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Forecasting tropical cyclone intensity change in the western North Pacific

Gwo-Fong Lin, Po-Kai Huang and Hsuan-Yu Lin

ABSTRACT

For typhoon warning centers, effective forecasting of tropical cyclone intensity is always required. The major difficulties and challenges in forecasting tropical cyclone intensity are the complex physical mechanism and the structure of tropical cyclones. The interaction between the tropical cyclone and its environment is also a complex process. In this paper, a model based on support vector machines is developed to yield the 12, 24, 36, 48, 72 h forecasts of tropical cyclone intensity. Furthermore, the forecasts resulting from the proposed model are compared with those from the Joint Typhoon Warning Center. Cross-validation tests are also applied to evaluate the accuracy and the robustness of the proposed model. The results confirm that the proposed model can provide accurate forecasts of tropical cyclone intensity, especially for a long lead-time. When the sample events are classified into five categories according to the Saffir-Simpson scale, the forecasts resulting from the proposed model have the best performance for events in categories 4 and 5. In addition, when a typhoon turns northward, although the water temperature drops rapidly, the proposed model still performs well. In conclusion, the proposed model is useful to improve the forecasts of tropical cyclones intensity.

Key words | maximum potential intensity, support vector machines, tropical cyclone intensity

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INTRODUCTION

Tropical cyclones are among the most devastating of natural disasters. Storm surges, destructive winds and flash floods frequently cause loss of human life and serious economic damage (Bengtsson 2007). Forecasting a tropical cyclone track has been significantly improved in the last two decades. However, there has been only little improvement in forecasting tropical cyclone intensity, especially beyond 24 h (DeMaria & Kaplan 1994, 1999; Demuth *et al.* 2006). To forecast tropical cyclone intensity effectively is one of the most difficult challenges during the life cycle of the cyclone because of the complex physical process, inner-core processes, surrounding environments, and underlying ocean water of tropical cyclones. Miller (1958) and Merrill (1987) concluded that how a tropical cyclone forms and intensifies is mainly related to the underlying warm ocean water, but the processes of interactions between tropical cyclones and their environments are poorly understood. Besides, the partial understanding of rapid intensification and physical mechanisms results in the low skill of the intensity forecasts, and other environmental effects such as vertical wind shear have been demonstrated to have significant impacts on the tropical cyclone development (Merrill 1988). Therefore, forecasting the tropical cyclone intensity is always a challenging task.

As a result of the complex physical processes of tropical cyclones, statistical forecast models are still competitive. For example, the National Hurricane Center (NHC) continues to run an operational intensity model using the simple Statistical Hurricane Intensity Prediction Scheme (SHIPS) (DeMaria *et al.* 2005). Climatology and persistence (CLIPER) and analogue techniques, such as hurricane analogue (HURRAN), are other kinds of model based on empirical methods. Besides, the concept of maximum potential intensity (MPI) is a tool to provide the upper bound on

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tropical cyclone intensity (Miller 1958). Emanuel (1986, 1988, 1995) and Holland (1997) continued to derive the MPI theory and proposed their own unique viewpoints about the mechanism of tropical cyclone intensification. The statistical or empirical models are easy to establish and have simple inputs, but the outcomes sometimes are hard to interpret with regard to the physical phenomenon. The dynamic models are even more complicated because of the requirement to set the initial conditions and to derive the mathematic equations. Up to now, most of the models in operation for forecasting tropical cyclone intensity still produce large forecast errors when the forecast lead time is beyond 24 h. Therefore, artificial neural networks (ANNs) are used herein for their powerful forecasting ability.

ANNs have been widely applied in various aspects of research in recent years for their ability and advantage in simulating linear and nonlinear systems without the need to make any assumptions. ANNs also have been proven to be a useful alternative to traditional or numerical methods for hydrological and atmospheric forecasting such as streamflow forecasting (e.g., Chau *et al.* 2005; Lin *et al.* 2006; Toth & Brath 2007; Lin *et al.* 2009a,c, 2010a,b; Wu *et al.* 2009; Remesan *et al.* 2010; Lin & Wu 2011; Pramanik *et al.* 2011; Wu *et al.* 2011; Adamowski *et al.* 2012), rainfall forecasting (e.g., Chattopadhyay & Chattopadhyay 2008; Lin *et al.* 2009b; Lin & Wu 2009; Chau & Wu 2010), cyclone intensity forecasting (Jin *et al.* 2008) and improving tropical cyclogenesis statistical model forecasts (Hennon *et al.* 2005). Constructing an ANN-based model needs the selection of suitable inputs and outputs. Proposing a systematic approach to determining effective factors is also an important process. Traditionally, the weather forecasting models were developed only based on the climatological and persistence factors. Elsberry *et al.* (1988) proved that the useful synoptic information could improve forecast accuracy. Hence, the weather forecasting model such as SHIPS uses the synoptic information and the climatological and persistence factors. Thus, an ANN-based model is developed in this paper for improving forecast accuracy using the climatological and persistence factors with the synoptic information, including oceanic data, atmospheric and typhoon data.

In this paper, a model based on support vector machines (SVMs) is proposed to obtain the 12, 24, 36, 48, 72 h forecasts of tropical cyclone intensity in the western North Pacific, and then the forecasts are compared with those issued by the Joint Typhoon Warning Center (JTWC). JTWC, located in Pearl Harbor, Hawaii, is a joint task force of United States Navy and Air Force. The forecasts of JTWC are based on some dynamic models such as the Global Forecast System and the Climate Forecast System, actual observed atmospheric data, and historical data. The SVM was first proposed by Vapnik (1995), and the objective function and the optimization algorithm are two particular properties for SVM. By means of the objective function based on the structural risk minimization (SRM) induction principle, the empirical risk and model complexity should be minimized simultaneously. In addition, the optimization algorithm can be quickly solved by a standard programming algorithm in accord with the determination of the architecture and weights that are expressed in terms of a quadratic optimization problem. The SVM has advantages over conventional ANN such as back-propagation network (BPN), which is the most frequently used neural network. The BPN is relatively time-consuming due to their learning procedure and iterative process. Furthermore, the SVM is more robust than BPN since the architectures and the weights of the SVM are guaranteed to be unique and globally optimal. Due to the aforementioned advantages for SVM, an SVM-based model is proposed in this paper.

THE DATA

Forecasting tropical cyclone track or intensity can be grouped into three categories: (1) empirical model, e.g., climatology, persistence of the past motion, and analogue techniques; (2) statistical model, e.g., statistical regression using grid-point values; and (3) dynamic model, e.g., a global or regional numerical weather prediction model via various physical processes and mechanisms. Some of them use the synoptic information or the CLIPER predictors (Pike 1985; Merrill 1987; Elsberry *et al.* 1988) to improve predictions. Law & Hobgood (2007) utilized 25 predictors to develop a discriminant function analysis (DFA) method for forecasting the short-term Atlantic hurricane intensity. The accuracy of the 24 h DFA method was tested and compared with the NHC 24 h intensity forecasts, and the result showed that the DFA method outperformed NHC. Some use both the synoptic information and the CLIPER predictors to develop a model (DeMaria & Kaplan 1994). Schade & Emanuel (1999) constructed a coupled hurricane-ocean model and performed a sensitivity test about the steady-state central pressure. During the sensitivity test, only a single parameter was changed, and all the other parameters were fixed at their original values. Their testing parameters include the sea surface temperature (SST), relative humidity, the ratio of the transfer coefficient of heat to that of momentum, and temperature depth. The results showed that all these testing parameters apparently affected tropical cyclone intensity change.

In this paper, the synoptic information and the CLIPER predictors are used as input to the proposed model. Factors which are most often used and closely related to tropical cyclone intensity change are adopted herein to construct the proposed model. They are SST, temperature depth, specific humidity, relative humidity, vertical wind shear, MPI, longitude of the cyclone center, latitude of the cyclone center, speed of the cyclone, and maximum wind speed. In this section, details of the input and output information is divided into the following four subsections: Oceanic data, Atmospheric data, Typhoon data, and MPI. The spatial and temporal resolutions of these 10 factors are summarized in Table 1.

Table 1 | The spatial and temporal resolutions of the 10 input factors

Input factor	Spatial resolution (degree)	Temporal resolution
Sea surface temperature	0.25	1 day
Temperature depth	2.5	6 h
Mixing ratio	2.5	6 h
Relative humidity	2.5	6 h
Vertical wind shear	2.5	6 h
Maximum potential intensity	0.25	6 h
Longitude of typhoon center	–	6 h
Latitude of typhoon center	–	6 h
Translation speed of the cyclone	–	6 h
Maximum wind speed	–	6 h

Oceanic data

The SST is obtained from the National Climatic Data Center (NCDC) Satellite Data Services. The SST data has a spatial resolution of 0.25° in latitude and longitude and a temporal resolution of 1 day. The SST data consist of two high resolution analysis products with optimum interpolation. One product is advanced very high resolution radiometer (AVHRR) infrared satellite SST data, and the other is advanced microwave scanning radiometer (AMSR) on the National Aeronautics and Space Administration (NASA) Earth Observing System satellite SST data. *In-situ* data from buoys and ships are used in the AVHRR and AMSE to adjust large-scale satellite biases (Reynolds *et al.* 2007). Because the AMSR is available after June 2002, the combination of AMSR and AVHRR products is available from June 2002.

Atmospheric data

Atmospheric data are obtained from the National Center for Environmental Prediction (NCEP), National Weather Service. Atmospheric data have a spatial resolution of 2.5° in latitude and longitude and a temporal resolution of 6 h. Atmospheric data are available for 17 pressure levels: 1,000, 925, 850, 700, 600, 500, 400, 300, 250, 200, 150, 100, 70, 50, 30, 20 and 10 hPa. In this paper, the temperature depth is the sum of the temperature differences between the bottom (1,000 hPa) and top (10 hPa) layer (Emanuel 1986; Schade & Emanuel 1999). The relative humidity is the average of the relative humidity values at 1,000–500 hPa. The mixing ratio is the average of the mixing ratios at 1,000–300 hPa. The vertical wind shear is the difference between wind speeds at 850 and 200 hPa (Law & Hobgood 2007).

Typhoon data

The best-track data contain typhoon position, speed of the typhoon and maximum 1-min sustained wind speed with a temporal resolution of 6 h. These CLIPER factors are obtained from JTWC. The maximum wind speeds are expressed in knots. As mentioned above, the combination of AMSR with AVHRR products is available from June

2002. Therefore, a total of 216 typhoon events are collected herein in the western North Pacific from June 2002 to December 2009.

In this paper, typhoon events selected herein for analysis need to reach category 1 status (65 knots) on the Saffir-Simpson hurricane scale (Simpson 1974). Dvorak (1975, 1984) indicated that once a cyclone develops to near hurricane strength (category 1), an eye develops, and then a 'mature cyclone' is formed. If a cyclone cannot reach category 1 status, the structure of cyclone is easily influenced by encountering some adverse environmental factors such as vertical wind shear (Erickson 1974; Simpson & Riehl 1958). Then, the development of cyclone is likely to retain or weaken, even though the water temperature is warm enough. In addition, typhoons making landfall or crossing over land but reaching its maximum intensity are excluded. Furthermore, some data are excluded from the prediction due to lack of complete forecasting information. Therefore, a total of 83 typhoon events are chosen. The 83 typhoon tracks in the western North Pacific basin are shown in Figure 1.

Maximum potential intensity (MPI)

The tropical cyclone is a complex dynamic and physical system, and its intensity is affected by its surrounding environments and ocean water underneath the eyewall. The process of interaction between a tropical cyclone and its environments is poorly understood, therefore, it is very difficult to forecast tropical cyclone intensity by means of physical or numerical concepts which lead to lots of difficulties constructing a physically based model. However, according to some important factors such as SST, atmospheric data or the surrounding environmental condition, the reasonable upper bound for tropical cyclone intensity (the so-called MPI) can be estimated. In this paper, the MPI developed by Emanuel (1986, 1988, 1995) is used herein. The MPI concept is briefly introduced below.

Emanuel (1986) proposed a unique theory of tropical cyclone structure and development. In the past, the ambient convective available potential energy (CAPE) is an important energy source for tropical cyclone development and maintenance in the majority of models. The CAPE also was used to calculate MPI, but Emanuel (1986) argued that energy exchange between the tropical cyclone and ocean water is more important than the surrounding CAPE. He also hypothesized that source energy entirely extracts from the ocean water. Emanuel (1986) developed an atmospheric model, and assumed that the storm is axisymmetric, in hydrostatic and gradient balance, and the dynamic mechanism is thermodynamically reversible. He assumed the tropical cyclone as a popular simple 'Carnot heat engine'. That is, air with the heat energy

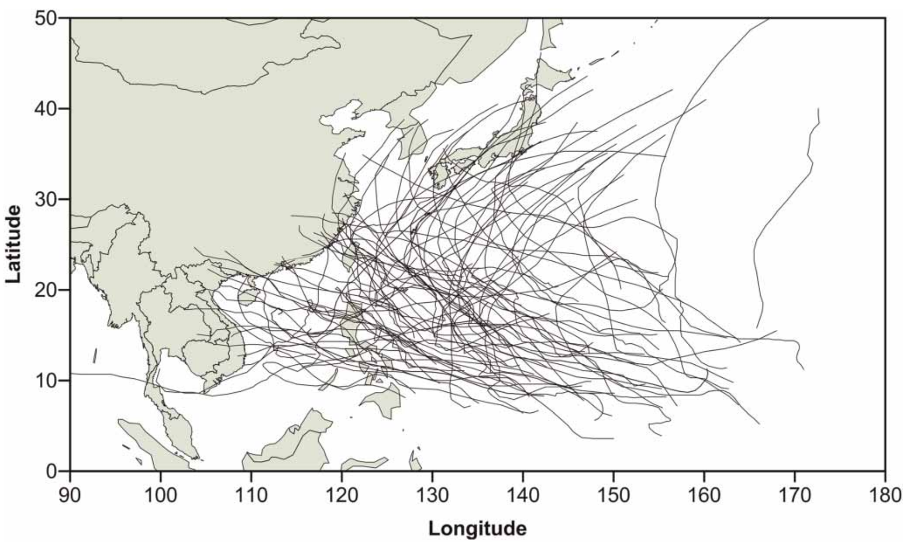

Figure 1 | The 83 typhoon tracks in the western North Pacific.

spirals in toward the storm center, acquires heat from the warm ocean water, turns upward along the eyewall, dissipates heat at the tropopause in the end, and then sinks back to sea surface.

Emanuel (1988) modified his original model to explain fully reversible thermodynamics. Next, Emanuel (1995) revised his numerical model for neglecting the eye dynamics, and suggested that estimated MPI is closely linked to the enthalpy and momentum exchange coefficients. Bister & Emanuel (1998) suggested that dissipative heating should be added in the numerical model. This can increase the maximum wind speeds of a tropical cyclone by about 20% and develop a more accurate model for predicting tropical cyclone intensity.

According to these aforementioned hypotheses and conjectures, the MPI can be estimated. In the beginning, the cyclone acquires the heat energy from the sea surface, but only a fraction of the heat energy is available for the heat engine. The estimation of the fraction is called the thermodynamic efficiency which is defined by

$$\varepsilon \equiv \frac{T_s - T_0}{T_0} \tag{1}$$

where ε is the thermodynamic efficiency, T_s is the temperature of the heat source (the ocean surface), and T_0 is the average temperature that is exported from the top of the cyclone. In a typical hurricane, ε is about 1/3. The rate of input of available energy for each square meter of sea surface covered by the cyclone is given by:

$$G = \varepsilon C_k \rho V_s (k_o^* - k_a) \tag{2}$$

where G stands for 'generation', C_k is a dimensionless coefficient called the enthalpy transfer coefficient, V_s is the maximum wind speed, and k_o^* and k_a are the enthalpy of the ocean surface and the actual enthalpy of the boundary layer air, respectively.

When mature cyclone intensity reaches a steady condition, the acquired energy almost equals the mechanical dissipation by means of friction acting between the powerful winds and the underlying sea surface within the cyclone. The rate of mechanical dissipation for each square meter of ocean surface is given by

$$D = C_D \rho V_s^3 \tag{3}$$

where D stands for 'dissipation', and C_D is the drag coefficient. The 'generation' in Equation (2) equals the 'dissipation' in Equation (3). Then, the estimation of MPI is given by

$$V_s^2 \cong \frac{T_s - T_0}{T_0} \frac{C_k}{C_D} (k_o^* - k_a) \tag{4}$$

The detailed description about MPI theory can also be obtained from Emanuel's website (Holland & Emanuel 1999).

ANALYSIS PROCESS

Linear interpolation

In the middle of last century, studies about the upper limit of tropical cyclone intensity were presented (Kleinschmidt 1951; Miller 1958; Malkus & Reiehl 1960). They modeled the tropical cyclone intensity by using atmospheric dynamics or cloud physics, simulating air parcel in the boundary layer, and depending on SST or height of the convective equilibrium level (EL). In the 1980s and 1990s, Emanuel (1986, 1988, 1995) revised the tropical cyclone thermodynamic structure and mechanism for estimating MPI. In addition, investigations of MPI by Holland (1997) are also widely recognized, and his methods are similar to Miller's concepts. In the recent decade, Emanuel (2000, 2003), Tonkin *et al.* (2000), Hobgood (2003) and Knaff *et al.* (2003) continued their research to improve tropical cyclone intensity prediction. But, the resolutions of data they used are limited and generally coarse. For example, the SST has a temporal resolution of 1 week or even 1 month, and has a spatial resolution of 2.5° or 5° in latitude and longitude.

Generally speaking, the size of the cyclone between 3 and 6 latitude degrees is considered 'average-sized'. If the spatial resolutions of atmospheric and oceanic data grids are too coarse, then the phenomenon of interaction between the tropical cyclone and its environment such as the cooling feedback effect cannot be displayed. In September 1983, super typhoon Forrest developed in the western Pacific Ocean. It is the fastest-developing tropical cyclone on record, with a pressure drop of 100 mb and a wind speed increase of 160 km h^{-1} in a 24 h period. An intense cyclone results in water temperature dropping significantly and rapidly (Lin & Liu 2003). Hence, some important and clinical information may be lost when a cyclone confronts this kind of rapid variation.

As the NCEP data have a spatial resolution of 2.5° in latitude and longitude, and the SST data have a spatial resolution of 0.25° in latitude and longitude, the NCEP data could be linearly interpolated into 0.25° in longitude and latitude. As the SST data have a temporal resolution of 1 day and the NCEP data have a temporal resolution of 6 h, the SST data can be linearly interpolated into 6 h too. In this way, the more detailed information about the interaction between ocean and atmosphere can be obtained to develop a more accurate model.

Data extraction from each typhoon event

After the interpolation processing, all the atmospheric and oceanic data have a spatial resolution of 0.25° in latitude and longitude and a temporal resolution of 6 h. Cione & Uhlhorn (2003) used airborne expendable bathythermograph (AXBT) and buoy-derived observations to archive SST data, and demonstrated that wind-induced SST is changed mostly in the inner-core of tropical cyclone. Emanuel *et al.* (2004) assumed that tropical cyclone intensity interacts with ocean, and water temperature changes underneath the eyewall along its path primarily. Hence, to pick up data that correlate with the cyclone intensity for the inputs of the proposed model, atmospheric and oceanic data are summed up over the grid-points within a radius of 150 km from the typhoon center. If the radius is too small, the information about the interaction between the tropical cyclone and ocean cannot be considered. If the radius is too large, the detailed information may be lost.

A sketch map is shown in Figure 2. The black solid line is the historical cyclone track, and the black circle shows the 150 km radius from the cyclone center. Each grid point has the oceanic and atmospheric data with a spatial

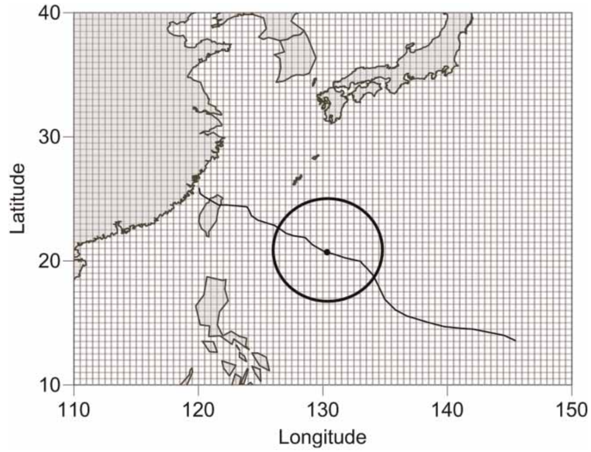

Figure 2 | Extract of oceanic and atmospheric data from grid points covered by the typhoon.

resolution of 0.25° in latitude and longitude. The model input is the averaged atmospheric and oceanic data of the grid points within the 150 km radius. If grid points are on land, the grid point data are assigned to zero (Emanuel 2000). Hence, using the methods described above, the corresponding atmospheric and oceanic data for the model inputs are obtained at every 6 h interval during the life cycle of the cyclone.

Model construction and performance measures

In this paper, a model based on SVM is constructed to yield the 12–72 h forecasts of tropical cyclone intensity. The SVM has two parameters: regularization parameter C and error tolerance e. The parameter C indicates the trade-off between the model complexity and the empirical error. When $C = 1$, the model complexity is as important as the empirical error. In addition, it is acceptable to set the error tolerance e of 1% for intensity forecasting.

The suitable inputs of the proposed model should be determined according to the performance of the model that uses different factors as input. Selecting a suitable input for a forecasting model is important. Therefore, the step for constructing a forecasting model in this paper is individually adding each factor in turn to the proposed model and evaluating the coefficient of efficiency (CE) of each factor. Then the factor with the highest CE will be the first input to the proposed model. The CE is given by

$$\mathrm{CE} = 1 - \frac{\sum_{t=1}^{n}\left(I_t - \hat{I}_t\right)^2}{\sum_{t=1}^{n}\left(I_t - \bar{I}_t\right)^2} \tag{5}$$

where n is the number of observations, I_t and $\hat{I}_t$ are the forecasted and the observed cyclone intensity at time t, respectively, and $\bar{I}_t$ is the average of observed cyclone intensity. The CE proposed by Nash & Sutcliffe (1970) is often used to evaluate the model performance. A CE of 1 indicates perfect forecasts.

In a similar manner, individually adding the other factors in turn to the model and evaluating the CE, one can find the second input. When the CE does not improve apparently, the procedure for adding that factor to the proposed model is stopped. In the end, the typhoon maximum wind speed, latitude of typhoon center, longitude of typhoon center and MPI are optimal input factors to the proposed model. As we all know, the distribution of SST is warm near the equator and cool near the poles. For this reason, the prevailing high SST is in the lower latitude, and low SST is in the higher latitude. Therefore, this has implications for the relationship between the latitude and the distribution of SST. The MPI is the theoretical maximum intensity of a tropical cyclone. Because some of the atmospheric factors and SST are considered for the estimation of MPI, therefore, this may be why these factors are the effective factors.

In the proposed model, the criterion for selecting a lag length of a certain input factor is the relative percentage error (RPE):

$$\mathrm{RPE} = \frac{E(n_i) - E(n_i + 1)}{E(n_i)} \times 100 \tag{6}$$

where $E(n_i)$ and $E(n_i + 1)$ are the root mean square error (RMSE) for models with n_i and $n_i + 1$ lag lengths, respectively. Generally speaking, the RMSE decreases with increasing lag lengths. When the PRE is less than 5%, the increase of lag lengths is terminated. For example, a lag length of 3 means data at time t, $t - \Delta t$, and $t - 2\Delta t$, where $\Delta t = 6$ h, will be used as input. Table 2 summarizes the optimal input combination of the proposed model. As shown in Table 2, maximum wind speed, latitude of typhoon center, longitude of typhoon center, and MPI are the effective factors, and each factor has a lag length of 2. The outputs are forecasts at $t + 2\Delta t$, $t + 4\Delta t$, $t + 6\Delta t$, $t + 8\Delta t$, and $t + 12\Delta t$, where $\Delta t = 6$ h. That is, the forecast lead times are 12, 24, 36, 48, and 72 h. The 12–72 h forecasts of tropical cyclone intensity resulting from the proposed model will then be compared with those from JTWC.

Table 2 | Inputs of the SVM model

Factor	Input
Maximum wind speed	$I_{t-\Delta t}$, I_t
Longitude	$X_{t-\Delta t}$, X_t
Latitude	$Y_{t-\Delta t}$, Y_t
MPI	$\mathrm{MPI}_{t-\Delta t}$, MPI_t

Note: $\Delta t = 6$ h.

For event-based data, the collected events are classified into two sets of data: training and testing. Some of the collected events are chosen as training data and used to construct the proposed model. Then the performance of the proposed model is tested by the remaining events which are not used in the training process. Different selections of training data and testing data yield different results and sometimes lead to different conclusions. To reach just conclusions, cross validations are conducted herein. Each single typhoon event is used to test the proposed model in turn. Then conclusions are drawn based on the overall performance for the testing events. Eighty three typhoon events are used in this paper.

RESULTS AND DISCUSSION

In the first subsection, for all 83 typhoon events, the 12, 24, 36, 48 and 72 h forecasts resulting from the proposed model will be compared with the official forecasts issued by JTWC. In the second subsection, all typhoon events are classified into five categories according to the Saffir-Simpson scale, and the model performance in each category is investigated. In the third subsection, all typhoon events are divided into two types according to the movement of the typhoon, and the model performance of these two types is investigated. Finally, the forecasts of the proposed model are compared with those of JTWC for two typhoon events (Haitang in 2005 and Morakot in 2009), both of which caused serious disasters in Taiwan.

Accuracy of cyclone intensity forecasts

The primary purpose of this subsection is to compare the intensity forecasts from the proposed model with the official forecasts issued by JTWC at 12–72 h ahead. The observed intensities (best-track) issued by JTWC from June 2002 to 2009 are used. The means and the standard deviation (SD) of RMSE values are calculated and summarized in Table 3.

As shown in Table 3, the mean RMSE values resulting from the proposed model and JTWC increase with increasing forecast lead time. However, the proposed model clearly yields significantly lower RMSE than JTWC. As shown in Figure 3, the improvement is up to 10.81% for the 12 h forecast. The improvements for 12–48 h forecasts are between 6 and 9%, but for the 72 h forecast the improvement is up to 10.21%. Generally speaking, the improvement of the proposed model increases with the increasing forecast lead time. Thus, it is concluded that the proposed model provides better forecasting performance at short and long lead times.

The SD values of the proposed model and JTWC also are presented in Table 3. The smaller the SD value is, the more robust the forecasting model is. The proposed model yields significantly lower SD than JTWC for the 12–72 h forecasts. This means that the performance of the proposed model is stable and reliable.

Table 3 | Statistics of the RMSEs resulting from the proposed model and JTWC at different lead times

	RMSE			
	Mean (kt)		SD (kt)	
Lead time (h)	JTWC	SVM	JTWC	SVM
12	10.13	9.03	2.68	2.31
24	15.41	14.39	4.48	3.81
36	19.59	18.05	6.00	5.16
48	22.68	20.69	7.32	6.58
72	26.27	23.61	8.81	8.46

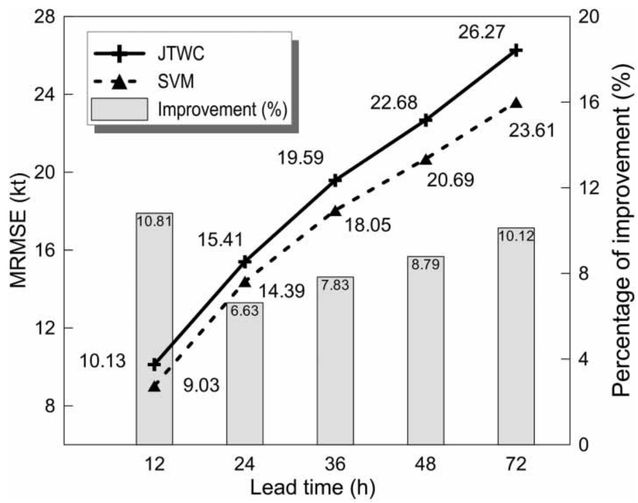

Figure 3 | Variation of MRMSE and improvement with lead time for the proposed model and JTWC.

Forecasting comparison for typhoons of different Saffir-Simpson scales

In this subsection, these 83 typhoon events are classified into five categories according to the Saffir-Simpson scale for assessing the forecasting ability of the proposed model and JTWC. The result of the classification of the typhoon events are summarized in Table 4. There are 15, 15, 7, 28, and 18 events in categories 1, 2, 3, 4, and 5, respectively. Figure 4 presents the mean RMSE values for the 12–72 h forecasts resulting from the proposed model and JTWC in each category. First of all, the proposed model outperforms JTWC in all five categories at the 12 and 24 h lead times. However, the proposed model performs slightly worse than JTWC in category 1 at the 36 h lead time and in

Table 4 | Number of typhoon events in five categories on the Saffir-Simpson scale

Category	Intensity (kt)	Number of events
1	64–82	15
2	83–95	15
3	96–113	7
4	114–135	28
5	>135	18

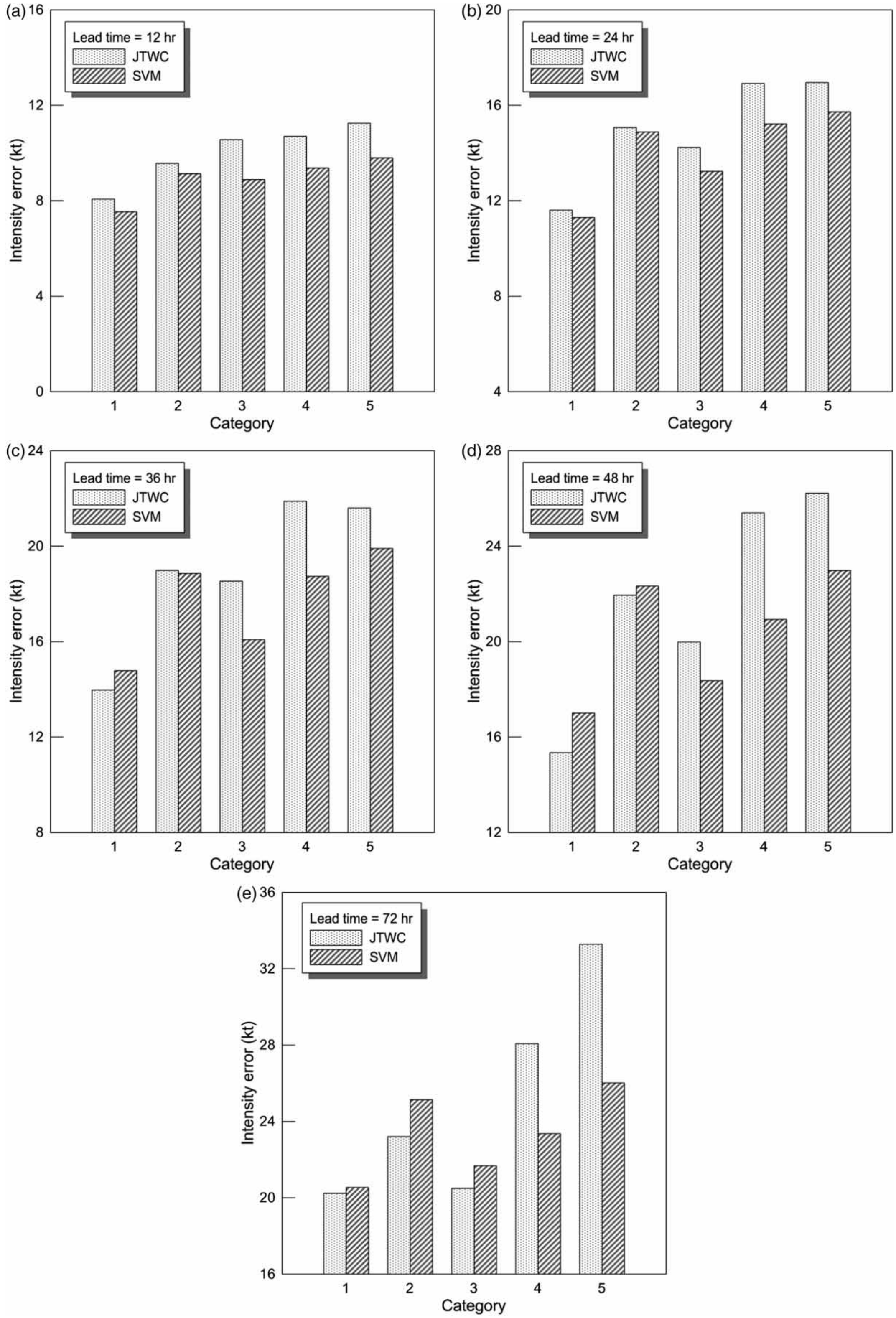

Figure 4 | Comparison of MRMSE in five categories for the proposed model and JTWC at (a) 12, (b) 24, (c) 36, (d) 48, and (e) 72 h lead times.

categories 1 and 2 at the 48 h lead time. At the 72 h lead time, the same phenomenon is found in categories 1, 2 and 3. However, in categories 4 and 5, the improvement of the proposed model increases with increasing lead time (from 12 to 72 h).

In general, if the water temperature is suitable for a cyclone to develop, the cyclone intensity will keep growing steadily. If the intensification rate of a cyclone is slow, the development of the cyclone is restrained by some adverse environmental conditions or self-regulating structure. However, the proposed model is not able to adjust and respond during these kinds of negative conditions because of no suitable information. Thus, the intensification rate of the cyclone estimated by the proposed model may be sometimes greater than the actual. Besides, when the water temperature is quite warm and environmental conditions are good, the intensification rate of the cyclone may be greater than climatology. Hence, the cyclone intensity can increase to category 4 and 5 in a very short time. Most forecasting models in operation cannot overcome this kind of rapid intensification process. However, the proposed model is able to take the rapid intensification process into account and respond immediately, because the inputs include cyclone intensities at time t and $t - \Delta t = 6$ h. Although the proposed model does not perform well in every category, the whole performance of the proposed model is still stable, especially for intense cyclones. If other effective factors or physical mechanism such as the internal structure of the typhoon could be investigated, the model performance might be further improved.

Forecasting comparison for typhoons moving westward or turning northward

Sufficiently warm SST is the main requirement for a tropical cyclone genesis, and an ocean temperature of 26 °C is considered the most basic condition to develop a cyclone. Figure 5 is the mean SST from June to October during 1971–2000. The black dashed line is the 26 °C SST isotherm, which is approximately along 30°N latitude. When a typhoon moves northward to 30°N latitude or higher, the cyclone intensity may weaken rapidly due to the rapid drop in ocean temperature in the higher latitude region. This kind of variation results in the forecasting difficulty. To test the performance of the proposed model and JTWC, typhoon events are divided into two types in this subsection. In the first type, the typhoon center turns northward into 30°N latitude or higher during its life cycle. In the second type, the typhoon center moves westward into the area covering the Philippines, Taiwan,

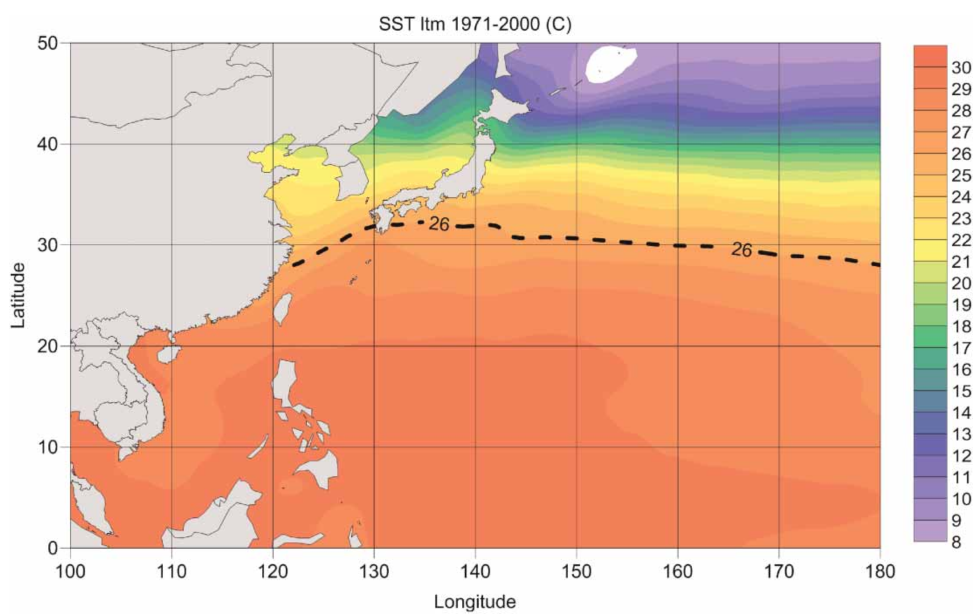

Figure 5 | Mean sea surface temperature in the western North Pacific basin from June to October during 1971–2000 (black dashed line is the 26 °C SST isotherm).

and Hong Kong. The numbers of events of these two types are 42 and 41, respectively.

Figures 6 and 7 show the results of the mean RMSE values resulting from the proposed model and JTWC for the aforementioned two types at different lead times. The result of the first type is given in Figure 6, and the performance is about the same for the proposed model and JTWC at

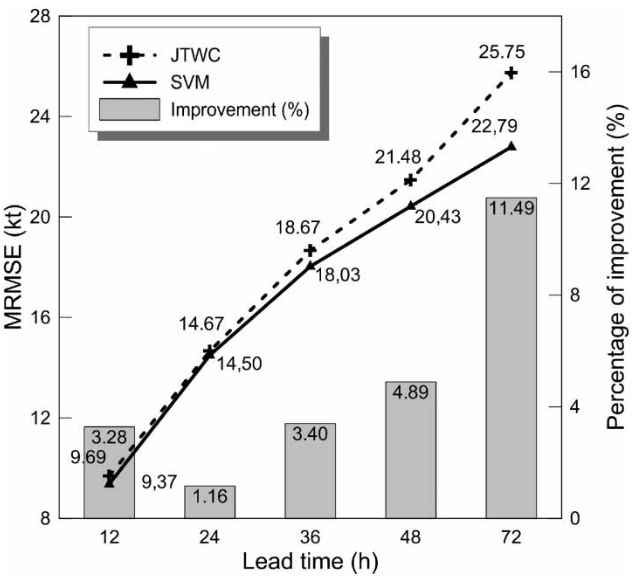

Figure 6 | Variation of MRMSE and improvement with lead time for the proposed model and JTWC (move westward).

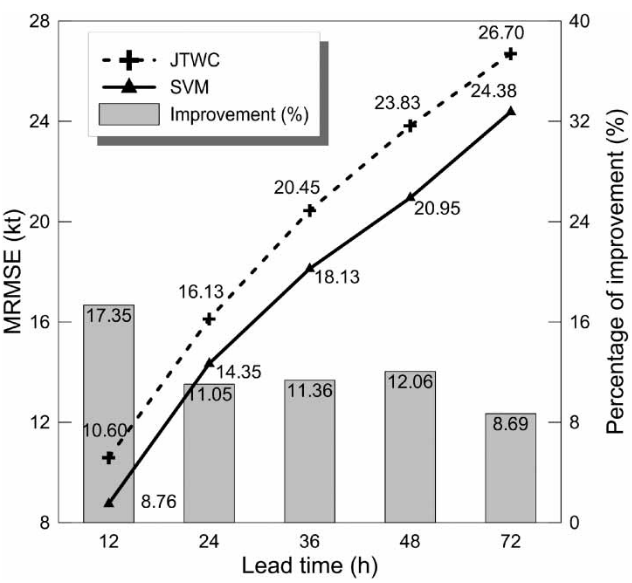

Figure 7 | Variation of MRMSE and improvement with lead time for the proposed model and JTWC (turn northward).

shorter lead times (12, 24 and 36 h). This is because when a typhoon moves westward in a lower latitude region in the western North Pacific, the water temperature is warm and variation is small. Hence, the effects of environmental uncertainty on the cyclone development are slight. For this reason, the forecasting ability of both proposed model and JTWC is about the same at short lead times. However, at longer lead times (48 and 72 h), especially for the 72 h forecast, the percentage improvement resulting from the proposed model is up to 11.49%. Dvorak (1975, 1984) indicated that an eye develops once a tropical cyclone develops to near hurricane strength. As mentioned before, the intensification rate of some typhoon events will rapidly accelerate when the cyclone structure becomes mature. Therefore, the proposed model can forecast well during the rapid intensification stage because of the inputs of the proposed model including typhoon intensities at time t and $t - \Delta t$ where $\Delta t = 6$ h. The result of the second type is presented in Figure 7. As shown in Figure 7, the proposed model outperforms JTWC regardless of short or long lead times. Especially for the 12 h lead time, the percentage improvement is up to 17.35%, and around 8–12% for the remaining lead times. This indicates that the proposed model still performs well no matter how the environment changes.

Haitang 2005 and Morakot 2009

Three super typhoons (Haitang, Talim and Longwang) made landfall in Taiwan in the 2005 typhoon season, and one typhoon (Morakot) in 2009. This subsection focuses on super Typhoon Haitang in 2005 and Typhoon Morakot in 2009. Typhoon Haitang was upgraded to a tropical storm (35 knots) on 12 July 2005, reached peak intensity on 16 July 2005 with an observed maximum sustained wind of 140 knots, made landfall in eastern Taiwan on 18 July 2005, and caused 12 deaths. Typhoon Morakot formed on 3 August 2009, intensified to category 2, and made landfall in Taiwan on 8 August. Typhoon Morakot took more than two days to pass through Taiwan and accompanied a very strong southwesterly flow, which resulted in an accumulated rainfall exceeding 2,000 mm and caused deadly mudslides and floods.

Table 5 compares the RMSEs resulting from the proposed model and JTWC for Typhoon Haitang and

Table 5 | The RMSEs resulting from the proposed model and JTWC for Typhoon Haitang (2005) and Typhoon Morakot (2009) at different lead times

	RMSE (kt)			
	Typhoon Haitang		Typhoon Morakot	
Lead time (h)	SVM	JTWC	SVM	JTWC
12	9.71	8.94	8.05	12.68
24	13.34	15.06	10.52	17.59
36	16.23	19.01	8.22	22.86
48	18.60	21.21	11.19	23.76
72	26.22	33.88	16.36	31.26

Typhoon Morakot at different lead times. Figures 8 and 9 are the comparisons of forecasted tracks at different lead times for Typhoon Haitang and Typhoon Morakot, respectively. In Figures 8 and 9, both red solid lines are the observed intensity from JTWC best track data. Green solid lines with triangle symbols are obtained by the proposed model at every 6 h consisting of 12, 24, 36, 48, and 72 h lead times, and blue solid lines with rhombus symbols are issued by JTWC. Figure 8(b) shows that JTWC underestimated intensities during the rapid intensification stage of Typhoon Haitang from 12 to 16 July. On the other hand, the proposed model fits the best track much better during this stage as shown in Figure 8(a). However, both of them did not perform well when Typhoon Haitang intensified near to its maximum intensity. This underestimation was also seen in other rapidly intensifying cases. Both of them forecasted more reasonable after Typhoon Haitang reached maximum intensity. Figure 9(b) shows that JTWC forecasted Typhoon Morakot could intensify to near 120 knots. However, when Typhoon Morakot reached its maximum, the observed maximum intensity was only 80 knots. Although the proposed model slightly underestimated intensities during Typhoon Morakot reaching its maximum intensities (Figure 9(a)), the proposed model still fits well during its life cycle. As a result, the proposed model performed well for the rapidly intensifying stage and it could immediately respond to rapid intensity change.

SUMMARY AND CONCLUSIONS

The cyclone intensity prediction is a complicated problem and hard to be modeled since the cyclone mechanism is highly nonlinear. The major purpose of this study is to

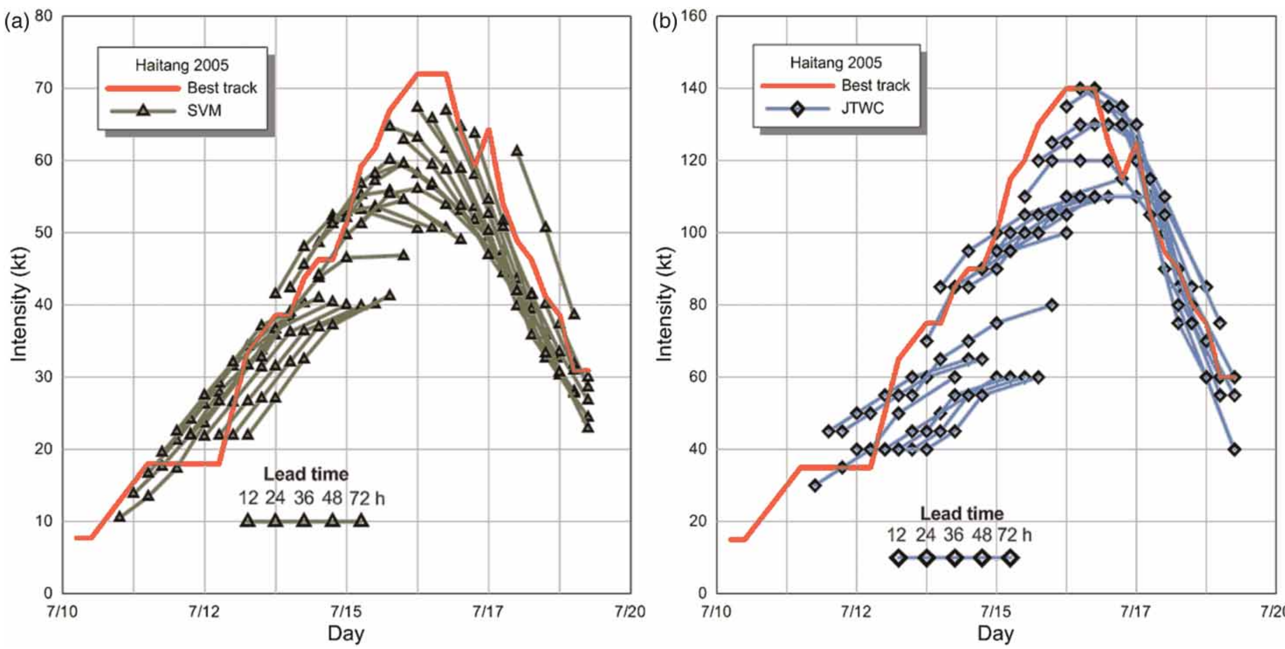

Figure 8 | Comparison of the observed intensity (the best track) with the forecasts resulting from (a) the proposed model, and (b) JTWC for Typhoon Haitang (2005). Each forecasted track made at every 6 h consists of 12, 24, 36, 48, and 72 h forecasts.

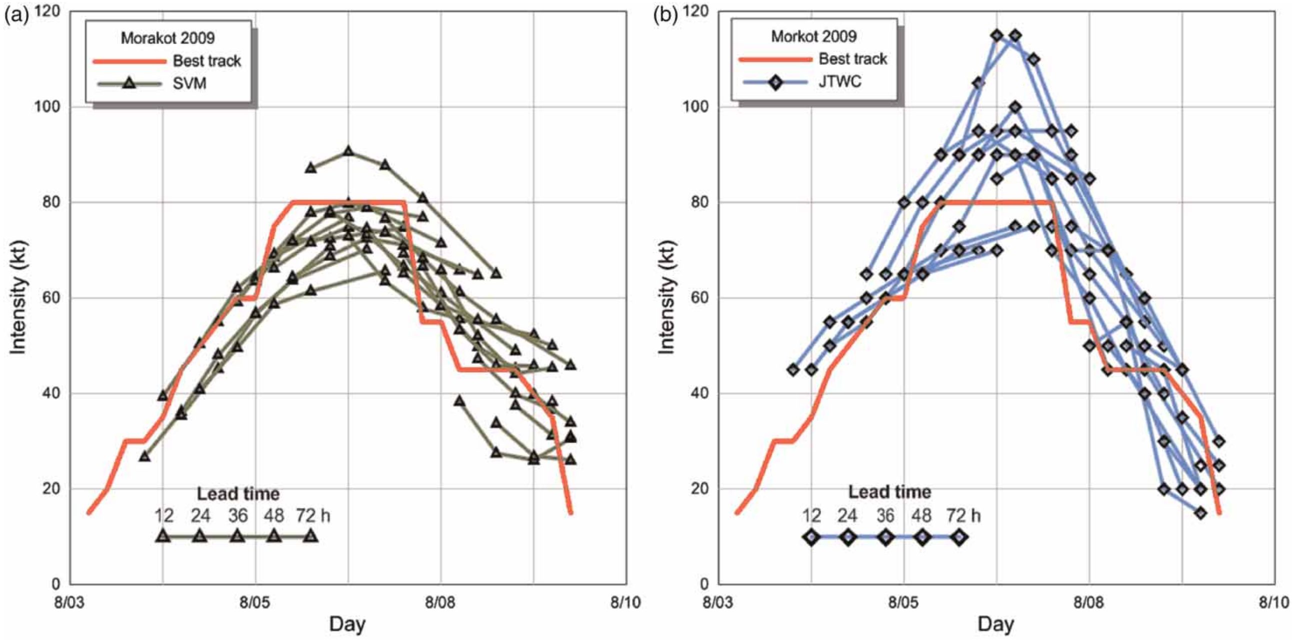

Figure 9 | Comparison of the observed intensity (the best track) with the forecasts resulting from (a) the proposed model, and (b) JTWC for Typhoon Morakot (2009). Each forecasted track made at every 6 h consists of 12, 24, 36, 48, and 72 h forecasts.

develop a model using SVM to yield the 12, 24, 36, 48 and 72 h forecasts of tropical cyclone intensity and to compare with the official forecasts issued by JTWC. The SVM-based model was developed using the synoptic information combined with the CLIPER predictors with higher spatial and temporal resolution. In addition, the MPI developed by Emanuel (1986, 1988, 1995) was also used as input to the proposed model. To obtain data that related to the cyclone intensity as input to the model, all data were extracted over the grid points within a radius of 150 km from the cyclone center. Typhoon events that reach category 1 status from June 2002 to 2009 are used herein. Moreover, typhoons making landfall or crossing over land but not reaching its maximum intensity are excluded. Therefore, a total of 83 typhoon events are chosen. As to the optimal input combination to the model, we found that maximum wind speed, latitude of typhoon center, longitude of typhoon center, and MPI are the effective factors.

First of all, the 12, 24, 36, 48 72 h forecasts of tropical cyclone intensity resulting from the proposed models are compared with those issued by JTWC, and the comparison shows that the proposed model yields significantly lower RMSE than JTWC. Especially for the long lead-time (72 h) forecasting, the percentage improvement resulting from the proposed model is up to 10.21%. Besides, the proposed model displays significantly lower SD than JTWC for the 12–72 h forecasts, which represents that the forecasting ability of the proposed model is useful and suitable with increasing forecast lead time. In addition, a total of 83 typhoon events are classified into five categories according to the Saffir-Simpson scale, and the results show that the forecasting ability of the proposed model performs better for short lead times (12 and 24 h) in five categories. For the lead times of 36, 48 and 72 h, the proposed model performs slightly worse in categories 1 and 2. It is worth noting that in categories 4 and 5 the improvement resulting from the proposed model increases with increasing forecast lead time. Generally speaking, the proposed model still demonstrates overall good forecasting ability. Lastly, when a typhoon moves into a region where water temperature changes rapidly, the proposed model clearly demonstrates the superiority of forecasting ability in different lead times. In conclusion, the advantage of the proposed model for forecasting cyclone intensity is confirmed. The use of higher resolution factors and effective SVM to construct the proposed model can indeed provide accurate forecasts of tropical cyclone intensity. The proposed modeling technique is expected to be useful for other complex problems with numerous factors. In the future, instead of SVM, other data mining techniques may be tried to examine whether the model performance can be improved.

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