Front. Earth Sci. 2019, 13(4): 672–681
https://doi.org/10.1007/s11707-019-0793-5

RESEARCH ARTICLE

A simplified index to assess the combined impact of tropical cyclone precipitation and wind on China

Peiyan CHEN (✉)[1,2], Hui YU[1,3], Ming XU[1], Xiaotu LEI[4], Feng ZENG[2,5]

1 Shanghai Typhoon Institute, China Meteotological Administration, Shanghai 200030, China
2 The Joint Laboratory for Typhoon Forecasting Technique Applications between Shanghai Typhoon Institute and Wenzhou Meteorological Bureau, Wenzhou 325000, China
3 Key Laboratory of Numerical Modeling for Tropical Cyclone, China Meteotological Administration, Shanghai 200030, China
4 Shanghai Meteorological Service, Shanghai 200030, China
5 Wenzhou Meteorological Bureau, Wenzhou 325000, China

Abstract Relationships between tropical cyclone (TC) precipitation, wind, and storm damage are analyzed for China based on TCs over the period from 1984 to 2013. The analysis shows that the maximum daily areal precipitation from stations with daily precipitation of $\geqslant$50 mm and the sum of wind gusts of $\geqslant$13.9 m/s can be used to estimate the main damage caused by TCs, and an index combining the precipitation and wind gust of a TC (IPWT) is defined to assess the severity of the combined impact of precipitation and wind. The correlation coefficient between IPWT and the damage index for affecting TCs is 0.80, which is higher than that for only precipitation or wind. All TCs with precipitation and wind affecting China are divided into five categories, Category 0 to Category 4, based on IPWT, where higher categories refer to higher combined impacts of precipitation and wind. The combined impact category is closely related to damage category and it can be used to estimate the potential damage category in operational work. There are 87.7%, 72.9%, 69.8%, and 73.4% of cases that have the same or one category difference between damage category and combined impact category for Categories 1, 2, 3, and 4, respectively. IPWT and its classification can be used to assess the severity of the TC impact and of combined precipitation and wind conveniently and accurately, and the potential damage caused by TCs. The result will be a good supplementary data for TC intensity, precipitation, wind, and damage. In addition, IPWT can be used as an index to judge the reliability of damage data. Further analysis of the annual frequency of combined precipitation-wind impact categories reveals no significant increasing or decreasing trend in impact over China over the past 30 years.

Keywords tropical cyclone, impact, precipitation, wind

1 Introduction

Tropical cyclones (TCs) are some of the most destructive natural phenomena in the world. The past decade has seen heightened hurricane activity with more than US$150 billion in damage in 2004 and 2005 on the mainland United States (Pielke et al., 2008). Although there was no clear increasing or decreasing trend in the damage caused by individual TCs, the total direct economic losses (DEL) from all TCs increased during the period 1984–2015 in China and the annual mean losses were approximately 44.7 billion Chinese Yuan (CNY) (Lei et al., 2009; Zhang et al., 2009; Chen et al., 2013; Zhao et al., 2015; Wang et al., 2016). Appropriate assessment and warming of TC severity from hazard zones are the keys to reducing damage and the loss of life and are always important topics in research about TC hazards.

Due to its convenience and practicality, the Saffir-Simpson hurricane scale (SSHS), which was developed based on maximum surface wind speed, is the most widely accepted and utilized method in the classification and assessment of the destructive power of hurricanes by meteorologists and decision-makers in United States. Similar to the SSHS, TCs are divided into six categories in China (GB/T 19201-2006). However, the SSHS does not consistently estimate the actual destruction caused by TCs (Kantha, 2006), and researchers have proposed other

Received January 22, 2019; accepted September 17, 2019

E-mail: chenpy@typhoon.org.cn

indices to replace it. Most of these indices are also related to maximum surface wind speed, such as the power dissipation index (PDI) (Emanuel, 2005), the hurricane intensity index (HII), the hurricane hazard index (HHI), the hurricane surge index (HSI) (Kantha, 2006 and 2013), the integrated kinetic energy (Powell and Reinhold, 2007), the hurricane severity index, and the Tropical Cyclone Potential Impact Index (TCPI) (Xiao et al., 2011). However, precipitation is a major hazard factor for TCs and it is one of the important parameters in damage assessment models for TCs (Chen et al., 2009; Yang and Xu, 2010; Lou et al., 2012; Xu et al., 2015). For example, Hurricane Harvey (2017) stalled over Texas and caused extreme precipitation, with the highest observed three-day precipitation amount, 1043.4 mm^3/dy, at Baytown. This resulted in extensive flooding with over 80 fatalities and large economic costs (Oldenborgh et al., 2017). With the exception of gales, the precipitation and translation speeds of TCs are mainly responsible for the DEL and destroyed houses (Chen et al., 2009). The absence of precipitation in the TC indices listed above is one source of the difference between estimate and actual categories. For this reason, Zhang et al. (2010) added a total vapor index to a total damage index (TDI) for TCs landfalling on China, and Rezapour and Baldock (2014) added a tropical cyclone rainfall index to a combined hazard index (TCHI) to estimate and rank severity of hurricanes landfalling on the continental United States. The results in both studies show that hazard indices that include rain factors are high correlate with DEL.

It should be noted that the sample size of TCs is very small in the studies of Rezapour and Baldock (2014) and Zhang et al. (2010), with only 19 hurricanes and 30 typhoons making landfall, respectively. Moreover, the column water vapor data used in Zhang et al. (2010) is estimated from satellite data. The gap between the column water vapor and observed rain at stations affects the accuracy of representativeness of the total column water vapor. The importance of rainfall and the ability of function which combines precipitation and wind in estimating and classifying the TC severity in China must be re-investigated and re-established based on observation data for large TC cases. Therefore, in this context, the assessment and classification method for the combined impact of tropical cyclone precipitation and wind on China has been investigated based on the past 30 years of observation data.

The data used here are described in Section 2. Section 3 presents the indices of TC-induced precipitation and wind. Classification of the combined impact of TC precipitation and wind are discussed in Sections 4. Section 5 presents the frequency characteristics of affecting TCs (ATCs). Finally, Section 6 contains discussion and conclusions.

2 Data and methods

This study considers TCs affecting China from 1984 to 2013. The 6-h best-track and intensity data for the TCs were obtained from the China Meteorological Administration (CMA) tropical cyclone database compiled by the Shanghai Typhoon Institute (STI) and can be downloaded from Typhoon Online Website. TC-induced precipitation and wind data at stations also obtained from this database (Ying et al., 2014). The TC-induced precipitation data contain daily precipitation, maximum 1 h precipitation, and the associated date and time. The TC-induced wind data contain the date and duration of wind speeds $\geqslant$10.8 m/s, and both the sustained wind and wind gusts with associated directions. The wind and precipitation patterns associated with TCs were manually determined from either synoptic charts or satellite imagery based on station observations. The interaction of TCs with other synoptic systems is quite complex over the land area of China. It makes the judgment on whether the precipitation and wind are induced by TCs difficult. Several crucial rules, such as the rule on remote TC torrential rain and adjacent frontal systems, were created to ensure that more comprehensive TC data were included. In general, the TC-induced precipitation and wind data that are used in this paper are credible and they were used as a baseline to develop a numerical technique to separate TC-induced precipitation from adjacent precipitation areas (Ren et al., 2001).

The density of stations and their spatial distribution affect the results of climatic analysis (Easterling et al., 1996; Wu et al., 2007). Therefore, the selection of stations is very important. Lu et al. (2018a) studied variations in the TC precipitation statistic with different spatial distribution of stations. It was found that total precipitation, mean annual precipitation, and mean daily precipitation were the same regardless of the spatial density of the stations and in spite of some minor differences on precipitation extremes. There are 1404 stations in China that have been moved less than 7.8 km between 1981 and 2010 after considering their history, data completeness, representativeness, and distance compared with other stations. These stations include the national basic weather station, the national reference climatological station, and the national general weather station. 1401 stations in 29 provinces are included in this study, similar to those stations included in the Climatological Atlas of Tropical cyclones over the Western North Pacific (1981–2010) published by STI/CMA (2017). More detailed information about stations were described in Lu et al. (2018a).

STI/CMA set some conditions to define an ATC in research and operational work regarding TC climate analysis and forecasting. STI/CMA (2006, 2017) considers a TC to be an ATC if any of the meteorological stations on China meets one of the following three conditions: 1) total precipitation of ⩾50 mm (Condition 1); 2) a sustained wind of ⩾13.9 m/s (Beaufort Scale (BS) 7) (or wind gusts of ⩾17.2 m/s (BS 8)) (Condition 2); or 3) total precipitation of ⩾30 mm and either sustained winds of ⩾10.8 m/s (BS 6) (or wind gusts of ⩾13.9 m/s (BS 7) (Condition 3). In this paper, the conditions as above are used to identify an ATC.

Of the 424 ATCs identified between 1984 and 2013, 329 (77.50%) meet Condition 1 and Condition 2, 42 (9.91%) meet only Condition 1, and 52 (12.26%) meet only Condition 2 (Fig. 1). The average annual frequency of ATCs is 14.1, which is slightly greater than the median annual frequency of 14 (Fig. 2). The maximum (minimum) number of ATCs in a year is 22 (8). ATCs with both heavy precipitation and strong winds (satisfying Conditions 1 and 2) have an average annual frequency of 11, similar to the median value, and a maximum (minimum) annual frequency of 18 (5).

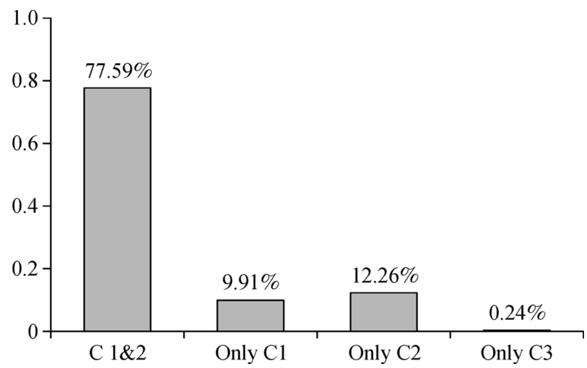

Fig. 1 Proportion of ATCs according to selected conditions (C1 to C3).

Damage data for most ATCs for the 2007–2013 period were collected and compiled by the National Bureau of Statistics of China and released by the Department of Civil Affairs of China, but for the 1984–2006 period, the data were collected by STI/CMA and the National Climate Center with support from a national "85" project and a CMA project. The damage data include the Deaths and Missing (*DM*; unit: persons), Affected Crop Area (*ACA*; unit: thousand hectares), Number of Destroyed Houses (*NDH*; unit: rooms), and *DEL* (unit: 0.1 billion yuan). Despite uncertainties in this data set, these records provide important information about the societal and economic effects of TCs in China (Lei et al., 2009; Zhang et al., 2009; Chen et al., 2013).

In most damage studies, *DEL* and casualties were chosen to represent the severity of the disaster caused by TCs (Pielke et al., 2008; Zhang et al., 2009; Zhang et al., 2010; Xiao et al., 2011). However, casualties are clearly affected by policy and capacity in disaster prevention and reduction, and DEL are influenced by social development. As a result, casualties and *DEL* typically have opposite trends (Lei et al., 2009; Zhang et al., 2009). For this reason, comprehensive indices have been developed to assess the severity of damage (Lu, 1995; Liang et al., 1999; Ma et al., 2008; Lei et al., 2009; Chen et al., 2013). The comprehensive evaluation index for TC damage (*TDPr*) developed by Chen et al. (2013), is comparatively objective by using principal component analysis in assessment of the severity of TC-caused damage for China, and the space span and time span of data in Chen et al. (2013) are similar to those in this study. Therefore, *TDPr* is used here and it can be calculated as follows:

$$TDPr = 0.3586DM + 0.3774ACA + 0.4581NDH + 0.2831RDEL, \tag{1}$$

where

$$RDEL = \frac{DEL}{GDP} \times 10000, \tag{2}$$

where *GDP* is the previous year's Gross Domestic Production in China in units of 0.1 billion CNY and *RDEL* is the Rate of Direct Economic Losses. Based on *TDPr*, the damage severity of TCs is divided into four categories from Category 1 to Category 4. Category 1, "Mild Disaster," is the lowest level of damage and Category 4, "Catastrophe," is the highest. The classification standards of damage are listed in Table 1. Here, Category 0 for TCs with no record of damage was added to the damage classification table.

3 Indices of TC-induced precipitation and wind

The characteristics of TC precipitation can be described by a number of variables, such as total TC precipitation,

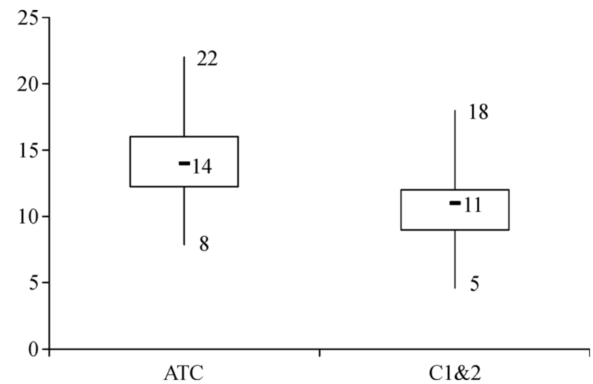

Fig. 2 Distribution of the annual frequency of ATCs and those that meet conditions 1 and 2 (C1&2). The upper and lower limits of the boxes represent the third (75%) and first (25%) quartiles of the annual frequency. The median of the annual frequency is denoted by a short bar in the box. The upper and lower ends of the whiskers represent the maximum and minimum of the annual frequency.

Table 1 Classification standards for TC damage based on *TDPr* (Chen et al. 2013)

Damage category	0	1	2	3	4
Description	No damage	Mild disaster	Medium disaster	Severe disaster	Catastrophe
TDPr	0	0–0.90	0.90–2.00	2.00–3.00	⩾3.00

maximum total precipitation at stations, maximum hourly precipitation at stations, number of rainstorm days, and area of precipitation. These variables can be divided into several groups according to the property they describe as follows: 1) variables that describe the total water in a TC, such as the total precipitation of a TC and maximum total precipitation at stations; 2) variables that describe the duration and area of precipitation, such as days and stations with heavy precipitation; 3) variables that describe the intensity of precipitation, such as the maximum hourly or daily precipitation; and 4) variables that describe the combined action of intensity and area of precipitation, such as the Maximum Daily Area Precipitation (*MDAP*) based on stations where the daily precipitation is ⩾ 50 mm.

To select a suitable variable to assess the precipitation effect, correlation coefficients between precipitation-related variables and *TDPr* were calculated for TCs with damage records (herein, DTCs). Among these variables, *MDAP*, the total accumulated precipitation at stations with accumulated precipitation of ⩾ 50 mm, and the maximum daily stations with daily precipitation of ⩾ 50 mm indicated the three highest correlation coefficients when correlated with *TDPr*. The coefficients between the three variables listed above and *TDPr* are listed in Table 2. This is a reasonable result because disaster is a cumulative process and fits well with variables that reflect the intensity and area of precipitation. In statistical pre assessment models for TC-induced damage developed by Chen et al. (2009), *MDAP* is one of the most important predictors. Not only is it a predictor selected by these models but it also shares the largest variance contribution to *ACA*, *DEL*, and *NDH*. Considering both the correlation coefficients and the role of *MDAP* in statistical damage pre-assessment models, *MDAP* is selected here to represent the impact of TC precipitation. For comparison with wind indices, the *MDAP* must be nondimensionalized. The index of TC precipitation (*IPT*) is then defined as follows:

$$MDAP = \max\left(\sum_{i=1}^{np_j} p_{ij}\right) \quad j = 1, \ldots, Nd_p; \tag{3}$$

$$IPT = MDAP/MDAP_{\mathrm{MX}}, \tag{4}$$

where P_{ij} is the daily precipitation (mm) at the i^{th} station on the j^{th} day; np_j is the number of stations with $P_{ij} \geqslant 50$ mm; and Nd_p is the number of precipitation days during a TC influence period. $MDAP_{\mathrm{MX}}$ is the maximum value of *MDAP* during a given period. Here, the period is from 1984 to 2013 and the $MDAP_{\mathrm{MX}}$, from TC Bilis in 2006, is 12679 mm. The distribution of Nd_p for DTCs during 1984–2013 is shown in Fig. 3. Fifty-seven DTCs caused 5 days of precipitation and the average and median Nd_p for all DTCs were both 5.0 days. Of the total DTCs, 17.8% caused 7 days or more precipitation over China. There are 5 TCs that caused more than 10 days precipitation (highest value: 17 days) and their tracks were all anomalous. They traveled slowly following unusual tracks over the area north of the South China Sea or the sea near south-eastern China.

A suitable wind variable was selected following a similar process. The correlation analysis shows that wind gust variables have higher correlation coefficients than those of extreme sustained wind with *TDPr*. Only the nine gust-related variables are listed in Table 2. The two variables with the highest correlation coefficients (0.68) are the sum of all wind gusts of ⩾ 13.9 m/s (GUST7_T) and the number of stations with observed wind gusts of ⩾ 13.9 m/s. The square and cube of GUST7_T have the next highest correlation coefficients. The number of stations with observed wind gusts of ⩾ 13.9 m/s represents the area of wind gusts and GUST7_T represents the area and intensity of wind gusts. Therefore, GUST7_T was selected to develop the TC wind index (*IWT*). The *IWT* is defined as follows:

$$\mathrm{GUST}_T = \sum_{i=1}^{nS_w} (\mathrm{GUST}_i),\ i = 1,\ 2\ldots,\ nS_w, \tag{5}$$

$$IWT = \mathrm{GUST7\_T}/\mathrm{GUST7\_T_{MX}}, \tag{6}$$

where, GUST_i is the wind gust (m/s) at the i^{th} station, and nS_w is the number of stations with wind gust ⩾ 13.9 m/s during a TC influence period. $\mathrm{GUST7\_T_{MX}}$ is the maximum value of GUST7_T in all ATCs during a given period. Here, the period is 1984 to 2013 and the $\mathrm{GUST7\_T_{MX}}$ is 4481 m/s for TC Winnie in 1997.

Two expressions are widely used to calculate the comprehensive index of two variables. One expression is deduced based on the assumption of the linear relationship between variables and can be described as follows:

$$y = ax_1 + bx_2 + \mathrm{c}, \tag{7}$$

where x_1 and x_2 are variables and y is the comprehensive index. The *a*, *b*, *c* parameters are determined by the stepwise regression method or correlation coefficients. If *a* and *b* are determined by the correlation coefficients, *c* is typically set to 0 (Zhang et al., 2010; Lu et al., 2018b; Chen et al., 2019). Another expression is deduced based on the assumption of nonlinear relationship between variables

Table 2 Variable names, abbreviations, and their correlation coefficients when correlated with *TDPr*. The coefficients are calculated using all TCs with damage records from 1984 to 2013

Name	Correlation coefficient
Maximum Daily Area Precipitation based on stations where the daily precipitation is ⩾50 mm (*MDAP*)	0.59
Total Accumulated Precipitation at stations with accumulated precipitation of ⩾50 mm	0.53
Maximum daily stations with daily precipitation of ⩾50 mm	0.56
Maximum station wind gust speed within the duration of an ATC	0.46
Sum of all wind gust speeds ⩾13.9 m/s (GUST7_T)	0.68
$(\mathrm{GUST7\_T})^2$	0.66
$(\mathrm{GUST7\_T})^3$	0.64
Stations with gust ⩾13.9 m/s	0.68
Sum of all wind gust speeds ⩾20.8 m/s	0.58
The square of the sum of all wind gust speeds ⩾20.8 m/s	0.57
The cube of the sum of all wind gust speeds ⩾20.8 m/s	0.56
Stations with wind gust speeds ⩾20.8 m/s	0.58

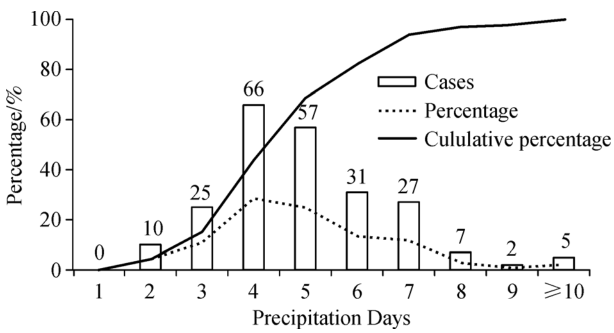

Fig. 3 Distribution of number of precipitation days over China during a TC influence period (Nd_p) based on DTCs from 1984 to 2013. Bars denote frequency and the numbers on the bars are the sample sizes. The black solid line is the cumulative percentage of Nd_p for all cases. The dotted line is the percentage of Nd_p from all cases.

and can be described as follows:

$$y = f(x_1) \times f(x_2). \tag{8}$$

For example, the storm surge index is calculated by the product of functions of maximum wind speed, the distance from the coast to the 30 m isobaths, the radius of 33 knot wind speed, etc. The typhoon disaster risk indices are calculated by the product of the intensity index of factors causing typhoon disasters and the vulnerability index (Kantha, 2013; Lu et al., 2018b; Xu et al., 2018).

The disaster mechanisms caused by strong wind and heavy rain are different. However, the destructive powers of these two factors will strengthen each other. Therefore, both expressions were used to assess the comprehensive impact of precipitation and wind. Several sensitivity experiments were tested and compared for the weights of items and more complicated formulations including more nonlinear terms. It is shown that the complicated formulations have not shown remarkable improvements. In addition, convenience and practicality are very important characteristics for practical application (Kantha, 2006). Therefore the minimization of the combined Impact index of Precipitation and Wind (*IPWT*) caused by a TC is defined as follows

$$IPWT = (IPT + IWT + IPT \times IWT)/2. \tag{9}$$

For cases used in this paper, both IPT and IWT are in the range of 0–1, and the *IPWT* ranges from 0 to 2.5. The probability distributions of *IPT* and *IWT* based on DTCs are shown in Fig. 4(a). Because the values of $IPT \times IWT$ are typically small, most of *IPWT*s are less than 1. The low $IPT \times IWT$ values are the reason that the right side of Eq. (9) is multiplied by 1/2 rather than 1/3. The majority of *IPT*s (*IWT*s) of DTCs are concentrated in a range from 0.05 (0.00) to 0.30 (0.20). In addition, the shape of the probability distribution of IWT is steeper than that of *IPT*; 97.4% of *IWT* and 90.4% of *IPT* are in the range of 0 to 0.5.

The correlation coefficient between *IPT* and *IWT* is 0.58. This means that most TCs have similar intensities of precipitation and wind, and TCs with heavier precipitation typically have stronger wind. The correlation coefficient between *IPT* (*IWT*, *IPWT*) and *TDPr* is 0.58 (0.68, 0.70). *IPWT* shows the closest relationship with *TDPr*, and is therefore more suitable for assessing the combined impact of precipitation and wind for a TC than the other two indices.

4 Classification of the combined impact of TC precipitation and wind

To assess the combined impact of precipitation and wind, it is necessary to first determine whether a TC will cause

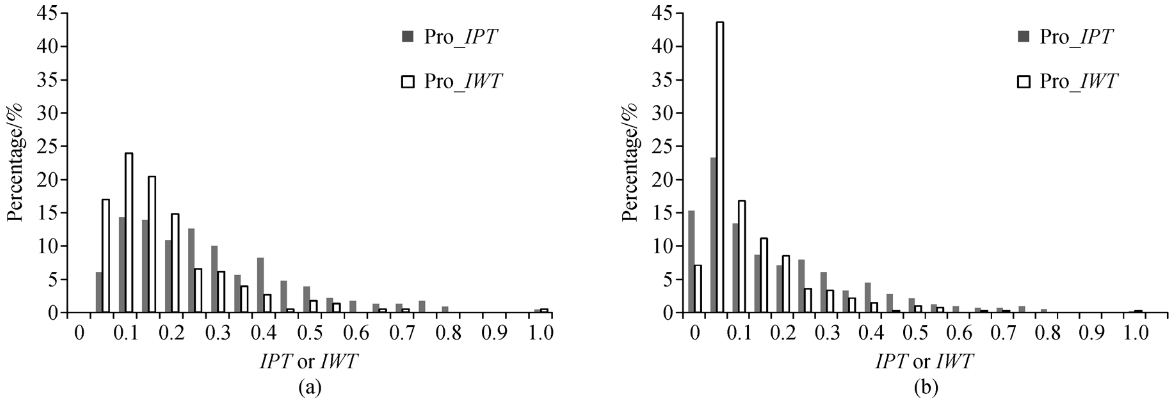

Fig. 4 The distributions of *IPT* and *IWT* based on DTCs (a) and ATCs (b) from 1984 to 2013. The solid (hollow) bar labeled Pro_*IPT* (Pro_*IWT*) is the percentage of TC cases with *IPT* (*IWT*) within the range labeled on the abscissa. Numbers on the abscissa (except for 0) are ranges of *IPT* or *IWT* values. For example, "0.1" in (a) means $0.05 < IPT$ (or IWT) $\leqslant 0.1$. The "0" means that *IPT* or *IWT* is 0.

damage. Therefore, the relationships among *IPT*, *IWT*, *IPWT*, and *TDPr* were investigated for all ATCs.

The correlation coefficients between *TDPr* and each of *IPT*, *IWT*, and *IPWT* based on ATCs are 0.70, 0.78, and 0.80, respectively. Figure 5 shows the distribution of *IPWT* at intervals of 0.05 for the ATCs. The three largest sample sizes are for ranges of 0–0.05, 0.1–0.15, and 0.05–0.1, with 173, 54, and 47 samples, respectively. Because 40.8% of the ATC's *IPWT*s fall between 0.0 and 0.05 (not including 0), the detailed distribution of *IPWT* lower than 0.05 in intervals of 0.01 is also shown in Fig. 5. The sample size in the range of 0 to 0.01 is still the largest (16.04% of all *ATC*s). There are no DTCs when *IPWT* is less than 0.0179 and there is only one DTC when *IPWT* is less than 0.0226. Figure 5 also shows that for the *IPWT* range of 0.02–0.25, the percentage of DTCs in ATCs increases with *IPWT*. In the *IPWT* ranges of 0.04–0.05, 0.05–0.10, and 0.10–0.15, a total of 41.2%, 61.7%, and 81.5% of the TCs are DTCs, respectively. There is only one tropical depression (TD) in 1985 without damage data whose *IPWT* is larger than 0.2100. The TD in August 1985 caused heavy precipitation and wind gusts over the area south of Guangxi Province, and resulted in flooding, especially over Qinzhou District (Lin and Lu, 1987). This means that the damage data of the tropical depression are missing. Therefore, all TCs with *IPWT*s larger than 0.2100 caused damage. The above analysis shows that the probability of a TC causing damage can be estimated from *IPWT*.

More details about the relationship between damage categories of ATCs and *IPWT* are shown in Fig. 6. In general, there is a greater percentage of high levels of damage with higher levels of *IPWT*. The distinction is evident when *IPWT*s are small. Thus, the damage severity of TCs can be estimated from their *IPWT*s in spite of the nonsignificant difference between damage Categories 3 and 4 when *IPWT*s are larger than 0.5.

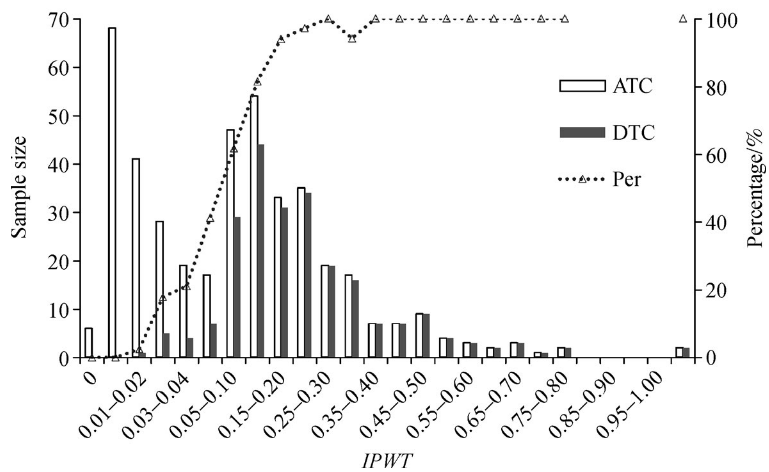

Fig. 5 Sample size distributions of ATCs and DTCs as a function of *IPWT* from 1984 to 2013. Note that the *IPWT* scale changes at 0.05. The numbers on the abscissa (except for 0) indicate ranges (not including the lower value). For example, 0.01–0.02 means $0.01 < IPWT \leqslant 0.02$. The 0 on the abscissa means that *IPT* or *IWT* is 0. "ATC" indicates the number of ATCs, "DTC" indicates the number of DTCs, and "Per" indicates the cumulative percentage of DTCs from all ATCs.

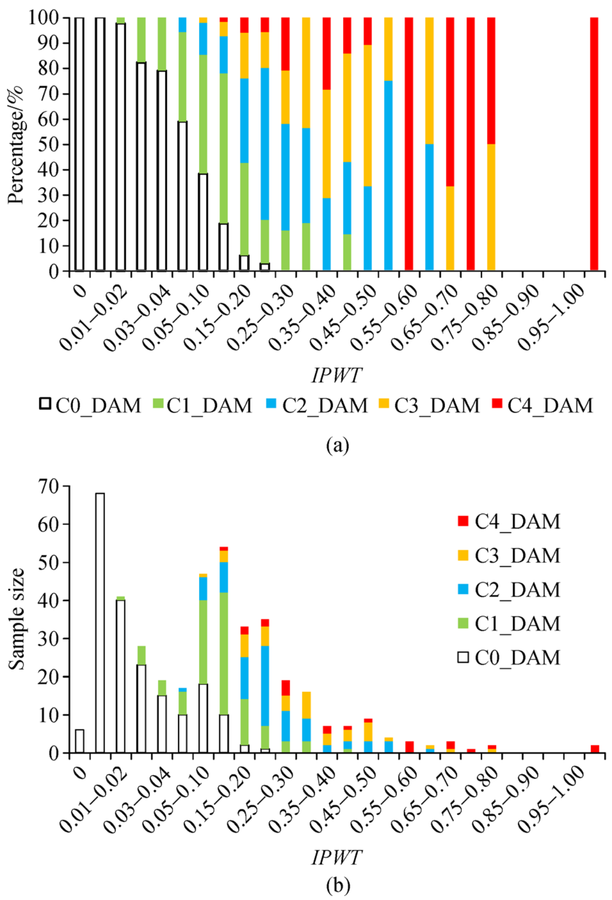

Fig. 6 Percentage (a) and sample size (b) distributions of damage categories for all ATCs from 1984 to 2013 as a function of *IPWT* condition (except for the tropical depression in August 1985). The numbers on the abscissa (except for 0) indicate statistical ranges. For example, 0.01–0.02 means 0.01 < *IPWT* ⩽ 0.02. The 0 on the abscissa means that *IPT* or *IWT* is 0. C*_DAM is damage severity category based on *TDPr*. C0_DAM means no damage record, whereas C4_DAM indicates the highest level of damage. More details about damage categories and *TDPr* can be found in Chen et al. (2013).

All ATCs are divided into five categories of combined impact of precipitation and wind, from Categories 0 to 4, based on their *IPWT*s values (Table 3). Combined impact Category 0 TCs (*IPWT* < 0.0234) represent 30.7% of all ATCs. Most combined impact Category 0 TCs have minimal effect and 98.6% of them from 1984 to 2013 have no damage record (Fig. 7). Of the remaining 69.3% of ATCs in combined impact Category 1–4, 49.8%, 25.6%, 14.7%, and 9.9% are in Category 1 (0.0234 ⩽ *IPWT* < 0.1480), Category 2 (0.1480 ⩽ *IPWT* < 0.2570), Category 3 (0.2570 ⩽ *IPWT* < 0.4200), and Category 4 (*IPWT* ⩾ 0.4200), respectively. Here, the TD in August 1985 that affected the coastal region of South China was not considered due to lack of damage data. There are 45.2%, 45.9%, 34.9%, and 36.7% of cases that have the same damage category and combined impact category for Categories 1, 2, 3, and 4, respectively. If the comparison is extended to the next category down, then 87.7% of cases with damage Category 1 have combined impact Category 1 or 0. The corresponding values for damage Categories 2–4 are 72.9%, 69.8%, and 73.4%, respectively. The results indicate that the combined impact category is closely related to the damage category and the combined impact categories based on *IPWT* can be used to estimate the damage category.

5 Frequency characteristics of ATCs

The Fourier analysis is used here to analyze the characteristics of periodicity of annual frequency of ATCs. A Fourier series is a method of representing a function as the sum of simple sine waves. It decomposes any periodic function or periodic signal into the weighted sum of a set of simple oscillating functions, namely, sines and cosines.

The annual frequency of all ATCs from 1984 to 2013 has a ~5-year cycle but no linear trend. The 5-year period is statistically significant (Fig. 8). The annual frequency of ATCs in combined impact Categories 1 and 2 also has no trend and a ~5-year period. None of the combined impact categories has a linear trend. In combined impact Category 4, the significant period is approximately 10 years and the minima occur at the end of each decade. These results indicate that the combined impact of precipitation and wind has no significant increasing or decreasing trend based on the annual frequency of ATCs. This is consistent with the trend of annual damage caused by individual TCs (Lei et al., 2009; Wang et al., 2016). In the past 10 years, the ATCs have shown a significant increase similar to the trend of DTCs (Zhao et al., 2015). The annual frequency of combined impact Category 4 TCs for the 1984–2013 study period was highest during the initial years and the final years of 2004–2013; however, during the initial years of the most recent 10-year period, the frequency of mild destructive TCs was significantly below average. Therefore, the main reason for the increasing number of ATCs and DTCs is that both mild and strong destructive TCs are higher than average.

6 Conclusions and discussion

Relationships among TC precipitation, wind, and damage were analyzed for China for the period 1984–2013. The maximum daily area of precipitation based on stations with daily precipitation of ⩾ 50 mm and the total of wind speeds of ⩾ 13.9 m/s can be used to represent the main damage caused by TCs.

An index combining the precipitation and wind gust of a TC, the *IPWT*, was defined from observed data to estimate the severity of the combined impact of precipitation and wind. The correlation coefficient between the *IPWT* and

Table 3 *IPWT* category definitions and sample sizes for ATCs

IPWT category	0	1	2	3	4
IPWT range	< 0.0234	[0.0234,0.1480)	[0.1480,0.2570)	[0.2570,0.4200)	⩾0.4200
Sample size	130	146	75	43	29
Percentage of all ATCs/%	30.7	34.4	17.7	10.2	6.9

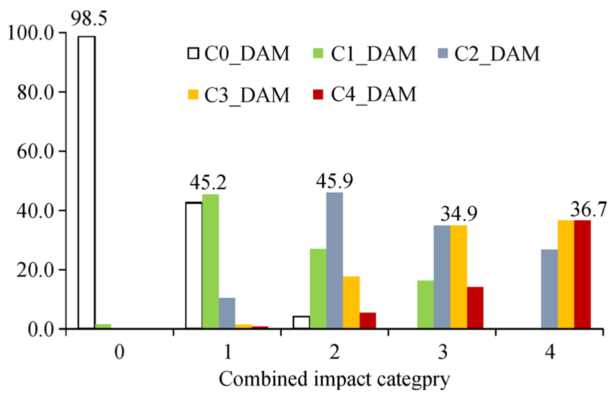

Fig. 7 Damage category distribution as a function of *IPWT* category. C*_DAM is the category of damage. The numbers on the bars are the percentages of cases in that impact category with the same *IPWT* and damage category.

the damage index is 0.70, which is higher than that only considering precipitation or wind gusts speed. All TCs that produce precipitation and wind gusts over China are divided into five categories, Categories 0 to 4, based on *IPWT*, with higher numbers representing greater combined impact of precipitation and winds. An *IPWT* Category 0 TC only has approximately a 1.5% chance of causing damage; an *IPWT* Category 4 TC will cause at least Category 2 damage and has a 73.4% chance of causing Category 3 or Category 4 damage over China. Moreover, *IPWT* is easy to calculate. Therefore, *IPWT* and its classification can be used to estimate the severity of the combined impact of TC precipitation and wind simply and accurately, and can be used to assess the potential damage caused by TCs. *IPWT* is higher and more directly correlated with damage than TC intensity. In some cases, a mild intensity TC with heavy precipitation and strong wind causes substantial damage for wide areas. *IPWT* will describe more a precise assessment of the destruction of TC and it will be good supplementary data for TC intensity, precipitation, wind, and damage.

Moreover, damage is closely related to not only TC factors such as precipitation, wind, and storm surge but also to disaster prevention and preparedness. Additionally, damage data are not always reliable because of the difficulty in collecting such data. *IPWT* is calculated

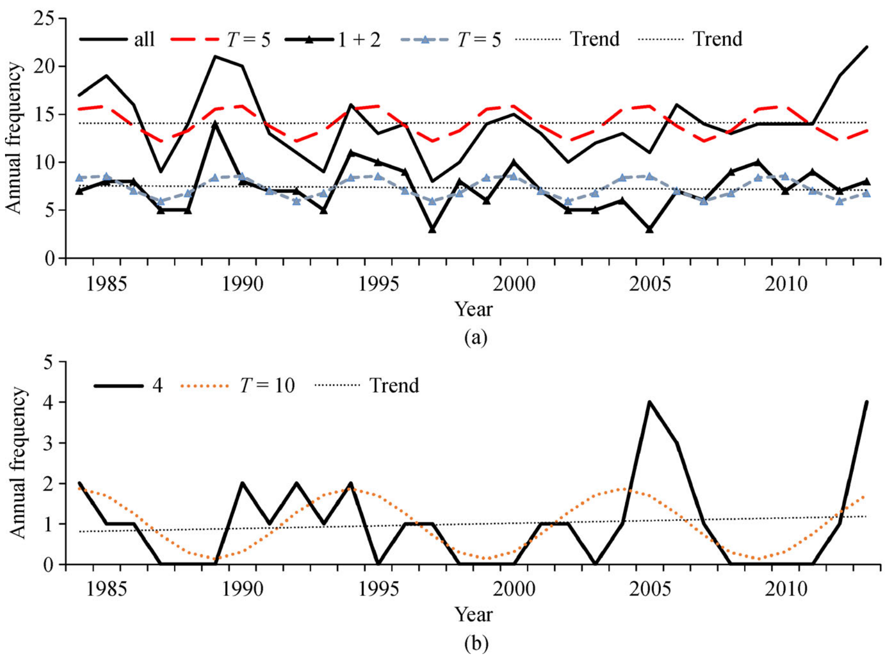

Fig. 8 Annual frequencies of ATCs during 1984–2013 in (a) and (b). The "all" means all ATCs. "Trend is the" linear trend. "$T = 5$" ("$T = 10$") means the period is 5 years (10 years). "1 + 2" is the total number of TCs with combined precipitation and wind impact Category 1 or Category 2. The "4" is the number with combined impact Category 4.

based on observed precipitation and wind. It is more objective than damage data and can be used in the study of climate change of TC destructive power.

Further studies on the annual frequency of *IPWT* categories, based on cases from 1984 to 2013, show no significant increasing or decreasing trend in the combined impact of precipitation and wind over China over the past three decades. The statistically significant period of the annual frequency of combined impact Category 4 TCs is approximately 10 years, with minima occurring at the end of each decade.

The main disaster-causing factors of TCs are rainstorms, wind gusts, and storm surges. *IPWT* combines precipitation and wind but does not include the impact of storm surges. However, some catastrophes are mainly caused by the intensity and extensive range of storm surges. This is one reason why a gap exists between the *IPWT* categories and damage categories for some disasters. To improve the skill in assessing the potential damage category based on disaster-causing factors, the impact of storm surges must be included in a combined index. We will continue the development of it in the future.

Acknowledgements This study was sponsored by the National Basic Research Program of China (Grant No. 2015CB452806), the National Natural Science Foundations of China (Grant Nos. 41475082 and 41875114), Shanghai Science & Technology Research Program (Grant No. 19dz1200101), and the Fundamental Research Funds of the STI/CMA (Grant No. 2019JB06).

References

Chen H Y, Yu H, Ye G J, Xu M, Yang Q Z (2019). Return period and the trend of extreme disastrous rainstorm events in Zhejiang Province. J Trop Meteorol, 25: 192–200

Chen P Y, Lei X T, Ying M (2013). Introduction and application of a new comprehensive assessment index for damage caused by tropical cyclones. Trop Cyclone Res Rev, 2: 176–183

Chen P Y, Yang Y H, Lei X T, Qian Y Z (2009). Cause analysis and preliminary hazard estimate of typhoon disaster in China. J Nat Disast, 18: 64–73 (in Chinese)

Easterling D R, Peterson T C, Karl T R (1996). On the development and use of homogenized climate datasets. J Clim, 9(6): 1429–1434

Emanuel K (2005). Increasing destructiveness of tropical cyclones over the past 30 years. Nature, 436(7051): 686–688

GB/T 19201–2006 (2006). Grade of tropical cyclones. Beijing: Standards Press of China

Kantha L (2006). Time to replace the Saffir-Simpson hurricane scale? Eos (Wash DC), 87(1): 3–6

Kantha L (2013). Classification of hurricanes: lessons from Katrina, Ike, Irene, Isaac and Sandy. Ocean Eng, 70: 124–128

Lei X T, Chen P Y, Yang Y H, Qian Y Z (2009). Characters and objective assessment of disasters caused by typhoons in China. Acta Meteorol Sin, 67: 875–883 (in Chinese)

Liang B Q, Fan Q, Yang J, Wang T M (1999). A fuzzy mathematic evaluation of the disaster by tropical cyclones. J Trop Meteorol, 15: 305–311 (in Chinese)

Lin Q W, Lu C J (1987). An analysis on satellite cloud imageries and radar echoes from the tropical depression “8.27”. J Guangxi Meteor: 13–16 (in Chinese)

Lou W P, Chen H Y, Qiu X F, Tang Q Y, Zheng F (2012). Assessment of economic losses from tropical cyclone disasters based on PCA-BP. Nat Hazards, 60(3): 819–829

Lu W F (1995). Assessment and prediction of disastrous losses due to tropical cyclones in Shanghai. J Nat Disast, 4: 40–45 (in Chinese)

Lu X Q, Yu H, Ying M, Qi L B (2018a). The effects of station network density on statistical analyses of tropical cyclone precipitation. J Trop Meteorol, 24(4): 421–431

Lu Y, Ren F M, Zhu W J (2018b). Risk zoning of typhoon disasters in Zhejiang Province, China. Nat Hazards Earth Syst Sci, 18(11): 2921–2932

Ma Q Y, Li G Y, Wang X R, Wang W G, Gao L Y (2008). A fuzzy synthetic evaluation model for typhoon disaster. Meteor Mon, 34: 20–25 (in Chinese)

Pielke R A Jr, Gratz J, Landsea C W, Collins D, Saunders M A, Musulin R (2008). Normalized hurricane damage in the United States:1900–2005. Nat Hazards Rev, 9(1): 29–42

Powell M D, Reinhold T A (2007). Tropical cyclone destructive potential by integrated kinetic energy. Bull Am Meteorol Soc, 879(2): 219–221

Ren F M, Gleason B, Easterling D (2001). A numerical technique for partitioning cyclone troical precipitation. J Trop Meteorol, 17(3): 308–313 (in Chinese)

Rezapour M, Baldock T E (2014). Classification of hurricane hazards: the importance of rainfall. Weather Forecast, 29(6): 1319–1331

STI/CMA (2006). Climatological Atlas for Tropical Cyclones Affecting China (1951–2000). Beijing: Science Press (in Chinese)

STI/CMA (2017). Climatological Atlas of Tropical Cyclones over the Western North Pacific (1981–2010). Beijing: Science Press

Van Oldenborgh G J, van der Wiel K, Sebastian A, Singh R, Arrighi J, Otto F, Haustein K, Li S, Vecchi G, Cullen H (2017). Attribution of extreme rainfall from Hurricane Harvey, August 2017. Environ Res Lett, 12(12): 124009

Wang Y J, Wen S S, Li X C, Thomas F, Su B D, Wang R, Jiang T (2016). Spatiotemporal distributions of influential tropical cyclones and associated economic losses in China in 1984–2015. Nat Hazards, 84 (3): 2009–2030

Wu H Y, Kang L H, Chen L L, Ma X M (2007). Effect of meteorological observation environment variability on homogeneity of temperature series in Zhiejiang Province. Mater Sci Technol, 35(1): 152–156 (in Chinese)

Xiao F J, Yin Y Z, Luo Y, Song L C, Ye D X (2011). Tropical cyclone hazards analysis based on tropical cyclone potential impact index. J Geosci (Prague), 21: 791–800

Xu H S, Lian J J, Bin L L, Xu K (2018). Joint distribution of muliple typhoon hazard factors. Scientia Geographica Sinica, 38(12): 2118–2124 (in Chinese)

Xu Q, Wei L, Jin Y, Zhao Q Y, Cao J (2015). A dynamically constrained method for determining the vortex centers of tropical cyclones predicted by high-resolution models. J Atmos Sci, 72(1): 88–103

Yang Q Z, Xu M (2010). Preliminary study of the assessment of methods for disaster-inducing risks by TCs using sample events of TCs that affected Shanghai. J Trop Meteorol, 16: 299–304

Ying M, Zhang W, Yu H, Lu X Q, Feng J X, Fan Y, Zhu Y, Chen D (2014). An overview of the China Meteorological Administration tropical cyclone database. J Atmos Ocean Technol, 31(2): 287–301

Zhang Q, Wu L G, Liu Q F (2009). Tropical cyclone damages in China 1983–2006. Bull Am Meteorol Soc, 90(4): 489–496

Zhang Q H, Wei Q, Chen L S (2010). Impact of landfalling tropical cyclones in mainland China. Sci China Earth Sci, 53(10): 1559–1564 (in Chinese)

Zhao S S, Ren F M, Gao G, Huang D P (2015). Characteristics of Chinese tropical cyclone disaster in the past 10 years. J Trop Meteorol, 31(03): 424–432 (in Chinese)