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The impact of super typhoon lekima on the house collapse rate and quantification of the interactive impacts of natural and socioeconomic factors

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ABSTRACT

Typhoon disasters cause billions of dollars in losses each year, and many countries around the world are adversely affected by these events. Presently, the determinant powers of both natural and socioeconomic factors on disaster losses (such as the house collapse rate following a typhoon), as well as their interaction effects, remain unclear. In this study, the GeoDetector method was used to quantify the impacts of natural and socioeconomic factors and their interactions on the house collapse rate caused by Super Typhoon Lekima in 2019; and then detect the dominant factor, involving in the spatial pattern of house collapses was identified by the local indicators of spatial association (LISA) method. This study found that in addition to natural factors, socioeconomic factors also played a non-negligible role in the house collapse rate caused by Super Typhoon Lekima. The dominant factor was maximum precipitation, and the statistical value of q was 0.39. Next in importance were the elevation and maximum wind speed. Among the interactive effects of 14 influencing factors, the interaction between maximum precipitation and the ratio of four-six floor buildings was the largest ($q = 0.74$). In southeastern Zhejiang and northern Shandong, highly concentrated areas of collapsed houses were found. The results of the study can be used to develop more specific policies aimed at safety improvements and successful property protection.

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1. Introduction

Typhoons are one of the most hazardous types of meteorological disasters globally (Liou et al. 2018); when they attack different parts of the world, they cause large losses of people and property, and have a great impact on society and the economy (Peduzzi et al. 2012; Lee et al. 2017; Chauhan et al. 2018; Sarkar et al. 2018; Chauhan et al. 2021). Typhoons are often accompanied by secondary disasters, such as floods and landslides, that can cause severe damage to or even the destruction of houses and infrastructure and pose a great threat to human life, especially in coastal areas (Kennish 2001; Wang et al. 2014).

Worldwide, it is recognized that with sea level rise and climate change, the frequency and intensity of typhoons will increase significantly (Xu et al. 2016; Yuan et al. 2020). Moreover, the suffering caused by natural disasters is also closely related to increased risks for various forms of psychopathology (Brown et al. 2013), and disturbances that occur within natural ecological environments, for example, forests and rivers, may take years to recover from (Anttila Hughes and Hsiang 2013). China is one of the countries around the world that is most severely affected by typhoons, especially in the eastern coastal region (Xu et al. 2016). Since the 1990s, the three worst typhoon incidents in China have resulted in economic loss surges of $2.7 billion on average (Kentang 2000). Moreover, typhoon disasters have seriously affected the lives of more than 250 million people (Liu et al. 2009; Xu et al. 2013). At the same time, with rapid population growth and economic development, these areas will become increasingly susceptible to the impacts caused by more frequent and stronger typhoons, floods, and other natural disasters (Syvitski et al. 2009). Therefore, better comprehension of typhoon characteristics and the statistical relationships between typhoon-induced disaster losses and natural and socioeconomic factors would be beneficial (Konrad and Perry 2010; Kunkel et al. 2010; Zhang et al. 2018).

Many previous studies have concluded that in addition to dangerous parameters, such as wind speed, ocean temperature changes, and the El Niño–Southern Oscillation cycle (Elsner and Liu 2003; Mei et al. 2015; Mei and Xie 2016; Chauhan et al. 2020), the risks of typhoon disasters are also closely related to the vulnerability of hazard targets and their disaster prevention and reduction capacities; thus, different degrees of damage can be caused to people's lives and living environments following a natural disaster. That is, along with rapid development and urbanization, the population and assets of a given region continue to increase due to natural disasters (Jongman et al. 2012). For example, in Africa, Di Baldassarre et al. (2010) revealed that during the 1950–2010 period, changes in the annual maximum flow and population growth increased the flood risk. Zhang et al. (2017) demonstrated that coastal urban regions are becoming more vulnerable and are being increasingly threatened by typhoons with population growth and growth of infrastructure facilities. Knutson et al. (2010) found that under future scenarios, cyclone-induced precipitation would increase by 20%; this increase will pose a great threat to the safety of lives and the property of people living in coastal lands and even in inland regions due to the corresponding flooding (Rappaport 2000; Lin et al. 2015; Zhang et al. 2018).

However, previous studies have mainly focused on quantifying impact factors separately, while the interactive effects of these factors on the house collapse rate caused

by typhoons have been ignored. Therefore, quantifying the impacts of the related factors and their interactions is key to obtain a deeper understanding of the impact mechanism; this understanding would enable the formulation of effective policies to control related damages and reduce casualties and property losses. This study aims to 1) quantify the determinant powers of potential factors and their interactions on the house collapse rate caused by Super Typhoon Lekima using the GeoDetector method; 2) examine the dominant factor affecting house collapses; and 3) identify the spatial pattern of the house collapse rate caused by Super Typhoon Lekima under the influence of the dominant factor using the LISA method.

2. Materials and methods

2.1. Study area and typhoon data

Many of the southeastern coastal regions in China are highly urbanized with dense populations and well-developed economies, but these regions are also highly susceptible to natural hazards such as super typhoons and coastal flooding (Zhang et al. 2017). The four provinces most affected by Super Typhoon Lekima, namely, Zhejiang, Jiangsu, Shandong, and Liaoning, are located in the eastern coastal region of China, which is densely populated and well-developed economically; this region spans a length of more than 18,000 km along the coastline (Figure 1). This region is often hit by natural disasters that, typically result in huge losses in terms of casualties and property. Therefore, it is essential to deploy rapid emergency measures against typhoon disasters in the eastern coastal areas of China.

On 10 August 2019, Super Typhoon Lekima made landfall in Wenling city, Zhejiang Province, and the maximum wind speed near the center of the typhoon was 52 m/s. After that, the storm returned to sea and made a second landfall in Qingdao city, Shandong Province, on 11 August 2019. This storm was the fifth strongest typhoon that has landed in mainland China since 1949, and a total of 14.02 million people were affected, mainly in Zhejiang, Shandong, Jiangsu, Liaoning, and other nearby provinces. The typhoon caused 15,000 houses to collapse, and 133,000 houses were damaged to varying degrees. The affected crop area was 11.37 thousand hectares, and the direct economic losses amounted to 51.53 billion yuan. In this study, data on the number of collapsed houses in Zhejiang, Jiangsu, Shandong, and Liaoning provinces affected by Super Typhoon Lekima were used along with maximum precipitation (MP) and maximum wind speed (WS) data to analyze the spatial characteristics of the house collapse rate and the determinant powers of natural and socioeconomic factors (Figure 1).

2.2. Potential impact factors

This study considered four typhoon-related aspects (hazard, characteristics of the disaster environment, vulnerability of hazard targets and disaster prevention and reduction capacity), the results from previous studies (Shen et al. 2009; Hu et al. 2018; Shi et al. 2020), and the data availability when selecting the potential impact factors to be used for the analysis; thus, 14 potential driving factors were selected for the analysis
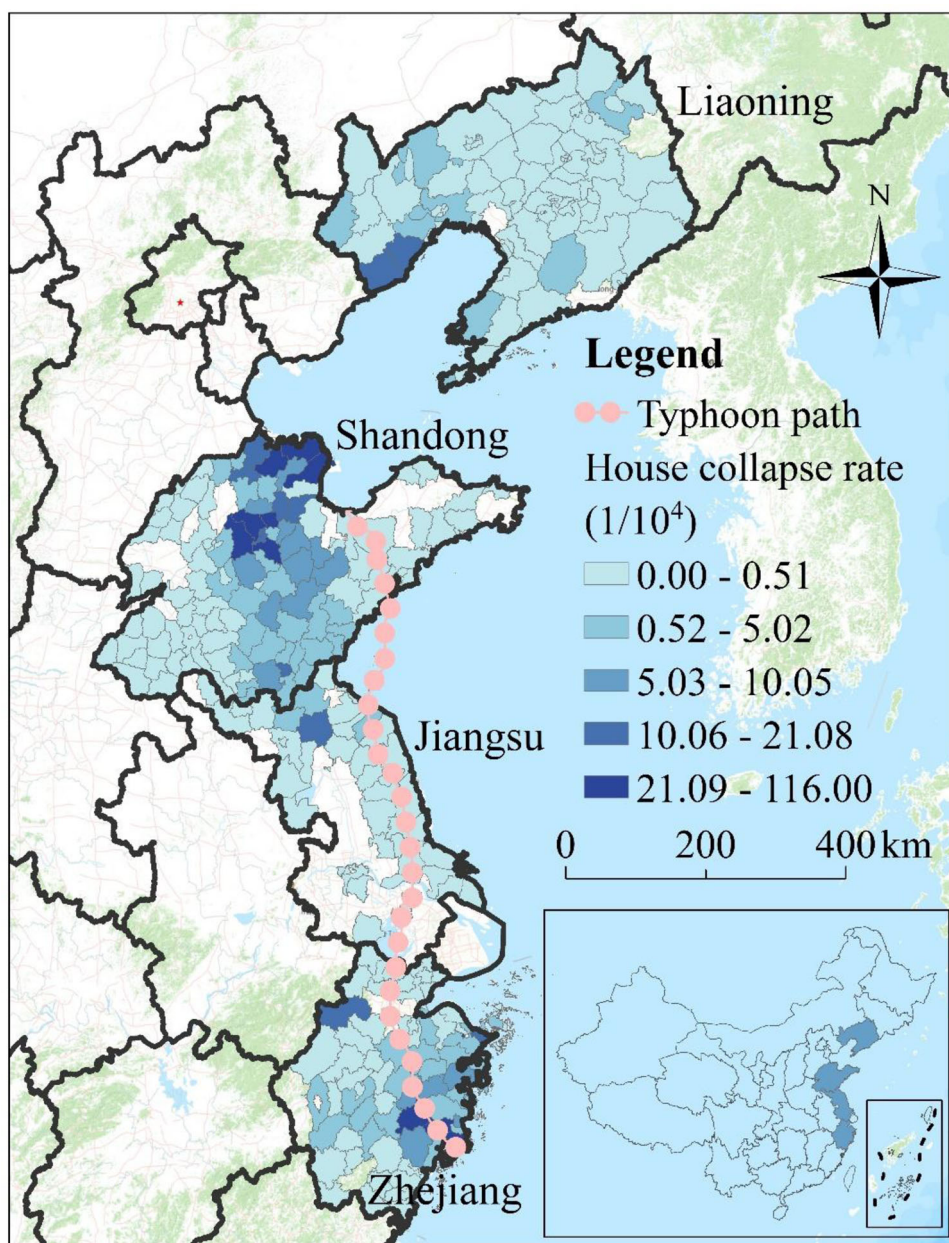
Figure 1. Spatial distribution of house collapse rate affected by Super Typhoon Lekima.

(Figure 2). Data on the house structures, including the ratio of steel-concrete houses (RS), ratio of brick-wood houses (RW), ratio of brick-concrete houses (RC), and data on building floors, including the ratio of bungalows, ratio of two-three floor houses (RTT), ratio of four-six floor (RFS), and ratio of seven-nine floor houses (RSN), were compiled. Data on other factors were also obtained, e.g. population density (PD), per capita gross domestic product (GDP) (hereafter PG), and proportion of tertiary industry (PT); these data were collected from the government's economic statistical
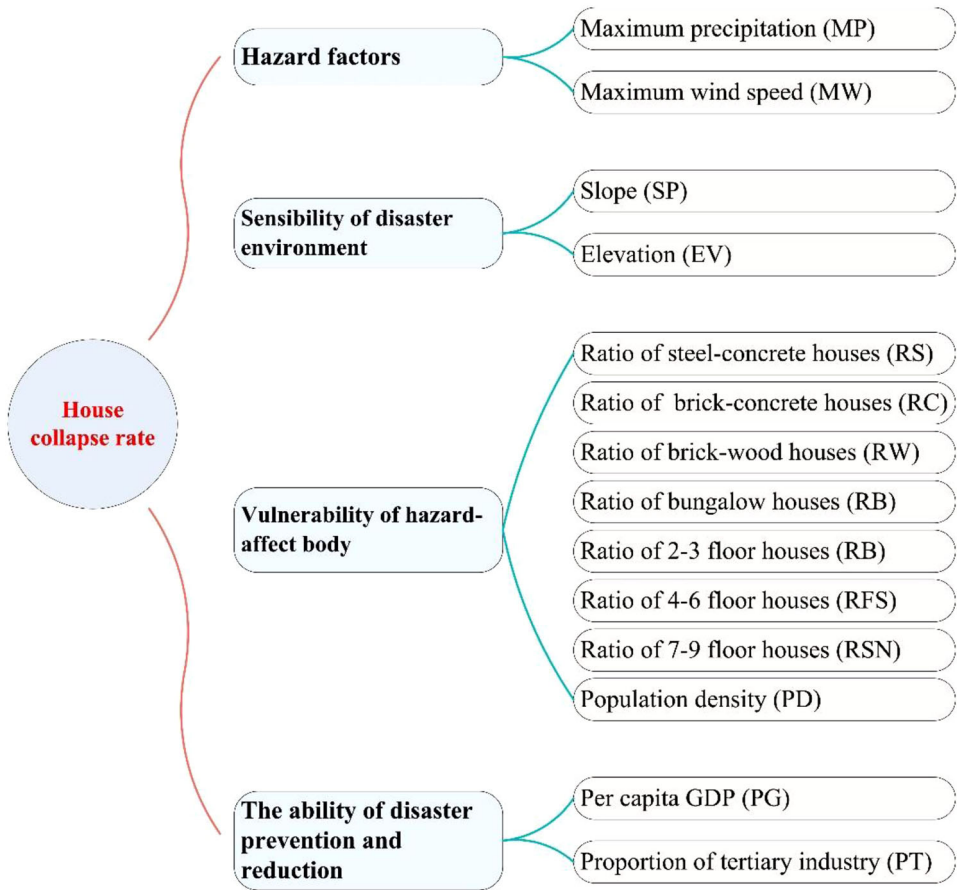
Figure 2. Potential impact factors related to the house collapse rate affected by Super Typhoon Lekima.

yearbooks for Zhejiang, Jiangsu, Shandong, and Liaoning provinces. Data on natural factors, such as the slope (SP) and elevation (EV), were collected with a resolution of 1 km × 1km from the resource and environmental data cloud platform (http://www.resdc.cn); these data were then extracted by using the zonal statistics tool in the ArcGIS10.3 software for each county in the study area.

2.3. Statistical analysis

In this study, to explain the house collapse rate caused by Super Typhoon Lekima, the determinant powers of natural and socioeconomic factors and their interactive effects were first quantified by the GeoDetector method, and the dominant factor was also determined. Then, the local indicators of spatial association (LISA) method was used to identify the spatial pattern of the house collapse rate under the intervention of the dominant factor, and these data were used to further classify the study area into hot and cold spots.

2.3.1. Geodetector

GeoDetector is good at detecting and quantifying spatial heterogeneity, which is one of the basic characteristics of geographic phenomena. The main concept of GeoDetector is that if the potential impact factor X has an effect on the response variable Y, Y will show a spatial distribution similar to that of the factor X (Wang et al. 2010; Wang and Xu 2017), which can reflect geographic phenomena more comprehensively and realistically. It has been employed in the fields of geology, environment, health, disasters and other many fields (Luo et al. 2016; Zhao et al. 2020; Wang et al. 2021; Zhang et al. 2021). In this study, GeoDetector was used to quantify the determinant powers of selected factors and their interactions on the response variable (house collapse rate) to further identify the dominant factor affecting the house collapse rate, as follows:

$$q = 1 - \frac{1}{N\sigma^2} \sum_{h=1}^{L} N_h \sigma_h^2 \tag{1}$$

where q measures the extent to which influence factor X explains the spatial heterogeneity of the response variable Y (house collapse rate) and ranges from 0 to 1. When the value of q is larger, is a stronger determinant power of the independent variable X on the response variable Y is indicated. The study area was divided into L layers, represented by $h = 1, 2, \ldots, L$. N and N_h represent the number of study units (counties) in the study area and in layer h, respectively. The terms σ_h^2 and σ^2 represent the variances in Y in layer h and in the study area, respectively.

Moreover, GeoDetector was used to identify the interactive effects between two random impact factors X, that is, to evaluate whether the interaction between X1 and X2 led to an increase or decrease in the individual determinant power of X1 or X2 on the response variable Y (Figure 3). Then, q (X1), q (X2), and q (X1∩X2) were calculated and compared.

It is worth mentioning that one of the advantages of GeoDetector is that there is no linear assumption about the variables, meaning that the multicollinearity of the selected factors can be ignored. Therefore, adding or excluding factors will not affect the results of other factors. All of the above processes were implemented in GeoDetector (www.geodetector.cn).

2.3.2. Spatial pattern detection

LISA was used to detect the hot and cold spots of the house collapse rate and to determine the class of spatial correlation between the two studied subjects, as follows:

$$I_{kl}^i = Z_k^i \sum_{j=l}^{n} W_{ij} Z_l^i \tag{2}$$

$$Z_k^i = \frac{x_k^i - \overline{x_k}}{\sigma_k}, \quad Z_l^i = \frac{x_l^j - \overline{x_l}}{\sigma_l} \tag{3}$$

where W_{ij} represents the spatial weight matrix, adopted as the first-order 'queen' adjoining form in GeoDa software; x_k^i and x_l^j are the variables k and l at locations i
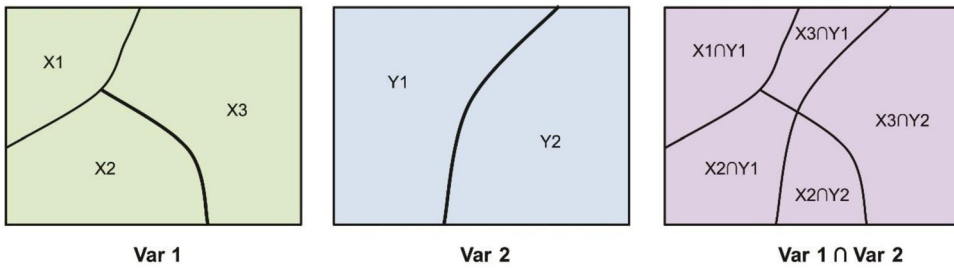
Figure 3. Illustration of the principle of the interaction detector.

and j, respectively; and $\overline{x}_k$ and $\overline{x}_l$ are the mean values of x_k and x_l, respectively. The terms σ_k and σ_l are introduced here to represent the variances in x_k and x_l, respectively.

Z_k^i and the corresponding spatial lag, WZ_l^i, at location i are shown on the vertical and horizontal axes of Moran's I scatter plot, respectively (Anselin et al. 2006), in which the first and third quadrants denote positive spatial associations; conversely, the second and fourth quadrants indicate negative spatial correlations. The positive and negative spatial correlations were further identified as one of the following four types: 'High-High', 'Low-Low', 'High-Low', and 'Low-High'. All of the LISA calculations were conducted using GeoDa software.

3. Results

3.1. Identification of the dominant factor

GeoDetector, in this study, quantified the determinant power of the 14 selected factors on the house collapse rate caused by Super Typhoon Lekima, and the q statistic values were ranked in descending order (Figure 4) to identify the dominant factor. The results showed that MP had the highest determinant power for the house collapse rate, with a q value of 0.39 ($p < 0.01$), followed by EV and MW, with q values of 0.31 ($p < 0.01$) and 0.30 ($p < 0.01$), respectively. SP was also closely related to the house collapse rate, with a q statistic value of 0.22 ($p < 0.01$) (Figure 4).

The PG was also found to be closely related to the house collapse rate, and this factor showed the greatest significance among the socioeconomic factors, with a q statistic value of 0.26 ($p < 0.01$). This finding indicates that regarding the house collapse rate, socioeconomic factors cannot be ignored (Figure 4).

The factors PT and PD showed significant determinant powers on the house collapse rate, and their q statistical values were 0.19 ($p < 0.01$) and 0.14 ($p < 0.01$), respectively. These findings indicate that the city type and population also have impacts on the house collapse rate following a typhoon (Figure 4).

Furthermore, the results suggested that the differences in the floor heights of houses also had a nonnegligible impact on the house collapse rate. Specifically, RSN and RFS had relatively high determinant powers, with q values of 0.23 ($p < 0.01$) and 0.14 ($p < 0.01$), respectively. Moreover, RTT and RB also played a part in the house
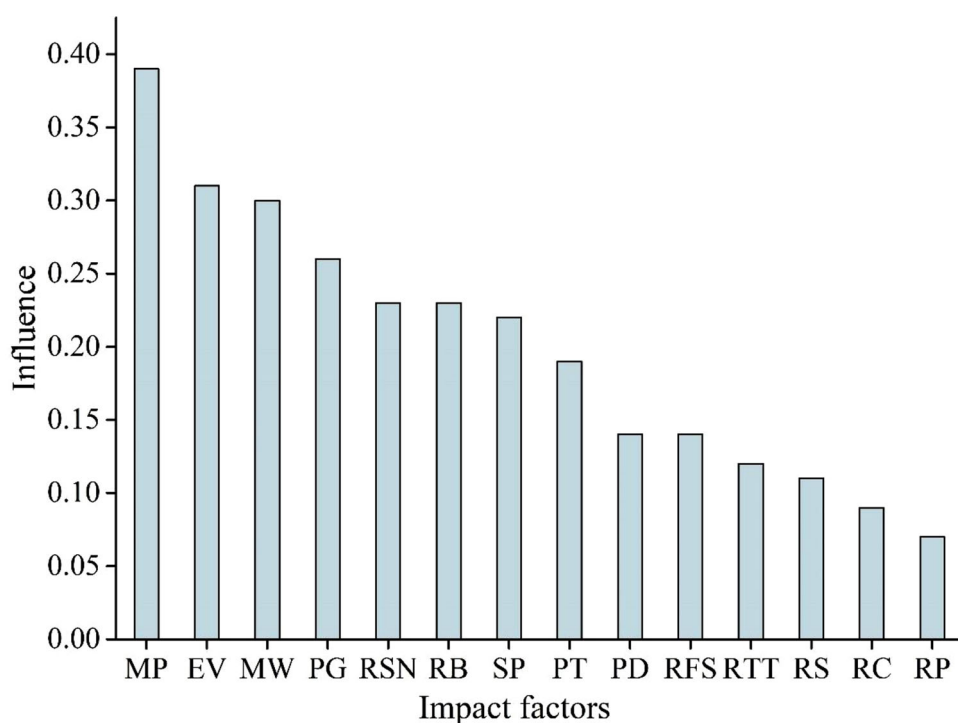
Figure 4. The results for q statistic values.

collapse rate, with q values of 0.12 ($p < 0.01$) and 0.07 ($p = 0.05$), respectively (Figure 4).

In terms of construction material, RW and RS had relatively high q values of 0.23 ($p < 0.01$) and 0.11 ($p < 0.01$), respectively. Moreover, RC had an impact on the house collapse rate, with a q statistic value of 0.09 ($p < 0.01$). These findings indicate that differences in the structures ofhouses also play nonnegligible roles in the house collapse rate following a typhoon (Figure 4).

3.2. Interactive effects among the factors

A total of 91 pairs of interactive effects between the 14 selected factors were calculated by using the GeoDector (Figure 5). Regarding the results obtained for the interactive effects, each pair of factors had a significantly greater q value than the corresponding q values of each of the two factors individually. These results indicate that not only the influence of a single factor, but also the interactions between two factors greatly impacted the rate of house collapse caused by Super Typhoon Lekima. Among the interactions calculated between two random factors, the highest q value was 0.74 (MP∩RFS), which indicates that the interactive effects between MP and RFS were the strongest. Similarly, high q values were obtained for MP∩PT, MP∩MW, and MP∩RTT, for which the values were 0.72, 0.70, and 0.69, respectively. These findings indicate that the interactive effects between natural and socioeconomic factors were far greater than the effects of individual factors.
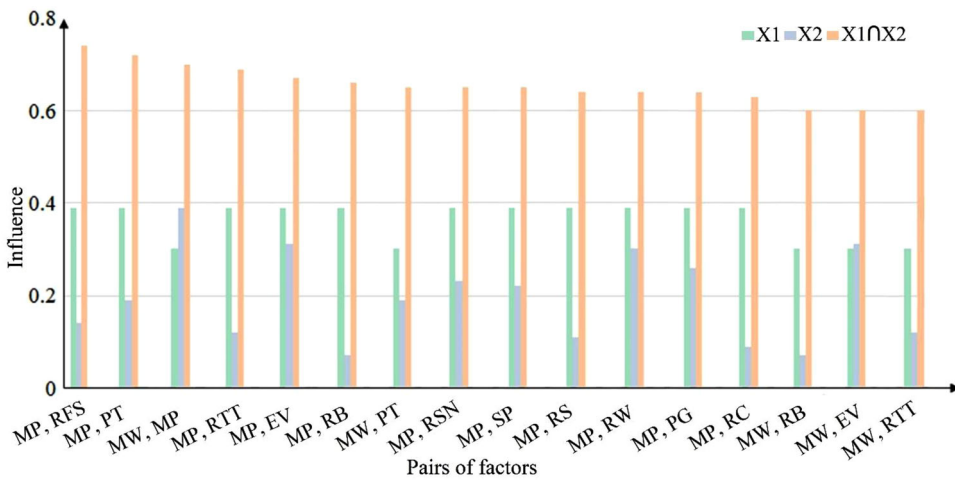
**Figure 5.** The interactive *q* value of each pair of factors.

3.3. Spatial pattern identification

According to the results obtained by GeoDetector, the dominant factor affecting the house collapse rate following Lekima was MP. Subsequently, the LISA model calculated the local Moran's *I* values under the intervention of MP and identified high-high and low-low clusters as well as high-low and low-high outlier values. The results showed that the local Moran's *I* value calculated between the house collapse rate and MP was 0.37 ($p < 0.001$), indicating that these factors had a significant and positive spatial correlation.

The results of the LISA tests were further used to identify hot spots (high-risk areas for house collapses caused by typhoons) and cold spots (low-risk areas for house collapses caused by typhoons). As shown in Figure 6, hot spot (high-high) areas were mainly located in southeastern Zhejiang and northern Shandong, indicating that the house collapse rates in these counties were serious. Meanwhile, the cold spots (low-low) areas were mainly located in northeastern Liaoning and western Shandong, indicating that the house collapse rates in these counties were low.

4. Discussion

Rapid economic development and the resulting climate change occurring in coastal regions have led to the annually increasing exposure of life and properties to risk factors. Here, in addition to a single factor analysis, the effect of interactions between two factors on the spatial pattern of the house collapse rate caused by Super Typhoon Lekima were studied by GeoDetector to provide a more comprehensive understanding of the impact mechanism of typhoons. A further analysis of these data revealed the dominant factor affecting the house collapse rate; this dominant factor was the MP. Then, the LISA model identified the spatial pattern of the house collapse rate under the intervention of MP. The results showed that in addition to natural factors, the influence of socioeconomic factors on the house collapse rate was great. Among the socioeconomic factors, MP, EV and MW had the largest influences on the house
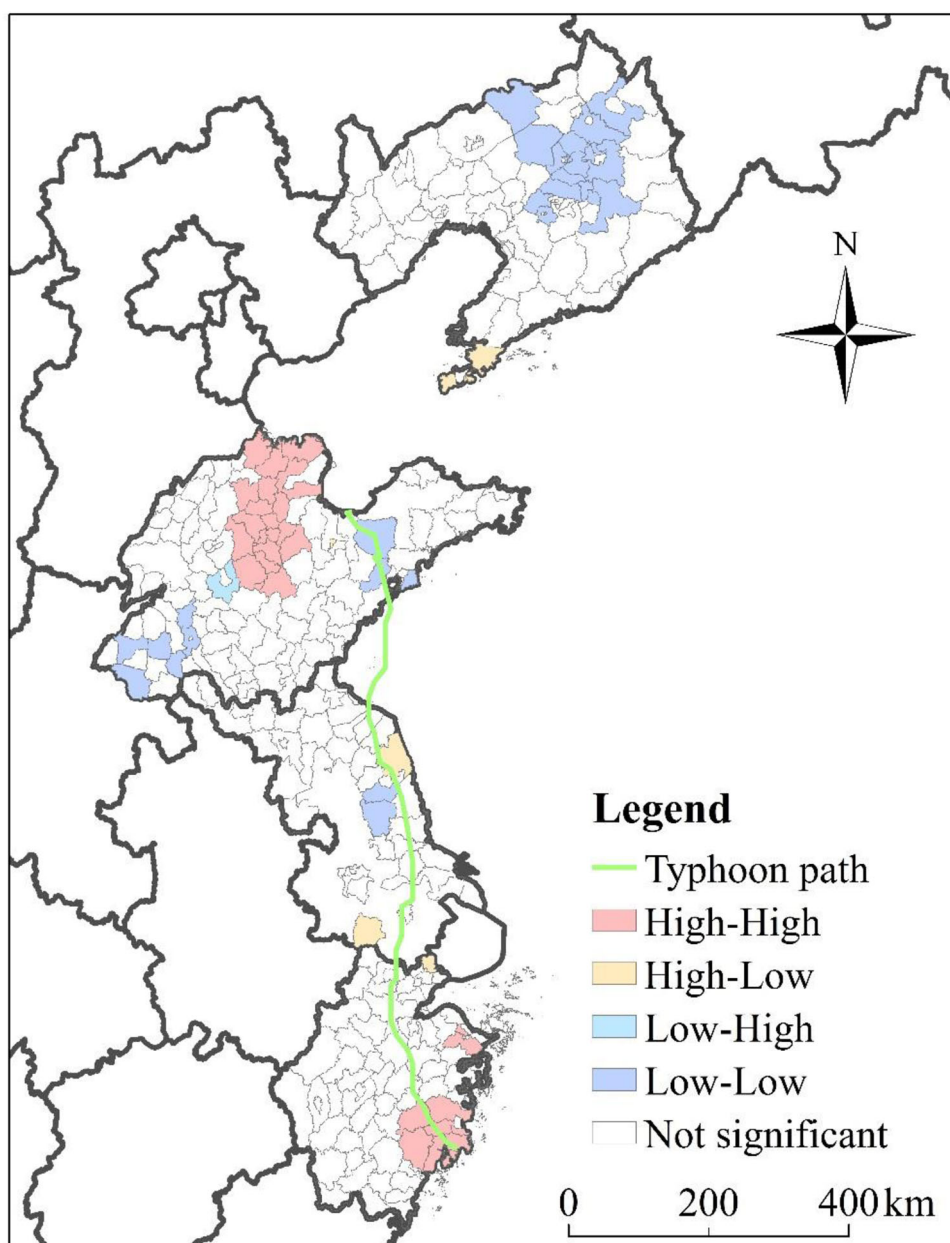
Figure 6. Spatial distribution of hot and cold spots for the house collapse rate caused by the Super Typhoon Lekima.

collapse rate. Furthermore, among the interactions of the impact factors, the interaction between MP and RFS was the strongest ($q = 0.74$). Areas with high house collapse rates were mainly distributed in southeastern Zhejiang and northern Shandong, areas which suffered from the most severe rainfall caused by Super Typhoon Lekima; the low-risk areas were mainly distributed in northern Liaoning and western Shandong.

Heavy precipitation caused by typhoons is an important factor that can lead to unpredictable disaster-related damage. Similarly, in this study, MP was found to be the strongest determinant factor on the house collapse rate ($q = 0.39$), which is consistent with the results of previous studies. For example, Hu et al. (2018) showed that extreme precipitation can result in flood disasters that will have great impacts on populations and property. At the same time, Lin et al. (2015) found that great population and economic losses are caused by typhoons globally. Zhang et al. (2021) quantified the associations between potential factors and the house collapse rate caused by Super Typhoon Mangkhut, which was similar to Lekima, and found that maximum precipitation was also the dominant factor influencing the house collapse rate caused by Super Typhoon Mangkhut. These results collectively indicate that heavy precipitation, which is a critical mechanism by which typhoons release energy, is one of the most important factors affecting disaster losses. In coastal areas, heavy precipitation and subsequent secondary disasters, such as floods and debris flows, have concomitantly resulted in huge disaster losses (Khouakhi et al. 2017). Moreover, economically well-developed and densely populated areas are highly sensitive to natural disasters (such as floods and rainstorms) and rising water levels. Therefore, the increasing scale and intensity of typhoon disasters will readily impact these areas (Zhang et al. 2008, 2012; Yang et al. 2015).

Previously published studies have shown that coastal regions with elevations of less than 5 m are more susceptible to sea level rise and storm surges worldwide (Atanas and Hristo 2009). The size of the coastal area in China with an elevation below 5 m, which is mainly distributed along the coast of southeast China, amounts to an area of approximately 143,900 km^2 (Huang and Cheng 2013). Therefore, evaluations of EV are of great significance to the house collapse rate caused by typhoons. In this study, we found a strong association between the house collapse rate and EV ($q = 0.31$), consistent with the results of previous studies. For example, Huang and Cheng (2013) pointed out that when a typhoon disaster strikes, house collapses are most common at low elevations, but the impacts of the disaster can expand to varying degrees. Similarly, Nigusse and Adhanom (2019) demonstrated that when an area is hit by a typhoon, the local elevation is one of the most important factors in disaster assessments. The potential reason for such findings may be that for houses at lower elevations, the impacts of storm surges and heavy precipitation resulting from typhoons are greater, and thus, houses at lower elevations may collapse more easily under these conditions; for houses at higher elevations, the impacts of storm surges and precipitation will be less severe than those at lower elevations, but higher-elevation houses may still collapse under the influence of the wind speed (Atanas and Hristo 2009; Huang and Cheng 2013).

In this study, the q value of the MW was 0.30, indicating that the wind speed also represents an important factor that cannot be ignored in relation to the house collapse rate caused by typhoons, similar to the results of some previous studies. For example, Nigusse and Adhanom (2019) found that strong wind speeds caused by typhoons will cause more people and buildings to suffer from more serious damage. Similarly, Li and Wang (2018) indicated that the strong wind speed brought about by a typhoon had an important impact on the collapse of houses. The possible

mechanism for this effect may be that disasters caused by typhoons are mainly related to heavy precipitation and strong wind speeds, and these water flows and winds may act to erode or destroy structures or components of houses and further aggravate the collapse rate, leading to casualties and serious economic losses.

LISA was used to reveal the spatial distribution of area that are at high-risk of house collapses under the influence of MP. The hot spots were mainly concentrated in the southeastern regions of Zhejiang county and northern Shandong county, and thus, these areas should receive more attention when they suffer typhoons. The cold spots were mainly distributed in northern Liaoning and western Shandong. It is worth noting that many studies have shown that both natural factors and socioeconomic factors also have significant impacts on the spatial patterns of natural disaster damage. PG and PD are generally believed to represent important factors in disaster damage assessments. Similarly, in this study, the interactive effect between PG and PD was 0.35, which was widely consistent with the results of other previous studies. For example, Ying et al. (2011) showed that disaster prevention and mitigation factors, such as those related to PG, can influence a region's ability to respond to disasters. Similarly, Hu et al. (2018) indicated that PD is related to the vulnerability of human communities affected by disasters such as floods caused by typhoons. Tian et al. (2016) pointed out that PD and PG can further increase the damage caused by typhoon disasters. These studies showed that rapid urbanization has promoted economic growth and population aggregation and that various types of infrastructure, such as new buildings, are constantly emerging to meet people's needs. Hence, the risk of typhoon-related damage increases further with an increase in urbanization because regions with high economic levels are accompanied by increased PDs, and roads and buildings are more concentrated in metropolitan areas (Nigusse and Adhanom 2019). Therefore, the impacts of disasters in these areas can increase or expand to some extent.

Additionally, as the GeoDetector results revealed, the interactive effects between all factors were significantly higher than the individual effects; that is, the interactions resulted in enhanced effects. Although the effects of natural factors on the house collapse rate caused by typhoons were significantly stronger than those of socioeconomic factors, in the past few decades, with rapid development and urbanization, the ecological environment and people's living environment have experienced significant changes (Gong et al. 2012). Therefore, the interactions between socioeconomic factors and natural factors will cause the impacts of disasters to increase to a certain extent, and these factors can promote each other to affect the house collapse rate.

Furthermore, GeoDetector can deal with multiplication relationships as well as other relationships, e.g. it can determine whether the interactive effects between two factors strengthen or weaken the determinant power of one of the factors individually by using q statistic values. Therefore, in this study, GeoDetector was used to quantify the determinant powers of natural and socioeconomic factors and their interactive effects on the house collapse rate caused by Super Typhoon Lekima, and the results could be used to provide a reference for predicting and estimating disaster losses in similar areas. In the future, this method may be used in conjunction with weather forecasts to assess disaster losses. The study has limitations that should be clarified.

The impact of natural disasters on the ecological environment system is complex because it is affected by complex evolutionary processes and increased human activities. However, in this study, only some house structures and natural and socio-economic factors were considered risk factors affecting the collapse rate of houses caused by Super Typhoon Lekima, and some meteorological factors (such as temperature and specific humidity) were ignored.

5. Conclusions

In this study, GeoDetector was used to quantify the determinant powers of natural and socioeconomic factors as well as their interactions to explain the house collapse rate caused by Super Typhoon Lekima and to further identify the dominant factor, which was found to be the maximum precipitation. Then, the LISA method was used to identify the spatial pattern of the house collapse rate under the intervention of the dominant factor, and the area of influence was classified into hot and cold spots. The results showed that the hot spots of the house collapse rate were mainly concentrated in southeastern Zhejiang and northern Shandong, while the cold spots were mainly concentrated in northern Liaoning and western Shandong. Moreover, both natural factors and socioeconomic factors influenced the house collapse caused by Super Typhoon Lekima. These findings illustrate that the spatial pattern of the house collapse rate is associated with the spatial differences of these impact factors and their interactions; these findings can lead to a better understanding of the impact mechanism of typhoon disasters and can, in turn, allow data to be collected and evaluated more scientifically and reasonably. Furthermore, the findings suggest that different regions should apply more specific strategies for disaster prevention, for the allocation of resources to increase their disaster response and recovery capabilities, and for the minimization of losses.

Data availability statement

The data that support the findings of this study are available on request from the corresponding author.

Disclosure statement

No potential conflict of interest was reported by the authors.

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