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NOTES AND CORRESPONDENCE

Relationship between Vertical Wind Shear and Typhoon Intensity Change, and Development of Three-Predictor Intensity Prediction Model

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Abstract

The relationship between vertical wind shear and tropical cyclone intensity change at each time interval of 12, 24, 36, 48, 60, and 72 h in the western North Pacific is investigated using the NCEP/NCAR reanalysis data from 1983 to 1996. As expected, regression coefficients at all time intervals are positive (storm intensity is represented by the minimum surface pressure), indicating that the vertical shear weakens storm intensity. When the total sample is stratified by latitude band, it is found that the intensity of low-latitude storms is more sensitive to vertical shear than that of high-latitude storms. This is consistent with theoretical results and observations for Atlantic storms.

A minimal predictor model of predicting tropical cyclone intensity change in the western North Pacific up to 72 h is presented. The model has only three predictors (potential intensification, intensity change during previous 12 hours, and vertical shear), but the explained total variance is shown to be reasonably good in comparison to other statistical models with larger numbers of predictors. The average intensity prediction errors from the three-predictor model are reduced when the multiple linear regression method is replaced by the back-propagation neural network.

1. Introduction

It has been well documented that the vertical wind shear has a negative influence on tropical cyclone development (e.g., Gray 1968). However, the degree of the dependency of tropical cyclone intensity change on vertical shear in connection with storm location, circulation, or intensity is not well understood. The theoretical results of DeMaria (1996) show that high-latitude, large, and intense storms are more strongly coupled in the vertical than low-latitude, small, and weak storms, and thus should be more resistant to vertical shear. He also presented some supporting observational evidence for that, using large-scale wind analyses from the 1989–1994 Atlantic hurricane seasons. It would be interesting to examine vertical shear and tropical cyclone intensity change in the western North Pacific where storm activity is higher than in the Atlantic, and the climatological flows associated with a typical tropical cyclone formation are somewhat different from those in the Atlantic (McBride 1995). The first objective of this study is to document vertical shear climatology and to correlate vertical shear with tropical cyclone intensity change in the western North Pacific, in terms of latitude stratification. For this, a 14-year NCEP/NCAR (National Centers for Environmental Prediction/National Center for Atmospheric Research) reanalysis data set is utilized.

It is often of insight to construct a minimal model which can explain essential features involved. Many climatology, persistence, and synoptic factors are

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known to affect tropical cyclone intensity change (e.g., Rodgers et al. 1994), and some influential factors are faithfully included in statistical tropical cyclone intensity prediction models (DeMaria and Kaplan 1994; Fitzpatrick 1997; Petty 1999). The second objective of this study is to develop a tropical cyclone intensity prediction model with only three predictors, including vertical shear, but whose performance is reasonably good in comparison to statistical models with larger numbers of predictors. A three-predictor intensity prediction model for western North Pacific storms is constructed using both multiple linear regression method and neural network.

In Section 2, data used are described. In Section 3, results of vertical shear and tropical cyclone intensity change are presented and discussed. In Section 4, a three-predictor intensity prediction model and results are presented. Discussion and conclusion are given in Section 5.

2. Data

Data used in this study are the positions and intensities of tropical cyclones, their synoptic winds, and sea surface temperatures (SSTs) in the western North Pacific during a 14-year period of 1983–1996. Storm positions and intensities in every 6-h interval are archived from the RSMC (Regional/Specialized Meteorological Centers) Tokyo-Typhoon Center. The storm intensity is represented by the minimum surface pressure. The NCEP/NCAR reanalysis data on a 2.5° latitude/longitude resolution in every 6-h interval are used to calculate vertical wind shear. To compute the potential intensification parameter described in Section 3, the NCEP monthly mean SST data on a 1° resolution for each year of 1983–1996 are utilized. Storms that remained over land or island are not included in the analysis. The total numbers of storms and analyses are 399 and 7556, respectively. The same data were used to develop multiple regression and neural network models with eleven predictors for predicting typhoon intensity (Baik and Paek 2000).

3. Vertical shear and intensity change

To evaluate the vertical shear of horizontal winds, the symmetric part of the storm circulation is first removed by subtracting azimuthally-averaged tangential and radial winds relative to the storm position from the analysis fields. Then, the area-averaged winds are computed over an area with a radius of 600 km from the storm center. The vertical shear is the magnitude of the difference between the area-averaged 850-mb and 200-mb horizontal wind vectors.

Table 1. Average vertical shear and number of cases in a 5° latitude band.

latitude (°N)	vertical shear ($m\ s^{-1}$)	number of cases
0° ≤ lat. < 5°	12.6	3
5° ≤ lat.<10°	12.9	453
10° ≤ lat.<15°	11.7	1410
15° ≤ lat.<20°	11.9	2314
20° ≤ lat.<25°	11.9	1538
25° ≤ lat.<30°	13.9	1041
30° ≤ lat.<35°	16.6	541
35° ≤ lat.<40°	19.1	204
40° ≤ lat.<45°	22.3	50
lat. ≥ 45°	24.6	2

Table 1 lists the average vertical wind shear and the number of analyses in a 5° latitude band. The average vertical shear in the region of latitude <10° N is about 1 m s^{-1} stronger than that in the region of 10–25°N, although the number of cases is much smaller. The average vertical shear at latitudes of 10–25°N is almost independent of latitude. In the region of latitude ≥20°N, the average vertical shear increases as the latitude increases. That is, storms tend to experience more vertical shearing environments as they move northward in that region. This is related to the increasing baroclinicity with increasing latitude. The average vertical shear for the total sample (7556 cases) is 12.8 m s^{-1}.

A regression analysis is performed to determine whether the relationship between the vertical shear and intensity change depends on latitude for western North Pacific storms. For this, the intensity change at each time interval of 12, 24, 36, 48, 60, and 72 h (dependent variable) is linearly correlated with the vertical shear (independent variable). The vertical shear is averaged along the storm track using observed future wind fields to take into account the time variations of synoptic flow around the storm. This perfect-prog calculation is different from that of DeMaria (1996) in which only the initial analyses were used to evaluate the vertical shear along the storm track. Each of the dependent and independent variables is normalized by subtracting the mean and dividing by the standard deviation. This normalization is also applied to the three-predictor intensity prediction model employing multiple linear regression method, which will be presented in Section 4. The normalization allows for comparing regression coefficients at differ-

Table 2. Normalized regression coefficients and number of cases at different time intervals. The dependent and independent variables are intensity change and vertical shear, respectively.

	12 h	24 h	36 h	48 h	60 h	72 h
coefficient	0.35	0.39	0.40	0.41	0.40	0.39
cases	5559	4707	3994	3391	2873	2411

ent time intervals and variables.

The normalized regression coefficients at different time intervals are listed in Table 2. All regression coefficients are positive, indicating that the vertical shear weakens storm intensity. This is consistent with many previous studies (DeMaria and Kaplan 1994; Fitzpatrick 1997; Petty 1999). A standard t-statistic test showed that all regression coefficients are statistically significant at the 99% level. The regression coefficient increases with increasing time interval up to 48 h, and then decreases afterwards but with very little changes in its magnitude. At each time interval, the magnitude of the regression coefficient is larger than that of Atlantic storms (DeMaria 1996), especially for the longer time intervals. This might be to some extent related to the difference in averaging the vertical shear along the storm track (perfect-prog vs. initial analysis fields).

In spite of well-documented negative influence of vertical shear on tropical cyclone intensity change, the involved physical mechanisms remain less clear. A ventilation process is the most usual explanation for the effect of vertical shear (Gray 1968), where the circulation, heat, and moisture at upper levels are advected away from the low-level system, and thus storm development can be inhibited. Using a two-layer diagnostic balance model, DeMaria (1996) proposed an alternative explanation of the effect of vertical shear on tropical cyclone intensity change. In a sheared environment, the potential vorticity pattern associated with the storm circulation becomes vertically tilted, and the balanced mass field requires a midlevel warming near the storm center which acts to reduce convective activity and therefore to inhibit storm development. The spatial data resolution in this study (2.5°) limits an investigation of the physical mechanisms for vertical shear effect on intensity change. The problem remains to be examined with higher resolution data at different stages of storm development.

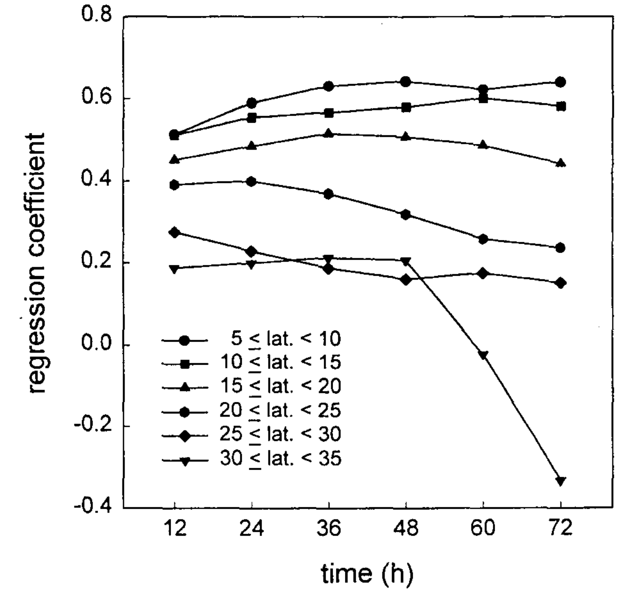

Fig. 1. Normalized regression coefficient as a function of time interval for each 5° latitude band. The dependent and independent variables are intensity change and vertical shear, respectively.

Next, the total sample is stratified into 5° latitude bands, and the resultant normalized regression coefficient as a function of time interval is shown in Fig. 1. Only the latitude bands for which the correlations of the intensity change with the vertical shear are available up to 72 h are included in this figure. Considering positive regression coefficients in Fig. 1, the regression coefficient decreases as the latitude increases at all time intervals, except for the latitude band of 30–35°N at 36 h and 48 h. This means that the intensity of low-latitude storms is more sensitive to vertical shear than that of high-latitude storms. That is, high-latitude storms are more resistant to vertical shear than low-latitude storms because of the stronger coupling in the vertical. This result agrees with the theoretical argument and observations for Atlantic storms (DeMaria 1996). The largest variation in the regression coefficient occurs in the region of 15–25°N at 60 h. It is interesting to note in Fig. 1 that the regression coefficient is negative at 72 h in the region of 30–35°N. Although the sample size in this latitude band is small (43 cases), the regression coefficient at 72 h is significant at the 95% level. The negative regression coefficient at 72 h indicates that storms are more likely to intensify even with increasing vertical shear. This situation can happen, for example, when a storm is expected to interact with mid-latitude upper-level trough in a way that acts to increase storm intensity even under its associated increasing vertical shearing environment.

4. Three-predictor intensity prediction model

Many studies have identified the factors influencing tropical cyclone intensity change (e.g., Rodgers et al. 1994). In this study, three most important predictors among possible candidates were chosen to develop a multiple linear regression model and a neural network model for predicting tropical cyclone intensity changes at 12, 24, 36, 48, 60, and 72 h.

The first predictor selected is the potential intensification variable (POT). POT is given by PMIN minus MPI, where PMIN is the initial storm intensity, and MPI is the maximum possible intensity. It is well-known that SST imposes an upper bound of tropical cyclone intensity (e.g., Emanuel 1988). In this study, MPI is calculated using the empirical function determined from a 31-year sample of western North Pacific storms (Baik and Paek 1998). SST at the storm center is determined by linearly interpolating the NCEP gridded data to the storm position and date. To take into account SST variations along the storm track, MPI is averaged along the track over the prediction interval. The second predictor is the intensity change during the previous 12 hours (DPMIN). The third predictor is the vertical shear of the horizontal winds at 850 mb and 200 mb (SHR), as described in Section 3. The latitude variable can be a dominant predictor (Hobgood 1998). This predictor is, however, excluded in the three-predictor model because the latitude variable is closely related to SST and the SST effect is included in the POT predictor. The effect of the initial storm intensity (PMIN) is included in the POT predictor.

Table 3 lists the normalized regression coefficients for the three predictors at different time intervals. All regression coefficients are significant at the 99% level, and each predictor has the same sign at all prediction intervals. The sign of the regression coefficients of POT is negative, indicating that storms are more likely to intensify further as POT becomes larger. The regression coefficient of POT increases in magnitude with increasing time interval, and becomes dominant for the longer time intervals. The positive regression coefficients of DPMIN imply that storms tend to intensify further if they have intensified during the previous 12 hours. DPMIN is a dominant predictor at 12 h, and relatively important at the shorter time intervals. The magnitude of the regression coefficient of DPMIN decreases with increasing time interval. SHR is positively correlated with the intensity change. The magnitude of the regression coefficient of SHR increases with time interval up to 48 h, and then remains the same. The percent of the variance explained by the multiple linear regression model increases with increasing time interval, ranging from 46.2% at 12 h to 62.5% at 72 h (Table 3). The explained variance is not much smaller than that of the statistical model with seven (Fitzpatick 1997) or eleven predictors (Baik and Paek 2000) for western North Pacific storms, and is comparable to that of the statistical model with eight predictors for eastern North Pacific storms (Petty 1999). Therefore, it appears that the three-predictor multiple regression model developed in this study is minimal in predictor number, but still contains essential climatology, persistence, and synoptic factors that play significant roles in tropical cyclone intensity change in the western North Pacific.

Table 3. Normalized regression coefficients for the three predictors at different time intervals. r^2 is the percent of the total variance explained by the multiple linear regression model, and N is the sample size.

variable	12 h	24 h	36 h	48 h	60 h	72 h
POT	-0.27	-0.40	-0.50	-0.58	-0.64	-0.70
DPMIN	+0.54	+0.41	+0.30	+0.23	+0.19	+0.16
SHR	+0.13	+0.18	+0.21	+0.22	+0.22	+0.22
r^2 (%)	46.2	46.3	48.6	53.0	58.0	62.5
N	5559	4707	3994	3391	2873	2411

Neural networks have been used widely for data analysis and prediction because of their excellent ability in handling nonlinear problems. This study employs the standard back-propagation neural network to construct a three-predictor intensity prediction model. This network repeatedly adjusts the connection weights in the network in a way that minimizes the error between the desired output and the actual output (Rumelhart et al. 1986). The neural network model constructed has an input layer of three units (three predictors: POT, DPMIN, and SHR), a hidden layer of six units, and an output layer of one unit (intensity change).

A hidden layer with six units were chosen after the sensitivity experiments of the intensity prediction error at 48 h to hidden-layer structure were performed with different numbers of hidden layers and different numbers of units in a hidden layer (giving the smallest error). The dependent (output) variable and independent (input) variables are properly scaled before the neural computation. For further details, see Zell et al. (1995), Baik and Hwang (1998), and Baik and Paek (2000).

For intensity prediction experiments, the total data are partitioned into the training (80%), validation (10%), and test (prediction) (10%) data sets in the neural network. In the regression, the same 80% data are utilized to rederive regression coefficients, and the same 10% data are used for the prediction sample. Figure 2 shows the average absolute intensity prediction errors from the multiple linear regression model and the neural network model. Also shown are the average absolute errors computed by assuming that the storm intensity will remain the same during the prediction time interval (no change case). The no change errors correspond

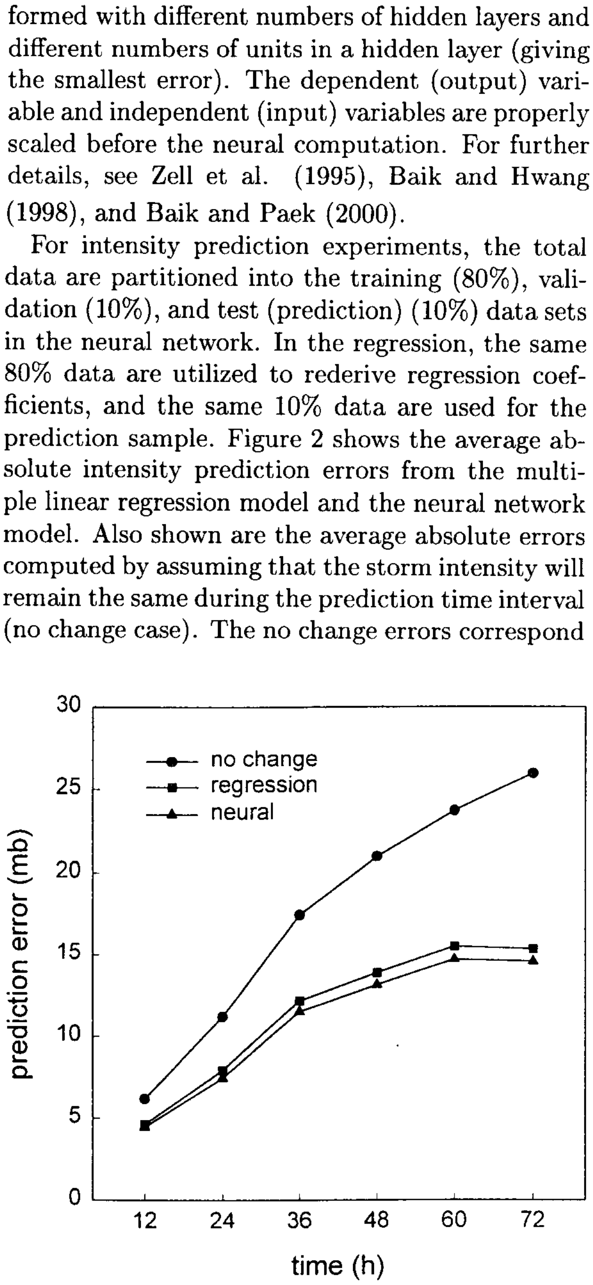

Fig. 2. Average absolute intensity prediction errors from the multiple linear regression model and the neural network model versus prediction time interval. Average absolute errors of no change prediction are also shown. The prediction sample sizes at 12, 24, 36, 48, 60, and 72 h are 556, 470, 399, 339, 287, and 241, respectively.

to the average magnitude of the observed intensity changes (DeMaria and Kaplan 1994). The intensity prediction error from both the three-predictor models increases with increasing time interval up to 60 h, and remains almost the same during the next 12 hours. At 48 h, the average errors from the regression and neural models are 13.89 mb and 13.16 mb, respectively. The ratio of the average error from the regression model to the no change error, for example, at 48 h is 0.66. This value is close to that of DeMaria and Kaplan (1994). The neural network model improves upon the multiple linear regression model by 4–6%. This improvement is due to the ability of the neural network to handle nonlinearity. The degree of the improvement of the neural network model upon the multiple linear regression model using the three-predictor (4–6%, Fig. 2) is smaller than that using eleven predictors (7–16%, Baik and Paek 2000) in the prediction of tropical cyclone intensity.

5. Discussion and conclusion

The results of Fig. 1 suggest that the intensity prediction might be improved if the latitude-dependent vertical shear were used, based upon the finding that low-latitude storms are more sensitive to vertical shear than high-latitude storms over the western North Pacific. To examine this, some tests with properly scaled SHR were undertaken using the regression approach. Results showed that the variance explained by the regression model and the average absolute intensity prediction error at each time interval are similar for the unscaled and scaled vertical shear cases. This is probably related to the fact that the average intensity error at each time interval is close to zero for the total prediction data sample (note that Fig. 2 is on the average absolute intensity error). However, it might be desirable to use a latitude-dependent vertical shear predictor if any statistical model tends to overpredict storm intensity at low latitude.

The observed intensity changes over 12, 24, 36, 48, 60, and 72-h periods are 6.19, 11.22, 17.42, 20.98, 23.74, and 25.97 mb, respectively (corresponding to no change cases in Fig. 2). The intensity prediction errors from the three-predictor multiple regression or neural network model (Fig. 2) are not small enough compared to the observed variability of tropical cyclone intensity. This holds true, even with intensity prediction models including larger numbers of predictors (DeMaria and Kaplan 1994; Baik and Paek 2000). Predicting tropical cyclone intensity remains a challenging task to tropical meteorologists.

Recently, Emanuel (1999) argued that tropical cyclone intensity can be reliably forecast using a simple coupled ocean-atmosphere model, given an accurate track forecast of a tropical cyclone. His result highlights a dominant role of oceanic forcing in determining intensity changes. The present study includes the vertical shear parameter (that is, surrounding atmospheric forcing) in a three-predictor intensity prediction model. A regression analysis was performed in which the vertical shear predictor was excluded. Results showed that the percents of the total variance explained by the two-predictor model (POT, DPMIN) at 12, 24, 36, 48, 60, and 72-h intervals are 1.3, 2.9, 4.1, 4.5, 4.6, and 4.4%, respectively, smaller than those explained by the three-predictor model (POT, DPMIM, SHR). The difference between the two models is small over all time intervals, implying that the performance of the two-predictor model excluding the synoptic wind shear information is not much behind that of the three-predictor model. This is because among the three predictors, the previous intensity change predictor (DPMIN) is important at the short-time intervals and the potential intensification predictor (POT) is dominant at the medium- and long-time intervals. However, the results of the two- and three-predictor regression models does not necessarily mean that the synoptic atmospheric forcing is negligible in comparison to the oceanic forcing over all time intervals, since the total variance explained by current statistical models is still not large enough to explain observed variabilities of tropical cyclone intensity changes. We do not know yet which forcing (atmospheric, oceanic or internal) explains dominantly the unexplained variance portion. This problem remains to be solved.

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