Uncertainty of Typhoon Pressure Field Properties for Typhoon Simulation

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Abstract

Accuracy of reproducibility of typhoon pressure fields and surface wind is most important for evaluating design wind speed by Monte-Carlo simulation. However, there is uncertainty when using observation data of natural phenomena such as typhoons. The uncertainty has two properties: aleatory uncertainty and epistemic uncertainty. Aleatory uncertainty can't be reduced because it includes rare and contingent events. Epistemic uncertainty can be reduced by the accumulation of data because it's due to lack of data, modelling inaccuracy, observation method deficiencies, and so on.

This paper presents a statistical modelling method that can reduce the epistemic uncertainty of the data. Firstly, probability distributions for the modelling parameters are shown for typhoon pressure fields to estimate the reproducibility of the observed parameters. We then evaluate the variance of the central pressure and gradient wind speed using different numbers of data and a method of estimating the distribution parameters.

Introduction

Wind resistant design in Japan is based on a standard wind speed determined by Japan's Building Standards Act. The standard wind speed is based on the annual maximum wind speed records at meteorological observatories all over the country. But, the meteorological observatory records cannot obtain the maximum annual wind speed for each wind direction. Thus, the building load guidelines and commentary by the Architectural Institute of Japan[1], considering that the main factor for strong wind is a typhoon, proposes wind direction characteristics evaluated by the Monte Carlo simulation method using a typhoon model (hereinafter referred to as typhoon simulation).

Reproducibility of a typhoon pressure field and accuracy of ground wind prediction is important when evaluating design wind speed by typhoon simulation. However, uncertainty exists in wind speed prediction using observation data of natural phenomena such as typhoons, so it is necessary to consider the influence of this uncertainty. There are two kinds of uncertainty: aleatory uncertainty due to extremely rare events, and epistemic uncertainty due to lack of knowledge and data [2]. The former is related to the accidental nature of an event, and even if new observation data are accumulated, it cannot be reduced. The latter is thought to be reducible by increasing the accuracy of accumulation and modelling of observation data. To improve modelling accuracy, the pressure field and wind speed field have been the subject of many researches. However, little research has been done on the accuracy of the probabilistic model. Although not considered in this research, examination of probability statistical accuracy is important when considering long-term climate change.

The authors examined a probability distribution suitable for modelling typhoon pressure fields, focusing on reproducibility of typhoon pressure fields [3]. In this study, we consider the influence of the distribution parameter estimation method and typhoon observation records' quality and quantity with respect to typhoon pressure fields and wind speed prediction. We also try to reduce the uncertainty.

Probability distribution

In the typhoon simulation, the typhoon pressure field parameters obtained from the best course data and meteorological observation records, such as direction of progress, speed of progress, central pressure and radius of maximum wind speed, are approximated by the probability distribution, and a random number is generated for each probability distribution to generate a virtual typhoon. Therefore, the approximation accuracy of the probability distribution becomes very important.

Statistical properties of typhoon pressure fields in Japan have been studied in detail by Fujii et al. [4]. For example, it has been proposed to model the central pressure as a lognormal distribution, and many researchers have modelled it according to this method. In this study, we use a Generalized Extreme Value (hereinafter referred to as GEV) distribution for the probability distribution of typhoon parameters. The cumulative distribution function of the GEV distribution is shown in equation (1)

$$F(x) = \exp\left\{-\left[1+\gamma\left(\frac{x-\mu}{\sigma}\right)\right]^{-\frac{1}{\gamma}}\right\} \quad , \; 1+\frac{\gamma(x-\mu)}{\sigma}>0 \tag{1}$$

Here, μ is a position parameter, σ is a scale parameter, and γ is a shape parameter. When $\gamma = 0$ a type I extreme value distribution (Gumbel distribution) is obtained, when $\gamma > 0$ it is a type II extreme value distribution (Frechet distribution), and when $\gamma < 0$ it is a type III extreme value distribution (reverse Weibull distribution).

Estimation of distribution parameters

There are various methods for estimating the distribution parameters. Common methods are the Maximum Likelihood Estimation method (hereinafter referred to as MLE method) and the Probability Weighted Moment method (hereinafter referred to as PWM method). The MLE method estimates parameters that maximize the likelihood function of the obtained observation data. However, Takara et al. [5] pointed out that variations in hydrological volume and estimation errors increase reliably depending on the number of observation data, because the population estimation conforms to the sample when there are insufficient observation data. The PWM method was proposed by Greenwood et al. [6] in 1979, and uses the moment weighted by sample non-exceedance probability rather than sample momentum. The PWM of the sample is defined by equation (2), and the relation between PWM and GEV parameters is defined by equations (3) to (5).

$$M_j = \int_0^1 xF^j dF \qquad (j = 0, 1, 2 \ldots) \tag{2}$$

$$M_0 = \mu - \frac{\sigma}{\gamma}\{1 - \Gamma(1-\gamma)\} \quad (3)$$

$$2M_1 - M_0 = a\Gamma(1+\gamma)\frac{1-2^{-\gamma}}{\gamma} \quad (4)$$

$$\frac{3M_2 - M_0}{2M_1 - M_0} = \frac{1-3^{-\gamma}}{1-2^{-\gamma}} \quad (5)$$

Shape parameter γ should be obtained by iterative calculation, but in this study, the approximate solution shown by equation (6) proposed by Hosking et al. [7] was used.

$$\gamma = 7.8590d + 2.9554d^2, \; d = \frac{2M_1 - M_0}{3M_2 - M_0} - \frac{\ln 2}{\ln 3} \quad (6)$$

In this study, we clarify the influence of modelling by parameter estimation with the MLE method and the PWM method for typhoon pressure fields.

Meteorological observation records used were the best track data provided by the Japan Meteorological Agency (hereinafter referred to as JMA) in the period between 1951 and 2010. We sampled a typhoon that passed 23^{O}N and 123^{O}E to 147^{O}E. At about the east longitude, it is divided into three more areas, as shown in Figure 1. The target data were for a typhoon whose central pressure reached 980 hPa or less when passing through 23^{O}N. The data sampling method was used in the following two cases. Case 1 was to increase the number of data years in order to investigate the influence of data quantity. Case 2 was to change the data period in order to investigate the influence of data quality. In this case, the number of data years was 30 years.

Figure 2 compares the observation records in Area 1 and the return period by the estimation method with 95% confidence intervals. The 95% confidence interval of the GEV distribution can be evaluated by the delta method [8]. Although the PWM method is well matched to the observation record up to the bottom of the distribution, the MLE method shows that the accuracy of the tail part of the distribution is not as well matched as in the PWM method. However, in both methods, the probability distribution shape is changed by changing the data years and data periods. This tendency indicates that the observation record characteristic varies depending on observation period.

Figure 3 compares the estimation accuracy of 0.2 percentile value (equivalent to 500 years return period) of central pressure for the MLE and PWM methods. In case 1, the central pressure tends to increase as the observation length becomes longer. And in Case 2, it is confirmed that there is a difference in the estimation accuracy of the central atmospheric pressure depending on the observation period. These results show that the MLE method is particularly sensitive to the quality and quantity of observation records.

Gradient wind speed

Gradient wind speed is evaluated using GEV parameters of each case. The Gradient wind speed model uses Myers & Malkin's equation (7), which takes account of changes in stream curvature based on Blaton's formula.

$$u_G = \frac{C\sin\theta_r - fr}{2}\sqrt{\left(\frac{C\sin\theta_r - fr}{2}\right)^2 + \frac{r}{\rho}\frac{\partial P(r)}{\partial r}} \quad (7)$$

Here, C is the moving speed of the pressure field, θ_r is the angle representing the direction of the typhoon's progress (counter clockwise is positive), and f is the Coriolis parameter. The pressure field is modelled using Schloemer's equation. The difference between central pressures was obtained assuming ambient pressure to be 1013 hPa, and the radius of maximum wind speed was calculated by the least squares method using equation (8) applied to the typhoon pressure field.

$$P = P_c + D_p \exp\left(-\frac{r_m}{r}\right) \quad (8)$$

Here, P_c is central pressure, D_p is difference between central pressure and ambient pressure, r_m is radius of maximum wind speed, r is distance from centre of typhoon.

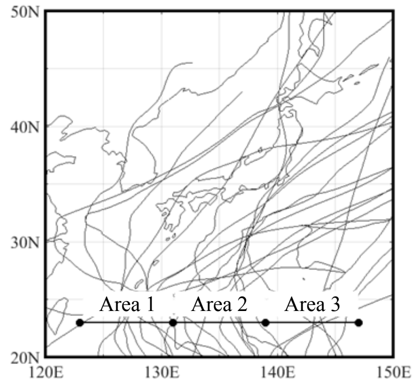

Figure 1 Typhoon best track data from JMA and sampling area.

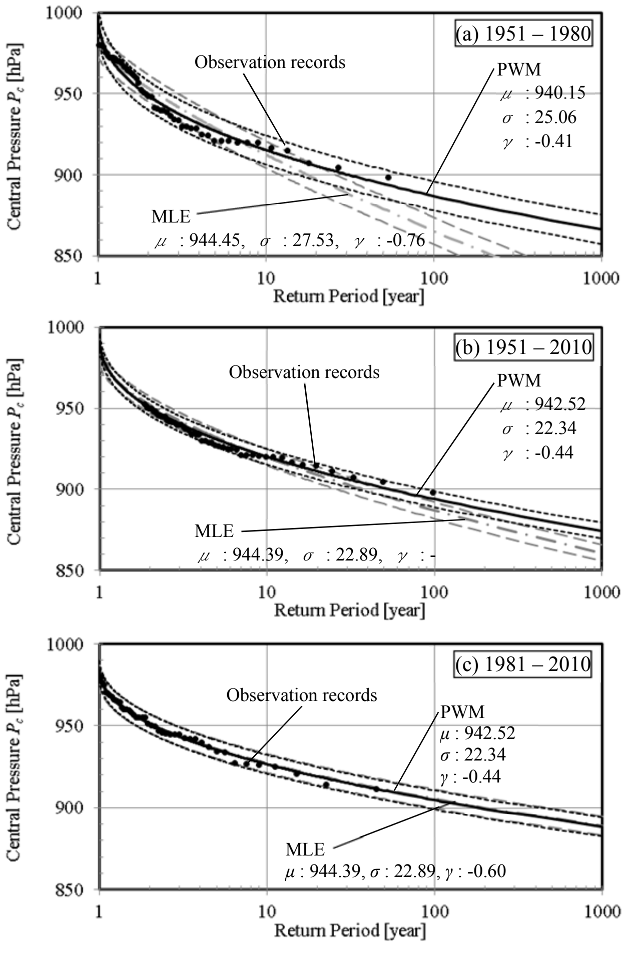

Figure 2 Comparison between observation records in Area 1 (123^{O}E to 131 ^{O}E) and return period with 95% confidence intervals which draw by dashed line. (b) shows the case of longer observed length than (a) [case 1]. (c) shows the case of observed period different from (a) [case 2].

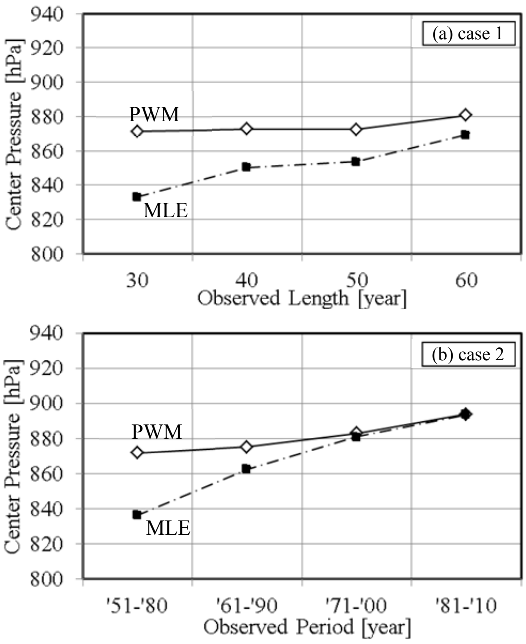

Figure 3 Comparison of 0.2 percentile values of central pressure by probabilistic parameter estimation methods. (a) shows the case of different observed length. (b) shows the case of different observed period.

Typhoon simulation models are generally divided into three types [9]. In this study, we applied the Area-Limited model (Full-Track type). Its initial parameters are shown in Table 1. The transition model after typhoon parameter generation was a linear regression model using time change of observation records. The analysis period was assumed to be 10,000 years.

Figure 4 compares gradient wind speed difference by a probabilistic parameter method for estimating central pressure. In addition, in order to clarify the influence of the initial parameters, the gradient wind speeds of two different points are shown. One is a result of 26^{O}N (close to 23^{O}N), and the other is a result of 35^{O}N (far from 23^{O}N). At 26^{O}N, Case 1, the Gradient wind speed tends to gradually decrease as the number of observed years increases, and there is a difference of about 5 m/s in the PWM method and about 7 m/s in the MLE method. For Case 2, the Gradient wind speed differs because the observed period is different, and there is a difference of about 5 m/s in the PWM method and about 9 m/s in the MLE method. On the other hand, at north latitude 35 degrees, there is no difference in data amount, data period, and Gradient wind speed with estimation method, and it is almost the same value.

It is thus confirmed that the closer the target point is to the initial parameter generation position, the easier the estimation accuracy of the probability model is.

Re-estimation of distribution parameters by resampled observation records

As shown in Figure 4, the gradient wind speed evaluation varies depending on the quality and quantity of the observation record and estimation method for the probability distribution because the influence of uncertainty is included in the observation record. Therefore, in this study we propose distribution parameters without influence of uncertainty and try to reduce uncertainty.

First, we re-sample the observation records to unify the length of the observation record and sample with the observation period shifted by one year, and create as many data sets X_i as possible. Here, four observation record lengths T_{year} are set: 30 years, 40 years, 50 years, 60 years. Distribution parameters θ_i were estimated from the obtained data set X_i, and the distribution parameter $\bar{\theta}$ was evaluated from the ensemble average. Figure 5 compares the observation records in Area 1 and the return period by the estimation method with 95% confidence intervals in which the probabilistic parameters $\bar{\theta}$ are estimated using re-sampled data set X_i. In the PWM method and the MLE method, the observation record is within the 95% confidence interval of the probability distribution model, and the probability distribution model can appropriately approximate the observation record. Furthermore, since the observation record is within the 95% confidence interval of the probability distribution model regardless of the length and duration of the observation record, re-estimated parameters can reduce the influence of uncertainty due to the quantity and quality of the observation records, by the probability distribution parameters estimation method.

Initial position		Probabilistic model of central pressure
Latitude	**Longitude**	
23^{O}	123^{O}to 147^{O}	GEV distribution
23^{O} to 43^{O}	123^{O} / 147^{O}	Normal distribution
Occurring inside the above		Constant 980 hPa

Table 1 Probabilistic model of central pressure at initial positions

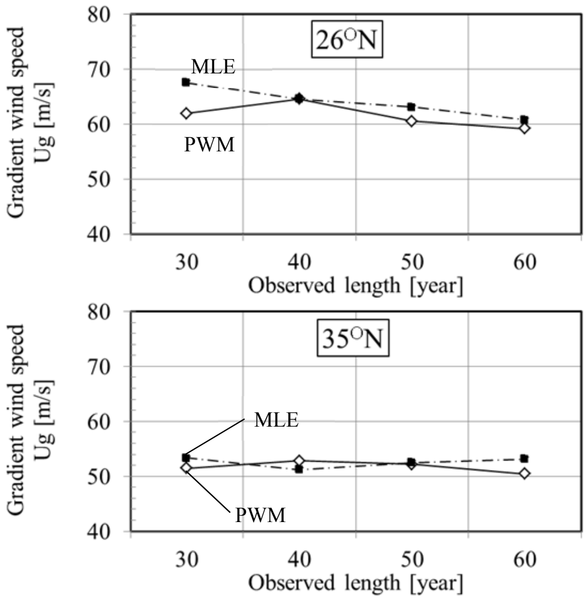

Figure 4 (a) Comparison of gradient wind speed by parameter estimation method (return period 500 years) in the case of different observed length

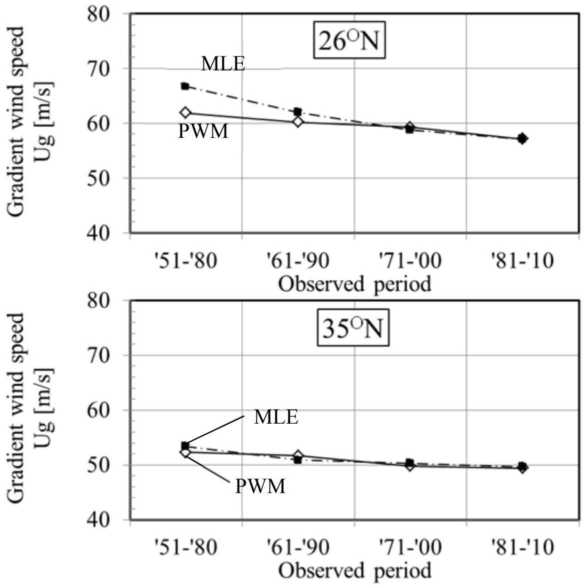

Figure 4 (b) Comparison of gradient wind speed by parameter estimation method (return period 500 years) in the case of different observed period

Figure 5 compares the observation records in Area 1 and the return period by the estimation method with 95% confidence intervals in which the probabilistic parameters $\bar{\theta}$ are estimated using re-sampled data set X_i. In the PWM method and the MLE method, the observation record is within the 95% confidence interval of the probability distribution model, and the probability distribution model can appropriately approximate the observation record. Furthermore, since the observation record is within the 95% confidence interval of the probability distribution model regardless of the length and duration of the observation record, re-estimated parameters can reduce the influence of uncertainty due to the quantity and quality of the observation records, by the probability distribution parameters estimation method.

Performance of Re-estimated distribution parameters

Figure 6 compares the return period value of gradient wind speeds obtained by typhoon simulation using re-estimated distribution parameters. Regardless of the parameter estimation method, the Gradient wind speed is almost the same at 26^{O}N even for a long return period.

Conclusion

In this study, we compared the central pressure estimation and the gradient wind speed estimation accuracy based on typhoon observation records and re-evaluated the observation record, and proposed an estimation method for the probability distribution parameters with reduced influence of the aleatory uncertainty and epistemic uncertainty. However, uncertainties include those caused by typhoon parameters, but the accuracy of modelling wind speed fields were not dealt with in this study. Thus, it is necessary to consider how these can be reflected in the typhoon model.

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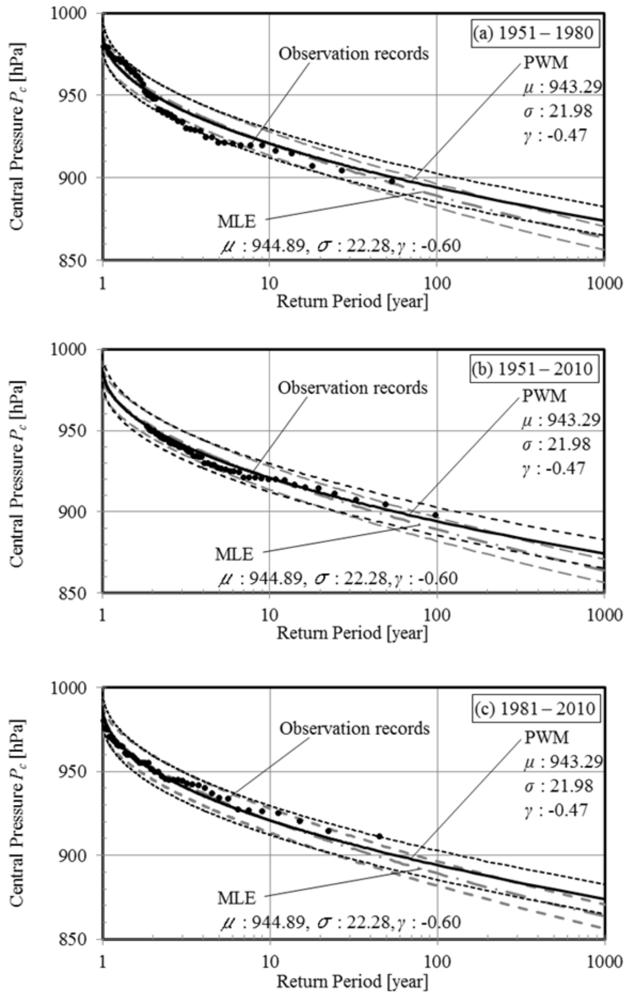

Figure 5 Comparison between observation records in Area 1 (123OE to 131 OE) and return period. Dashed line is 95% confidence intervals with probabilistic parameters estimated using re-sampled data X_i. (b) shows the case of longer observed length than (a) [case 1]. (c) shows the case of observed period different from (a) [case 2].

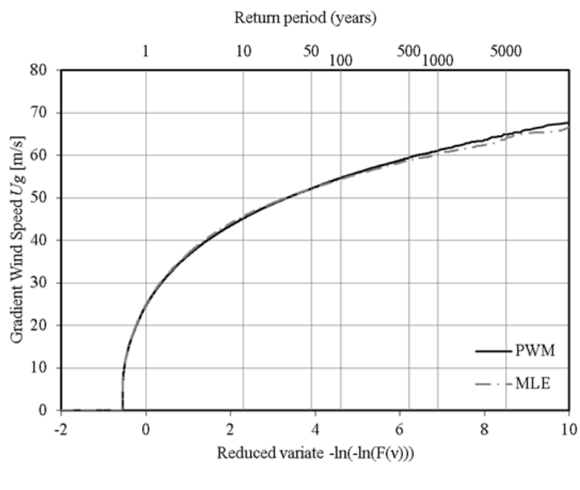

Figure 6 Comparison of the return period value of gradient wind speed by difference of parameter estimation method in case of 26^{O}N close to initial position of parameter generating point