An explicit approach to estimating cumulative tropical cyclone damage

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Abstract

Tropical cyclones (TCs) are among the costliest natural hazards affecting civil construction in coastal areas, which have caused extensive economic losses and social disruption world-wide. Moreover, the intensity and/or frequency of future TCs have been projected to change with time due to the potential impacts of climate change, indicating the potential of ever larger TC damages for coastal regions. The estimate of future TC damage should be conducted under a probability-based framework, taking into account the uncertainties associated with both the TC characteristics (e.g., intensity and frequency) and the vulnerability of the coastal communities of interest. In this paper, an explicit approach is developed to evaluate the TC damage for TC-prone areas considering the potential impacts of climate change. The cumulative density function of cumulative TC damage is estimated quantitatively. The proposed method is applied to TC damage assessment of Hong Kong, China – a TC-prone area which has suffered severely from historical cyclones. Sensitivity analysis is also performed to investigate the impacts of the time-variant characteristics of both the TC process and the TC damage conditional on one TC event on the cumulative damage costs for coastal areas.

Keywords: tropical cyclone, damage assessment, probability-based approach, climate change, TC damage

1. Introduction

Tropical cyclone (TC) winds, rainfalls and storm surges are responsible for the major natural hazards in coastal areas, which have caused enormous economic losses and social disruption around the world. For example, in the United States, eight out of the ten most expensive catastrophes before 2006 in terms of insured loss had been triggered by TCs (known as hurricanes in the Atlantic Basin) \([1]\). In China, historical records show that totally 181 TCs (known as typhoons in the Pacific Basin) made landfall during the period 1980–2004, resulting in cumulative damage costs of 422.36 billion Chinese Yuan (CNY) \([2]\). Moreover, the population and wealth in coastal areas (most are TC-prone regions) have a considerable steady increase, indicating the potential of ever larger economic and social losses in the future. The increasing importance is then evident to advance building and structural practice through improving predictions of TC damage for civil constructions and thereby supporting implementation of strategies for enhancing the structural performance economically.

The future TCs have been projected to respond to climate change in many studies. For instance, Mudd et al \([3]\) used a regression-based approach to show that in the Atlantic Basin, the annual occurrence rate of TCs (hurricanes) may increase from 8.4/year to 13.9/year at the end of the 21st century. Knutson et al \([4]\) predicted that the averaged intensity of future TCs at a global scale will likely become stronger with an increase of 2–11% by year 2100 due to the potential impacts of greenhouse warming. However, there are also some arguments that the future TC intensity may decrease while the frequency would decrease subjected to climate change (e.g., \([5, 6]\)). Emanuel \([7]\) reported that despite the insignificant trend in future TC frequency, an upward trend in TC destructive potential can be observed. As a result, the time-variation of TC characteristics (e.g., intensity, frequency) should be well incorporated in terms of estimating the TC damage. Some previous studies \([8, 9]\) considered a stationary TC process with constant occurrence rate and time-invariant intensity (measured by the maximum TC wind speed) and thus failed to reflect the non-stationarity in TC process subjected to the potential impacts of climate change \([10]\). Later researches \([11, 12]\) took into account the roles of the time-variant TC characteristics in damage assessment, employing a probabilistic model of the ‘annual’ maximum TC wind speed to represent the TC wind risk. Such a probabilistic model, however, may lead to an overestimated TC damage in the presence of the intermittence of TCs in some regions. Li et al \([13]\) and Wang et al \([14–16]\) employed a Poisson stochastic process to model the TC occurrence and assessed the TC damage based on a vulnerability model as a function of the maximum TC wind speed. The mean value and variance of the cumulative damage have been considered in existing methods regarding TC damage assessment, which cannot fully reflect all the characteristics of the TC damage under a probability-based context (e.g., the upper tail behaviour or a characteristic value with a 90th percentile value). A Gamma distribution has been suggested to approximately fit the probability distribution of the TC damage \([15, 16]\). However, the random nature associated with the TC damage has not been fully investigated. Moreover, in terms of damage assessment, especially for long-term reference periods, the utilization of a vulnerability model that was developed based on the damage reports/data associated with a single (or limited) TC event(s), as has been widely used in previous studies, would become questionable considering the time-variation of a community’s vulnerability (e.g., enhanced structural design and practice), indicating the importance of developing a vulnerability model that can capture the change of a community’s hazard-resisting capacity with time for use in TC damage assessment.

The scope of this paper is to develop a probabilistic approach for TC damage assessment for TC-prone areas under the context of climate change, taking into consideration the non-stationarity and intermittence in the TC process. This paper is organized as follows. Section 2 presents probabilistic models for both the stochastic TC occurrence process and TC damage. In Section 3, the probability distribution

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of cumulative TC damage is developed in an explicit form. Illustrative analyses are conducted in Section 4 to demonstrate the applicability of the proposed method, choosing Hong Kong, China, as an example. The conclusions are finally formulated in Section 5.

2. Probability models of TC process and TC damage
2.1. TC occurrence model

For a specific region of interest, TC events occur randomly in time. A Poisson point process can be used to describe the TC occurrence process [13–16]. With a mean occurrence rate of \( \lambda \), the probability that \( k \) events occur within a time interval of \([0, T]\) is determined by

\[
\Pr(N_T = k) = \frac{(\lambda T)^k}{k!} \exp(-\lambda T), \quad k = 0, 1, 2, \ldots
\]  

in which \( \Pr() \) denotes the probability of the event in the brackets, and \( N_T \) is the number of events within \([0, T]\). Wang et al [15] examined the historical TC data for both the Miami-Dade County (Florida, USA) and the Florida State respectively. For both scales of region, they found that a Poisson point process can reasonably model the occurrence process of TCs that made landfall. Herein, we examine the distribution of annual number of TCs that have caused direct economic losses to Hong Kong, China – a region that has suffered severely from historical cyclones. The probability mass function of the annual TC numbers is plotted in Fig. 1, where a historical period of 1988–2016 is covered. The data are available from the annual reports on TCs released by the Hong Kong Observatory of HKSAR (http://gb.weather.gov.hk/publica/pubtcc.htm). Totally 51 TC events had triggered direct damage losses within the considered 29 years, yielding an annual occurrence rate of 1.76/year. Fig. 1 shows that the annual number can be well modeled by a Poisson distribution with \( \lambda = 2.2/\text{year} \) (see Eq. 1) at a significance level of 2\%.

Further, taking into account the potential impacts of climate change, the occurrence rate of future TCs may vary with time correspondingly. In such a case, a non-homogeneous Poisson point process can be used to describe the non-stationarity in the TC occurrence. With a time-variant occurrence rate of \( \lambda(t) \), Eq. (1) is rewritten as follows for \( k = 0, 1, 2, \ldots \):

\[
\Pr(N_T = k) = \frac{\left( \int_0^T \lambda(t) \, dt \right)^k}{k!} \cdot \exp\left( -\int_0^T \lambda(t) \, dt \right)
\]

For illustration purpose, we examine the annual numbers of historical TCs that affected Hong Kong, as have been reported in [17]. Fig. 2 presents the annual number of TCs that resulted in direct economic losses to Hong Kong within a time period of 1988–2016, where a slightly upward trend can be observed, with a R-square value of 0.011. This trend is not evident of the non-stationarity in the TC occurrence from a view of statistics, due to the relatively small sample size and short duration that have been considered. The non-stationarity in the TC occurrence process will, however, be discussed in the following to illustrateively investigate its role in TC damage assessment, taking into account the potential changing scenarios of TCs in the future, as observed elsewhere [6].

2.2. TC damage model

The TC-induced damage for a specific region of interest associated with one TC event is by nature random, with uncertainties arising from both the TC intensity and the hazard-resisting capacity of the area. One of the methods to quantitatively measure the TC damage, under a probability-based framework, is to use a vulnerability model which links the possibility of occurrence of certain levels of damage to the maximum TC wind speed [8, 18]. For instance, Stewart et al [8] used the claim and loss information from Hurricane Hugo (1989) and Hurricane Andrew (1992) that were obtained from an insurer and developed a damage model as a function of the 10-min mean surface wind speed, where the ‘damage’ was defined as the amount paid out by the insurer divided by the total insured value. This regression-based vulnerability model was further used in damage assessment of coastal areas considering the potential impacts of climate change in later studies [11–16]. Using this model, the time-variation in the TC damage is reflected by either the non-stationarity in the TC process (e.g., time-variant intensity and/or frequency) or a simple modification of the vulnerability model (e.g., applying a deterministic reduction factor to the overall damage, as done in [11]). Wang et al [16] further discussed the impact of vulnerability model uncertainty on the cumulative damage assessment. However, the regression-based models have been, for the most part, developed based on the claim data that are available from insurance companies and may not span all significant wind speeds, especially those extreme ones with large return periods [19]. Moreover, the use of a single vulnerability model (or the simply modified ones) in the damage assessment of a long-term period is questionable as it cannot reflect the improvement of the hazard-resisting capacity of the area (e.g., the improvement of building code or practice). An illustrative example is that after Hurricane Andrew (1992), the Florida Building Code required significant changes to the construction of civil structures with greater resilience [20, 21]. As such, a more accurate damage model that reflects the time-variation of the area’s hazard-resisting capacity should be used in TC damage assessment, especially for long-term reference periods. Some other remarkable methods to establish a vulnerability model for a specific region of interest include the engineering-based damage assessment by considering sophisticated structure–load interaction and structural resistance, and the assembly–based vulnerability method linking the engineering demand variable to the response of structural and nonstructural systems and building contents damage [9, 19, 22–24]. However, the disadvantage of these methods is that they require multidisciplinary modelling skills, validation ensured by realistic TC damage data, and are of significant complexity compared with regression-based models, calling for more significant research efforts for the application to practical engineering [16, 25]. As a result, this paper only discusses the regression-based vulnerability models.

The probabilistic model of TC damage is expected to be
developed based on the damage loss records incorporating all the significant items, as soon as the historical data are accessible. Taking Hong Kong, China as an example, the TC damage losses associated with each TC event are available from Hong Kong Observatory (in the form of Annual Reports on TCs). The damage losses include those of agriculture, public works facilities, public utilities, private property and industry [17]. Many existing vulnerability models for TC damage assessment have been developed as a function of the TC wind speed [8, 18, 26, 27]. Examining the case for Hong Kong within a reference period of 1988–2016, the linear correlation coefficient between the TC damage costs and the maximum gust wind speed is relatively weak (0.2521 with a discount rate of 3.5%), indicating that the damage level associated with a TC event cannot be fully determined via considering the maximum wind speed only – that is, the association between the TC damage and the wind speed cannot be well described using a single functional relationship. This is explained by the fact that the TC damage is not only affected by the maximum wind speed but also some other factors such as the TC track and the TC decay process [28, 29], as well as some ripple effects associated with the infrastructure systems within the area. Some previous works have also examined the historical data by considering the relationship between the damage with more than one factors of the TCs rather than the maximum wind speed only (e.g., translational track, size and duration) [7, 30–32]. However, those empirical functional relationships are nevertheless associated with significant uncertainties due to the fact that only the TC profiles have been considered while some other elements such as the building vulnerability, terrain conditions and the non-structural damages remain unaddressed.

The probability distribution of the TC damage costs associated with each TC event can be fitted directly based on the historically recorded data. Such a fitting-based model can make direct use of the historical information and thus gives a “best” estimate of the probability distribution of the TC damage. Moreover, the time-variation of both the TC temporal characteristics (e.g., frequency and intensity) and the area’s hazard-resisting capacity would be automatically reflected by this fitting-based model because the damage data that have been used cover a historical period rather than a specific time point. For comparison purpose, recall that the vulnerability model in [33] has been developed based on historical TCs (hurricanes) Hugo (1989) and Andrew (1992) only, and thus does not involve the information on the subsequent changes in the building code and construction practice for the built environment. It is nevertheless noticed that the disadvantage of the fitting-based damage model is that it does not incorporate the relationship between the damage and the key factors such as the maximum wind speed, and thus cannot be used to identify the role of TC characteristics in the TC damage, especially in the presence of the non-stationarity in the TC processes due to the potential impacts of climate change. Finally, the historical TC damage data examined herein cover a historical period of 1988–2016, which are assumed in this paper to well predict the “future” changes after year 2016.

Fig. 3 gives the probability distribution of TC damage (with a discount rate of 3.5%) and the probability density function (PDF) of a Gamma distribution to fit the samples. If a random variable, say, $X$, follows a Gamma distribution, then its PDF, $f_X(x)$, takes the form of

$$f_X(x) = \frac{\Gamma(\alpha)}{\beta^\alpha \Gamma(\beta)} x^{\alpha-1} \exp(-x/\beta), x \geq 0 \quad (3)$$

where $\alpha$ and $\beta$ are the shape parameter and rate parameter, respectively, and $\Gamma(\cdot)$ is the Gamma function, $\Gamma(\alpha) = \int_0^\infty x^{\alpha-1} \exp(-x)dx$. With Eq. (3), the mean value and variance of $X$ are $\alpha \beta$ and $\alpha \beta^2$, respectively, giving a coefficient of variation (COV) of $1/\sqrt{\alpha}$. Fitting analysis in Fig. 3 gives $\alpha = 0.2361$, and $\beta = 111.94$, which results in a p-value of 0.6177 and is accepted at a significance level of 20%.

3. Probability distribution of TC damage

For a coastal region of interest, during the time interval $[0, T]$, the cumulative TC damage costs, $D(T)$, is estimated by $D(T) = \sum_{j=1}^{N_T} D_j$, where $N_T$ is the number of TCs within $[0, T]$ that cause economic losses to the region, and $D_j$ is the damage costs associated with the $j$th TC event. The estimate of $D(T)$ is based on the assumption that the dam-

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**Figure 1.** Probability mass function of the annual number of TCs that caused economic losses to Hong Kong.

**Figure 2.** Annual number of TCs that caused economic losses to Hong Kong: from 1988 to 2016.
Fig. 3. The histogram of the damage records and the PDF of a Gamma distribution to fit the samples.

With the TC occurrence process modeled as a non-stationary Poisson process with a time-variant occurrence rate of \( \lambda(t) \), we divide the time period \([0, T]\) into \( N \) identical sections (\( N \) is large enough so that at most one TC event may occur during each time interval). With this, the possibility of occurrence of a TC event during the \( j \)th time interval is \( \lambda \left( \frac{jT}{N} \right) \cdot \frac{T}{N} \). By definition, it follows,

\[
D(T) = \sum_{j=1}^{N} \hat{D}_j
\]

where \( \hat{D}_j \) is the cyclone damage costs associated with the \( j \)th time interval. Defining \( t_j = jT/N \), one has

\[
\hat{D}_j = B_j \cdot \hat{D}(t_j) / \left[ 1 + r(t_j) \right]^j
\]

in which \( \hat{D}(t_j) \) is the TC damage given the occurrence of one TC event in the \( j \)th time interval, \( r(t) \) is the time-variant discount rate which enables the future TC damage costs to be valued in present terms, and \( B_j \) is a Bernoulli random variable,

\[
Pr(B_j = 1) = \lambda(t_j) \cdot \frac{T}{N} ; Pr(B_j = 0) = 1 - Pr(B_j = 1)
\]

The moment generating function, \( \phi_X(t) \), of a random variable \( X \) is defined for all real values \( \tau \) by

\[
\phi_X(t) = \mathbb{E} \left[ \exp(tX) \right]
\]

An important property of moment generating functions is that the moment generating function of the sum of independent random variables equals the product of the individual moment generating functions. For example, consider \( n \) independent random variables \( X_1, X_2, \ldots X_n \) with moment generating functions of \( \phi_1(\tau), \phi_2(\tau), \ldots \phi_n(\tau) \), respectively. The sum of the \( n \) variables, \( X = X_1 + X_2 + \ldots + X_n \), has a moment generating function of \( \prod_{k=1}^{n} \phi_k(\tau) \).

Now we consider the distribution of \( D(T) \) during time period \([0, T]\). First, the moment generating function of \( D(T) \), \( \phi_D(\tau) \), is obtained as

\[
\phi_D(\tau) = \mathbb{E} \left[ \exp \left( \sum_{k=1}^{N} \tau \hat{D}_k \right) \right]
\]

By assuming the independence between \( D_1, D_2, \ldots D_N \) and the Taylor expansion of an exponential function (i.e., \( \exp(x) = \sum_{j=0}^{\infty} \frac{x^j}{j!} \) holds for any number \( x \)), Eq. (8) becomes

\[
\phi_D(\tau) = \mathbb{E} \left[ \prod_{k=1}^{N} \exp(\tau \hat{D}_k) \right] = \mathbb{E} \left[ \prod_{k=1}^{N} \left( \sum_{j=0}^{\infty} \frac{(\tau \hat{D}_k)^j}{j!} \right) \right]
\]

\[
= \prod_{k=1}^{N} \sum_{j=0}^{\infty} \mathbb{E} \left( \frac{(\tau \hat{D}_k)^j}{j!} \right)
\]

Taking the logarithmic form for both sides of Eq. (9), since \( \ln(1 + x) \) approximates \( x \) for a small value of \( x \), we have

\[
\phi_D(\tau) = \exp \left( \sum_{k=1}^{N} \ln \left( \sum_{j=0}^{\infty} \mathbb{E} \left( \frac{(\tau \hat{D}_k)^j}{j!} \right) \right) \right) = \exp \left( \sum_{j=1}^{\infty} \xi_j \tau^j \right)
\]

where

\[
\xi_j = \frac{1}{j!} \sum_{k=1}^{N} \mathbb{E} \left[ (\hat{D}_k)^j \right]
\]

The characteristic function, \( \phi_X(i\tau) \), of a random variable \( X \) is introduced to link the probability density function and the moment generating function of \( X \); it is actually the Fourier transformation of the PDF of \( X \). \( \phi_X(i\tau) \) is defined for all real values \( \tau \) by

\[
\phi_X(i\tau) = \mathbb{E} \left( e^{ix\tau} \right) = \int_{-\infty}^{\infty} \exp(i\tau x) \cdot dF_X(x)
\]

where \( F_X(x) \) is the cumulative density function (CDF) of \( X \); \( i = \sqrt{-1} \). If \( X \) is a continuous random variable with a PDF of \( f_X(x) \), Eq. (12) becomes

\[
\phi_X(i\tau) = \int_{-\infty}^{\infty} \exp(i\tau x) \cdot f_X(x) \cdot dx
\]

Eq. (13) implies that \( \phi_X(\tau) \) and \( f_X(x) \) is a Fourier transform pair. Thus,

\[
f_X(x) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \exp(-i\tau x) \phi_X(i\tau) \cdot d\tau
\]

Substituting Eq. (10) into Eq. (14), the PDF of \( D(T) \), \( f_D(x) \),
is obtained as follows,

\[
f_D(x) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \exp \left( \sum_{m=0}^{\infty} (-1)^m \xi_{2m+1} \tau^{2m+1} \right) \cdot \exp \left( i \sum_{m=0}^{\infty} (-1)^m \xi_{2m+1} \tau^{2m+1} + i\tau \right) d\tau
\]

(15)

By noting that for any real number \( x \), \( \exp(ix) = \cos x + i\sin x \), we let

\[
\theta(\tau, x) = \sum_{m=0}^{\infty} (-1)^m \xi_{2m+1} \tau^{2m+1} - x\tau
\]

(16)

with which Eq. (15) becomes

\[
f_D(x) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \exp \left( \sum_{m=0}^{\infty} (-1)^m \xi_{2m+1} \tau^{2m+1} \right) \cos \theta(\tau, x) d\tau
\]

\[
+ i \frac{1}{2\pi} \int_{-\infty}^{\infty} \exp \left( \sum_{m=0}^{\infty} (-1)^m \xi_{2m+1} \tau^{2m+1} \right) \sin \theta(\tau, x) d\tau
\]

Since the term \( \exp \left( \sum_{m=1}^{\infty} (-1)^m \xi_{2m+1} \tau^{2m+1} \right) \cdot \sin \theta(\tau, x) \) in Eq. (17) is an odd function of \( \tau \), the following equation holds,

\[
\int_{-\infty}^{\infty} \exp \left( \sum_{m=1}^{\infty} (-1)^m \xi_{2m+1} \tau^{2m+1} \right) \cdot \sin \theta(\tau, x) d\tau = 0
\]

(18)

Thus, Eq. (17) becomes

\[
f_D(x) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \exp \left( \sum_{m=1}^{\infty} (-1)^m \xi_{2m+1} \tau^{2m+1} \right) \cdot \cos \theta(\tau, x) d\tau
\]

(19)

Recall Eq. (11), with which one has

\[
\xi_j = \lim_{N \to \infty} \frac{1}{j!} \sum_{k=1}^{N} \mathbb{E} \left( B_k D^j(t_k) \right)
\]

(20)

By definition,

\[
\mathbb{E} \left[ (\widehat{D}(t_k))^j \right] = \int_0^{\infty} \frac{z^j}{(1+r(t))^j} \cdot f_0(z, t_k) dz
\]

(21)

where \( f_0(z, t_k) \) is the PDF of \( \widehat{D}(t_k) \). Substituting Eq. (21) into Eq. (20), we have

\[
\xi_j = \frac{1}{j!} \int_0^T \int_0^\infty \left( \frac{z}{(1+r(t))^j} \right)^j \lambda(t) f_0(z, t) dz dt
\]

(22)

With this,

\[
\xi_{2m} = \frac{1}{(2m)!} \int_0^T \int_0^\infty \left( \frac{z}{(1+r(t))^j} \right)^{2m} \lambda(t) f_0(z, t) dz dt
\]

(23)

and further,

\[
\sum_{m=1}^{\infty} (-1)^m \xi_{2m+1} \tau^{2m+1} = \int_0^T \int_0^\infty \sum_{m=1}^{\infty} (-1)^m \left( \frac{z\tau}{(1+r(t))^j} \right)^{2m} \lambda(t) f_0(z, t) dz dt
\]

(24)

We let \( \delta(\tau) = \sum_{m=1}^{\infty} (-1)^m \xi_{2m+1} \tau^{2m+1} \) for simplicity. By noting that \( \cos x = 1 + \sum_{m=1}^{\infty} \frac{(-1)^m x^{2m}}{(2m)!} \) for any real number \( x \), Eq. (24) becomes

\[
\delta(\tau) = \int_0^T \int_0^\infty \frac{z\tau}{(1+r(t))^j} \lambda(t) f_0(z, t) dz dt
\]

(25)

Similarly, since \( \sin x = \sum_{m=0}^{\infty} \frac{(-1)^m x^{2m+1}}{(2m+1)!} \) holds for any real number \( x \), the term \( \theta(\tau, x) \) in Eq. (16) becomes

\[
\theta(\tau, x) = \int_0^T \int_0^\infty \sin \left( \frac{z\tau}{(1+r(t))^j} \right) \lambda(t) f_0(z, t) dz dt - x\tau
\]

(26)

Substituting Eqs. (25) and (26) into Eq. (19), it follows,

\[
f_D(x) = \frac{1}{\pi} \int_0^\infty \exp \left( \delta(\tau) \right) \cos \theta(\tau, x) d\tau
\]

(27)

where \( \theta_0(\tau) = \theta(\tau, x) + x\tau \). Eq. (27) presents an explicit form of the PDF of \( D(T) \). Further, the CDF of \( D(T) \), \( F_D(x) \), is obtained as

\[
F_D(x) = \int_0^x f_D(y) dy = \frac{1}{\pi} \int_0^\infty \exp \left( \delta(\tau) \right) \cdot \left[ \sin \theta_0(\tau) - \sin \theta(\tau, x) - x\tau \right] d\tau
\]

(28)

The close-form solutions of the probability distribution of \( D(T) \) as in Eqs. (27) and (28) can be solved using numerical integral techniques. It is noticed that a two-fold integral is included in the calculation of \( f_D(x) \) and \( F_D(x) \), if one first calculates \( \theta(\tau, x) \) and \( \delta(\tau) \) and stores them on disk for further use. Some numerical techniques such as the Simpson’s rule [35] can be used to improve the integration efficiency. Although the Monte Carlo simulation (MCS) methods can also be used to find (usually approximate) the probability distribution of \( D(T) \), it is argued that the closed-form analytical solutions can offer insights that may be difficult to achieve through MCS, may support and even accelerate the development of more complex simulation-based analyses [36]. Nevertheless, the simulation-based method can be used to verify the accuracy of the proposed explicit solutions.

4. TC damage assessment: A case study in Hong Kong, China

Choosing Hong Kong, China as an example, the estimate of future TC damage costs is performed in this section using the proposed method.

Hong Kong is a coastal area which has suffered significantly from severe TCs. For instance, during a historical
period of 1956–2016, on average fifteen TCs fell within Hong Kong’s area of responsibility annually [17]. Triggered by these TC events, the averaged economic losses valued 15.92 million HK$ for each year (discount rate not considered).

4.1. Changing patterns of TC frequency and TC damage costs

The future TC occurrence rate and intensity may change with time due to the potential impacts of climate change. While this non-stationarity in the TC process has been well acknowledged and widely discussed, yet it is still in debate how exactly the future changes will be. From a view of civil engineers, however, our focus is not on the mechanism-based prediction of future TC scenarios, but on the impacts of such time-variant changes on the estimate of damages that have been caused to coastal communities.

In order to demonstrate the applicability of the proposed method, the TC damage assessment is conducted choosing Hong Kong, China as the area of interest. The future changing scenarios of both TC frequency and TC damage costs associated with one successful TC event can be roughly estimated through analyzing historical records. First, in terms of future TC frequency, Fig. 1 shows that for Hong Kong area, the average annual number of TCs that have caused economic losses is estimated to be 2.2/year. This figure is slightly greater than that predicted from regression-based analysis (i.e., 1.96/year as of 2016 according to Fig. 2) and thus offers a relatively conservative estimate of the TC occurrence rate. Next, the TC damage associated with each successful TC event (discount rate considered) is modeled by a Gamma distribution. As shown in Fig. 3, the mean value and COV are 26.429 (in million HK$) and 2.058, respectively, without the consideration of time-variation. In the following analyses, the initial time is set as year 2016. The initial TC occurrence rate is set 2.2/year and the initial mean value of TC damage costs is 16.67 (in million HK$). The COV of TC damage is constant over time (2.058, corresponding to $\alpha = 0.2361$ in Eq. (3)), and a discount rate of 3.5% [37] is considered unless otherwise stated.

Taking into account the potential impacts of climate change, we consider the case where the TC occurrence rate changes linearly with time, and the TC damage associated with a successful TC event follows a Gamma distribution with a linearly changing mean value and a constant COV. Mathematically, it follows,

$$\lambda(t) = \lambda_0 (1 + \kappa_\lambda t), \quad \beta(t) = \beta_0 (1 + \kappa_\beta t)$$

(29)

where $\lambda_0$ and $\beta_0$ are the initial occurrence rate of TC events and the initial rate parameter of the Gamma-distributed TC damage (see Eq. (3), and note that the mean value is proportional to $\beta$), $\kappa_\lambda$ and $\kappa_\beta$ are two time-invariant parameters reflecting the changing rates of TC frequency and mean intensity.

The changing rate of future TC frequency with time can be inferred from Fig. 2, where $\kappa_\lambda$ is found to be 0.008. Similarly, the change rate of future TC damage costs, $\kappa_\beta$, is 0.021 as revealed in fitting analysis of the historical data. Note that $\kappa_\lambda = 0.008$ so that the TC frequency would increase by 80% over 100 years and $\kappa_\beta = 0.021$ means that the mean value of TC damage costs associated with one successful TC event increases by 210% over a reference period of 100 years. It is emphasized that the changing rates adopted here are only representative of a likely pattern in the future. Keeping this fact in mind, in order to investigate the effects of time-variant TC frequency and the damage magnitude (conditional on the occurrence of one TC event) on the cumulative damage costs, four additional changing patterns are considered, namely Cases 1 through 4, as summarized in Table 1. The additional cases take into consideration different potential scenarios in the TC frequency and the TC damage costs conditional on the occurrence of a TC event. The consideration of cases 1 through 5 in the following analyses is to investigate the impacts of potential changing scenarios of future TC events on the estimate of TC damage; the selection of a specific changing scenario of future TCs to support a decision-making finally falls within the decision-maker’s side, which may need further evidence from the meteorologists.

** Table 1. ** Changing scenarios of TC frequency and TC damage costs associated with one successful TC event.

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<tr>
<th>Case No.</th>
<th>$\kappa_\lambda$</th>
<th>$\kappa_\beta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1*</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>0.016</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>0</td>
<td>0.042</td>
</tr>
<tr>
<td>4</td>
<td>0.016</td>
<td>0.042</td>
</tr>
<tr>
<td>5**</td>
<td>0.008</td>
<td>0.021</td>
</tr>
</tbody>
</table>

* Case 1 corresponds to the case of a stationary TC process without consideration of the potential impacts of climate change and time-invariant vulnerability of the area.

** Case 5 corresponds to the scenario of changing TC frequency and TC damage costs inferred from historical data.

4.2. Probability distribution of cumulative damage costs

Now we consider the probability distribution of cumulative TC damage costs, $F_D(x)$. Firstly, in order to demonstrate the validity of Eq. (28), the CDFs of $D(10)$ and $D(100)$ are obtained by Monte Carlo simulation with one million replications and are compared with the results by Eq. (28). For each simulation run, the procedure of generating a sample of $D(T)$ is as follows.

- Generate the number of TC events, $n_T$, which follows a Poisson distribution with a mean value of $\int_0^T \lambda(t) \, dt$.
- Simulate $n_T$ independent and identically distributed time points, $t_1, t_2, \ldots, t_{n_T}$ (in ascending order), with a PDF of $\frac{\lambda(t)}{\int_0^T \lambda(t) \, dt} \, dt \, 0 < t \leq T$.
- Corresponding to $t_k$, $k = 1, 2, \ldots, n_T$, generate a sample for the TC damage corresponding to $t_k$, $d(t_k)$, and set $d(t_k) = \frac{d(t_k)}{\int_{t_{k-1}}^{t_k} d(t) \, dt}$ for each $k$.
- The sum of all $d(t_k)$ is recorded as a sample of $D(T)$.

Fig. 4 plots the simulated histograms of $D(10)$ and $D(100)$ and the calculated CDFs with Eq. (28), where case
Conclusions can be made from this paper. The following areas, which also enables the impacts of climate change on TC damage costs to be incorporated. The accuracy of the proposed approach is verified through an comparison with the results obtain from Monte Carlo simulation.

5. Conclusions

A probability-based approach has been proposed in this paper to estimate the future TC damage costs for coastal areas, which also enables the impacts of climate change on TC damage costs to be incorporated. The following conclusions can be made from this paper.

- The proposed approach estimates the probability of cumulative TC damage costs in an explicit form, which takes into account the time-variation of future TC frequency and TC severity (reflected by the TC damage costs triggered by the TC event). The applicability of the proposed method is demonstrated through an application to the future TC damage assessment of Hong Kong, China – a TC-prone area. The accuracy of the proposed approach is verified through an comparison with the results obtain from Monte Carlo simulation.

- The selection/prediction of different changing patterns of future TC severity and/or frequency affects the probability distribution of cumulative TC damage costs significantly, which further determines the upper tail behaviour of damage costs and the characteristic values with a certain confidence level. Presenting the probability-based behaviour of TC damage costs employing the proposed method appears to be an important step toward risk-informed decision-making for TC-prone areas.

References


[12] Y. Li and M. G. Stewart, “Cyclone damage risks caused by enhanced greenhouse conditions and economic viability
Figure 5. CDFs of cumulative TC damage costs corresponding to the five cases in Table 1.