CrossMark

Spatiotemporal distributions of influential tropical cyclones and associated economic losses in China in 1984–2015

Yanjun Wang[1] · Shanshan Wen[2,4] · Xiucang Li[3] ·
Fischer Thomas[3] · Buda Su[1,2,3] · Run Wang[5] ·
Tong Jiang[1,3]

Abstract In China, influential tropical cyclones (ITCs) are defined as those that cause significant national economic losses. Based on direct economic losses, socioeconomic data, and tropical cyclone track data from the National Climate Centre of the China Meteorological Administration and the National Bureau of Statistics, this study investigated 249 ITCs that occurred during 1984–2015. National economic losses directly attributable to each ITC were normalized by the Consumer Price Index to facilitate a comparison of annual variability, and the spatiotemporal distribution of ITC-related economic losses was analyzed using different statistical methods. The Pearson correlation method was used to analyze annual variations, while abrupt changes were detected by the Moving t test, and the Yamamoto and Mann–Kendall tests. The possibility of periodicity of ITC frequency and economic losses was investigated using Red-noise spectra and wavelet analysis. The results revealed that although 249 ITCs affected China during 1984–2015, no significant monotonic trend in annual frequency was detectable; however, a significant upward trend was found for strong ITCs (ITC intensity greater than that of typhoons). Among the 22 provinces affected, Guangdong Province in southern China has the highest frequency of ITCs. An abrupt change in the annual frequency of ITCs occurred in 2007, and a periodic 3–6-year pattern was detected. Annual direct economic losses during 1984–2015 were approximately 44.7 billion CNY, and they have increased at the rate of 1.8 billion CNY

✉ Buda Su
   subd@cma.gov.cn

✉ Tong Jiang
   jiangtong@cma.gov.cn

[1] Collaborative Innovation Center on Forecast and Evaluation of Meteorological Disasters, Nanjing University of Information Science and Technology, Nanjing 210044, China

[2] State Key Laboratory of Desert and Oasis Ecology, Xinjiang Institute of Ecology and Geography, Chinese Academy of Sciences, Urumqi 830011, China

[3] National Climate Center, China Meteorological Administration, Beijing 100081, China

[4] University of Chinese Academy of Sciences, Beijing 101408, China

[5] Faculty of Resources and Environmental Sciences, Hubei University, Wuhan 430062, China

annually. The severest losses occurred in 1996. Although an obvious abruption occurred in 1992, a 2–3-year periodicity was detected in ITC-related losses. Temporally, most affected provinces showed a slight increase in ITC-related losses. Spatially, ITC-related losses were greatest in Zhejiang and Guangdong provinces. These findings could be helpful for raising local awareness and ensuring the preparedness of local government for mitigating ITC-related damage.

1 Introduction

Tropical cyclones (TCs) are common phenomena in many regions of the world. Recent research has indicated that earth's surface temperature warmed by approximately 0.85 °C between 1880 and 2012, and it is predicted that it will increase further in the future (Stocker et al. 2013). One potential consequence of increasing temperature is a rise in damage associated with extreme meteorological and climatological events, and it is widely believed that climate change will increase the frequency of occurrence of high-intensity TCs (Mendelsohn et al. 2012). During the past several years, TC-related damage has increased obviously. Two-fifths of the most economically costly natural disasters during 1950–2009 were attributable to TCs (Munich Re 2010). In 2015, overall losses caused by natural disasters were about 660 billion CNY (i.e., 100 billion dollars), 41 % of which were attributed to storms (Munich Re 2016).

The northwest Pacific Ocean is the area of the world where TCs are generated most often. Bordering this ocean area, China is among those countries most frequently affected by TCs, and it regularly suffers considerable related socioeconomic effects such as loss of life, stress of the affected population, damage to material assets, and destruction of agricultural production. During 2004–2015, of all the various types of weather- and climate-related disasters to affect China, the direct economic losses and number of fatalities attributable to TCs accounted for 18.3 and 50.2 % of the total, respectively. Taking 2015 as an example, six TCs made landfall on the Chinese mainland, which caused direct economic losses of more than 68.4 billion CNY, accounting for 0.11 % of the annual total gross domestic product (GDP). Among this six, typhoon Mujigae was considered the strongest October storm to have hit China since 1949; it caused at least 19 fatalities and resulted in losses of over 30 billion CNY (China Meteorological Administration 2016a, b).

Previous studies have often focused on the basic characteristics of generated or landing TCs, as well as on their causes and on the effects of their wind and precipitation (Wu et al. 2005; Xiao et al. 2010; Yin et al. 2013; Deng et al. 2015). The confidence of long-term trends regarding past global TC frequency and intensity is low (Knutson et al. 2010). With regard to the western North Pacific Ocean, Liu and Chan (2013) discovered that TC activity has exhibited significant interdecadal variation over the last few decades with two distinct active and inactive periods. According to an analysis of landfalling TCs in China during 1983–2006, variabilities on interannual and interdecadal time scales have also been found (Zhang et al. 2009), while long-term trends in landfall frequency were considered not significant. In contrast, greater confidence has been placed in predictions of future TC activity. Climate change is expected to increase the frequency of high-intensity storms in many ocean basins, and therefore, attention has increasingly been focused on the phenomenon of TC-related economic losses. It has been widely claimed that irrespective of

how TC intensity changes in response to global warming, the scale of related economic losses will be largely attributable to socioeconomic developments, such as the increasing wealth and numbers of the population in exposed areas (Pielke et al. 2005). As population, economic assets, and adaptive technology show significantly different patterns of spatial distribution, TCs of similar intensity always have different degrees of impact. To best capture the interannual and intersite variabilities of TC-related damage, it is reasonable to normalize historical losses to values more representative of the contemporary context (Changnon et al. 1997). Only normalized data should be used to compare economic damage attributable to TCs at different locations and at different times (Kron et al. 2012). Although a considerable amount of such research has already been done, it has focused mainly on the USA (Choi and Fisher 2003; Miller et al. 2008; Pielke et al. 2008; Schmidt et al. 2010; Nordhaus 2010; Mohleji and Pielke 2014; Estrada et al. 2015). Fischer et al. (2015) used three normalization methods to investigate the characteristics of TC-related economic losses in China. They highlighted that China's economic vulnerability and exposure to TCs have increased following its rapid socioeconomic development. Gemmer et al. (2011) studied direct economic losses corrected with the Consumer Price Index (CPI) in Fujian Province at the county scale; however, normalized TC-related economic losses have seldom been studied.

There are many public databases related to natural disasters in the world, e.g., the Emergency Event Database (EM-DAT, Centre for Research on the Epidemiology of Disasters, http://www.em-dat.net/) of the Center of Research on Epidemiology of Disasters in Brussels (CRED), US database for Foreign Disaster Assistance (OFDA), and Natural Hazards Assessment Network (NATHAN) of Munich Re (available at: http://www.munichre.com). These databases can provide worldwide data because their temporal coverage is constantly being improved. With regard to losses, not only original losses but also losses after consideration of the effects of inflation, normalized data are better for comparative and analytical purposes, and thus, they tend to be used in the majority of studies. However, in China, whether officially announced by the China National Committee for Disaster Reduction or recorded in books such as the Yearbook of Natural Disaster in China, disaster databases only include data at current prices; i.e., normalized data are not available for use (CMA 2016a, b).

For better understanding of the impact of past TCs in China, attention should be focused on the economic losses they have caused. Specifically, the spatiotemporal characteristics of TCs that have affected China significantly should be established, and the pattern of variation and trends of economic losses investigated.

In this study, we collected data on all cyclones generated in the northwest Pacific Ocean during 1984–2015. We concentrated on influential TCs (ITCs), i.e., those that caused significant economic losses in China, to analyze their interannual and interdecadal variations, as well as their spatial distribution. Then, a spatiotemporal analysis of normalized economic losses was performed. Finally, our conclusions are presented and some ideas for future research are outlined. This analysis of the basic characteristics of economic losses related to TCs will enhance the scientific understanding of TCs by providing a more accurate picture of the trends of TC-related impacts to researchers and decision makers. The normalization method is not limited to TC disasters, and it could be useful as an independent check on the output of more complex catastrophe models.

2 Data and methods

2.1 Data

The data used in this study comprised the best-track dataset for TCs that occurred in the northwest Pacific Ocean during 1984–2015, derived from the Shanghai Typhoon Institute of the China Meteorological Administration (CMA). These data included maximum 2-min sustained wind speed, minimum sea surface pressure, and individual TC 6-h track point locations.

Data on economic losses caused by TCs are published annually in the Yearbook of Natural Disaster in China, but only with coarse temporal resolution and only since 2004. Therefore, to obtain a relatively complete database of economic losses (1984–2015), information from different sources was compiled and modified, e.g., the Tropical Cyclone Disasters Databank of the National Climate Center (1984–1999), CMA Economic Losses National Survey at County Level (1984–2015), Yearbook of Natural Disaster in China (2004–2015), and China Climate Impact Assessment Report (1991–2015) (China Meteorological Administration 2001, 2016a, b). These databases are all compiled under the same rules, i.e., the Classification of Tropical Cyclones Standardization [GB/T19201-2006], which was written by the CMA (Chinese Standardization Administration Committee 2006). Under this rule, data derived from different sources can be homogeneous. These datasets comprise information on both provincial and county level for each TC event, and they tend to be more comprehensive than the dataset provided by the China Ministry of Civil Affairs, which contains only annually cumulated province-level data.

Inflation was accounted for using the CPI on the province level, and the GDP of China was obtained from the China Statistical Yearbook (1984–2015) (National Bureau of Statistics 2015). The GDP data were used to calculate the relative ratio of economic losses to annual GDP in China.

2.2 Methods

Of all the TCs generated in the northwest Pacific Ocean during 1984–2015, this study focused on the ITCs, i.e., those TCs that caused significant economic losses in China. These included TCs that did not make landfall, but still caused economic losses. Selected ITCs tracks are shown in Fig. 1.

2.2.1 Normalization of economic losses

A normalization of economic losses provides an estimate of the cost of disaster-related damage had a historical disaster occurred under another year's societal conditions. One of the most frequently used normalization methods involves the simple adjustment of losses based on the inflation ratio. In this study, we used the CPI to account for inflation. CPI reflects the variation of price changes related to the process of economic development, and it is an important indicator of the rate of inflation. In the current study, economic losses and socioeconomic data from ITCs were normalized to 2015 levels. After CPI normalization, annual or event-based losses were evaluated as if all events had happened in 2015. We analyzed the CPI data on the province level instead of the national level, as was undertaken by Zhang et al. (2009). A typical equation for normalized losses can be written as follows:
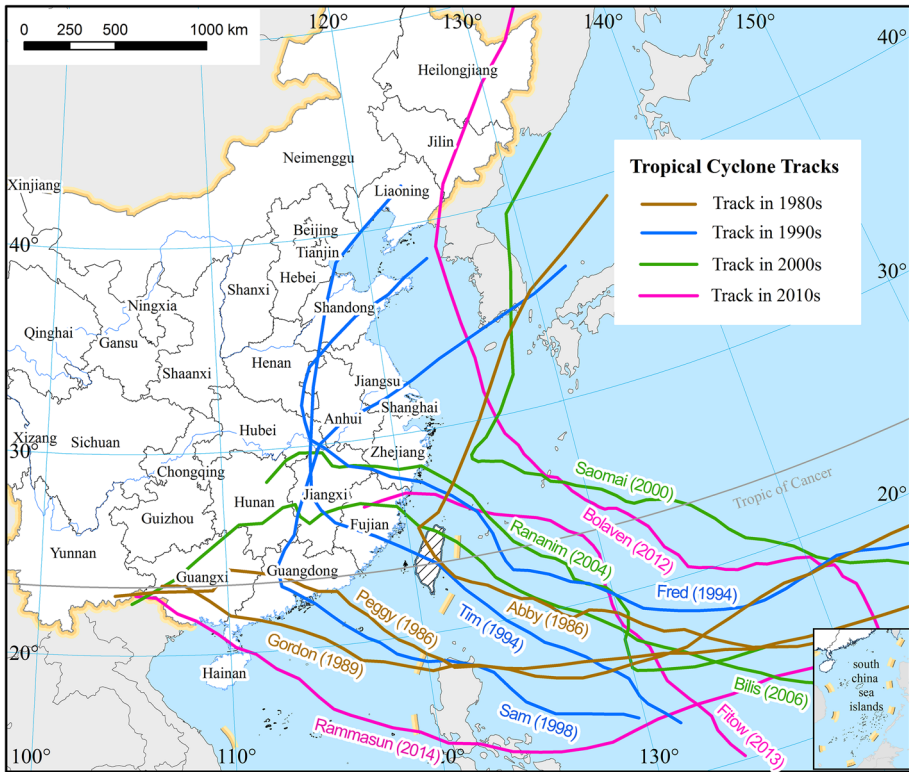
Fig. 1 Selected influential tropical cyclones in China during 1984–2015

$$EL' = EL \times \frac{CPI_s}{CPI_t} \tag{1}$$

where EL′ refers to inflation-adjusted losses, EL represents the original economic losses, CPI is the Consumer Price Index for every province, s is the (chosen) year one wishes to normalize to, and t is the year in which the losses occurred.

2.2.2 Statistical methods

Linear trends were calculated using the Pearson correlation. Student's t test was used to determine significance, and the p-values were calculated based on a Student distribution (Wilks 1995).

   For the analysis of statistical parameters (frequency and economic loss series), there are various traditional methods for detecting abrupt changes, such as the Moving t test, and Mann–Kendall and Yamamoto tests (Yamamoto et al. 1985; Kendall and Charles 1975; Mann 1945). Among these, the Moving t test and the Yamamoto method are renowned for their intuitive, simple, and convenient application. They can be used to detect a change point on a scale of several years by testing the significance of the difference between the means of two groups of samples, and they have been used extensive in China to study abrupt change (Yamamoto et al. 1986). In this study, the size of the subsets was taken as five and the t statistic was used. The nonparametric Mann–Kendall method is

recommended by the World Meteorological Organization, and it has been used widely to analyze trends in environmental time series. Abrupt changes detected by the Mann–Kendall method reflect a significant change in trend in the analyzed series, while those detected by the Moving t test or the Yamamoto method indicate a significant difference between the averages of two subsequent series.

Time series analyses of the frequency of ITCs and their losses were analyzed using Red-noise spectra analysis, and wavelet spectra analysis was applied to resolve any possible cyclic nature of these variations. Wavelet analysis is useful in time–frequency analyses because it provides a continuous measure of synchronization and because peaks and troughs in wavelike signals can be revealed (Torrence and Compo 1998). Red-noise spectra analysis was selected for use here because it is designed specifically to handle unevenly spaced noisy data (Schulz and Mudelsee 2002). It estimates the Red-noise spectra directly from unevenly spaced time series without requiring interpolation. In this study, it was performed using the REDFIT tool of the PAST statistics package (Hammer et al. 2001).

Different periodic and mutagenesis analysis methods might obtain different results, and each method has its own virtues and shortcomings. Therefore, applying several methods in tandem has the benefit of broadening the detection range and improving the quantitative degree, and thus, results that are more accurate might be revealed.

2.2.3 Classification of TCs

The CMA provides the class of TC intensity for each track point, based on the classification of the newest TC grade standards of the China Typhoon Network of the CMA (Table 1) (Chinese Standardization Administration Committee 2006). As the ITCs considered in this study also included TCs that did not make landfall in China, ITC intensity was based on the intensity at the point of landfall, or at the closest point to it.

3 Analyses and results

3.1 Frequency and intensity of ITCs

The variations of annually generated TCs, landfalling TCs, and ITCs are shown in Fig. 2. During 1984–2015, 817 TCs were generated in the western North Pacific Ocean and the South China Sea bounded by 0°–45°N, 100°–180°E, of which 228 made landfall in China. The highest number (37) of generated TCs occurred in 1994, while the lowest number on record (14) occurred in 1998 and 2010. A downward trend in the number of generated TCs

Table 1 Classification of tropical cyclones

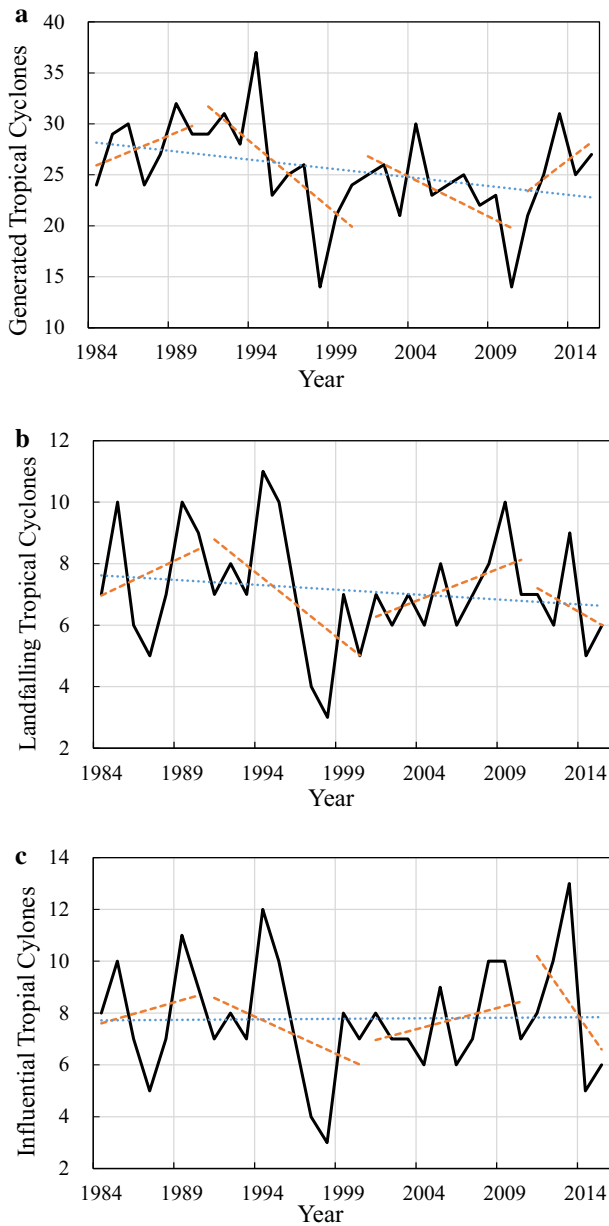| Tropical cyclone intensity class	Acronym	Wind speed (m s^{-1})
Tropical depression	TD	10.8–17.1
Tropical storm	TS	17.2–24.4
Strong tropical storm	STS	24.5–32.6
Typhoon	TY	32.7–41.4
Strong typhoon	TY	41.5–50.9
Super typhoon	SuperTY	≥51.0

Fig. 2 Annual frequencies of tropical cyclones in China during 1984–2015: **a** generated tropical cyclones; **b** landfalling tropical cyclones; **c** influential tropical cyclones (frequency: *solid line*; decadal trend: *dashed line*; linear trend: *dotted line*)

since 1984 can be identified. The total number of ITCs over the same period was 249 with an average of 7.8 ITCs affecting China annually. The minimum number of ITCs (3) occurred in 1998, followed by 1997 (4), 1987 (5), and 2014 (5). The frequencies of

generated TCs and landfalling TCs have decreased in the past decades, whereas the frequency of ITCs has no overall statistically significant trend.

Significant interdecadal variation was found in all of these TC series. For ITCs, two high-frequency periods and one low-frequency period were identified. From 1984 to the mid-1990 s, ITCs had higher frequency compared with the entire period; i.e., 8.3 ITCs affected China annually (1984–1996) and 1994 had the highest number (12). The frequency of ITC occurrence in 1997–1998 was the lowest during the past 32 years. From 2001 onward, an average of 7.9 ITCs per year (year^{-1}) was reported to have caused economic losses. A clear upward trend was established in the 2000s, but this decreased in recent years (2011–2015), contrary to the number of generated TCs but consistent with the number of landfalling TCs. In 2013, 13 ITCs caused damage in China, breaking the previous record of 12 in 1994.

The proportions of ITCs and landfalling TCs to the total number of TCs generated over the western North Pacific Ocean and South China Sea present slight increasing trends from 1984 to 2015, with the period of obviously high proportion in 2008–2013. Although the rate of increase in the number of ITCs is slightly higher than that of landfalling TCs, the percentages of ITCs and landfalling TCs in 2013 were 42 and 29 %, respectively (Fig. 3).

In terms of intensity, ITCs can be divided into two categories: one comprising tropical depressions, tropical storms, and strong tropical storms; and the other comprising those ITCs whose wind speeds are >32.7 m s^{-1}, i.e., typhoons (TYs), strong typhoons (STYs), and super typhoon (SuperTYs). Hereafter, we denote these two categories as less severe and severe ITCs, respectively (Fig. 4a). It was found that the total number of less severe ITCs has decreased significantly at a rate of 0.6 times per decade. Conversely, the total number of severe ITCs has increased markedly at a rate of 0.7 times per decade (significant at the 95 % confidence level). Compared with ITCs, less severe landfalling TCs show a higher rate of decrease (0.9 times per decade), while severe landfalling TCs present a slightly lower rate of increase (0.5 times per decade). The highest number of severe ITCs during the past 32 years was seven, which comprised three TYs and four STYs that occurred in 2012.

The results of the Mann–Kendall test, Moving t test, and Yamamoto test for detecting change points in the annual frequency of ITCs during 1984–2015 in China are shown in Fig. 5a–c, respectively. Two possible change points were detected by the Moving t test method at around 1996 and 2007. However, the abrupt change in the mid-1990s was not
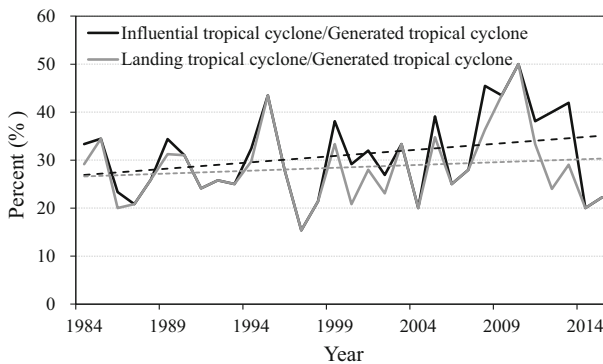

Fig. 3 Proportion of influential and landfalling tropical cyclones to total tropical cyclones in China (*solid line*) and their trend (*dashed line*) during 1984–2015

Fig. 4 Annual frequency of influential and landfalling tropical cyclones above and below typhoon intensity (*solid line*) and their trend (*dashed line*) during 1984–2015: **a** influential tropical cyclones and **b** landfalling tropical cyclones
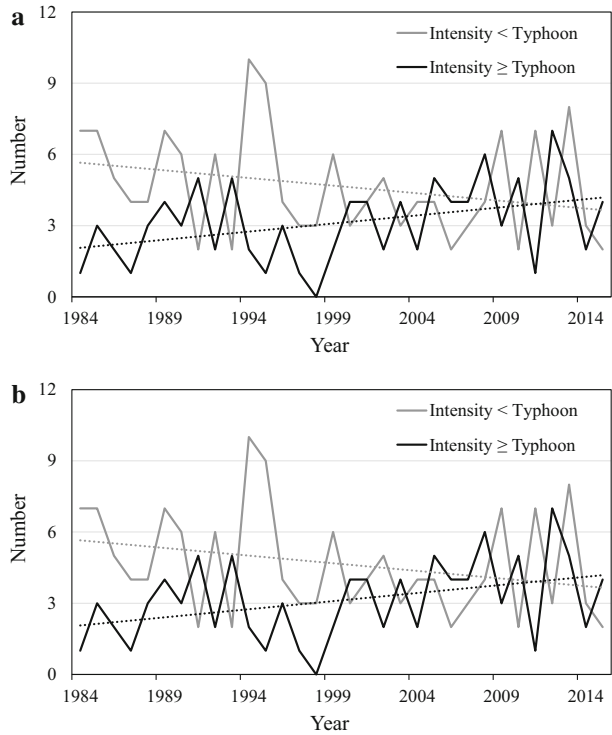
found by the two other methods; hence, 2007 might be the only turning point (at over the 90 % confidence level) in the annual frequency of ITCs in China during 1984–2015.

With regard to the periodicities of annual frequency of ITCs over the 32-year period, the detection results based on the Red-noise spectra and Morlet wavelet analysis showed similar outcomes. During the entire period (1984–2015), the variance in the 3–6-year band was significantly above the 95 % confidence level, indicating a strong annual signal (Fig. 6).

3.2 Spatial distribution of ITCs

Overall, 22 provinces in China, including all coastal provinces as well as several inland provinces, were affected by the 249 ITCs that occurred during 1984–2015 (Fig. 7). Southeast coastal regions are in the high-risk area, where the maximum occurrence of ITCs was 121 in Guangdong (3.9 times year^{-1}), followed by Fujian, Zhejiang, Guangxi, and Hainan provinces, which were affected 91, 75, 66, and 65 times, respectively, i.e., all more than twice annually.

Inner Mongolia is included in the 22 provinces affected by landfalling TCs, which has been questioned by many people. The only record of economic loss here was attributed to SuperTY Herb in 1994, which had such widespread influence that 13 provinces were affected, eight out of which were inland provinces such as Guizhou, Hubei, and Inner Mongolia.

The increases in the numbers of ITCs during 1984–2015 in Yunnan, Jiangxi, Fujian, Guangxi, Hainan, Anhui, and Shandong provinces were all significant at the 90 %

Fig. 5 Change point detection of influential tropical cyclones in China during 1984–2015. **a** Mann–Kendall test. UF is the forward sequence and UB is the backward sequence calculated using the same equation but with a reversed series of data. When the UF and UB curves intersect at a certain time, the intersection point located within the confidence interval denotes the change time. **b** Moving *t* test. MTT is the Moving *t* statistic curve. An abrupt change occurs when the curve is above the confidence line. **c** Yamamoto method. Similar to the Moving *t* test
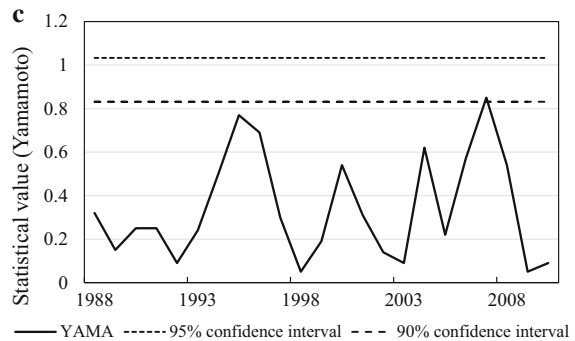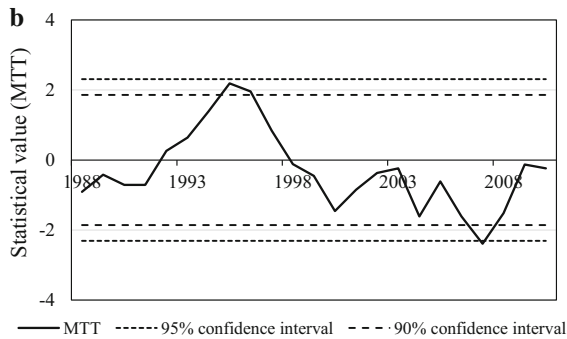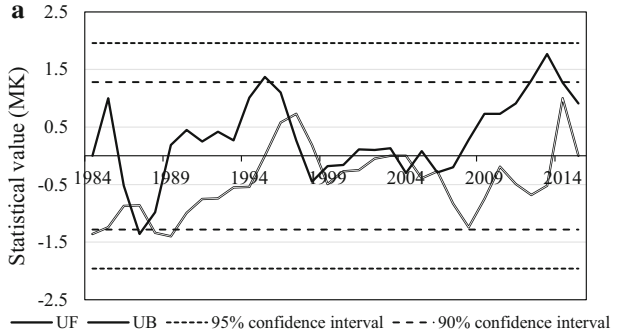
confidence level. The trends in the first three provinces reached the 95 % confidence level, with occurrences of 0.27, 0.58, 0.54 times per decade, respectively (Fig. 7). In all, 24 ITCs were recorded in Jiangxi Province after 2000, nearly five times higher than in the previous 16 years of the study period. Five of the six ITCs in Yunnan occurred during the past 8 years (2008–2015).

Fewer than half the affected provinces had TC landfalls, which included Guangdong, Fujian, Hainan, Zhejiang, Guangxi, Shandong, Jiangsu, Liaoning, and Shanghai provinces, sorted by the total number of landfalls. Some provinces had fewer landfalling TCs than ITCs, such as Jiangsu, Zhejiang, and Guangxi provinces.
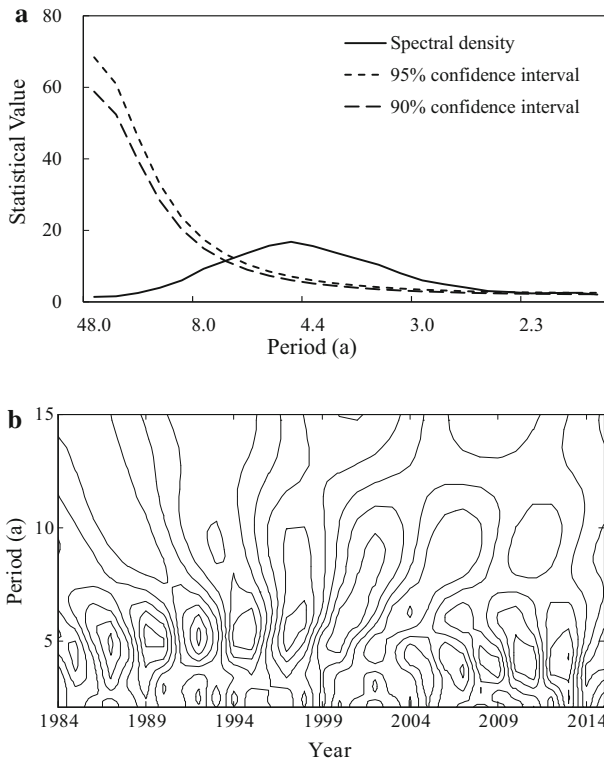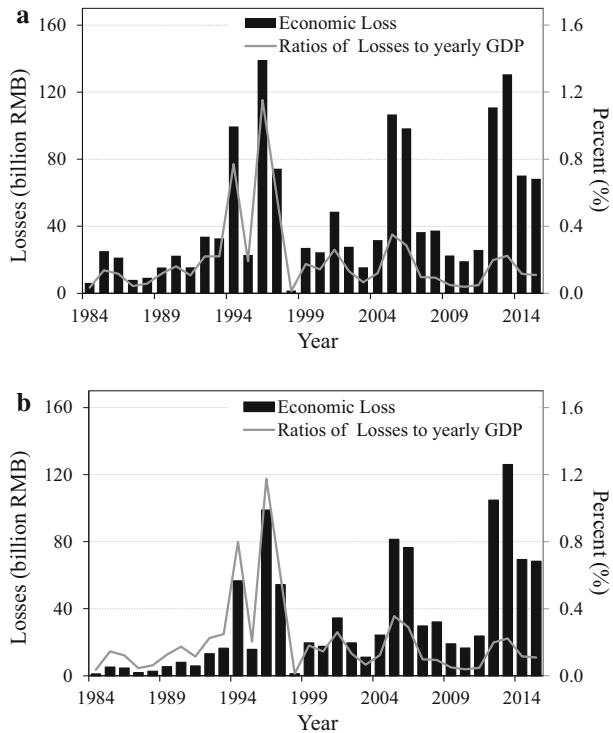
Fig. 6 Periodicity analysis of annual frequencies for influential tropical cyclones in China during 1984–2015. **a** Red-noise spectra analysis. *Solid line* is the spectrum curve. When it is higher than the standard spectrum curve (different confidence level), a cycle can be detected. **b** Morlet wavelet analysis. Explained according to the *closed circles*

3.3 Variation of direct economic losses

The CPI-normalized annual economic losses caused by the 249 ITCs across the 22 provinces are presented in Fig. 8a. It can be seen that they show clear interannual fluctuations and an obvious upward trend. The annual losses increased at a rate of 1.8 billion CNY year^{-1} (at a confidence level of 99 %), and the increment stemmed mainly from a few ITCs (1994, 1996, 2005, 2006, 2012, and 2013) with high economic losses; i.e., their annual losses were all >98 billion CNY. Extremely costly years can be found in three periods: the mid-1990s, mid-2000s, and recent 4 years (2012–2015). The highest loss was 139.2 billion CNY in 1996 (original loss in 1996 was 98.9 billion CNY). The subsequent costliest years were 2013 (130.7 billion CNY) and 2012 (110.9 billion CNY), which were recorded as the two costliest years in the original loss series (Fig. 8b).

During 1984–2015, losses caused by ITCs in China were 44.7 billion CNY year^{-1}, which accounted for 0.21 % of the annual total GDP on average. The proportion of losses to GDP reached a peak in 1996, when the losses accounted for up to 1.2 % of GDP. Subsequent losses were all <0.5 % of GDP, although some fluctuation occurred. The ratio differences between annual losses and GDP after 1996 were lower than that among ITC causing economic losses.

Fig. 7 Frequencies of influential tropical cyclones and their trends at the provincial scale in China. Numbers on the map denote total frequency of influential and landfalling (*parentheses*) tropical cyclones during 1984–2015

Figure 9 shows the abrupt changes for annual CPI-normalized losses attributable to ITCs during 1984–2015 in China. According to the results obtained by the Moving *t* test and the Yamamoto method, two possible change points were found at around 1992 and 1997 (Fig. 9b, c). The regimes of economic losses are quite different both before and after the detected abrupt changes. For the Moving *t* test result, the entire series shows a general increase until 1993 (the largest negative statistical value), after which it declines until 1997 (the largest positive statistical value). For the Yamamoto test, losses showed abrupt changes in 1992 (at a confidence level of 95 %) and in 1997 (at a confidence level of 90 %). Figure 9a illustrates the time series detected using the Mann–Kendall method, with statistical values at the 95 % confidence level in 1992. It shows that an abrupt increase in losses occurred in the early 1990s, which is consistent with the results of the two other methods. Therefore, the abrupt change from relatively low to high annual economic losses in the early 1990s is credible because it was detected by all three methods.

The periodicity results are presented in Fig. 10. As shown in the Red-noise spectra analysis in Fig. 10a, the frequency spectrum curve of ITCs losses is higher than that of the standard spectrum for a cycle or 2–3 years (significant at the 95 % confidence level). However, this period was not revealed as significant by the Morlet wavelet analysis before 2000. After 2000, two principal periods of 2–3 and 8–9 years are found (Fig. 10b).

Fig. 8 Annual economic losses
of influential tropical cyclones
and the percentage of GDP in
China during 1984–2015:
a inflation-adjusted losses and
b original losses

Therefore, taken together, economic losses caused by ITCs in China possibly fluctuated with periods of approximately 2–3 and 8–9 years after 2000.

3.4 Spatial characteristics of direct economic losses

The provincial distribution of average annual economic losses is visualized in Fig. 11a. Annual losses of all the affected provinces in China gradually reduced from the southeast to the north. Zhejiang Province experienced the highest average annual losses (11.5 billion CNY), followed by Guangdong and Fujian provinces with average losses of 11.1 billion and 5 billion CNY year^{-1}, respectively. High losses can be attributed to high frequency of ITCs. The losses of Beijing, Tianjin, and Guizhou provinces and Inner Mongolia were the least, mainly because of the low frequency of ITCs (Fig. 7). For example, Guizhou Province has suffered annual losses of about 0.18 billion CNY since 1984, which were attributable to two ITCs that occurred in 2002 (tropical storm Vongfong) and 2014 (typhoon Kalmaegi). Serious losses can also be contributed by one or several individual costly ITCs. Although Hebei and Yunnan provinces have been affected by eight and seven ITCs, respectively, the annual loss exposure of Hebei Province was 2.6 billion CNY (cf. < 0.2 billion CNY in Yunnan Province), with an overall loss of 82.3 billion CNY over the past 32 years. The principal reason for this was the high losses contributed by one ITC named Herb in 1996, which caused economic losses of up to 65.5 billion CNY.

With regard to the spatial distribution of the linear tendency of average annual losses on the provincial scale, significant upward trends were detected in about half of the affected areas over the period 1984–2015 (Fig. 12a). Losses in Anhui, Jiangxi, and Yunnan

**Fig. 9** Change point detection of annual inflation-adjusted losses for influential tropical cyclones in China during 1984–2015. **a** Mann–Kendall test. UF is the forward sequence and UB is the backward sequence calculated using the same equation but with a reversed series of data. When the UF and UB curves intersect at a certain time, the intersection point located within the confidence interval denotes the change time. **b** Moving *t* test. MTT is the Moving *t* statistic curve. An abrupt change occurs when the curve is above the confidence line. **c** Yamamoto method. Similar to the Moving *t* test
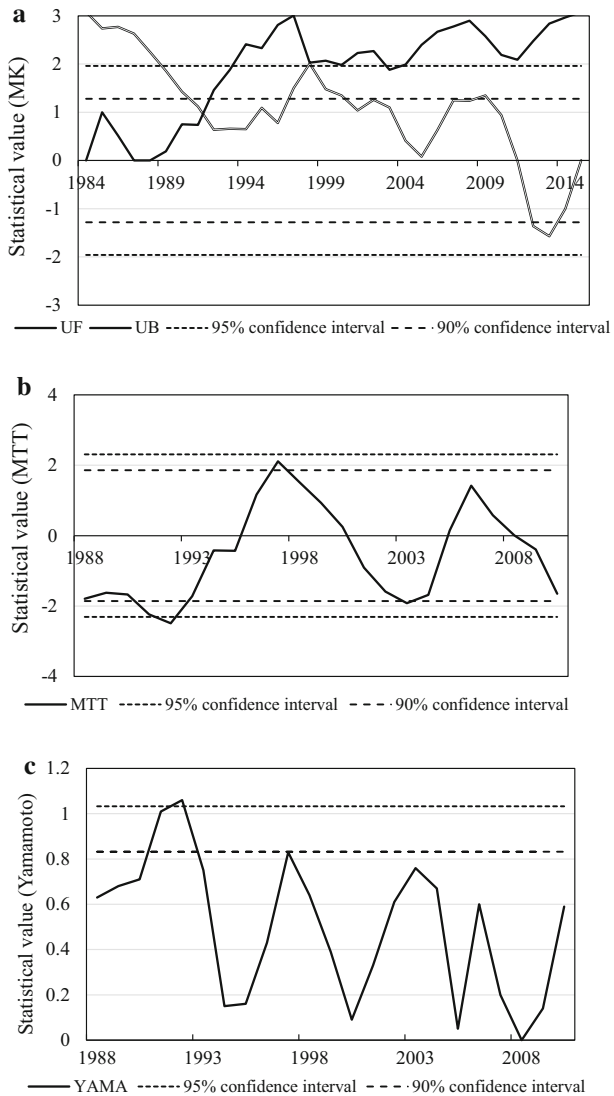
provinces increased most obviously (significant above the 99 % confidence level), at rates of 69 million, 45 million, and 26 million CNY year^{-1}, respectively. Guangxi, Hainan, Hubei, Jiangsu, Shanghai, and Zhejiang provinces all had increasing loss trend at above the 95 % confidence level.

When compared with the CPI-normalized losses described above, a similar pattern was found in the original losses, i.e., the reduction from the southeast to the north (Fig. 11b). However, the loss values were much lower and the differences between provinces were slightly smaller relative to the CPI-normalized results. The southeastern coastal areas that experienced the highest annual original losses were Zhejiang, Guangdong, and Fujian provinces, with corresponding losses were 8.7 billion, 8.1 billion, and 3.7 billion CNY, respectively.

Fig. 10 Periodicity analysis of annual inflation-adjusted losses for influential tropical cyclones in China during 1984–2015. **a** Red-noise spectra analysis. *Solid line* is the spectrum curve. When it is higher than the standard spectrum curve (different confidence level), a cycle can be detected. **b** Morlet wavelet analysis. Explained according to the closed *circles*
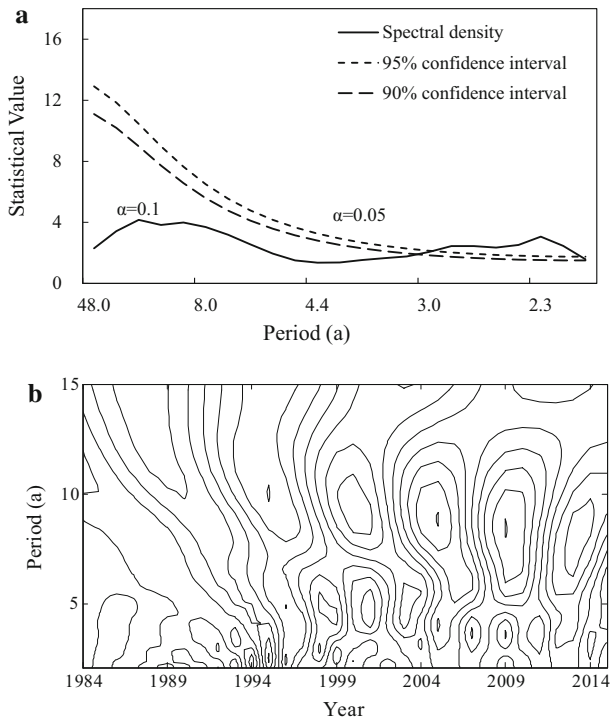
Overall, the provinces that suffered the greatest economic losses were not those that presented the most obvious trend of increase. In Guangdong, Fujian, and Zhejiang provinces, ITCs have brought the largest economic losses during 1984–2015; however, no trend of increase could be detected from the CPI normalized. However, in the original losses, these provinces all showed a high rate of increase of 0.67 billion, 0.57 billion, and 0.2 billion CNY year^{-1}, respectively, significant at the 99 % confidence level (Fig. 12b).

4 Conclusion and discussion

China is one of the countries affected most severely by TCs, and it suffers severe devastation and numerous fatalities each year. In this study, a new definition for tropical cyclones that cause significant economic losses in China (ITCs) was proposed. Direct economic losses, socioeconomic data, and TC track data were used to analyze the characteristics of ITCs and their associated economic losses.

Although original losses are helpful for comparison with other natural disasters that occur in the same year and suitable for updating annual datasets, normalized losses have advantages when conducting long-term studies based on homogeneous time series (Pielke et al. 2008; Kron et al. 2012). Because a complete normalization of economic losses in China is not directly available, a normalization approach based on the provincial CPI of the year of each ITC event was applied to obtain a long-term series appropriate for capturing interannual and inter variabilities.
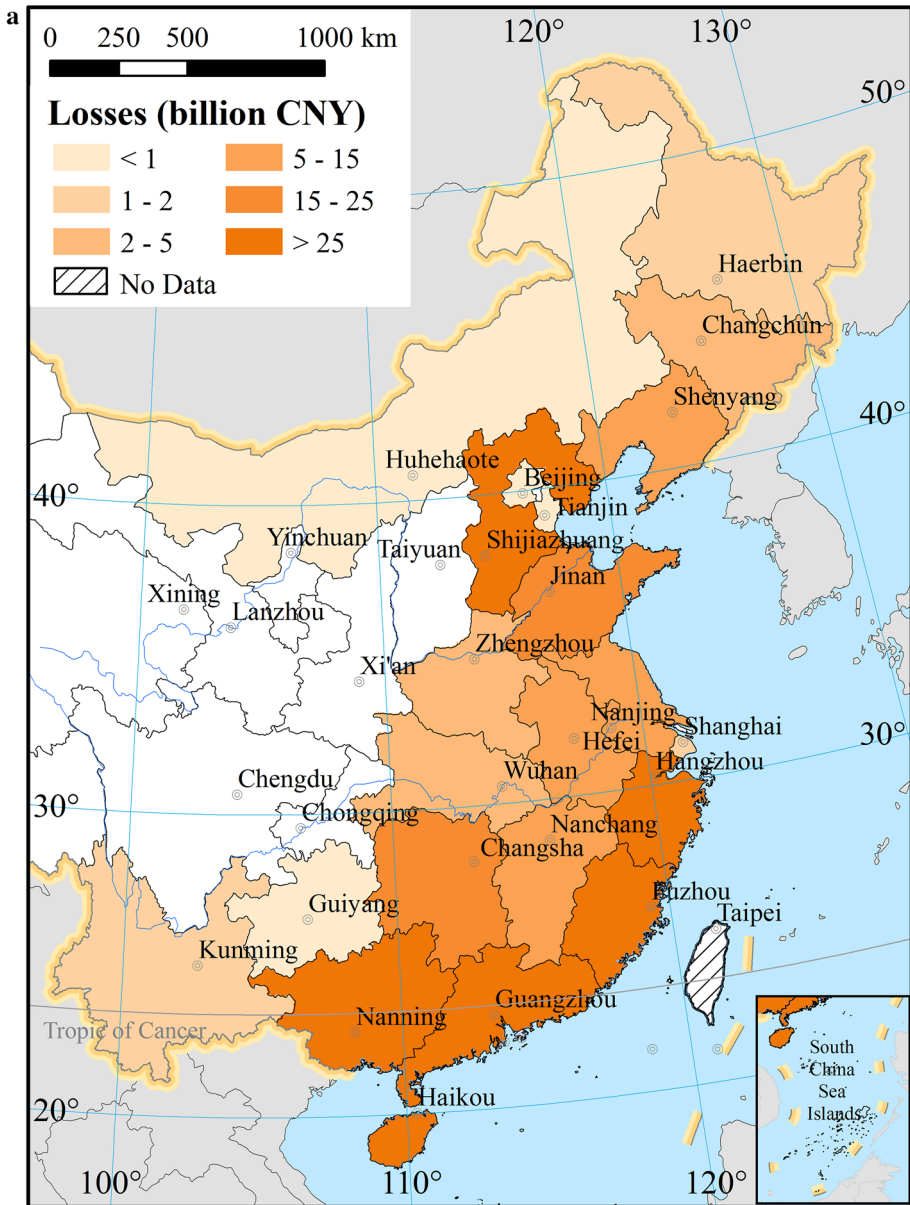
🖄 Springer

Fig. 11 Spatial distribution of average annual losses of influential tropical cyclones during 1984–2015: **a** inflation-adjusted losses and **b** original losses

During 1984–2015, 249 ITCs were selected from 817 TCs that were generated in the western North Pacific Ocean and South China Sea. Landfalling TCs in the same period numbered 228. The numbers of severe ITCs and severe landfalling TCs (i.e., wind speeds >32.7 m s^{-1}) were found to have increased (significant at the 95 % confidence level). No monotonic trend in ITC frequency was found during 1984–2015, although the year of 2007
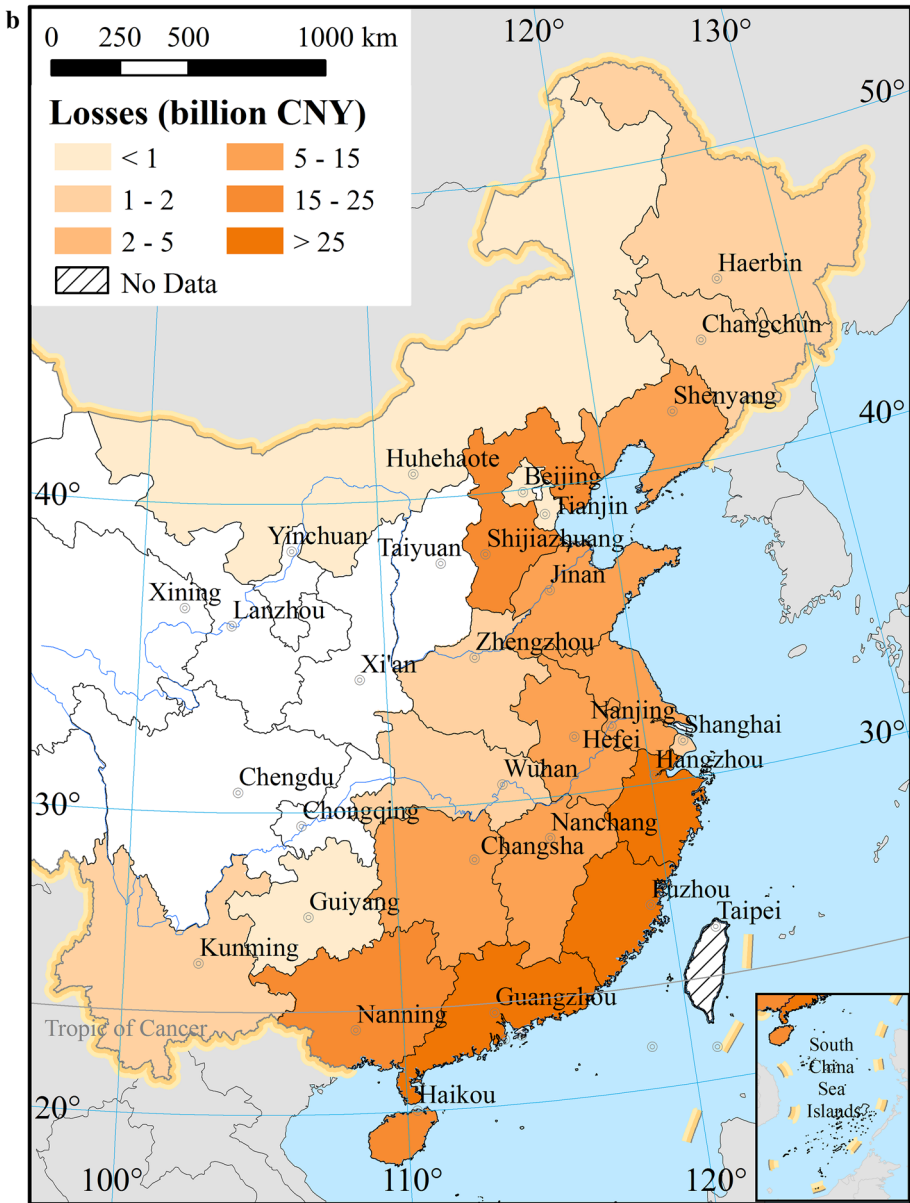
Fig. 11 continued

might be a turning point in the annual frequency, and a periodical 3–6-year pattern was detected. The highest frequency of ITCs during the past 32 years occurred in 2013; the lowest was in 1998 during an obviously inactive period, which might have been related to unfavorable atmospheric conditions (Liu and Chan 2013). In comparison with previous studies that have focused only on TCs making landfall, some consistent variations in the
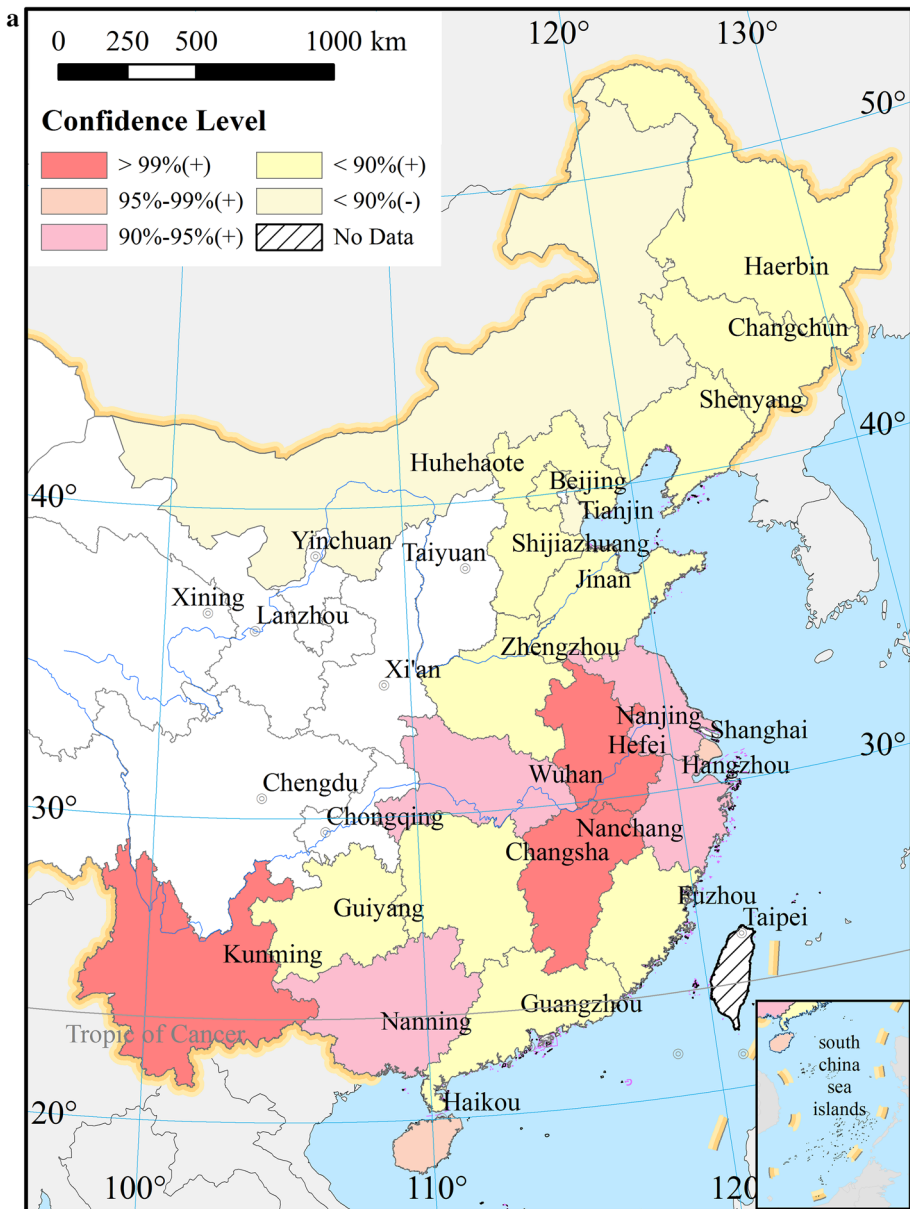
Fig. 12 Tendency of average annual losses of influential tropical cyclones during 1984–2015: **a** inflation-adjusted losses and **b** original losses

frequency series were found, i.e., the variation in intensity (Yang et al. 2009; China Meteorological Administration 2015).

Overall, 22 provinces have been affected by ITCs during 1984–2015. Guangdong Province has been affected most with a frequency of 121 (3.9 times annually), followed by Fujian, Zhejiang, Guangxi, and Hainan provinces, which have been affected 91, 75, 66, and
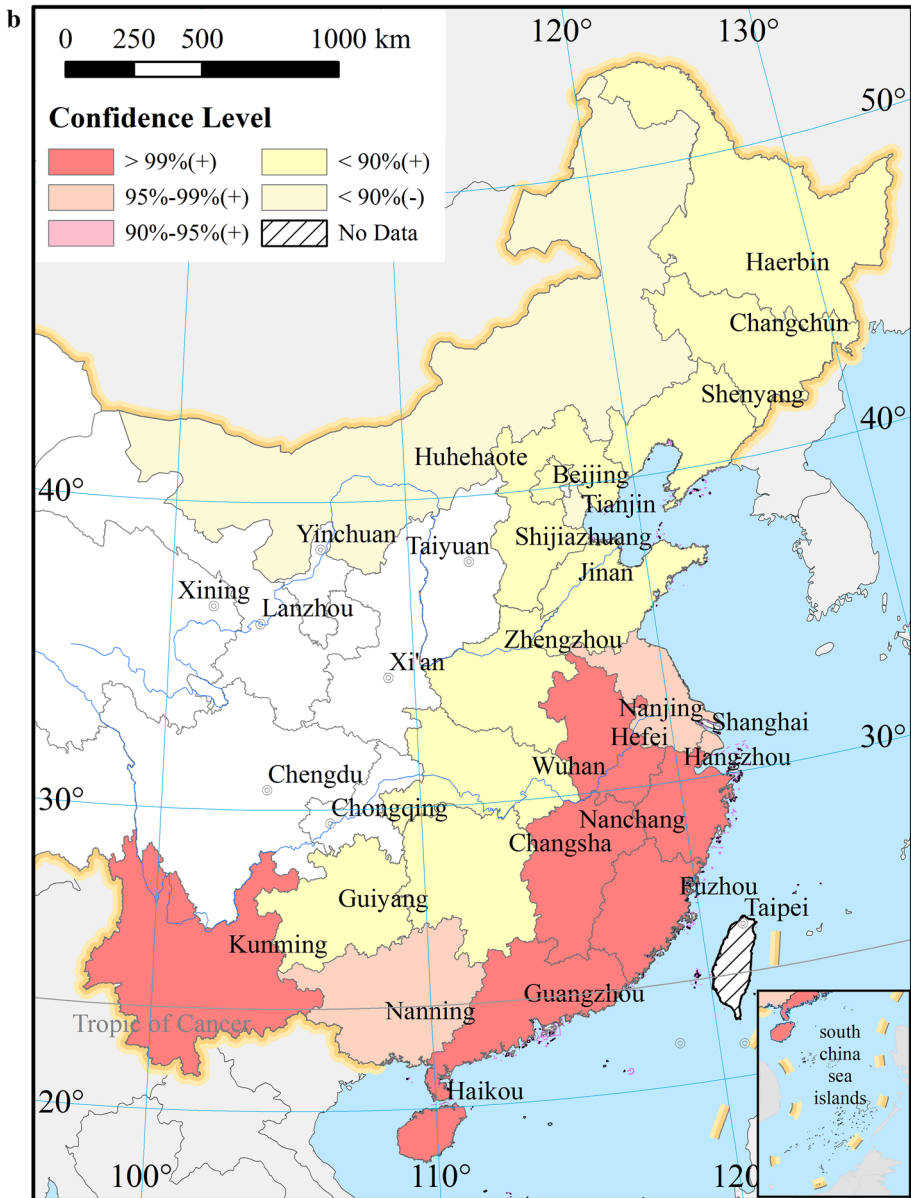
Fig. 12 continued

65 times, respectively. The frequencies of ITCs in Yunnan, Jiangxi, and Fujian provinces were significantly increased at the 95 % confidence level, with rates of 0.27, 0.58, and 0.54 times per decade. Among these three, Fujian Province has also experienced landfalling TCs; however, the tendency of landfalling TCs showed a downward trend with time, which has been found in previous studies (Yang et al. 2009; Zhang et al. 2013).

Annual direct economic losses caused by ITCs in China are about 44.7 billion CNY, with a significant rise of 1.8 billion CNY per year at the 99 % confidence level. Interannual and interdecadal variations were found with the mid-1990s, mid-2000s, and recent 4 years (2012–2015) indicated as three periods of obvious large losses; the maximum loss reached 139.2 billion CNY in 1996. Super typhoon Herb, which occurred in 1996, was the costliest ITC since 1984. After making comparative analyses of the different proportions in different years, high economic losses did not equate to high GDP proportions, e.g., the ratio differences between annual losses and GDP after 1996 were lower than that among ITC causing economic losses. An obvious abruption was found at 1992, and a 2–3-year periodicity of ITC losses was detected during 1984–2015. Compared with the CPI-normalized losses, both of the two costliest years in the original loss series (2013 and 2012) fell one place in the ranking, mainly because of China's rapid socioeconomic development.

In general, average annual economic losses of the affected provinces decreased gradually from the southeast to the north. The southeastern coastal areas of Zhejiang, Guangdong, and Fujian provinces experienced the three highest average annual losses of 11.5 billion, 11.1 billion, and 5 billion CNY, respectively. The trends of losses in Anhui, Jiangxi, and Yunnan provinces increased significantly at the 99 % confidence level at rates of 69 million, 45 million, and 26 million CNY year^{-1}, respectively. Compared with the CPI-normalized losses, the original losses showed a similar spatial pattern but with much lower values and some differences among the provinces. No significant trends were detected in the CPI-normalized losses associated with ITCs in Guangdong, Fujian, and Zhejiang provinces during 1984–2015; however, the results based on the original loss series all showed significant increases at a high rate.

Many studies considering economic losses associated with weather hazards have been undertaken. Inflation, population growth in vulnerable areas, and increasing wealth contribute substantially to the increase in such losses (Choi and Fisher 2003; Nordhaus 2010; Schmidt et al. 2010). Different normalization methods have been used by different researchers, and despite criticisms, the CPI-normalized method is the most prominent and widely used approach (Munich Re 2016). In China, increasing TC-related losses are mainly due to the rapid socioeconomic development of the past several decades, and although this has been widely acknowledged, specific analyses remain lacking (Zhang et al. 2009, 2013). Therefore, research into the economic losses in China associated with TCs requires further attention.

The findings of this study will enhance scientific knowledge on the effects of TCs and enable decision makers and the public to implement effective adaption measures and take suitable precautions to mitigate the effects of TCs. For better understanding of the effects of TCs, the assessment of associated sector-based losses will be the focus of future research.

References

Changnon SA, Changnon D, Fosse ER et al (1997) Effects of recent weather extremes on the insurance industry: major implications for the atmospheric sciences. Bull Am Meteorol Soc 78:425–431

China Meteorological Administration (2001) Tropical cyclone disasters dataset (1984–1999). Operation Center of the China Meteorological Administration (CMA), Beijing

China Meteorological Administration (2015) China National assessment report on risk management and adaptation of climate extremes and disasters. China Meteorological Administration (CMA). China Meteorological Press, Beijing **(in Chinese)**

China Meteorological Administration (2016a) Yearbooks of Meteorological Disaster 2016. China Meteorological Administration (CMA). China Meteorological Press, Beijing **(in Chinese)**

China Meteorological Administration (2016b) China climate impact assessment reports. China Meteorological Administration (CMA). China Meteorological Press, Beijing **(in Chinese)**

Chinese Standardization Administration Committee (2006) Classification of tropical cyclones (GB/T19201–2006). Chinese standardization press, Beijing **(in Chinese)**

Choi O, Fisher A (2003) The impacts of socioeconomic development and climate change on severe weather catastrophe losses: Mid-Atlantic Region (MAR) and the US. Clim Change 58(1–2):149–170

Deng Z, Xun H, Zhou M et al (2015) Impacts of tropical cyclones and accompanying precipitation on infectious diarrhea in cyclone landing areas of Zhejiang Province, China. Int J Environ Res Public Health 12(2):1054–1068

Estrada F, Botzen WJW, Tol RSJ (2015) Economic losses from US hurricanes consistent with an influence from climate change. Nat Geosci 8:880–884

Fischer T, Su B, Wen SS (2015) Spatio-temporal analysis of economic losses from tropical cyclones in affected provinces of China for the last 30 years (1984–2013). Nat Hazards Rev 16:04015010

Gemmer M, Yin YZ, Luo Y et al (2011) Tropical cyclones in China: county-based analysis of landfalls and economic losses in Fujian Province. Quat Int 244:169–177

Hammer Ø, Harper D, Ryan P (2001) PAST-PAlaeontological Statistics, ver. 1.89. Palaeontol Electron 4(1):1–9

Kendall MG, Charles G (1975) Rank correlation methods. Oxford University Press, New York

Knutson TR, McBride JL, Chan J et al (2010) Tropical cyclones and climate change. Nat Geosci 3(3):157–163

Kron W, Steuer M, Löw P et al (2012) How to deal properly with a natural catastrophe database—analysis of flood losses. Nat Hazards Earth Syst Sci 12:535–550

Liu KS, Chan JCL (2013) Inactive period of western North Pacific tropical cyclone activity in 1998–2011. J Clim 26(8):2614–2630

Mann HB (1945) Non-parametric tests against trend. Econometrica 13:245–259

Mendelsohn R, Emanuel K, Chonabayashi S et al (2012) The impact of climate change on global tropical cyclone damage. Nat Clim Change 2:205–209

Miller S, Wood RM, Boissonnade A (2008) An exploration of trends in normalized weather-related catastrophe losses. Clim Extrem Soc 225–247

Mohleji S, Pielke R Jr (2014) Reconciliation of trends in global and regional economic losses from weather events: 1980–2008. Nat Hazard Rev 15(4):04014009

National Bureau of Statistics (2015) China statistical yearbook 2015. National Bureau of Statistics, China Statistics Press, Beijing **(in Chinese)**

Nordhaus WD (2010) The economics of hurricanes and implications of global warming. Clim Change Econ 1:1–20

Pielke RA, Landsea C, Mayfield M et al (2005) Hurricanes and global warming. Bull Am Meteorol Soc 86:1571

Pielke RA, Gratz J, Landsea CW et al (2008) Normalized hurricane damage in the United States: 1900–2005. Nat Hazard Rev 9(1):29–42

Re M (2010) Natural catastrophes 2009—analyses, assessments, positions, TOPICS GEO. Munich Re, Munich

Re Munich (2016) Natural catastrophes 2015—analyses, assessments, positions, TOPICS GEO. Munich Re, Munich

Schmidt S, Kemfert C, Höppe P (2010) The impact of socio-economics and climate change on tropical cyclone losses in the USA. Reg Environ Change 10:13–26

Schulz M, Mudelsee M (2002) REDFIT: estimating red-noise spectra directly from unevenly spaced paleoclimatic time series. Comput Geosci 28(3):421–426

Stocker TF, Qin DH, Plattner GK et al (2013) Climate change 2013: the physical science basis. In: Intergovernmental Panel on Climate Change, working group I contribution to the IPCC fifth assessment report (AR5). Cambridge University Press, New York

Torrence C, Compo GP (1998) A practical guide to wavelet analysis. Bull Am Meteorol Soc 79(1):61–78

Wilks DS (1995) Statistical methods in atmospheric science. Elsevier, New York

Wu L, Wang B, Geng S (2005) Growing typhoon influence on East Asia. Geophys Res Lett 32:L18703. doi:10.1029/2005GL022937

Xiao FJ, Xiao ZN (2010) Characteristics of tropical cyclones in China and their impacts analysis. Nat Hazard 54(3):827–837

Yamamoto RT, Iwashiman T, Sanga NK (1985) Climatic change: a hypothesis in climate diagnosis. J Meteorol Soc Jpn 63:1157–1160

Yamamoto RT, Iwashima T, Sange NK (1986) An analysis of climate jump. J Meteorol Soc Jpn 64:273–1981

Yang YH, Ying M, Chen BD (2009) The climatic changes of landfall tropical cyclones in China over the past 58 years. Acta Meteorol Sin 67(5):689–696 **(in Chinese)**

Yin J, Yin Z, Xu S (2013) Composite risk assessment of typhoon-induced disaster for China's coastal area. Nat Hazards 69(3):1423–1434

Zhang Q, Wu LG, Liu QF (2009) Tropical cyclone damages in China: 1983-2006. Bull Am Meteorol Soc 90(4):489–495

Zhang J, Wu LG, Zhang Q (2013) Tropical cyclone damages in China under global warming. J Trop Meteorol 19(2):120–129