A simplified statistical model for regional offshore typhoon wind risk assessment

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ABSTRACT

The accuracy of typhoon wind risk assessment methods is of great significance for offshore or coastline areas. Due to the practical limitations of typhoon measurement, it is common to perform Monte-Carlo simulation (MCS) to extrapolate such data to thousands of years to estimate the extreme wind speed. However, there are technical limitations for engineering applications of this technique, and the computational costs are significant for assessment on a regional level. For the preliminary typhoon risk assessment for a region, a simplified statistical method (SSM) is proposed in this paper. In the proposed method, the extreme wind speed is estimated with the extended "Improved Method of Independent Storms" (XIMIS) method, based on simulated wind field results using the best track typhoon data, i.e., the historical typhoon record information. The results of the simplified statistical method are validated by comparison with local code wind speeds and with full track MCS results in the Northwest Pacific basin using the best track database of the Joint Typhoon Warning Center (JTWC). Finally, the proposed SSM method is used to produce a wind map for typhoon risk assessment in offshore and coastal regions of southeast China, with high efficiency and acceptable accuracy.

KEYWORDS Typhoon risk assessment; improved method of independent storms; simplified statistical model; wind field model; full track simulation.
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1. Introduction

Many populated areas and highly developed cities are located along the coastline and thus exposed to potential typhoon threats. Buildings and infrastructure are typically designed based on local design codes using speeds based on data or records from discrete anemometer stations, without a rigorous typhoon wind climate study. A key limitation of relying on a single anemometer station to predict typhoon risk is that the samples associated with typhoons are not often sufficient to conduct a robust extreme value analysis, because of their low occurrence frequency in a particular location. To increase the sample size, a longer recording period, e.g., several decades, will ideally be required. But the data quality is then often affected by urbanisation over such periods, especially in developing countries. Anemometer stations are mainly onshore, and it is not ideal to extrapolate from onshore stations to offshore areas. For example, a code can only consider the wind speed variation between coastal and inland areas due to different ground roughness, but it cannot predict the wind speed variation in further offshore areas, which is mainly governed by the relative position between the studied sites and typhoon tracks.

To overcome these limitations, typhoon numerical simulation methods have been developed, including mesoscale typhoon numerical simulation in the meteorological field (Lakshmi et al., 2017) and parametric numerical simulation based on the Monte Carlo concept (Vickery and Skerlj, 2000). Mesoscale typhoon numerical methods can present a more refined and realistic typhoon wind field evolution process based on a more complicated physics basis. However, its practical application for extreme wind speed prediction is limited because of the high computing resource requirements for the simulation. MCS methods based on a parametric model are more widely used because they are more cost effective for the much larger numbers of simulations required to statistically represent typhoon information with a simplified wind field model (Chen and Duan, 2018; Li and Hong, 2014).

Typhoon MCS methods have two typical sub-categories: sub-regional track model (Xiao et al., 2011) and full track model. The latter has become the mainstream method as it can simulate the evolution process of a typhoon, i.e., from generation to dissipation. It usually has a genesis model, a track model, an intensity model, and a filling model.

Vickery and Skerlj (2000) first developed this methodology, and the framework has been adopted and developed by other researchers. Hall and Jewson adopted the multivariate normal distribution model to improve the track model (2007). To improve the intensity model, Powell and Emanuel combined the Markov Chain method into a full track model (Powell et al., 2005 and Emanuel et al., 2006). Li et al. simplified the Vickery's track and intensity model by considering the collinearity problem in linear regression modelling (2014). Cui et al. used Bayesian optimisation and quadtree decomposition to improve the performance of the Vickery model and demonstrated more accurate results (2021). Lee et al. developed a new statistical dynamic model to simulate typhoon activities, which includes an environmental index-based genesis model, a beta-advection track model, and an autoregressive intensity model (2018). In Lee's model, all three components were dependent on the local environmental conditions. Similarly, Chen and Duan (2018) also proposed a statistical dynamic typhoon simulation method to extend the applicability of the model, such as extending the model to future climate scenarios. In the statistical dynamic model, the track model is more dependent on environmental parameters and reflects more physical characters, compared with using a regression method based on historical data in the purely statistical model.

For typhoon risk assessment purposes, the MCS method usually will be performed for thousands of years to obtain the typhoon statistical properties, with the combination of a parametric wind field model, like the Yan Meng model (Yan et al., 1995). However, it is technically not easy to develop a well-calibrated full-track typhoon model. And even then, it is very expensive to model tracks and intensities for the tens of thousands of years of synthetic typhoons needed to ensure that the number of samples is sufficient to be statistically representative. The cost will be even higher for regional typhoon risk assessment, where the wind field model needs to be run for multiple locations and for all the years of local windstorms entering 250 km of each grid.

This paper proposes a simplified statistical model (SSM), considering both the aims of efficiency and accuracy. The SSM uses the more limited number of typhoons obtained from the typhoon best track data of JTWC together with the extreme value analysis method of XIMIS (Harris, 2009). Because it is based on the best track data, it avoids the technical challenge of developing the full track model, as well as the associated computation. In addition, by focusing on the best track data (50-60 years) rather than the synthetic typhoon data (at least 10,000 years), it saves the computational cost of running the wind field model, with a reduction to about 0.5% compared to the MCS method.

The proposed SSM will be validated by comparison with the results from full-track MCS which is conducted for 10,000 years in the Northwest Pacific basin, and the local code design wind speed in selected cities.

Finally, a wind map for typhoons in the offshore area of southeast China will be presented. This is not currently covered by any local code.

2. The simplified statistical mode

2.1. Outline

The best track database of JTWC provides historical typhoon track information, i.e., longitude, latitude, and the maximum wind speed V_{max} at a 10 m height above the sea with a 6-hour timestep. Typhoon intensity (V_{max}) is used only from 1970 as the data prior to the satellite era are felt to be less reliable.

A parametric typhoon wind field model is used to calculate the typhoon-induced wind speed time history at any location and height of interest for all historical typhoons, with the maximum wind speed of each storm recorded at a selected location.

Based on these maxima, extreme value analysis is carried out using the XIMIS method. This is repeated over a grid of locations to complete a regional typhoon risk assessment.

2.2. Wind field model

The existing widely used wind field models include the Batts wind model (1980), the Vickery wind model (Vickery et al., 2000), and the Yan Meng wind model (1995), among others. The wind field model provides typhoon wind speeds in a 3D field, based on key typhoon wind field parameters such as central pressure or maximum wind speed, maximum wind speed radius, bearing angle, and typhoon centre position.

Xie et al. (2014) compared the wind speed based on the Yan Meng Model, the CE model, and the Shapiro model and concluded that the Yan Meng model shows good agreement with the measured data. The Yan Meng model is also commonly used in recent studies for typhoon wind hazard assessment (Guo et al., 2019; Huang et al., 2021). Thus, the Yan Meng wind field model is adopted in this paper to calculate the typhoon-induced wind speed.

The model wind field at gradient height is described as follows:

$$v_g(r,\beta) = \frac{V_T \sin\beta - rf}{2} + \sqrt{\left(\frac{V_T \sin\beta - rf}{2}\right)^2 + \frac{r}{\rho_a}\frac{\partial p(r)}{\partial r}}\,, \quad (1)$$

$$p(r) = p_c + (p_n - p_c)\cdot exp[-(R_{mw}/r)^B]\,, \quad (2)$$

where v_g is the wind speed in free atmosphere, β is the typhoon angle, V_T is the translation speed, f is the Coriolis parameter, ρ_a is the air density, $p(r)$ is the pressure at the distance r from the typhoon centre, p_n represents the surrounding ambient air pressure, p_c is the air pressure at the typhoon centre, R_{mw} is the maximum wind speed radius, and B is the Holland B parameter.

A comparison of the wind field model was made with "typhoon 2018/08/22" obtained from an anemometer in South Korea as shown in Figure 1. The measured typhoon-induced wind speeds and the predictions of the wind field model are in reasonable agreement, which indicates suitably good performance of the Yan Meng model.

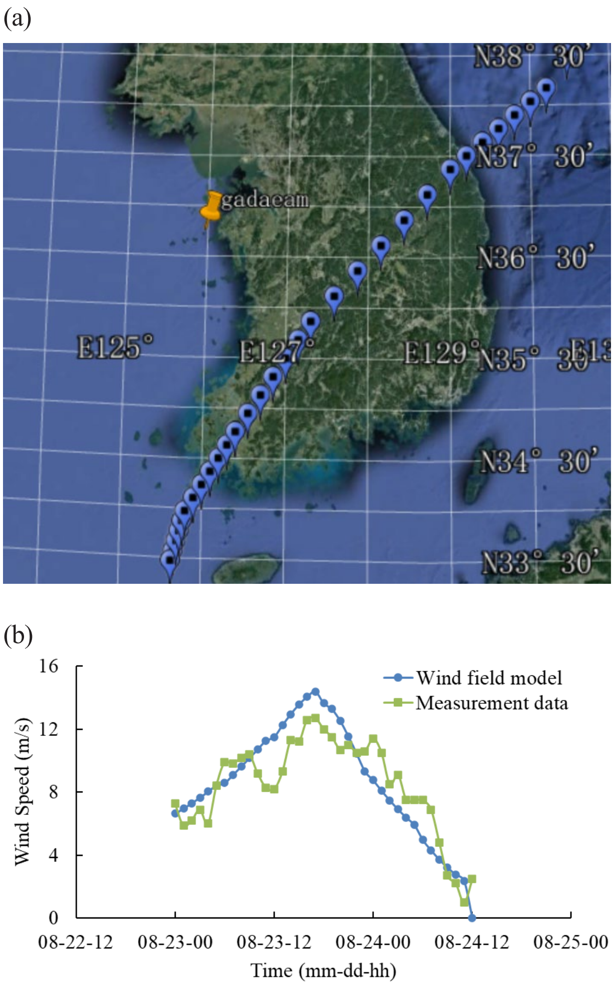


Figure 1. Validation of Yan Meng wind field model: (a) typhoon path; and (b) simulated wind speed and measured wind speed

Using the generated wind velocity field, the wind speed time history at any location and height of interest throughout the entire historical typhoon event can be obtained. This can then be used to derive extreme wind records for the locations of interest due to all the typhoons in the record (since 1970).

2.3. Extreme value analysis method: XIMIS

The number of typhoon-induced wind speeds at a site using real track data is limited and the storms occur irregularly, several in some years, none in others. Traditional fitting methods based on annual maxima (i.e., using only the largest storm of a given year) ignore some of the already limited data and may not have typhoon records in some years. Independent storm methods use all the storm data. As noted by Harris (2009), with limited data sets, the scatter due to the sampling error is large if only one data value per year is used. There is also a systematic convergence error if the extreme distribution asymptote for the annual maximum wind speed is derived using insufficient samples. This was considered by Harris who proposed various improved methods leading to XIMIS, an extension of "improved method of independent storms" (Harris, 2009; Gavanski and Cook, 2019).

The average annual rate of occurrence of storms is denoted by $a = N/R$, where N is the total storm number, and R is the observation period. From extreme value theory, the appropriate asymptotic form when the parent distribution is of the exponential class is the Fisher-Tippett (Type I) distribution.

$$\emptyset(q) = \exp[-\exp(-y)] = \exp[-\exp\{-\alpha\,(q-\gamma)\}] \quad (3)$$

where q is an extreme variate, y is the standard reduced variate, and α, γ are the dispersion and mode location parameters, respectively. The extreme variate q may be taken as v^w.

In wind engineering application, wind speed may often be considered to have a Weibull-distribution with an exponent value w which may vary from 1 to 3 but is often closer to 2. It is found that in most cases, $w = 2$ provides a reasonable fit. Thus, for an exponential distribution, the values of $q = v^2$ are used rather than the values of v. As noted in Harris (2009), the motivation of squaring is to accelerate the convergence, by ensuring that the underlying parent distribution is close to exponential (Poisson).

The procedure is as follows. The unbiased mean reduced variate for the largest peak can be expressed as $\bar{y}_1$ as in Equation (4). And then, assuming the Poisson process model for independent events, the reduced variate for other ranks $\bar{y}_{m+1}$ is given by Equation (5).

$$\bar{y}_1 = ln(R) + 0.5772\,, \quad (4)$$

$$\bar{y}_{m+1} = \bar{y}_m - 1/m\,, \quad (5)$$

Given the set of ranked values of q_m, together with the $\bar{y}_m$, a weighted least squares method is used to fit the Gumbel plot and derive the values for the parameters α and γ using Equations (6) and (7).

$$\alpha = \frac{\sum_{m=1}^{N} w_m \bar{y}_m q_m - (\sum_{m=1}^{N} w_m \bar{y}_m)(\sum_{m=1}^{N} w_m q_m)}{\sum_{m=1}^{N} w_m q_m^2 - (\sum_{m=1}^{N} w_m q_m)^2}\,, \quad (6)$$

$$\gamma = \sum_{m=1}^{N} w_m q_m - (1/\alpha) \sum_{m=1}^{N} w_m \bar{y}_m\,, \quad (7)$$

where wm is the statistical weight of the m-th storm. The weights wm are calculated using Equations (8) and (9) based on the expected variance.

$$w_m = \frac{1/\sigma_m^2}{\sum_{m=1}^{N} 1/\sigma_m^2}\,, \quad (8)$$

$$\sigma_m^2 = \begin{cases} \pi^2/6 & m = 1 \\ \sigma_{m-1}^2 - \frac{1}{(m-1)^2} & m > 1 \end{cases}, \quad (9)$$

Using the fitting parameters α and γ, the extreme wind speed for different return periods Ry can be calculated from the following equation.

$$v_{Ry} = \sqrt{\gamma + (1/\alpha) L_n Ry} \, , \qquad (10)$$

2.4. Process summary

The process is illustrated in Figure 2, based on historical typhoon records.

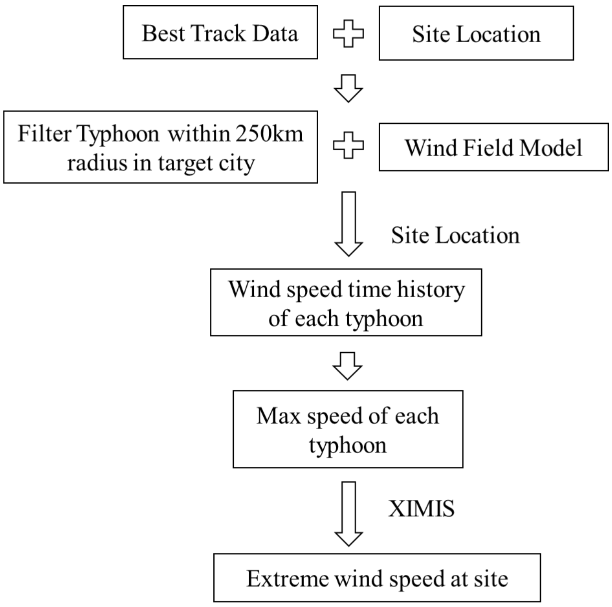


Figure 2. Flowchart of the simplified statistical method.

3. Validation using a statistical dynamics synthetic typhoon full track model

To validate the performance of the proposed SSM, a statistical dynamics synthetic typhoon full track model is used. This is expected to give more precise results based on a more complete typhoon model. The model used is mostly due to Chen and Duan (2018) and consists of four main parts:

(1) Genesis model: The annual typhoon number and genesis locations will be generated by a kernel probability density function method based on the JTWC dataset,

(2) Track model: A beta-advection model is used to simulate the typhoon movement, which consists of two components: the steering flow velocity (U_{steer}, V_{steer}) and beta drift velocity (Bx and By):

$$U = U_{\mathrm{steer}} + B_x \, , \qquad (11)$$

$$V = V_{steer} + B_y \, , \qquad (12)$$

(3) Intensity model: Seven independent variables are selected to develop the autoregressive function of the intensity model: relative intensity $I = V_{max}/PI$, maximum wind velocity V_{max}, potential intensity PI (Bister and Emanuel, 2002), sea surface temperature SST, vertical wind shear VS, latitudinal translational wind speed U, and longitudinal translational wind speed V. The lag-one autoregression function equation (13) is used to calculate the intensity at the second position, while Equation (14) is used for subsequent positions.

$$\mathrm{L_n}\, I_2 - \mathrm{L_n}\, I_1 = \mathrm{LR}(\mathrm{L_n}\, I_1, SST_2, SST_1, PI_2, PI_1, V_{\mathrm{max}1}, VS_2, VS_1, U_1, V_1), \qquad (13)$$

$$\mathrm{L_n}\, I_{i+1} - \mathrm{L_n}\, I_i = \mathrm{LR}(\mathrm{L_n}\, I_i, \mathrm{L_n}\, I_{i\text{-}1}, SST_{i+1}, SST_i, SST_{i\text{-}1}, V_{\mathrm{max}\, i}, V_{\mathrm{max}\, i\text{-}1}, PI_{i+1}, PI_i, PI_{i\text{-}1}, VS_{i+1}, VS_i, U_i, V_i) \, , \qquad (14)$$

where LR means the linear regression operator and the subscript, i, represents the timestep.

(4) Filling model: The Vickery decay model, shown in Equation (15) is adopted here as the filling model. The relationship between V_{max} and Δp_0 was derived based on JTWC data and is shown in Equation (16).

$$\Delta p(t) = \Delta p_0 \exp[-(a_0 + a_1 \Delta p_0 + e_a)t] \, , \qquad (15)$$

$$\Delta p_0 = \begin{cases} -2.84 + 0.6 \exp(V_{\mathrm{max}}^{\ 1.198}) \, , \text{ ocean} \\ -2.00 - 0.517 \exp(V_{\mathrm{max}}^{\ 1.234}) \, , \text{ land} \end{cases} , \qquad (16)$$

where Δp_0 (hPa) is the central pressure difference at the time of landfall; Δp (hPa) is the central pressure difference in t hours after landfall; a_0, a_1, e_a are two empirically derived filling parameters and a normal random error item, respectively (Hong et al., 2016).

A full track model for thousands of years is used to obtain sufficient samples to define the wind speed probability distribution P($v>\bar{V}$) directly. The probability that the typhoon wind speed is exceeded during the time period, t, is:

$$P_t(v > \bar{V}) = 1 - \sum_{x=0}^{\infty} P(v < \bar{V} | x) p_t(x) \, , \qquad (17)$$

where P($v>\bar{V}$ | x) is the probability that velocity v is less than $\bar{V}$ given that x typhoons occur, and $pt(x)$ is the probability of x typhoons occurring during the time period, t.

The process of typhoon risk assessment based on a full track model is illustrated as Figure 3, which is obviously more complex when compared with Figure 2.

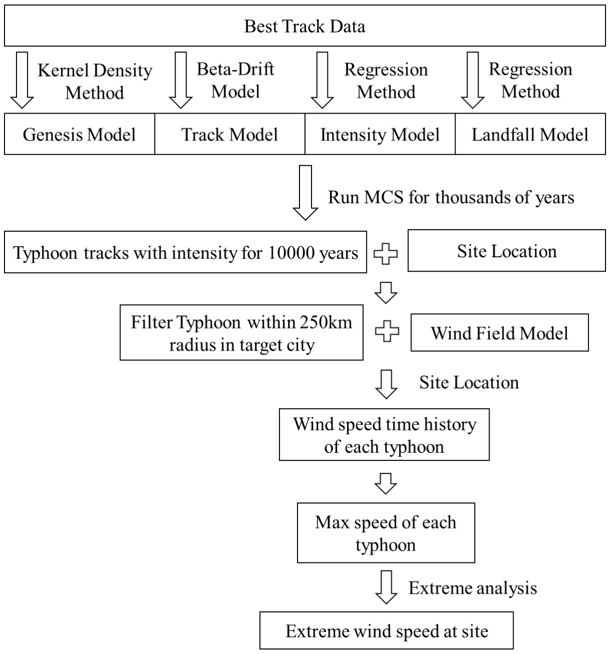


Figure 3. Flowchart of the full track model.

The simulation randomly generated 10,000 years of typhoon storms in the NWP basin and the results are compared with JTWC historical data using a sample with the same time length, as illustrated in Figure 4, which aims to show qualitatively the validity of the typhoon full track model.

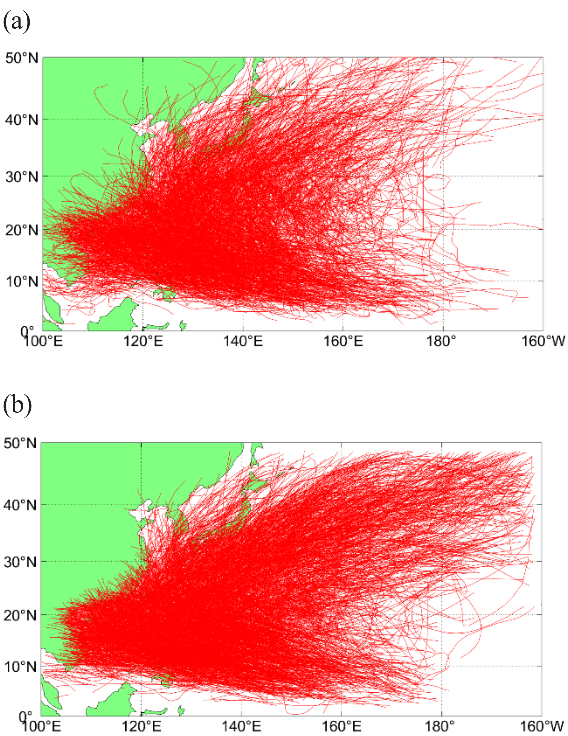


Figure 4. Track comparison of (a) historical typhoon tracks; and (b) simulated typhoons in the NWP basin.

To demonstrate the validity of the full track model more numerically, some locations are selected to derive extreme wind speeds based on typhoon samples within 250 km. The results are compared with the local code design wind speed and other references (Li and Hong, 2015; Chen and Duan, 2018), as listed in Table 1. The results of the full-track typhoon model adopted in this paper agree reasonably well with the local code values and other references.

Table 1. Extreme wind speed estimates for the selected cities (hourly-mean, 10 m height of open terrain, in m/s).

City	MCS	Code	L&H	C&D	Ry
Shanghai	26.2	27.8	21.0	27.7	50
Ningbo	29.2	26.5	25.8	30.1	
Wenzhou	31.3	29.0	32.0	30.5	
Guangzhou	26.7	26.5	25.6	/	
Shenzhen	31.8	32.5	/	30.7	
Fuzhou	30.7	31.4	29.4	28.2	
Xiamen	31.4	33.5	33.6	32.3	
Manila	33.5	36.6	/	/	
Seoul	25.2	24.4	/	/	100

Note that a divisor of 1.067 was used to adjust the mean wind speeds from a 10-min-mean to hourly mean.

4. Results and discussion

In this paper, a comparison is made of the extreme wind speeds obtained using the proposed SSM method as in Section 2, using MCS as in Section 3, and from local codes as a further reference. These are shown for a 50-year return period in Table 2 and 100-year return period in Table 3.

The tables cover the selected coastal cities of southeast China with Seoul representing further north and Manila representing further south. The wind speeds calculated by using the SSM method show reasonable agreement with the MCS method in the two tables.

Table 2. Comparison of SSM, MCS, and Code Speeds, 50-year return period, hourly-average at a 10 m height of open terrain, in m/s.

City	SSM	MCS	Code
Shanghai	26.6	26.2	27.8
Ningbo	29.5	29.2	26.5
Wenzhou	31.7	31.3	29.0
Guangzhou	28.1	26.7	26.5
Shenzhen	33.7	31.8	32.5
Fuzhou	34.3	30.7	31.4
Xiamen	34.1	31.4	33.5
Manila	34.8	33.5	36.6
Seoul	24.2	22.0	/

Table 3. Comparison of SSM, MCS, and Code Speeds, 100-year return period, hourly-average at a 10 m height of open terrain, in m/s.

City	SSM	MCS	Code
Shanghai	28.7	29.1	29.0
Ningbo	31.7	31.7	29.0
Wenzhou	33.9	34.0	31.4
Guangzhou	29.9	29.1	29.0
Shenzhen	35.9	34.5	35.6
Fuzhou	36.6	34.5	34.6
Xiamen	36.4	33.8	36.5
Manila	37.0	36.4	/
Seoul	26.3	25.2	24.4

The variation in extreme wind speed against the return period is illustrated in Figure 5. The legend "MCS" is for the Monte-Carlo simulation results using the statistical dynamics synthetic typhoon full track model, and "Code" is the design wind speeds in the local code for corresponding cities. SSM demonstrates acceptable extreme wind speeds compared with the MCS results for 50-year and 100-year return periods, which are the focus for structural design. However, SSM predicts higher speeds than MCS at lower return periods.

Taking Guangzhou as an example, the wind speed ratio between the SSM and MCS methods is 1.05 (28.1 m/s over 26.7 m/s) for a 50-year return period, while the ratio increases to 1.14 (23.2 m/s over 20.4m/s) for a 10-year return period. The reasons for this are not clear yet, but it may be due to the difference that MCS directly calculates the extremes while SSM estimates the extremes by fitting an extreme distribution. However, the impact of a relatively larger difference at a low return period will be less critical with the consideration that such difference will be diluted when combined with the synoptical wind climate with its increasing contribution in the combined wind climate during a low return period. By contrast, for long return periods, such as 50 and 100 years, the typhoons are normally more governing in regard to the extreme wind speed.

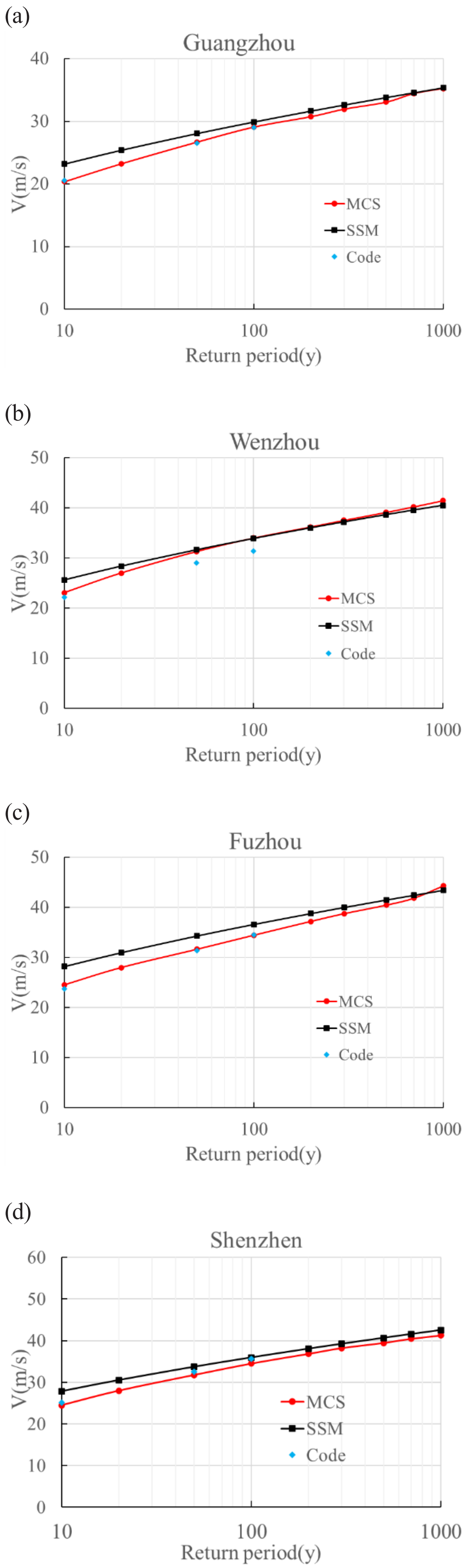


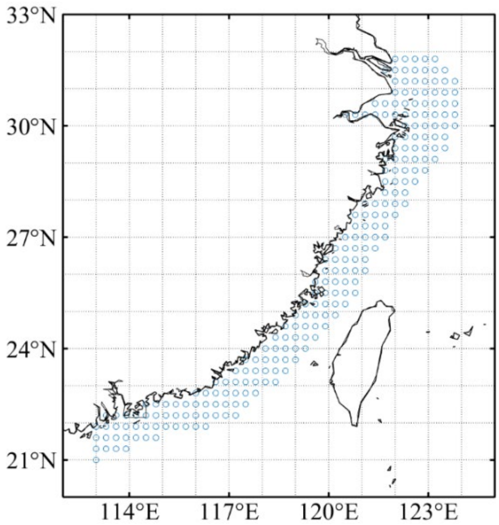
Figure 5. Comparison of the extreme wind speed from SSM, MCS, and local code.

This paper also extends the comparison between SSM and MCS to a regional level for the offshore region of southeast China. The calculation grids are shown in Figure 6(a). The MCS simulation results are shown in Figure 6(b) and the wind map by researchers Hong and Sheng (2022) is shown in Figure 6(c) as a further comparison. It is worth noting that Figure 6(c) is presented with a 10 min-mean wind speed rather than hourly-mean, and the offshore region is narrower than our study region. For comparisons below, the speeds shown in Figure 6(c) shall be divided by 1.067.

For some typical regions, like Hangzhou Bay, the MCS simulation results in this paper vary from 32 m/s to 36 m/s, while the results of the H&S reference vary from 31 m/s to 36 m/s (allowing for the 10-minute speed adjustment). Along the south-east offshore region, the wind speed is between 36m/s and 44m/s based on the H&S paper, while the wind speed range is 38m/s~44m/s in the current MCS.

Figure 6(d) shows a similar wind map based on SSM. SSM presents the results from 32 m/s to 36 m/s for Hangzhou Bay, while the results are 38 m/s~46 m/s along the southeast offshore region. MCS indicates a smoother variation of results compared to SSM. This is reasonable because the MCS results are based on a 10,000-year simulation, rather than the about 50 years of full-track data used for SSM, and so MCS is naturally inclined to provide smoother results. SSM gives relatively more discrete results due to the smaller sample size associated with full-track data, but this could be improved with some further 'geographic smoothing' or 'area smoothing'. Even without this, the SSM results remain very comparable with MCS results, generally with a typical 5% difference for most grids.

(a)



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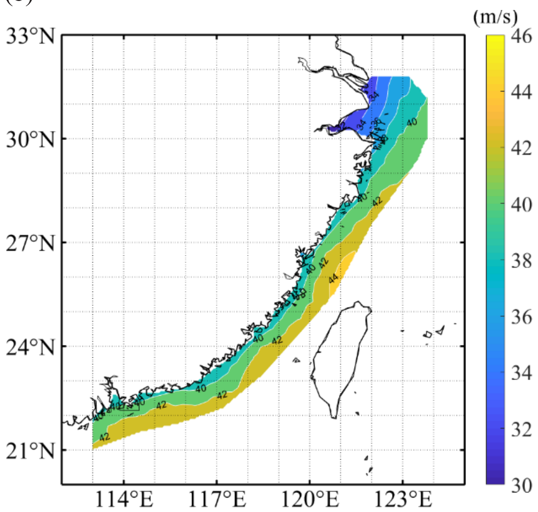
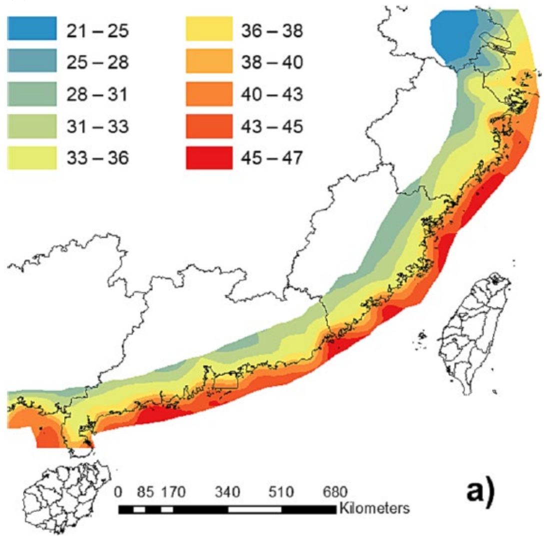


(c)



(d)

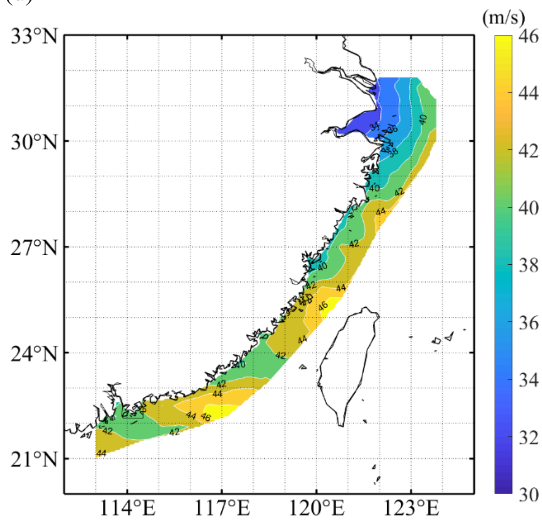


Figure 6. Wind map for the offshore region of the southeast China basin: (a) Study region; (b) MCS results; (c) Hong and Sheng's results; (d) SSM results.

Finally, it is worth noting that the effort to obtain the extreme wind speed results based on SSM is significantly smaller than that using MCS, both through the reduced technical complexity and through much smaller computation demand, as can be seen by comparing the methods as summarised in Figures 2 and 3. For MCS, to satisfy statistical accuracy, tens of thousands of typhoon samples are required to be run in the model for at least 10,000 years. For Shenzhen, as an example, the number of typhoons will be about 26,000 within a 250 km radius, while it is only about 130 (for 50 years) in SSM; the value of the efficiency difference between the two methods is even more obvious when looking at a grid of results for a regional typhoon risk study.

5. Conclusion

This study proposes a simplified statistical method to quantify the typhoon risk for preliminary assessment based on a wind field model of full-track typhoon records and using the XIMIS statistical method to fit the results from all independent storms affecting a particular site, i.e., in a similar way to its use with anemometer data. The proposed SSM method is compared with code values and the MCS method, which is currently the mainstream method for typhoon risk assessment. The conclusions are:

- The framework and methodology of a simplified statistical model for regional offshore typhoon risk assessment is presented.
- The proposed simplified statistical method, i.e., SSM, shows acceptable agreement with full-track MCS results for the 50- and 100-year design wind speed in the studied cities, although SSM currently predicts slightly higher extreme wind speeds at short return periods such as 10 years, which are normally not the focus for offshore wind design. Besides, the relatively large difference at a low return period will be diluted when combined with synoptic wind climate which has a gradually declined contribution in a combined wind climate from a short period to long period.
- A regional wind risk assessment of the offshore region of southeast China is shown. Although SSM gives more variation geographically compared with the relatively smooth wind map of MCS, it is in reasonable agreement with the MCS wind map with around a 5% error range for most locations. This provides good support for using the SSM method for preliminary study purposes. Improvements may be made using a rational area smoothing method as is used with anemometer data.
- From an efficiency perspective, the proposed SSM method significantly reduces both the technical complexity, and the computation demand compared with MCS, especially for a regional typhoon risk assessment.

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