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A soft-computing cyclone intensity prediction scheme for the Western North Pacific Ocean

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Abstract

A soft-computing cyclone intensity prediction scheme (SCIPS) is introduced using an artificial neural network (ANN) approach and adding ocean heat content, as an additional predictor to the normally used atmospheric parameters, to predict tropical cyclone intensity change in the western north Pacific Ocean. We used 1997–2004 data to develop and validate this scheme. The ANN-based estimations have been compared with observations and estimations using the multiple linear regression (MLR). SCIPS performance improves upon MLR as the lead hour increases from 12 to 120 h and also for high intensifying cyclones.

Keywords: **cyclone intensity prediction change; artificial neural network approach; ocean heat content**

1. Introduction

Prediction of tropical cyclone intensity has been a challenging problem. Modest improvements of operational intensity forecasts, at best, have been realized in recent years (DeMaria *et al*., 2007). Of particular interest for this study are operational intensity forecasts in the western North Pacific, which have shown little improvement in the last few years. In 2011, statistical-dynamic methods outperformed the pure dynamic methods and the official forecasts (Falvey, 2012). Despite realizing the complexities involved in the cyclone intensity prediction, there has been a continuous effort in improving its accuracy. As the existing numerical and statistical models have shortcomings, DeMaria and Kaplan (1999) developed a statistical-dynamic approach called Statistical Hurricane Intensity Prediction Schemes (SHIPS) for use in North Atlantic and North Eastern Pacific Oceans. This approach combines statistical method with environmental predictors from numerical weather forecasts. Another example of this approach is the Statistical Typhoon Intensity Prediction Scheme (STIPS: Knaff *et al*., 2005) operational at Joint Typhoon Warning Centre (JTWC), which has led to consensus methods (Sampson *et al*., 2008).

In statistical-dynamic approach used in SHIPS and STIPS, the predictors are taken from a dynamic model and a multiple linear regression (MLR) is then used to predict the change in cyclone intensity. In addition to using a purely statistical approach like MLR, artificial neural network (ANN) is another non-dynamic numerical method that has been used in many oceanography studies (Ali *et al*., 2004; Tolman *et al*., 2005; Jain and Ali, 2006; Swain *et al*., 2006; Jain *et al*., 2007; Ali *et al*., 2012a, 2012b, 2012c), meteorological studies (French *et al*., 1992; Liu *et al*., 1997; Ali *et al*., 2007; Sharma and Ali, 2012), and in satellite parameter retrieval techniques (Krasnopolsky *et al*., 1995; Krasnopolsky and Schiller, 2003). Roebber *et al*. (2003) and Marzban *et al*. (2007) apply ANNs to the problems of snow-to-liquid ratio (SLR) and ceiling/visibility forecasts, respectively. They show that where a MLR technique might be workable save for the noisiness of the data, an ANN can provide useful results. Similarly, Swain *et al*. (2006) demonstrated that the ANN approach is superior to MLR in estimating ocean mixed layer depth. Jin *et al*. (2008) combined ANN and genetic algorithm techniques and proved that this approach could give a better typhoon intensity prediction compared with the climatology and persistence method.

In most tropical cyclone intensity models sea surface temperature (SST) is the only oceanographic parameter used to represent the heat exchange. However, tropical cyclones have long been known to interact with the deeper layers of the ocean than sea surface alone (Perlroth, 1967; Gray, 1979; Holliday and Thompson, 1979; Price, 1981; Emanuel, 1986; Shay *et al*., 2000). Similarly, Namias and Canyan (1981) observed patterns of lower atmosphere anomalies being more consistent with the upper ocean thermal structure variability than with SST. Using a coupled ocean-atmospheric model, Mao and Pfeffer (2000) concluded that the rate of intensification and final intensity of the tropical cyclones was more sensitive to the initial spatial distribution of the mixed layer than to SST alone. Ali *et al*. (2012a, 2012b, 2012c) reported that more than 50% of the cyclone intensities in the north Indian Ocean have a significant (at 95% level) negative correlation with SST. Thus it is the deep surface layer, not simply the surface itself that is important to cyclone intensification. Ali *et al*. (2013a, 2013b) suggested using ocean mean temperature, which can be computed from the ocean heat content (OHC) derivable from satellite altimetry, as an alternative to SST.

The sea surface height anomaly (SSHA) derived from satellite altimeters, available since 1993, has provided significant information about ocean eddies and allow for the estimation of oceanic heat content. Typically positive (negative) SSHAs corresponding to more (less) upper OHC. Such information has been used to study tropical cyclones. Shay *et al*. (2000) and Mainelli *et al*. (2008) conclude that the upper OHC may be important for forecasting tropical cyclone intensity change, particularly for those tropical cyclones that become most intense. Hurricane Opal, in the Gulf of Mexico, intensified unexpectedly, where its core pressure dropped from 965 to 916 hPa over a 14-h period after crossing a warm core eddy with more OHC that had gone undetected by the SST from advanced very high resolution radiometer (Shay *et al*., 2000; Goni and Trinanes, 2003). Ali *et al*. (2007) prove how warm (cold) core eddies with more (less) OHC are related to tropical cyclones that intensify (dissipate) in the Bay of Bengal. Lin *et al*. (2013) show how ocean subsurface warm features like eddies are critical for the rapid intensification of cyclones and the associated storm surge. More information can be found in a review article about the application of satellite-based ocean observations to tropical cyclone forecasting is also provided in Goni *et al*. (2009).

It is demonstrated that ANN technique is superior to MLR. For example, Swain *et al*. (2006) have shown that ANN is superior to MLR in estimating the ocean mixed layer depth. Roebber *et al*. (2003) and Marzban *et al*. (2007) demonstrate that ANN can give better results compared with MLR. However, the limitation of ANN technique is the training dataset covering all possible scenarios. Thus, though ANN is superior to MLR and OHC is important for tropical cyclone intensity predictions, no forecast scheme is presently available that uses both OHC as a predictor and the ANN technique for intensity change estimation. In this article, we use an ANN approach to estimate the change in cyclone intensity using OHC and the environmental factors in the western North Pacific region. The results obtained by this method, called the soft-computing cyclone intensity prediction scheme (SCIPS), are compared with the observed intensity changes and with those obtained from MLR and MLR-based operational forecasts.

2. Data

The tropical cyclone intensity information from the JTWC's best track analysis is often determined solely from the satellite-based methods and is heavily weighted towards intensity estimated using the Dvorak (1984) technique. This technique provides estimates of maximum 1-min average surface wind speeds. These best track intensities are provided to the nearest 5 knot (kt, where $1\,\text{kt} = 0.514\,\text{ms}^{-1}$) at 12-hourly intervals. For this reason we use these units for the current intensity (CI) throughout the rest of this article.

Table I. The potential parameters used in SCIPS development.

Number	List of parameters	Description
1	DELV	Predictand (intensity change from the initial forecast time)
2	PER	12 h intensity change leading to $t = 0$
3	VMX^2	CI squared
4	MPI	Maximum potential intensity, Knaff *et al.* (2005)
5	MPI^2	MPI squared
6	VMXM	Vmax times mpi
7	SHRD	200–850 hPa shear magnitude
8	USHR	200–850 hPa zonal wind shear magnitude
9	RHHI	500–300 hPa relative humidity
10	T200	Temperature at 200 hPa
11	Z850	850 hPa vorticity
12	E925	Theta E at 925 hPa
13	VXSH	CI times SHRD
14	SQRH	Square root of oceanic heat content/TCHP

SCIPS development closely follows that of SHIPS and STIPS. Accordingly, the dependent variable or the predictand is the intensity change from the initial forecast time (DELV) from 12 to 120 h, at 12-h interval of all the storms. The independent variables (the predictors) are those documented in the literature to influence the cyclone intensity change. The potential independent parameters used in this study are 12-h intensity change leading to $t = 0$ (PER), CI squared (VMX^2), maximum potential intensity (MPI), MPI squared (MPI^2), CI times MPI (VMXM), 200–800 hPa vertical shear magnitude (SHRD), 200–850 hPa zonal vertical wind shear magnitude (USHR), 500–300 hPa relative humidity (RHHI), temperature at 200 hPa (T200), 850 hPa vorticity (Z850), theta E at 925 hPa (E925), CI times SHRD (VXSH) and square root of OHC (SQRH) over the western north Pacific Ocean (Table I). These independent parameters are taken from analyses created by the US Navy's Navy Operational Global Analysis and Prediction System (NOGAPS) (Hogan and Rosmond, 1991; Hogan *et al*., 2002). The description, derivation and the justification of the predictors are provided in Knaff *et al*. (2005). Additional justification can be found in DeMaria and Kaplan (1999) albeit for different tropical cyclone basins. We added two more years (2004 and 2005) of data to the database of the present analysis. In addition, we added SQRH, the square root of OHC, as a new predictor. The square root transformation is based on the physics based conversion of potential energy (i.e. OHC) to wind speed. OHC takes the form of Leipper and Volgenau (1972) and comes from analyses created by the Atlantic Oceanographic and Meteorological Laboratory (Tropical Cyclone Heat Potential, version 1.0) that uses the method of Goni *et al*. (1996) to estimate the thickness of the upper ocean. All these predictors are calculated at $t = 0$. In this study, we considered the intensity changes caused by the environmental and climatological factors only, not those caused by landfall. Hence, we considered the intensity changes of the cyclones before the landfall. Another reason in considering oceanic tropical cyclones is the availability of both OHC and SST information. The predictors used in the study are broadly divided into three categories: (1) those related to ocean, (2) those related to the thermodynamics and (3) those related to wind fields. OHC values are determined at the storm centre through interpolation while moisture and wind field related parameters are area averaged (Knaff *et al*., 2005). Our aim is to infer how much SCIPS improves over the present MLR used in STIPS. Hence, we consider all the 13 predictors without considering which of them are significant or redundant.

3. Approach

3.1. ANN approach

A neural network is a parallel and adaptive system, capable of resolving paradigms that linear computing cannot. The approach is based on biological neural network and its nonlinear formulation makes the processing elements very flexible. The analysis can be used as a standalone application or as a complement to other statistical analysis. The system is developed with a systematic step-by-step procedure where the input/output training data conveys the information which is necessary to discover the optimal operating point. Thus ANN analysis requires three sets of data for (1) training, (2) verification and (3) validation. A training dataset is used to train the model and verification set to test the model using independent data during the training process. Finally, the ANN stores the trained model to predict the output using only the input parameters. This trained and verified model is then used for validation. We divided the dataset accordingly into three sets; the 1997–1999 for training, from 2000 to 2002 for testing and from 2003 to 2004 for validation. The total number of observations used in the analysis (together for training, verification and validation) for different forecast hours is given in Table II. These values decrease as the lead hour increases; for example, 12-h forecasts have 2606 observations and 120-h forecasts have 916 observations. Out of this total number of observations, about 35% are used for training, 35% for verification and 30% for validation. During this period, 25 severe cyclones (with wind speeds greater than 130 kt) were reported out of the total number of 34. Thus, the dataset is large enough to be representative of most if not all potential scenarios. The popular ANN models are radial basis functions, multi-layer perceptrons (MLP) and linear models. MLP approach has been used by Ali *et al*. (2012a, 2012b, 2012c, 2013a, 2013b) to estimate the tropical cyclone heat potential and the ocean windstress. We tried all the models and found that an MLP network provided the least error and best results. We used MLP with 13 inputs, 5 hidden units and 1 output.

3.2. MLR approach

To determine the improvement in cyclone intensity prediction by SCIPS over the typically used statistical method MLR, we also develop a model that predicts DELV by the MLR approach using all the predictors used for ANN. Unlike ANN approach where three sets of data are used, MLR requires only two sets of data, one for training and the other for testing. Hence, the data used for training and verification of the ANN model (1997–2002) are used for training the MLR and the data during 2003–2004 for validation. We obtained the multiple regression coefficients using MLR training period 1997–2002. These coefficients are then used to predict DELV using the predictors of the validation dataset of 2003–2004. This allows for a homogeneous comparison of the ANN-based and MLR-based intensity predictions.

Table II. Comparison of statistical parameters by ANN (MLR) for different lead hours of the validation dataset.[a]

	12 h (2606)	**24 h (2359)**	**36 h (2132)**	**48 h (1912)**	**60 h (1702)**	**72 h (1509)**	**84 h (1339)**	**96 h (1186)**	**108 h (1045)**	**120 h (916)**
R	0.47	0.58	0.63	0.63	0.69	0.67	0.68	0.69	0.67	0.66
	(0.43)	(0.54)	(0.59)	(0.61)	(0.63)	(0.64)	(0.65)	(0.66)	(0.65)	(0.57)
AEM	5.76	9.22	11.77	13.68	14.43	17.15	18.53	19.25	21.32	22.40
	(5.97)	(9.47)	(12.3)	(14.3)	(16.4)	(18.3)	(19.2)	(20.7)	(22.0)	(23.98)
Bias	0.11	0.20	−0.05	−0.80	−1.06	−0.43	0.99	2.09	1.90	4.31
	(1.26)	(3.39)	(5.96)	(8.74)	(11.46)	(14.60)	(18.21)	(21.8)	(25.6)	(30.6)
RMSD	7.96	12.36	15.30	18.10	18.94	21.90	23.16	23.96	25.84	26.09
	(8.32)	(12.60)	(16.2)	(18.6)	(20.94)	(22.89)	(24.10)	(26.33)	(26.42)	(28.28)
AMPE	0.81	0.69	0.63	0.58	0.51	0.54	0.52	0.500	0.51	0.51
	(0.79)	(0.42)	(0.85)	(0.87)	(0.88)	(0.89)	(0.91)	(0.92)	(0.94)	(0.86)
SI	1.13	0.93	0.81	0.76	0.67	0.68	0.65	0.62	0.62	0.59
	(1.18)	(0.95)	(0.86)	(0.79)	(0.75)	(0.72)	(0.68)	(0.68)	(0.64)	(0.64)

[a]Forecast times are listed in the first row with the total number of observations (for training, verification and validation) in parenthesis. Descriptions of the statistics (left column) are provided in the text. Units for this table are shown in kt, except for R and SI.

4. Performance of SCIPS

To evaluate SCIPS model we statistically compare the observed DELV to the estimated DELV using the independent 2003–2004 validation dataset. The multiple correlation coefficient (R), absolute error mean (AEM: the absolute difference between the two parameters), the bias, the root mean square difference (RMSD), the absolute mean percentage error (AMPE: percentage ratio of the AEM) and the scatter index (SI: the ratio of RMSD to the data mean) for SCIPS and MLR are shown in Table II. The values in parentheses refer to MLR. This statistical analysis shows that SCIPS is superior to MLR method. *R* has gradually increased from 0.7 to 0.8 from 12 to 120 h forecast for the SCIPS approach. *R* of greater than 0.8 from 60 h lead hour onward indicates that this method performs better for longer range forecasts. *R* values for MLR are always smaller than those produced by the SCIPS method. The R values of both ANN and MLR are statistically significant at the 99% level. The AEM difference between SCIPS and MLR is more as the lead time increases. Though SCIPS results in a just slight improvement in terms of RMSD when compared with MLR method, SCIPS significantly reduces the forecast biases. The largest bias of SCIPS (MLR) is 4.3 (30.6). The lower values of SI (i.e. less variability in the forecast errors) from SCIPS indicate the improvement in the accuracy of the forecast.

To address the practical significance of the SCIPS results, it is important to know whether the performance of ANN varies as a function of intensity change. For this purpose, we subdivide the independent (validation) data into seven classes of intensity changes ranging from 5-kt increase in intensity in 12 h to 30-kt increase in 12 h with an interval of 5 kt per 12 h. Then we computed the difference between SCIPS and MLR in AEM and RMSD for different forecast hours. The differences between SCIPS and MLR for AEM and RMSD for different forecast hours for 10 kt, 25 kt and 30 kt per 12 h, respective intensity changes are shown in Figure 1. Two significant results emerge from this analysis: (1) The performance of SCIPS increases as the change in intensity increases from 5 kt to 30 kt per 12 h and (2) the performance becomes more significant as the lead hour increases from 12 to 120 h. For 30 kt per 12 h intensity change, SCIPS performance improved from 4.4 kt for 12-h forecast to 10.5 kt for 108-h forecast in both AEM and RMSD.

To look at which parameter is more sensitive for each forecast hour, we carried out a sensitivity analysis. For this purpose, first we computed the sum of squares of residual with all the predictors and then by removing one by one predictor from the neural network. The ratio of the full model sum of squares of residuals versus the reduced model is then calculated for each forecast hour. The average for all the forecast hours of this sensitivity parameter is shown in Figure 2 (lowest value showing highest sensitivity). The static term CI squared (VMX^2) has the highest (1.3) influence on the cyclone surface wind speed change. This result suggests that the storm intensity at $t = 0$ is relatively important for the future forecasts. This is likely because this parameter plays a key role along with the MPI for determining the potential intensity change that is possible to forecast. For instance weaker storms have the general tendency to intensify, all other factors held constant. As VMX^2 plays a key role along the CI, the product of these two parameters, VMXM, plays the second significant role. OHC plays the fourth important role in predicting the storm intensity change. This analysis also suggest that variations of many of the atmospheric thermodynamic predictors (RHHI, T200, E925) play a lesser role than the oceanic thermodynamics predictors (MPI, which is a function SST, and SQRH) or dynamic predictors related to vertical wind shear (VXSH and SHRD).

We compared our results with the STIPS real time forecasts. The RMSD in DELV of the real time forecasts compared with the actual intensities during our validation period increased from 9.8 kt for 12-h forecast to 32.9 kt for 120-h forecast. The reason the RMSDs being higher than ANN and even MLR is that these are based on real-forecasts of the model parameters. The ANN, the MLR and the STIPS model are developed using observed tracks, best track intensities and model analyses or the 'Perfect Prog' assumption discussed in Kalnay (2003). On the other hand, the STIPS forecasts use the operational intensity

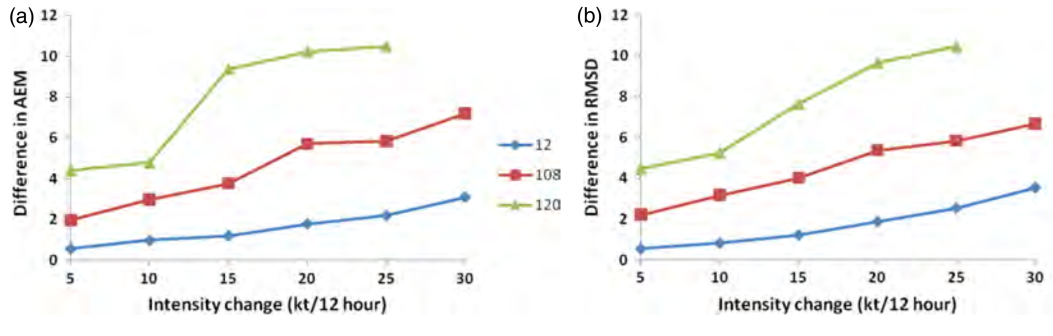

Figure 1. Difference (kt) between the ANN and MLR estimations as a function of intensity change for 12, 108 and 120-h forecasts for (a) AEM and (b) RMSD.

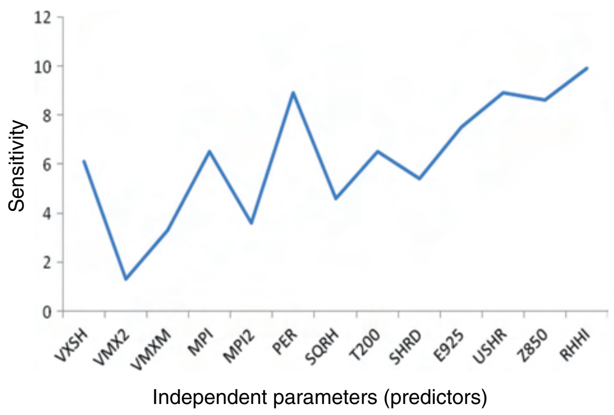

Figure 2. Average (12–120 h) sensitivity of the predictors; lowest value having the highest sensitivity.

estimates, the forecast track and the model predictors are based on forecast fields but not model analysis fields. Each of these factors, which have their own errors, acts to degrade the forecasts. As the forecast lead increases, the track and predictand errors increase. It is also noteworthy that our independent tests of both the ANN and MLR made use of best track initial intensities, model analyses for the predictor estimation, and no track errors. In total, we studied 34 hurricanes during this period and 25 out of them are categorized as severe hurricanes with wind speeds equal to or greater than 130 kt. As for all cases examined, ANN predicted better than MLR, use of the former is recommended.

5. Conclusions

The challenging and complex problem of cyclone intensity predictions is addressed by developing a new scheme called SCIPS by using an ANN approach. We also added a new parameter, ocean heat content as one of the predictors. Out of the 13 predictors, this parameter has fourth rank. The SCIPS predictions improved the intensity forecasts made by more widely used MLR. The performance of SCIPS compared with MLR increases as a function of both intensification and lead forecast hour. Results presented here suggest testing of the SCIPS model formulation in a real-time setting and the development of similar models in other tropical cyclone basins may be a fruitful endeavour.

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