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A Neural Network Model for Predicting Typhoon Intensity

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Abstract

Using the back-propagation neural network, a model for predicting tropical cyclone intensity changes in the western North Pacific at 12, 24, 36, 48, 60, and 72 h is developed. The data used include the storm positions and intensities, the NCEP/NCAR reanalysis fields, and the sea surface temperature fields for western North Pacific storms occurred during a 14-year period of 1983-1996.

The predictors of the neural network model are selected based upon those of the multiple linear regression model. A regression analysis shows that the vertical wind shear predictor is consistently important over the prediction intervals. The average intensity prediction errors from the neural network model with climatology, persistence, and synoptic predictors are 7-16 % smaller than those from the multiple linear regression model with the same predictors. Even the performance of the neural network model with only climatology and persistence predictors is slightly superior to that of the multiple regression model that includes synoptic predictors as well. It is revealed that the neural network model does not always improve upon the regression model for every year during the 14 years. However, the number of years that the neural network model is superior to the regression model is (much) larger than the number of years in the reversed situation, and appears to increase with decreasing prediction interval. Sensitivity experiments show that the average intensity prediction errors from the neural network model seem to be insensitive to the number of hidden layers or the number of units in hidden layer. However, there is some room for further improvement of the neural network model upon the regression model with a better hidden-layer structure for tropical cyclone intensity prediction. This study suggests that the neural network model that includes climatology, persistence, and synoptic predictors can be used as an effective tool in tropical cyclone intensity forecasts.

1. Introduction

There have been many observational studies that investigate the factors affecting tropical cyclone intensity change (e.g., Molinari and Vollaro 1989; DeMaria et al. 1993; Rodgers et al. 1994). These include the sea surface temperature, the vertical shear of horizontal wind, the flux convergence of upper-level relative eddy angular momentum, the tropospheric water vapor flux, the land effect, and so on. The interaction of a tropical cyclone with its underlying ocean may result in a negative feedback (Khain and Ginis 1991; Schade and Emanuel 1999). The vertical wind shear is well-known to be detrimental to storm intensification (Merrill 1988; DeMaria 1996). It is also well-known that when a tropical cyclone interacts with the large-scale flow in such a way that the upper-level flow becomes more cyclonic, it can intensify (Holland and Merrill 1984; Molinari and Vollaro 1989; DeMaria et al. 1993).

Despite our understanding of the role that an individual factor plays on tropical cyclone intensity change, the factors controlling the evolution of storm intensity are still poorly understood and debatable. Present operational numerical models seem to be inadequate to meet reliable forecasts of tropical cyclone intensity. The problem of forecasting tropical cyclone intensity remains a real challenge.

Much effort has been made to statistically relate tropical cyclone intensity change to climatology, persistence, and synoptic factors and provide improved intensity forecast guidance. Nyoumura and Yamashita (1984) represented tropical cyclone intensity change in the western North Pacific as a function of sea surface temperature (SST) and land

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coverage. Elsberry et al. (1988) incorporated synoptic wind information in a statistical model for the western North Pacific basin and demonstrated that the model performance is improved when the sample is stratified by initial storm intensity. DeMaria and Kaplan (1994), hereafter DK, developed a Statistical Hurricane Intensity Prediction Scheme (SHIPS) for the Atlantic basin, which combines climatology and persistence with synoptic predictors. They showed that the average intensity prediction errors from the SHIPS model are 10–15 % smaller than the errors from a model that uses only climatology and persistence predictors, but the SHIPS model explains only 36–54 % of the variability of the observed intensity changes. Satellite data, in addition to climatology, persistence, and synoptic predictors, were utilized in a statistical intensity prediction model for western North Pacific storms by Fitzpatrick (1997). Hobgood (1998) constructed a statistical model with climatology and persistence predictors for the eastern North Pacific basin. Petty (1999) subsequently included synoptic predictors in a statistical model for the same basin and indicated that the model is better suited to handle the rapid deepening and weakening stages of intense storms.

All studies mentioned above are based upon the standard regression method to predict tropical cyclone intensity. An alternative method would be to use artificial neural networks, or simply neural networks. Since neural networks can handle unknown nonlinear behavior existing in variables well, they can be an effective alternative to traditional statistical techniques (Gardner and Dorling 1998; Hsieh and Tang 1998). Recently, Baik and Hwang (1998) applied a neural network approach to the intensity prediction of tropical cyclones over the western North Pacific and showed that the neural network model is superior to the multiple regression model. They considered, however, only climatology and persistence predictors.

In this study, we extend our previous study (Baik and Hwang 1998) by including synoptic predictors in a neural network model. It will be shown that a neural network-based model that contains climatology, persistence, and synoptic predictors is capable of providing improved forecasts of tropical cyclone intensity. In Section 2, data and predictors used in this study are described. In Section 3, intensity prediction models based upon neural network and regression method are described. In Section 4, the factors affecting tropical cyclone intensity change in the western North Pacific are discussed in detail and the performance of the neural network model is compared with that of the regression model. Also, the sensitivity of intensity prediction errors to neural network structure is examined. Finally, conclusions follow in Section 5.

2. Data and predictors

The data used in this study are for tropical cyclones and their surrounding environments in the western North Pacific during the period 1983–1996. The storm positions and intensities in 6-h intervals are archived from the RSMC (Regional/Specialized Meteorological Centers) Tokyo-Typhoon Center. In this study, storm intensity is represented by the minimum surface pressure and storms over land or islands are excluded. The NCEP/NCAR (National Centers for Environmental Prediction/National Center for Atmospheric Research) reanalysis data on a 2.5° latitude/longitude grid and every 6 hours (00Z, 06Z, 12Z, 18Z) are used to compute synoptic parameters. The NCEP monthly mean sea surface temperature data for each year on a 1° latitude/longitude grid (Reynolds 1988; Reynolds and Marsico 1993) are utilized to calculate the potential intensification variable described below. The total number of analyzed storms during the 14-year period is 399.

This study aims to develop a neural network model whose performance is generally better than that of a multiple regression model in the prediction of tropical cyclone intensity changes in the western North Pacific at 12, 24, 36, 48, 60, and 72-h intervals. In the development of regression- or neural network-based model, it is important to include independent or input variables (predictors) that significantly affect dependent or output variable (intensity change in the present study). This study considers 17 possible factors. The eight climatology and persistence variables are the same as those in Baik and Hwang (1998). These are: 1) initial storm intensity (PMIN), 2) intensity change during previous 12 hours (DPMIN), 3) absolute value of Julian date-244 (JDATE), 4) initial storm latitude (LAT), 5) initial storm longitude (LONG), 6) magnitude of storm motion vector (SMT), 7) eastward component of storm motion vector (SMU), and 8) northward component of storm motion vector (SMV). The climatological peak frequency of western North Pacific storms is observed around early September (Julian date 244) and this is included in the JDATE variable.

The synoptic environment of a tropical cyclone and its underlying ocean state play important roles in determining the evolution of tropical cyclone intensity, as briefly mentioned in the introduction. In addition to the above eight climatology and persistence variables, nine variables are included to take into account the effects of synoptic and oceanic environment. These nine variables are loosely called the synoptic variables in this study.

Since the energy to drive tropical cyclones comes mainly from the oceans in the form of latent and sensible heat fluxes, SST information should be properly included in an intensity prediction model. Following DK, Fitzpatrick (1997), and Hobgood (1998), the potential intensification variable (POT) given by

$$\mathrm{POT} = \mathrm{PMIN} - \mathrm{MPI} \tag{1}$$

is introduced. POT is the difference between the initial storm intensity (PMIN) and the maximum possible intensity (MPI). Note that in the previous studies just mentioned, the storm intensity is expressed by the maximum wind speed, while in this study it is expressed by the minimum surface pressure. Observational and theoretical studies (Miller 1958; Merrill 1987; Emanuel 1988) indicate that SST imposes an upper bound of tropical cyclone intensity. MPI in (1) is evaluated using the empirical equation that was determined using a 31-year sample of western North Pacific tropical cyclones and the NCEP monthly mean SST data for each year (Baik and Hwang 1998). To account for SST variations along the storm track, MPI is averaged over the future storm track during the prediction period (DK; Fitzpatrick 1997). SST at the storm position needed to compute MPI is obtained by linearly interpolating the gridded SST data to the storm position and date, assuming that the SST analysis fields represent the middle of each month.

The importance of vertical wind shear in tropical cyclone intensity change has been addressed by numerous studies (e.g., Merrill 1988). Following DK, for the calculation of the vertical wind shear variable (SHR), the azimuthally averaged tangential and radial winds relative to the storm position are first subtracted from the analysis fields. SHR is the magnitude of the difference between the area-averaged 850-mb and 200-mb horizontal wind vectors. The area-averaged winds are evaluated over an area with a radius of 600 km from the storm center. SHR is averaged along the future storm track to account for vertical wind shear variations along the storm track during the prediction period. In the present study, the best track data and the perfect-prog fields of wind, temperature, and water vapor (that is, observed future fields) are utilized to develop an intensity prediction model and evaluate its performance in an idealized situation. In operational intensity forecasts, information of forecast track and analyzed (or predicted synoptic) fields could be used to calculate relevant predictors. Another investigated shear variable is the time tendency of SHR (DSHR), which is computed using the vertical wind shears at the initial storm position and 24-h storm position (DK).

Tropical cyclones are more susceptible to the large-scale flow in the upper troposphere than in the lower troposphere (Holland and Merrill 1984). This is because in the lower troposphere the inertial stability is large and therefore the interaction with the large-scale flow is limited. The observational results of DeMaria et al. (1993) indicate that a statistically significant relationship can be found between the 200-mb relative eddy angular momentum flux convergence and the subsequent intensity change when hurricanes interact with upper-level troughs in the midlatitude westerlies or upper-level cold lows in low latitudes. To take into account the effect of the interaction with the large-scale flow on intensity change, two momentum variables are included — the flux convergence of relative eddy angular momentum at 200 mb (REFC) and the flux convergence of planetary eddy angular momentum at 200 mb (PEFC). These variables can be expressed by

$$\mathrm{REFC} = -\frac{1}{r^2}\frac{\partial\left(r^2\overline{u'_L\nu'_L}\right)}{\partial r}, \tag{2}$$

$$\mathrm{PEFC} = -\overline{f'u'}, \tag{3}$$

where r is the radius from the storm center, u the radial wind, ν the tangential wind, and f the Coriolis parameter. The overbar and prime in (2) and (3) represent an azimuthal mean and a deviation from the azimuthal mean, respectively. The subscript L on u and ν in (2) denotes that these quantities are calculated in a Lagrangian coordinate system moving with the storm (Molinari and Vollaro 1989; DeMaria et al. 1993). Following DK, REFC (PEFC) is radially averaged from $r = 100$ km (700 km) to 900 km (1500 km) and these variables are evaluated from the analysis fields at the beginning of the prediction period.

The integrated relative angular momentum at 850 mb (SIZE) is included to represent the outer circulation of the storm. This variable can be expressed by

$$\mathrm{SIZE} = \int_{r_1}^{r_2} (r\nu) r dr, \tag{4}$$

where $r_1 = 400$ km and $r_2 = 800$ km are taken (DK). SIZE is calculated using the field at the beginning of the prediction period.

The land coverage variable (LAND) is included to account for the land effect on storm intensity. LAND is the percent of land coverage in a 10° latitude by 10° longitude area centered at the storm location and averaged along the storm track during the prediction period.

DeMaria and Kaplan (1999) showed that storm intensification is favored when the 200-mb temperature is colder than normal. To account for this thermodynamic effect on the intensity change of western North Pacific storms, the temperature at 200 mb (T200) is included. T200 is averaged over an area with a radius of 1000 km from the storm center and calculated using the initial temperature field.

The last variable considered is the horizontal moisture flux at 850 mb (MFLX). This is given by

Table 1. Possible predictors used in this study.

1)	PMIN	initial storm intensity
2)	DPMIN	intensity change during previous 12 hours
3)	JDATE	absolute value of Julian date – 244
4)	LAT	initial storm latitude
5)	LONG	initial storm longitude
6)	SMT	magnitude of storm motion vector
7)	SMU	eastward component of storm motion vector
8)	SMV	northward component of storm motion vector
9)	POT	initial storm intensity – maximum possible intensity
10)	SHR	magnitude of vertical wind shear between 850 mb and 200 mb
11)	DSHR	time tendency of vertical wind shear magnitude
12)	REFC	200-mb relative eddy angular momentum flux convergence
13)	PEFC	200-mb planetary eddy angular momentum flux convergence
14)	SIZE	850-mb relative angular momentum
15)	LAND	land coverage
16)	T200	200-mb temperature
17)	MFLX	850-mb horizontal moisture flux

$$\mathrm{MFLX} = \overline{qu_L}, \tag{5}$$

where q is the water vapor mixing ratio. MFLX is evaluated as a net 850-mb horizontal moisture flux across r = 1000 km from the storm center. Similar to the REFC, PEFC, SIZE, and T200 variables, MFLX is calculated using the analysis fields at the beginning of the prediction period. Table 1 lists the possible predictors used in this study.

3. Development of intensity prediction models

In this study, the performance of a neural network model in predicting tropical cyclone intensity change in the western North Pacific is evaluated against that of a multiple linear regression model. Also, the impacts of including synoptic predictors are examined by comparing the performance of an intensity prediction model with climatology, persistence, and synoptic predictors with that of a prediction model that includes only climatology and persistence predictors. For these purposes, four kinds of intensity prediction models are developed — the multiple linear regression model with climatology and persistence predictors, the neural network model with climatology and persistence predictors, the multiple linear regression model with climatology, persistence, and synoptic predictors, and the neural network model with climatology, persistence, and synoptic predictors.

Since Rumelhart et al. (1986) introduced the back-propagating algorithm, neural networks for data analysis and prediction have been rapidly developed and improved. A review of the applications of neural network models to data analysis and prediction in meteorology and oceanography is given by Hsieh and Tang (1998). A typical neural network consists of three layers of units that are fully connected — a layer of input units, a layer (or layers) of hidden units, and a layer of output units (see Fig. 1). The back-propagation neural network repeatedly adjusts the connection weights in the network so as to minimize the error between the desired output and the actual output (Rumelhart et al. 1986). The back-propagating algorithm is known to be most useful when one tries to solve a problem in which the relation between input and output is nonlinear and training data are abundant (Hinton 1992).

This study employs the standard back-propagation neural network in the SNNS (Stuttgart Neural Network Simulator) (Zell et al. 1995) to construct neural network models for predicting tropical cyclone intensity changes at 12, 24, 36, 48, 60, and 72-h time intervals. Data are partitioned into the training, validation, and test (prediction) data sets to make a neural network generalize best. The training data set is utilized to train a neural network, the validation data set is used to determine its performance on patterns that are not trained during the learning, and the test data set is used to finally check its overall performance (Zell et al. 1995). It is convenient to make values of the dependent variable lie between 0 and 1 by a proper transformation, because the sigmoid (or logistic) function takes values in that range. For this, the dependent variable is normalized by subtracting the mean and dividing by the standard deviation. Then, each of the calculated values is divided by twice the maximum absolute value among those and finally 0.5 is added. Each of the independent variable is divided by its maximum absolute value, hence yielding its values between -1 and 1. For further details, see Zell et al. (1995) and Baik and Hwang (1998). Figure 1 shows the structure of a three-layer neural network model used in this study. In this network, the input layer has 11 units (that is, 11 predictors listed in Table 2), the hidden layer has 11 units, and the output layer has 1 unit that corresponds to the tropical cyclone intensity change variable.

A multiple linear regression model for predicting tropical cyclone intensity change at each time interval is constructed following the standard statistical technique (e.g., Walpole and Myers 1989). Each of the dependent and independent variables is normalized by subtracting the mean and dividing by the standard deviation. This enables us to compare regression coefficients for different variables and different prediction intervals (DK; Fitzpatrick 1997; Hobgood 1998; Petty 1999).

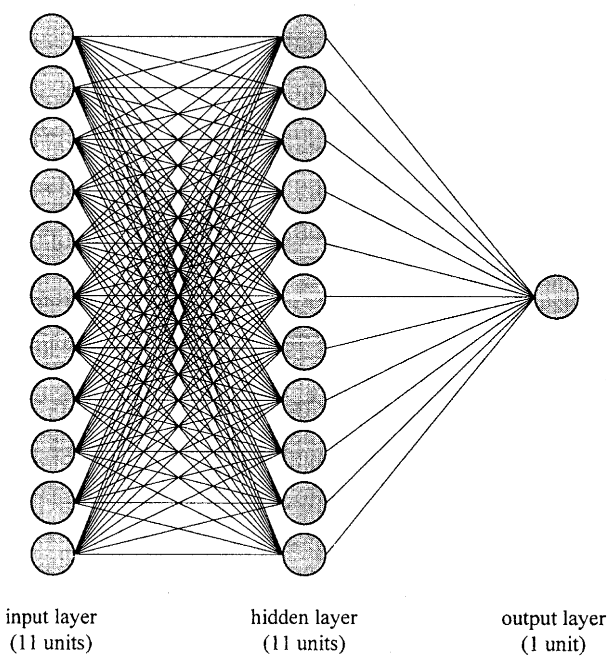

Fig. 1. The structure of a three-layer neural network used in this study. The input layer, hidden layer, and output layer have 11 units, 11 units, and 1 unit, respectively.

4. Results and discussion

The predictors of the multiple linear regression and neural network models with climatology and persistence variables are the first eight variables listed in Table 1. For a selection of predictors for the regression model with climatology, persistence, and synoptic variables, a backward stepwise procedure is used for each regression. This begins with four climatology variables (PMIN, DPMIN, JDATE, and LAT) and the nine synoptic predictors listed in Table 1. The variables LONG, SMT, SMU, and SMV are excluded to avoid the inclusion of too many climatology and persistence predictors. The excluded four variables are relatively much less important than the included four variables in contributions to the total variance (not shown). Through this backward stepping procedure, independent variables are excluded in the regression equation when they are not statistically significant at the 95 % confidence level over all prediction time intervals. Independent variables are retained in the regression equation when they are statistically significant at the same confidence level at one or more of the prediction intervals.

Table 2 lists the normalized regression coefficients of eleven predictors selected using the backward-stepping procedure. The regression coefficients without the superscript (*) are statistically signifi-

Table 2. Normalized regression coefficients for climatology, persistence, and synoptic predictors and different time intervals. All regression coefficients are statistically significant at the 95 % confidence level except for those with superscript (*). 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
PMIN	-0.24	-0.34	-0.39	-0.43	-0.44	-0.44
LAT	+0.16	+0.25	+0.32	+0.36	+0.39	+0.41
DPMIN	+0.51	+0.38	+0.26	+0.18	+0.13	+0.09
SHR	+0.14	+0.20	+0.24	+0.25	+0.25	+0.25
JDATE	+0.12	+0.17	+0.21	+0.24	+0.25	+0.26
LAND	+0.10	+0.12	+0.13	+0.12	+0.11	+0.10
POT	-0.04	-0.06	-0.09	-0.11	-0.14	-0.19
SIZE	-0.04	-0.04	-0.04	-0.05	-0.05	-0.04
MFLX	+0.04	+0.04	+0.05	+0.04	+0.04	+0.03
REFC	-0.02*	-0.02*	-0.02*	-0.01*	-0.02*	-0.02
PEFC	+0.00*	+0.00*	-0.01*	-0.02*	-0.03	-0.04
r^2 (%)	49.3	51.8	56.0	61.5	66.8	71.3
n	5559	4707	3994	3391	2873	2411

cant at the 95 % level and the predictors are listed in order of the prediction-interval averaged magnitude of the regression coefficients. All regression coefficients except for those of REFC and PEFC are statistically significant at all prediction intervals. The regression coefficients of REFC (PEFC) are only significant at 72 h (60 and 72 h). For every predictor except for PEFC, the regression coefficient has the same sign at all prediction intervals.

The most important predictor in the six regression equations is the initial (that is, current) storm intensity (PMIN). In a statistical intensity prediction model for the eastern North Pacific that includes synoptic variables, the initial storm intensity was also the most important predictor (Petty 1999). PMIN is negatively correlated with storm intensification. That is, weak (strong) storms are more likely to experience intensification (weakening) than weakening (intensification). This is because stronger storms have an intensity that is closer to their maximum possible intensity and thus have less potential for further intensification (DK). The magnitude of the normalized regression coefficient of PMIN is largest among the eleven predictors at 36, 48, 60, and 72 h and increases with increasing prediction interval up to 60 h.

The second most important predictor is the latitude (LAT). LAT is positively correlated with intensification. This is because SST tends to decrease toward north in the western North Pacific and storms moving northward are more likely to move over colder water, hence undergoing weakening in their intensity. The regression coefficient of LAT becomes larger for the longer time intervals. At 72 h, its value is 0.41. The relatively large coefficient of LAT, especially after 36 h, implies that SST variations with latitude significantly influence intensity changes of western North Pacific storms. Another plausible reasoning for the positive correlation between LAT and intensity change is that as storms move northward, they can experience the environment of increasing vertical wind shearing due to the increasing baroclinicity. This situation is unfavorable for intensification. As discussed by Hobgood (1998), these two factors can be combined to give the high correlation between LAT and intensity change in the western North Pacific. Interestingly, in a statistical model with climatology and persistence predictors (including potential intensification and land predictors) for the eastern North Pacific, the latitude was found to be the most important parameter (Hobgood 1998).

The intensity change during the previous 12 hours (DPMIN) is the third most important predictor. The correlation between DPMIN and intensity change is positive. That is, storms are likely to intensify further if they have intensified during the previous 12 hours. The regression coefficients of DPMIN exhibit that this predictor is dominant over all other predictors at 12 and 24 h. The coefficient decreases as the time interval increases, from 0.51 at 12 h to 0.09 at 72 h. These results indicate that the intensity change in the past 12 h is the most important predictor in short-term intensity forecasts. This is consistent with the results of Hobgood (1998) and Petty (1999).

The next important predictor is the vertical shear of horizontal winds between 850 mb and 200 mb (SHR). Although the physical mechanisms that can explain how the vertical wind shear affects tropical cyclone intensity are not fully understood, the fact itself that the vertical wind shear is detrimental to storm intensification is well-known. As should be expected, the correlation between SHR and intensity change is positive, meaning that the vertical wind shear inhibits storm intensification. The regression coefficient of SHR increases over the first 36-h prediction intervals. After 24 h, its values are similar to each other. This agrees with the results for western North Pacific storms by Fitzpatrik (1997) and Atlantic storms by DeMaria and Kaplan (1999).

The Julian date variable (JDATE) represents how far the storm date is deviated from that of climatological peak frequency for western North Pacific storms (Baik and Hwang 1998). It is expected that the storm environment including SST becomes, in a climatological sense, more favorable for storm intensification as the storm date is closer to the climatological peak frequency date. This is reflected as the positive regression coefficient of JDATE in Table 2. The influence of JDATE on intensity change is larger for the longer prediction intervals than for the shorter ones. It is found that the relative importance of JDATE among predictors is similar in statistical intensity prediction models that include synoptic predictors [sixth order in the SHIPS model (DK), fourth order in the EPIC model (Petty 1999), and fifth order in the present model].

Although the cases that storms moved over land (or islands) are eliminated in this study, storms can be still influenced in their intensity when they are close to land. The land coverage predictor (LAND) included is positively correlated with intensity change. That is, storms tend to become weakened as the land coverage increases. The regression coefficients of LAND are nearly the same over the prediction intervals (0.10–0.13). This is different from the result from the SHIPS model (DK), in which the coefficient decreases with increasing prediction interval. Note that the land variable in this study is represented by the percent of land coverage in a 10° latitude by 10° longitude area centered at the storm location and averaged over the future storm track. On the other hand, the land variable in the SHIPS model is represented by the distance to the nearest landmass and determined from the storm location at the prediction time. These differences between the two models can contribute to the result difference.

The potential intensification variable (POT) is a measure of further intensification of a storm from its current intensity to the maximum possible intensity. Negative regression coefficients of POT in Table 2 imply that storms tend to intensify further as POT becomes larger. The magnitude of the regression coefficient of POT increases with increasing time interval. At all prediction intervals, the magnitude of the regression coefficient of POT is much smaller than that in the SHIPS model (DK). In the SHIPS model, the POT variable was found to be most important among the selected ten predictors. In the calculation of POT, PMIN and MPI are needed (see (1)) and MPI is a function of SST. As already discussed, LAT is highly correlated with SST. Since the two most important predictors in this study are PMIN and LAT, much less variance is left to be explained by POT. This is consistent with the result of Hobgood (1998). Strictly speaking, *independent* variables should be selected as predictors in a statistical regression model. However, among the eleven predictors listed in Table 2, for example, PMIN is not strictly independent of POT. In a future study, it is desirable to select predictors that are independent (or almost independent) of each other. In the SHIPS model (DK), the initial storm intensity variable is not included because it is highly correlated with POT. The much smaller magnitude of the regression coefficient of POT in the present model than in the SHIPS model is related to the inclusion of the initial storm intensity and latitude predictors in this study. Indeed, our calculations revealed that when PMIN (or LAT) or both PMIN and LAT is (are) eliminated in the regression analysis, the POT becomes the most important predictor. This is consistent with the result of DK.

The storm size predictor (SIZE), which is the integrated relative angular momentum at 850 mb, is negatively correlated with storm intensification. This means that storms are more likely to intensify as their outer circulation becomes stronger. This agrees with the results of DK and Petty (1999). The magnitude of the regression coefficient of SIZE remains almost unchanged over the prediction intervals.

The sign of the regression coefficient of the 850-mb moisture flux predictor (MFLX) is positive. This result is expected because the net inward low-level moisture flux is favorable for storm intensification. All predictors presented above are statistically significant at the 95 % level over all prediction intervals and the signs of their regression coefficients are consistent with the physical reasoning.

The remaining two predictors are related to the upper-level eddy momentum flux convergence parameters — the 200-mb relative eddy angular momentum flux convergence (REFC) and the 200-mb planetary eddy angular momentum flux convergence (PEFC). The positive sign of REFC and PEFC corresponds to a situation in which the momentum fluxes are acting in a way that makes the upper-level flow more cyclonic. This situation is known to be favorable for storm intensification (e.g., Molinari and Vollaro 1989). As expected, the sign of REFC and PEFC is negative except for the PEFC cases at 12 and 24 h, even in which cases its regression coefficient is very close to zero. Note that REFC (PEFC) is only statistically significant at 72 h (60 and 72 h). In this study, the dependent variable is intensity change. It would probably be possible to choose the actual storm intensity as a dependent variable. However, in this case, the results would be harder to interpret physically.

The percent of the total variance explained by the multiple linear regression model is listed in Table 2. The percent of the total variance increases with increasing time interval, ranging from 49.3 % at 12 h to 71.3 % at 72 h. A comparison of Table 2 with that corresponding to the multiple linear regression model with the eight climatology and persistence predictors (not shown) indicates that the inclusion of synoptic predictors increases the explained total variance over all prediction intervals. The difference between the two regression models ranges from 2.1 % at 12 h to 7.6 % at 60 h. The degree of improvement in the explained variance by including synoptic variables for western North Pacific storms (this study) is smaller than that for Atlantic storms (DK), but slightly larger than that for eastern North Pacific storms (Petty 1997).

As already mentioned, some variables used in this study are not strictly independent of each other, but serially correlated. This can artificially inflate the explained variance. Also, the use of too many variables can increase the chance that a variable will be found to be significant by chance, resulting in variance inflation. The use of a partial correlation analysis and higher significance values are ways to avoid serial correlations and fewer predictors will reduce variance inflation, probably without changing the actual prediction errors very much. These serial correlations and inflated variance problems are, however, believed not to affect the overall results of the present study which aims at developing a neural network model which includes synoptic predictors and comparing its performance to that of a multiple regression model.

It is important to sensibly select input units (predictors) among possible variables in order to construct a well-performed neural network model. In this study, the predictors of the neural network model are selected based on those of the multiple linear regression model. Here, the same predictors as those selected for the multiple linear regression model are utilized for input units for the neural network model. That is, the eleven predictors listed in Table 2 are also the eleven input units for the neural network model that includes climatology, persistence, and synoptic variables. A further study is needed to determine relatively significant input variables among possible candidates for a well-performed network.

For the neural prediction of tropical cyclone intensity change, the total data are partitioned into 80 %, 10 %, and 10 % of the total, which consist of the training, validation, and test data sets, respectively. For comparison of results, the same 80 % data are used to construct a multiple linear regression model and the same 10 % data are used for prediction data set in the regression model.

Figure 2a shows the average intensity prediction errors from the four constructed models versus prediction time interval. These are the multiple linear regression model with climatology and persistence predictors (R-CP), the neural network model with climatology and persistence predictors (N-CP), the multiple linear regression model with climatology, persistence, and synoptic predictors (R-CPS), and the neural network model with climatology, persistence, and synoptic predictors (N-CPS). In all models, the average intensity prediction error increases with increasing time interval up to 60 h. After that time, the error reduces in the R-CP, N-CP, and R-CPS models, but increases in the N-CPS model. Among the four models, the performance of the N-

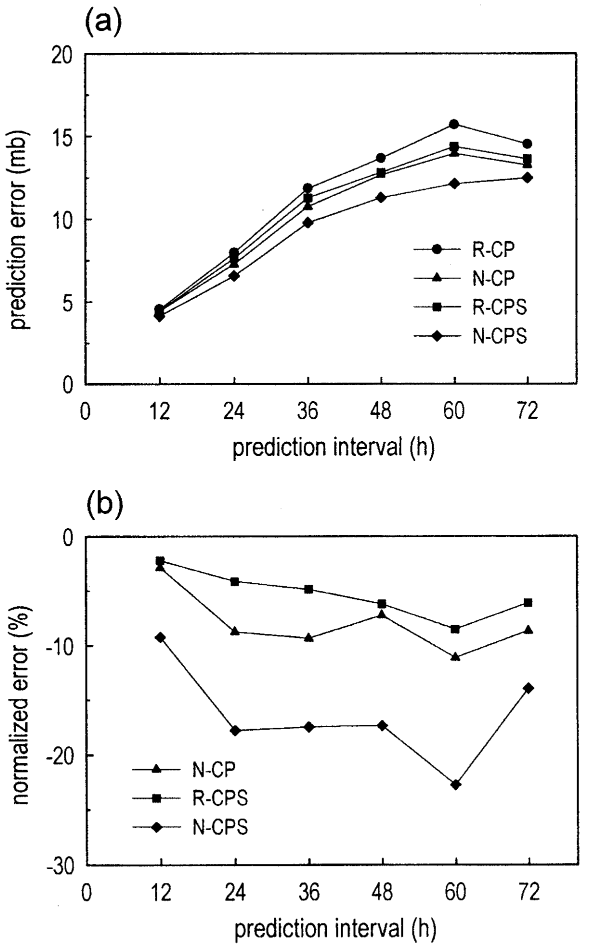

Fig. 2. (a) Average intensity prediction errors (mb) from the multiple linear regression model with climatology and persistence predictors (R-CP), the neural network model with climatology and persistence predictors (N-CP), the multiple linear regression model with climatology, persistence, and synoptic predictors (R-CPS), and the neural network model with climatology, persistence, and synoptic predictors (N-CPS) versus prediction time interval. (b) Normalized intensity prediction errors (%) from the N-CP, R-CPS, and N-CPS models relative to the R-CP model versus prediction time interval.

CPS model in predicting tropical cyclone intensity is the best and that of the R-CP model is the worst. It is interesting to observe that the performance of the N-CP model is slightly better than that of the R-CPS model.

The average magnitudes of the observed intensity changes at 12, 24, 36, 48, 60, and 72-h time intervals in the data sample are 6.19, 11.22, 17.42, 20.98, 23.74, and 25.97 mb, respectively. The prediction errors in Fig. 2a are not small enough compared to these natural changes of tropical cyclone intensity. This shows a real difficulty of predicting tropical cyclone intensity and requires our continuous research effects to better forecast intensity. Considering our current state of tropical cyclone intensity forecasts, the results from the neural network model are quite encouraging.

Figure 2b shows the normalized intensity prediction errors from the N-CP, R-CPS, and N-CPS models relative to the R-CP model versus prediction time interval. The normalized error is computed using

$$\mathrm{NE} = \frac{\mathrm{E_m} - \mathrm{E_r}}{\mathrm{E_r}} \times 100(\%), \qquad (6)$$

where $\mathrm{E_m}$ is the average error from the N-CP or R-CPS or N-CPS model and $\mathrm{E_r}$ is the average error from the R-CP model. A negative normalized error indicates improvement upon the R-CP model. By including synoptic predictors in the multiple linear regression model with climatology and persistence predictors, the regression model (R-CPS) is improved by 2–9 %. With the same climatology and persistence predictors, by replacing the regression method by the neural network, the neural network model (N-CP) improves upon the regression model (R-CP) by 3–11 %. By including synoptic predictors and replacing the regression method by the neural network, the neural network model (N-CPS) improves upon the regression model (R-CP) by 9–23 %. With the same climatology, persistence, and synoptic predictors, the neural network model (N-CPS) improves upon the regression model (R-CPS) by 7, 14, 13, 12, 16, and 8 % at 12, 24, 36, 48, 60, and 72 h, respectively. The average improvement is as large as 12 %.

Figure 2 indicates that the neural network model is superior to the multiple linear regression model in tropical cyclone intensity prediction. A reason for this is that the neural network has an internal ability to account for complex nonlinear interactions between units by including the nonlinear activation function. However, no general theory has been proposed which makes it possible to determine the exact relationship between input and output units by analyzing network weights. This black-box nature of neural networks may limit its usefulness if the problem under investigation is to understand a physical process through variables. This nature does not matter, however, if the problem is concerned with operational forecasts or is not to find an exact input-output relationship. In this somewhat practical viewpoint, the results of Fig. 2 suggest that the back-propagation neural network can provide potential in the operational forecasting of tropical cyclone intensity.

Sarle (1994) described the connections between neural networks and statistical models. The multilayer perceptron used in this study corresponds to the multiple nonlinear regression model. Therefore, it might be, in principle, possible to develop a multiple nonlinear regression model whose prediction performance is similar to that of a neural network model. However, it is very difficult to find a best-performed nonlinear functional relationship between dependent and independent variables in a multiple nonlinear regression model. Moreover, physical interpretations to nonlinear terms are not always possible. As stated by Sarle (1994), neural networks and statistics are not competing methodologies for data analysis and prediction and better communication between the two fields would benefit both. For example, as was done in this study, the choice of input units for the neural network and some physical interpretations can greatly benefit from the multiple linear regression method.

Figure 3 shows the normalized intensity prediction errors from the neural network model with climatology, persistence, and synoptic predictors (N-CPS) relative to the multiple linear regression model with the same predictors (R-CPS) as a function of year at prediction intervals of 24, 36, 48, and 60 h. To simulate a real-time forecast environment, for the intensity prediction of a particular year, the data sample eliminates that year to construct multiple regression and neural network models. For example, for the intensity prediction of 1991 tropical cyclones over the western North Pacific, the data sample of 1983–1990 and 1992–1996 is used to construct the two models. At 24 h, the neural network model in predicting tropical cyclone intensity is superior to the regression model over all years except for one year (1992). At 36 h, except for two years (1986 and 1996), the improvement of the neural network model upon the regression model is observed over 12 years. At 48 h, the neural network model improves upon the regression model over all years except for three years (1986, 1987, and 1996). At 60 h, the performance of the neural network model is better than the regression model for nine years and the largest improvement occurs in 1995 (22 %). Figure 3 shows that the neural network model does not always improve upon the regression model for every year during the 14-year period. However, the number of years that the neural-based prediction is superior to the regression-based prediction is (much) larger than the number of years that the regression-based prediction is superior to the neural-based prediction and appears to increase with decreasing prediction interval.

There are some interesting features in the normalized errors in Fig. 3. For example, in 1987 the neural network model is better than the regression model at 24 h, but afterwards its skill decreases with time. The neural network model is eventually worse than the regression model at 48 h and becomes worse with time. Another example is that in 1992 the neural

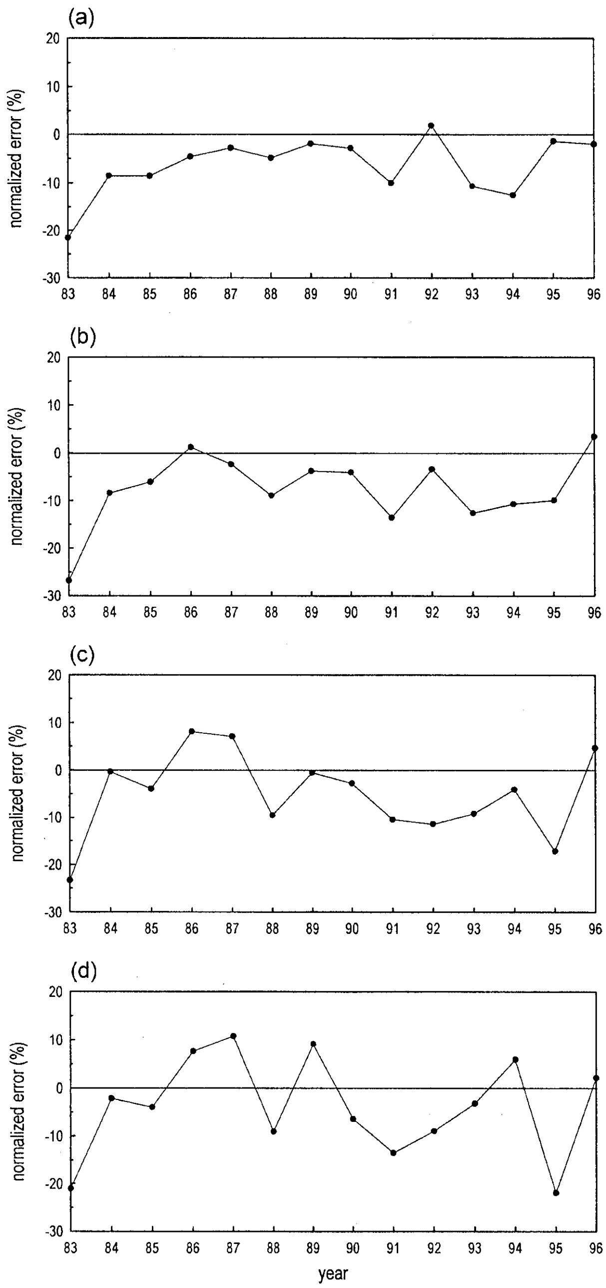

Fig. 3. Normalized intensity prediction errors (%) from the neural network model with climatology, persistence, and synoptic predictors (N-CPS) relative to the multiple linear regression model with the same predictors (R-CPS) as a function of year at the prediction time intervals of (a) 24 h, (b) 36 h, (c) 48 h, and (d) 60 h.

network model is slightly worse than the regression model at 24 h, but afterwards becomes better with time. At 36 and 48 h, the neural network model improves upon the regression model by 3 and 11 %, respectively. In this study, no attempts are made to stratify the data sample (for example, by storm intensity) or characterize year-to-year variabilities in storms and their environment. With these points taken into account, a further study is required to examine under what conditions the neural model performs better than the regression model in predicting tropical cyclone intensity or vice versa.

In multilayer perceptrons, the hidden units are internal and not part of the input or output. Their introduction to neural networks is, however, crucial for nonlinear learning representations. The sensitivity of tropical cyclone intensity prediction errors to hidden-layer structure is investigated with climatology, persistence, and synoptic variables. A selected time interval is 48 h. Figure 4a shows the average intensity prediction errors as a function of the number of hidden layers. In these sensitivity experiments, the number of hidden layers varies from one (the N-CPS case at 48 h in Fig. 2a, hereafter called the control case) to five, but the number of units in each hidden layer is the same as that of input units (that is, eleven). The average intensity prediction errors appear to be nearly equal in all five cases. The error is, however, minimum when the number of hidden layers is two. The error difference between the control case and the case with two hidden layers is 0.21 mb. The neural network models of the control case and the case with two hidden layers improve upon the multiple linear regression model by 11.9 and 13.5 %, respectively. Therefore, 1.6 % more improvement at 48 h occurs when the number of hidden layers changes from one to two. Results of another sensitivity experiments are plotted in Fig. 4b which shows the average intensity prediction errors as a function of the number of units in hidden layer. In these experiments, the number of hidden layers is one and the number of units in hidden layer varies with 11, 11 ±2, and 11 ±4. Note that the case with eleven hidden units is the control case. This figure shows that the average intensity prediction errors remain almost unchanged with the number of hidden units, but there is a tendency that the error decreases slightly as the number of units in hidden layer increases. The maximum error difference among the five cases is 0.15 mb. The control case and the case with 15 hidden units improve upon the multiple linear regression model by 11.9 and 12.7 %, respectively. Therefore, 0.8 % more improvement at 48 h occurs when the number of hidden units changes from 11 to 15.

Figure 4 indicates that the intensity prediction errors from the back-propagation neural network model seem to be insensitive to the number of hidden layers or the number of units in hidden layer, within the ranges of tested values. However, as shown above, there is some room for further improvement of the neural network model upon the multiple linear regression model by constructing a better hidden-layer structure for tropical cyclone intensity prediction. This needs to be investigated further.

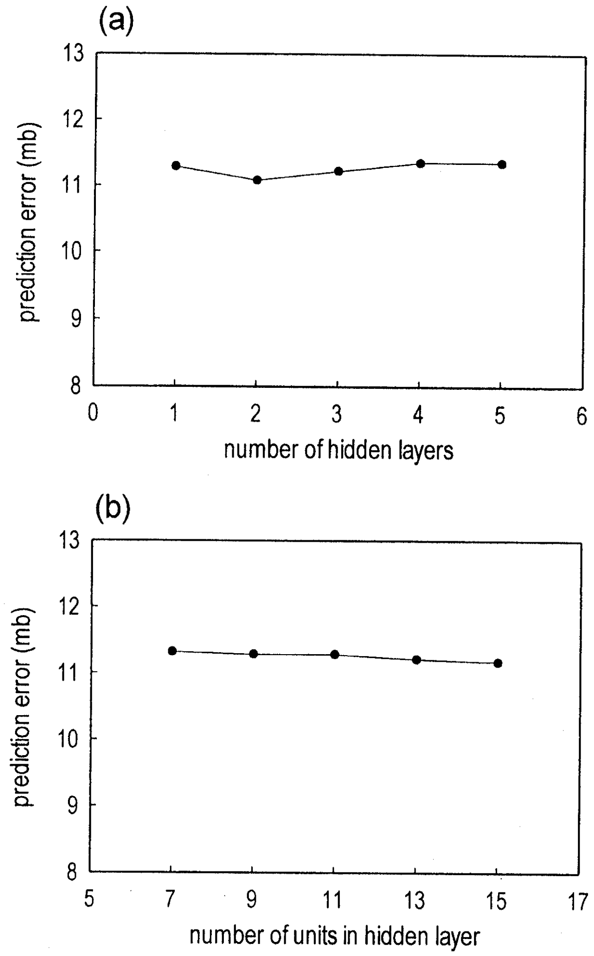

Fig. 4. (a) Average intensity prediction errors (mb) at 48 h versus number of hidden layers. Each neural network structure is the same as that of the N-CPS model in Fig. 1 except that the number of hidden layers varies. (b) Average intensity prediction errors (mb) at 48 h versus number of units in hidden layer. Each neural network structure is the same as that of the N-CPS model in Fig. 1 except that the number of units in hidden layer varies.

5. Conclusion

In contrast with our understanding of tropical cyclone motion and operational track forecasts, the physical mechanisms for tropical cyclone intensity change in a varying environment are poorly understood and objective guidance for operational intensity forecasts is very limited. In this study, a neural network model that includes climatology, persistence, and synoptic predictors was developed to predict tropical cyclone intensity changes in the western North Pacific up to 72 h and its performance was compared with that of corresponding multiple linear regression model. It was revealed that the neural network model appears to improve upon the multiple linear regression model in intensity prediction and there is some room for further improvement of the neural network model with a better hidden-layer structure. These results suggest that the neural network model that includes synoptic predictors can be used as an effective tool in operational tropical cyclone intensity forecasts. A further improvement of the neural-based intensity prediction model is underway and its incorporation into an operational typhoon forecast cycle is expected.

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台風の強度を予測するためのニューラルネットワークモデル

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バックプロパゲーション型ニューラルネットワークを使って、北西太平洋での熱帯低気圧の強度の変化を 12, 24, 36, 48, 60, 72 時間について予測するモデルを開発した。用いたデータは、1983–1996 の 14 年間の北西太平洋の熱帯低気圧に対する、低気圧の位置、強度、NCEP/NCAR の再解析、それに海面水温である。

ニューラルネットワークの予測因子は重線形回帰モデルの予測因子に基づいて選ばれた。回帰分析により、予測因子の一つ風の鉛直シアーが全ての予測時間に渡って一貫して重要であることを示した。予測因子として気候学的、持続的、総観的因子を用いたニューラルネットワークモデルによる平均予測誤差は、同じ予測因子を用いた重線形回帰モデルに比べて 7–16 さらに、予測因子として気候学的、持続的因子のみを用いたニューラルネットワークモデルの性能でさえも、総観的因子まで含んだ重線形回帰モデルの性能をわずかに上回った。ニューラルネットワークモデルの性能は 14 年間の全ての年について回帰モデルを上回るわけではないけれども、ニューラルネットワークモデルの方が良い年の方が逆の年よりもずっと多く、その傾向は短い予測時間の方が顕著である。感度実験により、ニューラルネットワークモデルの平均強度予測誤差は、隠れ層や隠れ層のニューロンの数には敏感ではないことを示した。しかし、熱帯低気圧強度予測のために、より良い隠れ層の構造を用いることにより、回帰モデルに比べてニューラルネットワークモデルをさらに改良する余地がいくらかある。この研究は、予測因子として気候学的、持続的、総観的因子を用いたニューラルネットワークモデルが熱帯低気圧の強度予報において有効な道具として使えることを示唆している。