risk households settle in high-risk areas prone to disasters for economic reasons, middle-income households opt to move out of high-risk areas [44]. Unlike the previous two cases, high-income households can avoid the damage caused by natural disasters by purchasing more expensive buildings and insurance, so they prefer to settle in areas with high comfort value, while these areas often have a high risk of natural disasters [44]. Other studies found similar evidence [45–47]. These results underscore that public information can have a significant impact on residents' decisions, which demonstrates the importance of information provided by policymakers. Considering the high cost of obtaining information about low-income people, the government is obliged to inform residents of the current and future disaster risks that different regions may face. As a result of all these improvements, the more developed countries are less affected by natural disasters than the less developed countries. These works have shown that economic losses from natural disasters are related to the economic development level [3,9–11]. There is an "inverted U-shaped" relationship between natural disaster losses and income levels. Specifically, at low-income levels, natural disasters cause smaller losses. With the improvement of income level, the natural disaster losses will continue to rise. As income levels continue to rise, there will be an inflection point in disaster losses, which means that they will gradually decrease. This phenomenon is similar to the "Environmental Kuznets Curve" theory established in environmental science [48–51]. The reason why the losses from natural disasters show the same pattern is that, at low levels of development, individuals and governments are more willing to engage in profitable activities with high disaster risks, such as cutting down trees, which increases the risk of flooding, drought and landslides. Conversely, as income levels, education levels, and fiscal systems in these regions improve, natural disaster losses will decrease [8,52]. The above findings imply that for different levels of development, regional disaster losses are different.

There seems to be an inverted U-shaped relationship between social development and disaster losses from the above research. However, Schumacher and Strobl [11] argued that “loss-development” relationship is affected by the probability of natural disasters occurring in a region, as known as hazard exposure. Their study uses a theoretical model to show that if two countries are exposed to the same level of natural disaster, the more developed one tends to suffer less damage because it invests more in preventive measures. At the same time, if two countries have the same development level, the low risk one will suffer more from natural disasters because it invests less in preventive measures. Their model explains the formation of loss-development relationship from the perspective of social development level and government agency. When the level of wealth is high enough, or the probability of natural disasters is high enough, the marginal benefit of spending on preventive measures is higher than the marginal cost, that is, it is profitable to invest in preventive measures. This indicates that low-risk areas may not invest in natural disaster prevention, which increases the losses in these areas when natural disasters occur. In general, an important aspect of hazard exposure is topographic feature. Topographic features can affect the probability of a country or region being affected by natural disasters. And it is not only the frequency of disasters, but also the intensity of disasters that still affect the damage in a region [15–17,53,54]. For example, hurricanes, floods and droughts are likely to occur more frequently in China than in other countries [55]. These disasters also vary in intensity and frequency in the sub-regions of China, which brings different impacts on those regions. As a result, there may be different relationships between these natural disasters and economic growth when considering hazard exposure.

We have already explained the possible non-linear relationship between disaster losses and economic growth. Still, other socioeconomic factors can reduce the damage suffered from natural disasters. The damage caused by natural disasters can be influenced by the level of fiscal expenditure, which was supported by several studies [56–58]. Although empirical studies have come to the conclusion that the impacts of natural disasters lie on fiscal balance and social equity [59,60], the level of fiscal expenditures has a significant impact on the losses caused by natural disasters [61]. Fiscal expenditure determines the level of infrastructure construction in the region and the ability to prevent and reduce disasters [61]. Pre-disaster education is vital to disaster prevention and mitigation efforts. People who participate in drills tend to perform better in the face of natural disasters than those who do not [62–64]. There are also empirical studies showing that people with high education levels can cope well with natural disasters without being affected by disasters [65,66]. After a natural disaster, the affected population will not only suffer physical damage, but also be more vulnerable to psychological trauma [67]. Better medical facilities can reduce the death toll of disasters to some extent, which is essential for disaster prevention and reduction efforts [64].

To summarized, limited literatures show that natural disaster impacts on countries at different development stages is heterogeneous. This inverted U-shaped relationship may have different turning points depending on the type of natural disaster. There may even be other linear or non-linear relationship based on different types of disasters and different research areas. Moreover, few studies have considered hazard exposure into “loss-development” relationships, which can be vital for this kind of analysis. Therefore, we further explore the relationship between economic growth and storm surge losses using provincial data from China and take the hazard exposure into account.

Based on literature review, we proposed these hypotheses:

Hypothesis 1. Losses from storm surge disasters increase and then decrease with economic growth.

Hypothesis 2. The levels of regional financial expenditure, education and medical treatment can reduce the losses from storm surge disasters.

Hypothesis 3. Increased hazard exposure will offset the reduction in storm surge disasters losses caused by economic growth.

3 Material and Methods

This study used the empirical analysis approach to explore the relationship between storm surge disaster losses and economic growth. The study area is 11 coastal provinces and municipalities in mainland China (Fig. 1).

Fig. 1. Study area

3.1 Basic Empirical Analysis

We set up several regression models to verify the role of various socioeconomic factors in storm surge disasters based on previous studies. Firstly, we will start with the basic specification relating storm surges damage to the level of economic development:

$$\log \log (Loss_{it} + 1) = \alpha + \beta_1 \log \log PGDP_{it} + \log \beta_2 \log PGDP_{it}^{\ 2} + \varepsilon_{it} \tag{1}$$

$$= \alpha + \beta_1 \log \log PGDP_{it} + \log \beta_2 \log PGDP_{it}^{\ 2} + \varepsilon_{it} \tag{2}$$

Where i denotes the number of samples, which represents provinces and municipalities; t denotes the number of years. $Loss_{it}$ is provincial direct economic loss (1×108 CNY) of storm surge disasters annually from 2000 to 2020. $Death_{it}$ is provincial death toll of storm surge disasters annually from 2000 to 2020. We use these two indicators as the storm surge disaster losses, which are taken from the China Marine Disaster Bulletin. *PGDPit* is annually GDP per capita (CNY) from China's 11 coastal provinces from our study area, which is converted to 2000 price levels through the Consumer Price Index (CPI). The data of GDP per capita and CPI were obtained from the China Statistical Yearbook.

Direct economic loss and death toll are commonly used to measure the damage of natural disasters. Notably, the data types of these two indicators are different. The direct economic loss is a continuous variable, while the death toll is a counting variable. Meanwhile, the dependent variable of Eqs. (1) and Eqs. (2) may consist of many zeros, because storm surge disasters do not occur every year and do not necessarily cause damage if they do occur. Therefore, we use generalized linear estimation (negative binomial model and tobit model) to solve the truncation in the data as Kellenberg and Mobarak [10] and Schumacher and Strobl [11] did. At the same time, when the variables are log-transformed (Loss), we de-zero all the dependent variables to ensure that the zero value is still zero after the log-transformed.

Natural disasters can harm the economy, as indicated by numerous studies [3]. However, many scholars have criticized this view. They argued that this empirical result is sensitive to the types of disasters included, the specifications of the models used, and the country sample was chosen [68]. To verify the impact of storm surge disasters on China's economic growth, we choose GDP per capita (CNY) as an indicator of economic growth, which has been commonly applied in this academic field [3,8,10,12,18,38,69].

Then, we attempt to explore the above framework on a longer time scale. We assume that there is an "inverted U-shaped" relationship between storm surge damage and economic growth in a certain period. However, if we extend the period, these assumptions may turn out to be false or incomplete conclusions. The "loss-development" relationship may become monotonous as the study time changes. Therefore, to ensure the robustness of this study, we further expand the research period of Eq. (1) and Eq. (2) from 1978 to 2020. Data on direct economic losses and death tolls from storm surges from 1978 to 1999 were obtained from the Collection of Storm Surge Disasters Historical Data [70]. Similarly, GDP per capita (CNY) from China's 11 coastal provinces from our study area, which is converted to 2000 price levels through the CPI.

3.2 Empirical analysis considering multiple socio-economic factors

Next, we extend the above models by considering additional socioeconomic variables:

$$log\ log\ (Loss_{it}+1) = \alpha + \beta_1\ log\ log\ PGDP_{it} + \beta_2\ log\ log\ PGDP_{it}^2 + \beta_3\ log\ log\ PFE_{it} + \beta_4\ log\ log\ Student_{it} + \beta_5 Teacher_{it} + \beta_6\ log\ log\ Physician_{it} + \beta_7\ log\ log\ Hospital_{it} + \varepsilon_{it} \tag{3}$$

$$Death\ toll = \alpha + \beta_1\ log\ log\ PGDP_{it} + \beta_2\ log\ log\ PGDP_{it}^2 + \beta_3\ log\ log\ PFE_{it} + \beta_4\ log\ log\ Student_{it} + \beta_5 Teacher_{it} + \beta_6\ log\ log\ Physician_{it} + \beta_7\ log\ log\ Hospital_{it} + \varepsilon_{it} \tag{4}$$

Where PFE_{it} represents fiscal expenditure per capita; $Student_{it}$ is the number of college students per 100000 people; $Teacher_{it}$ is the number of teachers per 100 primary school students; $Physician_{it}$ represents the number of physicians per 10000 people; $Hospital_{it}$ is the number of medical institutions.

In this paper, we aim to determine the impact of different fiscal expenditure levels on storm surge disasters' damage. We select per capita fiscal expenditure (PFE) as an indicator from the study area. The calculation of per capita fiscal expenditure is shown in Eq. (5):

$$PFE_{it} = \frac{FE_{it}}{Population_{it}} \tag{5}$$

Where *i* denotes the number of samples, which represents provinces and municipalities; t denotes the number of years. *FE* is the total fiscal expenditure of the sample, and Population is the total population of the sample in year *t*. The data of fiscal expenditure were collected from the China Statistical Yearbook (2000-2020). In addition, we used the ratio of the GDP of coastal prefecture-level cities to the GDP of the whole province to adjust the fiscal expenditure. The data source of GDP of prefecture-level cities is the China City Statistical Yearbook (2000-2020).

We select the number of university students per 100000 people (Student) and the number of teachers per 100 primary school students (Teacher) as indicators representing the level of educational development. These two indicators are chosen because the behavior of children and adults has an important impact when a natural disaster strikes [65,66]. These indicators are selected from the China Statistical Yearbook (2007-2020). Due to gaps in the data, the values for the remaining years are filled using the linear interpolation method.

Finally, we select the number of physicians per 10000 people (Physician) and the number of medical institutions (Hospital) in the region as the indicators of the medical development level. Our data source is the China Statistical Yearbook (2000-2020).

The above socio-economic factors represent the financial level, education level and medical level of the region respectively. In our literature review, these factors all play important roles in theoretical or empirical models for natural disasters. In our empirical analysis, we assume that these factors have a restraining effect on storm surge damage.

3.3 Storm surge disaster hazard exposure index

As Schumacher and Strobl [11] mentioned, hazard exposure can affect the result of our empirical study. From an empirical point of view, ideally, we would like to find a function that reflects the probability of natural disasters in an area. We referred the work from the World Bank Hazard Management Unit and the Center for Hazards and Risks Research Unit at Columbia University [55], to construct an index system of storm surge disaster hazard exposure in China. The detailed information of hazard exposure index can be seen in the supplementary material. In this study, the weight of each index is calculated by entropy weight method.

Our index system includes seven indicators: storm surge disasters intensity, economic activities, topographic features, agricultural activities, coastal population density, regional roadway density, and regional railway density. In the positive indicators' standardization, the following formula is adopted:

$$y_{ij} = \frac{x_{ij} - min\,(X_i)}{(X_i)\ - min\,(X_i)} \times 100 \tag{6}$$

In the negative indicators' standardization, the following formula is adopted:

$$y_{ij} = \frac{(X_i)\ - x_{ij}}{(X_i)\ - min\,(X_i)} \times 100 \tag{7}$$

Where x_{ij} refers to the value of indicator i in the j sample, y_{ij} refers x_{ij} after normalization. The entropy weight method is used to calculate the weight of each index. Firstly, we establish the deviation matrix p_{ij} in Eq. (8):

$$p_{ij} = \frac{y_{ij}}{\sum_{j=1}^{n} y_{ij}} \tag{8}$$

Second, for the information entropy Ei of index Yi, we adopt the definition of Eq. (9):

$$E_i = -\frac{\sum_{j=1}^{n} p_{ij} ln\, p_{ij}}{\ln n} \tag{9}$$

Then, the weight wi of each indicator is:

$$w_i = \frac{1 - E_i}{k - \sum_{i=1}^{k} E_i} \tag{10}$$

Finally, we get the score matrix S calculated based on normalized data:

$$S = YW \tag{11}$$

where $Y = [Y_1, Y_2, \dots, Y_k], W^T = [w_1, w_2, \dots, w_k]$.

Table 1. Descriptive statistics summary.

Indicator	Attribute	Definition	Data source
Intensity index (0.2936)	+	The frequency and intensity of storm surges in the region within a year	Calculation from authors
Topographic feature (0.0395)	-	Average DEM (meter) within one kilometer of coastline	Calculation from authors
Coastal population density (0.1868)	+	The population density of the coastal zone (5km)	Center for International Earth Science Information Network - CIESIN - Columbia University, 2022
Economic activities (0.0965)	+	GDP per capita of a region	the China Statistical Yearbook (2000-2020)
Agricultural activities (0.1257)	+	The proportion of primary industry of a region	the China Statistical Yearbook (2000-2020)
Roadway density (0.1297)	+	Total mileage of regional railways	the China Statistical Yearbook (2000-2020)
Railway density (0.1282)	+	Total mileage of regional roadways	the China Statistical Yearbook (2000-2020)

Noted: The numbers in parentheses are the weights. The gaps in the data for the remaining years are filled using the interpolation method. Detailed definitions and calculations of the indicators are shown in the supplementary material.

Then, we add hazard exposure to improve our empirical model:

$$log\ log\ (Loss_{it} + 1) = \alpha + \beta_1\ log\ log\ PGDP_{it} + log\ \beta_2 log\ PGDP_{it}{}^2 + \beta_3 HZ_{it} + \beta_4\ log\ log\ PGDP\ \times HZ_{it} + \beta_5\ log\ log\ PGDP_{it}{}^2 \times HZ_{it} + \varepsilon_{it} \tag{12}$$

$$= \alpha + \beta_1\ log\ log\ PGDP_{it} + log\ \beta_2 log\ PGDP_{it}{}^2 + \beta_3 HZ_{it} + \beta_4\ log\ log\ PGDP\ \times HZ_{it} + \beta_5\ log\ log\ PGDP_{it}{}^2 \times HZ_{it} + \varepsilon_{it} \tag{13}$$

where HZ_{it} is regional hazard exposure score.

At this point, we have shown how our empirical models are established. First, we consider the most direct relationship between economic growth and storm surge losses through a basic empirical framework. Secondly, we added some socio-economic factors that may affect disaster losses to the basic framework as control variables to verify the impact of different aspects of social development (as opposed to economic development) on storm surge disaster losses. Finally, we consider the effect of hazard exposure on the loss-development relationship in our theoretical model. Hazard exposure is a comprehensive index that takes into account disaster intensity, economic activities, agricultural activities, topographic features, traffic line density and population density. And the reason why we did this is because we tried to look at what is the effect of different hazard exposures on storm surge disasters losses.

Table 2. Formatting sections, subsections, and subsubsections.

Indicator	Mean	SD	Median	Max	Min
Loss	9.44	22.15	0.53	154.22	0.00
Death	3.77	23.95	0.00	324.00	0.00
GDP per capita	35365.34	21013.93	30691.94	101883.65	4652.00
Intensity index	4.35	5.29	2.00	24.00	0.00
Mean_DEM_1km	41.23	67.41	19.94	249.44	3.74
CPD	1162.07	745.10	1052.82	4203.63	476.09
Agri	9.99	7.80	8.60	0.29	36.40
Roadway density	96406.47	70973.49	97786.00	286814.40	4325.00
Railway density	2680.64	1902.64	2478.60	7941.17	200.00
PFE	7771.49	6674.92	6240.61	33743.43	544.07
Student	2559.56	939.91	2352.00	4888.16	812.41
Teacher	5.66	0.89	5.63	7.74	3.71
Hospital	24367.10	22549.39	16323.00	86939.00	1947.00
Physician	10.48	6.97	9.71	32.92	1.18

4 Results

4.1 Distribution of storm surge disaster losses

Captions The change of storm surge disaster loss indicators shows different characteristics in different periods, as shown in Figure 2a and Figure 2b. Overall, from 1978 to 2020, storm surge disasters caused direct economic losses of 783 million CNY per year on average in China's coastal provinces, while causing an average of 11.18 deaths per year. From 1978 to 1999, China's coastal provinces suffered an average annual direct economic loss of 628 million CNY due to storm surges. The figure rose to 944 million CNY from 2000 to 2020. This is in line with our intuitive understanding of natural disasters: with economic growth, the accumulation of capital and property will aggravate the losses of natural disasters. The pattern is reversed for the number of deaths. From 1978 to 1999, the annual average death toll from storm surges in China's coastal provinces was 18.26, but from 2000 to 2020, it dropped to 3.77. This shows that with the progress of natural disaster forecast technology, the protection of life safety is easier to achieve than the safety of property. This is also in line with our understanding of natural disasters, because when natural disasters happen, as long as the risk forecast can be done, residents in the risk area can be evacuated from the danger area, while property and capital are not easy to be done so.

All eleven coastal regions of China suffered economic losses and casualties from storm surge disasters from 1978 to 2020, as shown in Figure 3a and Figure 3b. Among them, Guangdong, Fujian, Zhejiang, and Hainan were the provinces that experienced the most severe economic losses. The cumulative economic losses in these four regions amounted to 307.09 billion CNY, which represents 82.94% of the economic losses from storm surge disasters across China for the study period. These four regions also had the highest number of fatalities, with a total of 4317 deaths from storm surge disasters between 1978 and 2020, accounting for 81.59% of all deaths in China. Both losses and death tolls all showed a spatial agglomeration pattern, which was mainly concentrated in the southeast coastal areas of China. These areas are affected by tropical cyclones all year round, so storm surge disasters have a severe impact on these regions.

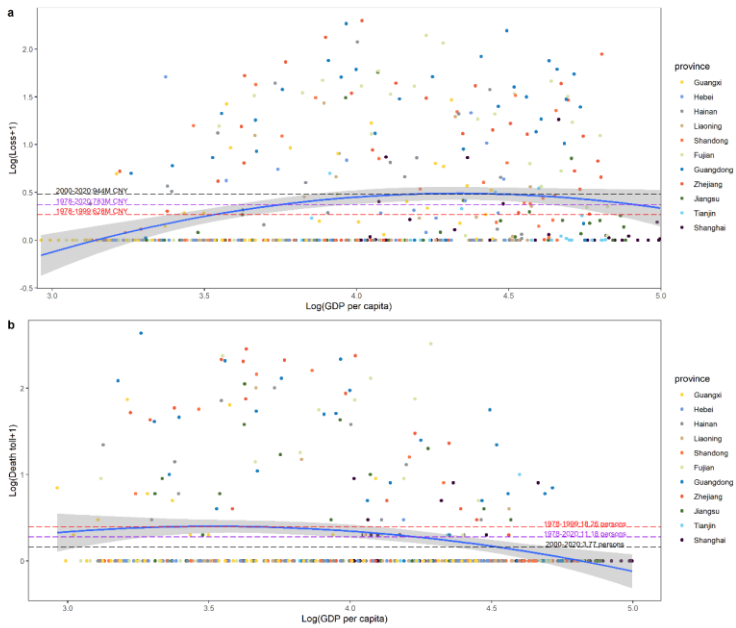

Fig. 2. Distribution of storm surge disaster losses (a), death tolls (b) in 11 coastal provinces of China from 1978 to 2020. Noted: The blue line is the regression trend line of the quadratic term. The dashed line is the mean value of regional storm surge disaster loss indicators in different periods.

We investigated the relationship between storm surge disaster losses and economic development. In our study, this was measured by the relationship between different storm surge loss indicators and GDP per capita. As shown in Figure 3, the damage caused by storm surge disasters is the most severe in areas with medium and high levels of economic development, while the damage is not significant in areas with low and high levels of economic development. This result indicates that there may be an "inverted U-shaped" curve in the relationship between storm surge disaster loss and social development, as found by other studies[10,11]. Nonetheless, this relationship needs to be further explored.

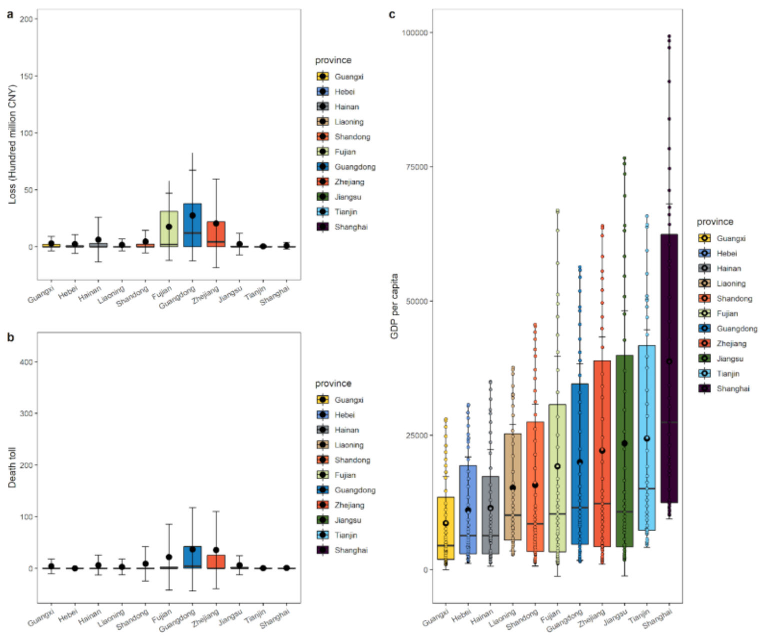

Fig. 3. Distribution of storm surge disaster losses (a), death tolls (b) in 11 coastal provinces of China from 1978 to 2020.
Noted: The order of regions is from least to most according to the GDP per capita (2000 price level). The solid point is the mean value of GDP per capita and storm surge damage indicators.

4.2 The relationship between economic growth and storm surge losses

4.2.1 Based on basic regression results

Table 3. Regression results of losses using generalized linear model (Tobit estimates).

Variable	**Loss**					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	2000-2020	1978-1999	1978-2020	2000-2020	1978-1999	1978-2020
Log(PGDP)	-0.011 (0.213)	1.024** (0.362)	0.719*** (0.118)	20.023*** (5.943)	17.373* (7.888)	7.067*** (1.979)
Log(PGDP)^2	\	\	\	-2.276*** (0.67)	-2.228* (1.06)	-0.784*** (0.243)
Constant	0.278 (0.961)	-4.507** (1.370)	-3.04*** (0.497)	-43.646*** (13.083)	-34.333* (14.504)	-15.699*** (3.996)
Year-fixed	Yes	Yes	Yes	Yes	Yes	Yes
Observations	231	242	473	231	242	473
Left-censored	86	173	259	86	173	259
Log-likelihood	-255.972	-200.008	-466.454	-250.053	-197.707	-461.086
Shaped	\	\	\	Inverted-U	Inverted-U	Inverted-U
Turning point	\	\	\	25307.133	8124.141	31985.000

Noted: (1) Standard errors are shown in parentheses. (2) *, **, and *** are 10, 5, 1% significance levels.

Table 4. Regression results of death toll using generalized linear model (Negative binomial estimates).

Variable	**Death toll**					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	2000-2020	**1978-1999**	**1978-2020**	**2000-2020**	**1978-1999**	**1978-2020**
Log(PGDP)	-5.919^{***} (1.029)	-0.068 (0.813)	-2.447^{***} (0.393)	145.769^{***} (33.064)	35.043^{*} (16.436)	29.975^{***} (6.522)
Log(PGDP)^2	\	\	\	-17.081^{***} (3.789)	-4.839^{*} (2.252)	-4.079^{***} (0.818)
Constant	27.119^{***} (4.580)	3.152 (2.967)	11.915^{***} (1.591)	-308.733^{***} (71.951)	-60.155^{*} (29.836)	-51.799^{***} (12.848)
Year-fixed	Yes	Yes	Yes	Yes	Yes	Yes
Observations	231	242	473	231	242	473
2×Log-likelihood	-493.208	-987.002	-1492.590	-482.199	-984.026	-1475.616
Shaped	\	\	\	Inverted-U	Inverted-U	Inverted-U
Turning point	\	\	\	18492.370	4177.272	4719.344

Noted: (1) Standard errors are shown in parentheses. (2) *, **, and *** are 10, 5, 1% significance levels.

Table 3 and Table 4 show the estimates of our basic empirical framework based on Eq. (1) and Eq. (2). Not surprisingly, we can see that GDP per capita and its quadratic term are both statistically significant in all two regressions. The non-linear (inverted-U) relationship of “loss-development” can be seen in different time scales. Furthermore, the turning point of the loss-development relationship is not only related to the storm surge loss indicators, but also related to the study period. Our calculation of the coefficient shows that the turning point of direct economic losses is predicted earlier than that of the death toll. For Loss, the turning point occurs at 8124 to 31985 CNY. While for Death toll it occurs at 4177 to 18492 CNY. We compared the turning point with provincial per capita GDP and found that from 1978 to 2020, the development level of most regions has exceeded the turning point for Loss, and all regions for Death toll. Only Guangxi Province and Hebei Province have not passed the turning point for Loss. This means that these areas are likely to suffer more damage in the face of storm surge disasters, as their economies grow.

As shown in Table 3 and Table 4, we tested the "lost-development" monotone relationship for all two regression models. The reason we did this was to test whether the hypothesis of a non-linear relationship between disaster losses and economic growth is correct. We found that different disaster indicators have different causal relationships with economic growth. For Loss, the regression models containing quadratic terms perform better than the regression models containing only primary terms in the same period of time (see Log-likelihood). This conclusion can also be obtained from the transformation of monotone model coefficients. Direct economic losses from storm surge disasters increased monotonically with economic growth from 1978 to 1999, and then decreased monotonically from 2000 to 2020. However, for Death toll, the “loss-development” monotonic relationship seems to perform better than the non-linear relationship (see 2×Log-likelihood). The death toll and economic growth show monotonously decreasing trends over different time horizons, as we noticed the coefficients in column (1) to column (3) in Table 4. The above results indicated that the impact of storm surge disasters on society depends on different measurement aspects of loss. At this point, **hypothesis 1** is confirmed.

We further investigated the regional “loss-development” relationship using provincial panel data from 1978 to 2020 for Loss and Death toll based on Eq. (1) and Eq. (2) (Table 5 and Table 6). For direct economic losses, only the Fujian Province panel showed a statistically significant inverted U-shaped “loss-development” relationship. This may be

Table 5. Regression results of provincial losses using generalized linear model from 1978 to 2020 (Tobit estimates).

Variable	Loss										
	Tianjin	**Hebei**	**Liaoning**	**Shandong**	**Jiangsu**	**Shanghai**	**Zhejiang**	**Fujian**	**Guangdong**	**Guangxi**	**Hainan**
Log(PGDP)	6.319 (9.474)	4.227 (10.881)	12.305 (16.215)	2.584 (7.055)	7.468 (5.259)	10.576 (10.052)	7.578 (5.054)	24.797*** (6.961)	7.712 (5.889)	8.732 (5.125)	8.169 (7.318)
Log(PGDP)^2	-0.688 (1.103)	-0.417 (1.390)	-1.423 (1.978)	-0.206 (0.883)	-0.838 (0.628)	-1.179 (1.120)	-0.854 (0.621)	-2.878*** (0.831)	-0.844 (0.727)	-1.036 (0.668)	-0.973 (0.939)
Constant	-14.750 (20.234)	-10.557 (21.133)	-26.967 (33.073)	-7.113 (13.929)	-16.564 (10.894)	-23.778 (22.435)	-15.845 (10.151)	-52.084*** (14.466)	-16.425 (11.779)	-17.924 (9.736)	-16.977 (14.121)
Observations	43	43	43	43	43	43	43	43	43	43	43
Left-censored	34	30	32	24	26	27	12	17	13	20	24
Log-likelihood	-32.269	-30.421	-28.046	-37.856	-29.452	-42.198	-49.280	-37.000	-51.672	-29.790	-40.275
Shaped	Inverted-U	Inverted-U	Inverted-U	Inverted-U	Inverted-U	Inverted-U	Inverted-U	Inverted-U	Inverted-U	Inverted-U	Inverted-U
Turning point	\	\	\	\	\	\	\	20273.72	\	\	\

Noted: (1) Standard errors are shown in parentheses. (2) *, **, and *** are 10, 5, 1% significance levels.

Table 6. Regression results of provincial death toll using generalized linear model (Negative binomial estimates).

Variable	Death toll										
	Tianjin	Hebei	Liaoning	Shandong	Jiangsu	Shanghai	Zhejiang	Fujian	Guangdong	Guangxi	Hainan
Log(PGDP)	\	\	\	94.757*** (7.898)	54.569** (20.363)	95.298 (53.196)	56.076*** (2.441)	73.027*** (17.657)	11.879 (13.131)	41.192 (24.131)	39.972*** (4.658)
Log(PGDP)^2	\	\	\	-12.611*** (1.053)	-7.119** (2.560)	-11.057 (6.043)	-7.579*** (0.326)	-9.497*** (2.259)	-1.807 (1.633)	-6.017 (3.305)	-5.484*** (0.631)
Constant	\	\	\	-174.618*** (14.787)	-101.740* (40.139)	-204.604 (116.654)	-99.063*** (4.557)	-135.583*** (34.070)	-15.003 (26.084)	-68.334 (43.633)	-70.309*** (8.565)
Observations	\	\	\	43	43	43	43	43	43	43	43
2×Log-likelihood	\	\	\	-50.37	-141.86	-84.31	-133.17	-179.10	-291.15	-111.9360	-257.4040
Shaped	\	\	\	Inverted-U	Inverted-U	Inverted-U	Inverted-U	Inverted-U	Inverted-U	Inverted-U	Inverted-U
Turning point	\	\	\	5713.71	6801.91	\	5003.15	6992.49	\	\	4408.07

Noted: (1) Standard errors are shown in parentheses. (2) *, **, and *** are 10, 5, 1% significance levels. (3) Negative binomial regression could not be performed in Tianjin, Hebei and Liaoning because of insufficient samples.

attributed to the effectiveness of disaster mitigation measures for storm surge disasters in Fujian Province. While there are five provinces showed the same pattern for death toll. Similarly, the regional turning point showed the same trend as the national turning point, with the death toll turning points are predicted earlier than the direct economic loss. The turning points are predicted from 4408 CNY to 6992CNY. There may be a nonlinear relationship (inverted U-shape) between storm surge disaster losses and economic growth in both national and regional panel data.

4.2.2 Based on regression results considering multiple socioeconomic factors

Table 7. Regression results considering multiple socioeconomic factors.

Variable	Loss	Death toll
	2000-2020	**2000-2020**
Log(PGDP)	31.770^{***} (5.742)	169.059^{***} (32.318)
Log(PGDP)^2	-3.199^{***} (0.643)	-17.807^{***} (3.627)
Log(PFE)	-1.155^{***} (0.336)	-6.328^{***} (1.768)
Log(Student)	-3.782^{***} (0.721)	-8.674^{**} (3.353)
Log(Teacher)	-3.157^{**} (1.015)	-11.967^{*} (4.846)
Log(Physician)	-1.087^{**} (0.384)	-4.204^{*} (1.885)
Log(Hospital)	0.327 (0.289)	-0.765 (1.427)
Constant	-58.501^{***} (11.922)	-330.033^{***} (68.479)
Observations	231	231
Left-censored	86	\
Log-likelihood	-213.66	\
2×Log-likelihood	\	-460.51
Shaped	Inverted-U	Inverted-U

Noted: (1) Standard errors are shown in parentheses. (2) *, **, and *** are 10, 5, 1% significance levels.

We next consider the impacts of different socioeconomic factors on the "loss-development" relationship. Due to the data availability, the period of panel data selected in this part of the study is from 2000 to 2020. Consistent with previous theoretical modeling [59], the results shown that, after taking into account multiple socioeconomic factors, the non-linear relationship of "loss-development" does not change. The increase in per capita fiscal expenditure level has a restraining effect on storm surge disaster losses, whether the indicator is direct economic loss or death toll (Table. 7). Similarly, regional education level also reduces the loss of storm surge disaster. The effect of the number of medical facilities on storm surge losses was not statistically significant. This may be because storm surge hazards cause damage to infrastructure, including medical facilities, so they do not reduce storm surge damage. **Hypothesis 2** was observed to be corrected in this study.

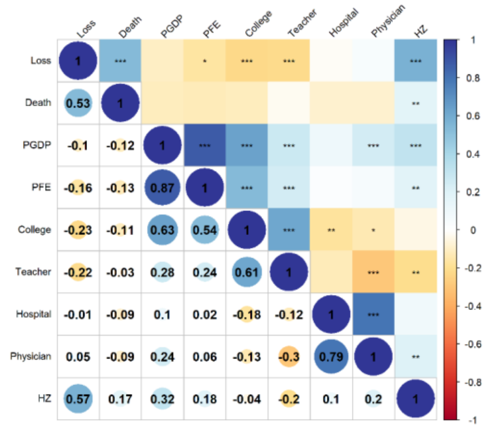

Fig. 4. Heat map for correlation analysis. Noted: The numbers in the bottom half represent the correlation coefficients, using Pearson's method. The size and color of the circle indicate the level and sign of the correlation coefficient. The asterisk in the top half represents statistical significance. *, ** and *** represent the significant level of 0.05, 0.01 and 0.001.

From Figure 4, we can see that economic growth is strongly correlated with socio-economic factors affecting storm surge hazard losses. In the more developed regions, the level of fiscal expenditure, education level and medical level will be improved to different degrees. This also explains the origin of the non-linear relationship between loss and development. Although economic growth makes capital more concentrated, improved disaster management ability can reduce the losses caused by natural disasters to some extent. However, the above analysis does not take into account the vulnerability indicators such as disaster intensity, topographic features and population density of the affected areas. As can be seen from Figure 4, the more developed the economy is, the higher their hazard exposure seems (see the correlation between HZ and PGDP). We will discuss the impact of hazard exposure on the "loss-development" relationship in next Section 4.4.

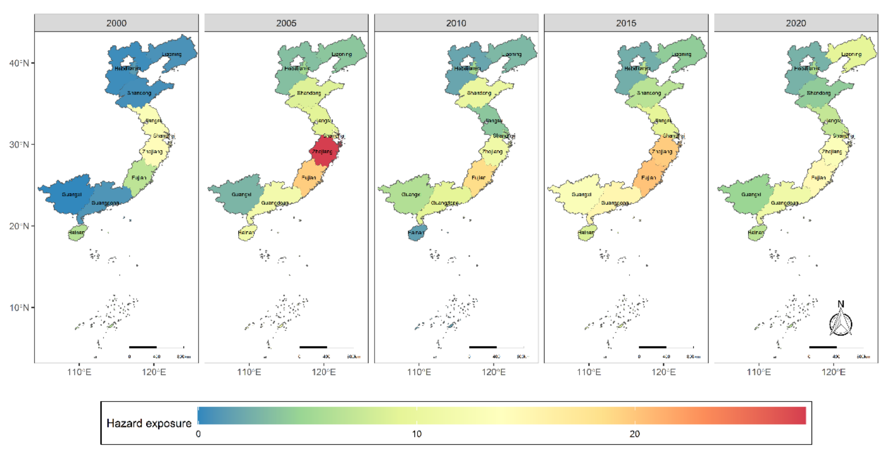

Fig. 5. Storm surge hazard exposure scores in 11 coastal regions in China from 2000 to 2020.

Figure 5 shows the change of the storm surge hazard exposure (HZ) scores in China from 2000 to 2020. HZ scores ranged from 0 to 34.37. As can be seen, Guangdong, Guangxi, Fujian and Zhejiang province are regions with the highest hazard exposure scores. HZ score of southeast coastal areas of China is higher than that of other areas. On average, Guangdong, Zhejiang and Fujian provinces had the highest HZ scores, with 15.45, 14.61 and 14.83, respectively. The frequency and intensity of storm surge disasters are higher in these areas than in other areas, which results in higher HZ in these areas because the weight of disaster intensity is the highest (see Table 1, Figure S1, and Figure S3). We showed the results of scores of each secondary index of HZ in Figure S2 to Figure S8. Most indicators of vulnerability have increased over time. Since the agricultural activity index is a negative indicator, the decline in the score of the agricultural activity index also increases HZ (see Figure S6).

4.3 Storm surge hazard exposure and its role in "loss-development" relationship

As shown in Figure 5 and Figure S1, HZ scores increase over time for most of the coastal regions in China. This may imply a relationship between social development and HZ, in which higher levels of development are likely to increase HZ. It should be noted that HZ scores increased and then decreased in some regions, such as Guangdong, Zhejiang and Shandong province. Although the main driving force of HZ is disaster intensity, coastal zone disaster prevention and mitigation capacity may be crucial for HZ. It also suggests that Guangdong, Zhejiang and Shandong province may be better at disaster prevention and mitigation than other regions.

Table 8. Regression results considering interaction effect of hazard exposure.

Variable	**Loss**			**Death toll**		
	2000-2020	**2000-2020**	**2000-2020**	**2000-2020**	**2000-2020**	**2000-2020**
Log(PGDP)	\	15.474^{*} (6.706)	13.997^{*} (6.871)	\	119.682^{*} (58.055)	154.695^{*} (69.720)
$Log(PGDP)^2$	\	-1.799^{*} (0.766)	-1.508^{*} (0.677)	\	-13.313^{*} (6.696)	-16.975^{*} (7.841)
HZ_i	0.089^{***} (0.006)	1.890^{***} (0.172)	1.916^{***} (0.397)	0.330^{***} (0.040)	8.605^{***} (1.283)	12.997^{***} (2.510)
$Log(PGDP)\times HZ_i$	\	-0.741^{*} (0.366)	-0.744^{*} (0.367)		-3.019 (5.987)	-5.191 (5.641)
$Log(PGDP)^2\times HZ_i$	\	0.075^{*} (0.037)	0.074^{*} (0.036)		0.257 (0.673)	0.523 (0.635)
Log(PFE)	\	\	-0.405 (0.224)		\	-3.529^{*} (1.549)
Log(Student)	\	\	-1.111^{*} (0.493)		\	0.958 (3.056)
Log(Teacher)	\	\	0.529 (0.715)		\	2.460 (4.787)
Log(Physician)	\	\	-0.236 (0.256)		\	-1.560 (1.808)
Log(Hospital)	\	\	0.241 (0.190)		\	0.075 (1.307)
Constant	-0.472^{***} (0.076)	-33.562^{*} (14.648)	-28.634^{*} (13.636)	-2.605^{***} (0.462)	-270.690^{*} (130.241)	-345.088* (151.714)
Observations	231	231	231	231	231	231
Left-censored	86	86	86	\	\	\
Log-likelihood	-172.344	-137.27	-130.12	\	\	\
2×Log-likelihood	\	\	\	-478.58	-439.93	-429.19
Shaped	\	Inverted-U	Inverted-U	\	Inverted-U	Inverted-U

We then explored the relationship between HZ and storm surge disaster losses, as shown in Table 8. When we only consider the effect of HZ on storm surge disaster losses, we find that HZ has a fairly significant effect on both Loss and Death toll. In general, the greater the HZ, the greater the disaster losses. More importantly, HZ affects the loss-development relationship. The loss-development relationship may depend on an area's risk of storm surge disasters. The coefficient of interaction term shows that although economic growth has a role in reducing disaster loss to some extent, the increase of HZ will reduce this effect. In other words, for areas with a higher likelihood of storm surge disasters, greater wealth may reduce the economic losses suffered later in development at a lower rate. This is challenging for local disaster prevention and response planning. Governments need to take into account the probability and intensity of natural disasters while weighing economic growth and reducing losses from natural disasters. At the same time, we see that the role of socioeconomic factors that can reduce natural disasters decreases after we account for HZ. This indicates that storm surge disaster losses in China are still primarily determined by HZ, which supports **Hypothesis 3**.

5 Discussion

Equations Our findings indicate that the relationship between natural disaster losses and economic growth is not simply linear, which is consistent with the conclusions of previous studies. The empirical model demonstrates that, at both the national and provincial levels, there is also an inverted U-shaped relationship between losses from storm surges and economic development levels in China. It may suggest that the losses caused by storm surges do not always increase with economic development. This is because, due to the rapid economic growth, countries or regions will increase their investment in disaster prevention and mitigation, which improves the ability to predict and resist storm surges. However, the same result may not be applicable in all the provinces, not only because of the differences in the level of economic development of different provinces, but also owing to the different risks they face. At the same time, we also observed that different disaster indicators may have different loss-development relationships. The "inverted U-shaped" relationship between direct economic losses and economic growth seems more significant than the number of deaths. This proves that China's efforts to reduce storm surge disaster casualties have been relatively successful. In other words, this is easier to achieve than reducing the direct economic losses of natural disasters. As we mentioned earlier, moving residents out of risk areas is easier and more realistic than moving capital. This requires local governments to invest more protective measures in areas at high risk of storm surge disasters, such as sea walls and levees, to protect the property safety of coastal residents. In recent years, the Chinese government has made efforts in coastal disaster prevention and mitigation, including promoting Nature-based Solutions (NbS). In the pilot areas, NbS has achieved certain results, which can effectively reduce the risk in the coastal zone, and provide many environmental benefits for the region, including blue carbon, ecosystem services and ecotourism [26]. We believe that China and other regions should continue to implement effective disaster reduction strategies for coastal areas to achieve sustainable development in those regions.

As we mentioned in our work, HZ may play an important role in the loss-development relationship. Through our analysis, the models show different loss patterns for provinces with different HZ when facing storm surge disasters. In other words, HZ may affect the role of economic growth in reducing disaster losses. The impact of HZ is challenging for policy makers to develop disaster prevention and mitigation policies. Local authorities need to have a clear understanding of local economic development trends and the prevalent storm surge risk to tailor their policies to reduce the damage caused by natural disasters. We further want to highlight that the assumption that the two objectives of natural disaster risk reduction and economic growth are compatible may be wrong. As Kellenberg and Mobarak [10] explained, risk averse individuals are likely to make different risk-return trade-off choices at different income levels. For extremely poor regions or countries, the marginal benefits of deforestation for economic development activities are likely to outweigh the marginal costs of disaster prevention and mitigation. Similarly, a poorer household may find it in their interest to relocate to a densely populated urban area in search of better employment opportunities, even if this means an increased risk of exposure to disasters, while a wealthier household may not find it beneficial to do so. These conclusions underline the importance of planning for disaster prevention and mitigation. Development policies that aim solely at eradicating poverty through economic development may increase the risks associated with natural disasters in the region. In addition, when faced with the different impacts caused by storm surge hazards, policy makers also need to consider different means to reduce the negative impacts. In dealing with economic losses and affected population caused by storm surges, disaster management authorities need to strengthen storm surge forecasting capacity. Governments should also relocate residents living in high-risk areas to reduce casualties caused by storm surges.

The above discussion is of general significance. That is to say, the above discussion is also applicable to other countries or regions, especially developing countries. They tend to face higher exposure in areas with lower income levels, especially in small island countries. This is challenging for local policy makers. Governments must balance economic growth with reducing disaster losses. In other words, they need to invest more in disaster prevention and mitigation infrastructure and less in others. At the same time, this study argues that in areas with low hazard exposure, it is also necessary to invest in protection infrastructure. The empirical results in this study support these views. When the risk level is low, losses rise with wealth, making an investment in protection infrastructure worthwhile. When wealth levels are high, or hazard exposure is serious enough, the marginal benefits of protection infrastructure will outweigh the marginal costs. In conclusion, we emphasize the importance of investing in disaster prevention and mitigation infrastructure.

6 Conclusion

This study explored the relationship between economic growth and storm surge disaster losses in China and found robust evidence of a non-linear relationship between economic development and storm surge disaster-related losses in China's coastal provinces. There is an "inverted U-shaped" relationship between economic growth and storm surge disaster-related losses. Our findings also suggest that we must pay more attention when modelling and exploring the relationship between economic growth and natural disaster losses. More precisely, there is no simple "increase in wealth - decrease in loss" relationship, causing policy-making more difficult. However, one of the main outstanding features to emerge from our analysis is that natural disaster risk is a vital mover behind any relationship between economic losses and economic growth. Thus, it seems necessary to generate and provide more information about current and potential hazards' risk in the different areas where people live or plan to move. This information is helpful for managers to understand disasters and their possible risks more scientifically to reduce disaster losses.

This study is an important reference for the development of disaster prevention and mitigation planning in coastal areas of China and other countries. In future research, scholars should focus on individual as well as family choices to understand the micro-level mechanisms of disasters to deepen our understanding of the relationship between economic development and natural disasters.

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