SURFACE LATENT HEAT FLUX AND INNER-CORE RAINFALL ASSOCIATED WITH RAPIDLY INTENSIFYING TROPICAL CYCLONES AND ITS APPLICATION IN TROPICAL CYCLONE INTENSITY PREDICTION OVER WESTERN NORTH PACIFIC

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ABSTRACT:

Regression models for 24-h typhoon intensity forecast based on the Statistical Typhoon Intensity Prediction System (STIPS) are developed by adding two new predictors: surface latent heat flux taken from the third release of the Objectively Analyzed Air-sea Fluxes and inner-core rain rate obtained from Tropical Rainfall Measuring Mission (TRMM) Multi-satellite Precipitation Analysis. The microwave optimally interpolated SST produced by Remote Sensing Systems is used to estimate maximum potential intensity. The models predictors include environmental information from National Center for Environmental Prediction Global Forecasting System final analysis and best track from Japan Meteorological Agency Regional Specialized Meteorological Center Tokyo. Results from a stepwise linear regression model show that the inclusion of these two satellite-based predictors provides 1%–3% reduction in overall intensity changes. To take into account the non-linearity of the forecast, a neural network (NN) model is developed. Results from the NN show a 5%–11% reduction of the mean absolute forecast error.

1. INTRODUCTION

While the forecast of TC track has improved steadily over the past decades, the forecast of TC intensification remains a major challenge. An evaluation of the National Hurricane Center and Joint Typhoon Warning Center (JTWC) operational tropical cyclone intensity forecasts for the three major northern hemisphere tropical cyclone basins (Atlantic, eastern North Pacific, and western North Pacific) for the past two decades indicates almost no improvement in intensity forecasting while the track forecasts have seem steady improvement (DeMaria et al. 2007).

Latent heat transfer at the air-sea interface, which can be quantified by surface latent heat flux (SLHF), and latent heat release occurring within the inner-core region in the atmosphere, which could be indicated by inner-core rain rate (IRR), are two major heat sources for TC intensification. Gao and Chiu (2010) showed that there are statistical differences in the SLHF and IRR field associated with rapidly intensifying (RI) and non-RI TCs, suggesting that these parameters have the potential to enhance forecast skills. This study reports on the impact of SLHF and IRR on 24-h intensity prediction of TCs over the western North Pacific.

2. DATASETS

Intensity and location information of each TC are take from best track data produced by Japan Meteorological Agency Regional Specialized Meteorological Center Tokyo (RSMC Tokyo). This post analysis best track data contain 6-h location, minimum central pressure, and 10-min maximum sustained wind speed (MWS) of all TCs over the western North Pacific including the South China Sea. Environmental data are derived from National Centers for Environmental Prediction (NCEP) Global Forecasting System (GFS) final (FNL) gridded analysis (Yang et al. 2006) at $1.0° \times 1.0°$ and 6-h resolution. The 0.25

degree every 3 hourly rainfall data are taken from Tropical Rainfall Measuring Mission (TRMM) Multisatellite Precipitation Analysis (TMPA) (Huffman et al. 2007). Daily gridded SLHF data at $1° \times 1°$ resolution are obtained from the third release of the Objectively Analyzed Air-sea Fluxes (OAFlux) (Yu et al. 2008). The microwave (MW) Optimally Interpolated (OI) daily SST (Wentz et al. 2000) at $0.25° \times 0.25°$ resolution produced by Remote Sensing Systems together with best track data is utilized to estimate maximum potential intensity (MPI). Data for the period 2000-2008 are analyzed. This period represents an intersection of all available data used in this study.

3. LINEAR REGRESSION MODEL

Multiple linear regression models are used to predict over-water 24-h intensity (i.e. MWS) change (predictand, DELV) from the initial forecast time. This model is based on STIPS with the addition of surface evaporation and inner core rainfall and is termed Statistical Typhoon Intensity Prediction including surface Evaporation and inner core Rainfall (STIPER).

3.1 Model formulation

Table 1 summarizes the predictors (including 16 original and two new satellite-based predictors, SLHF and IRR) used in this study. The computation of the traditional climatological and environmental predictors follows the approach in the Statistical Typhoon Intensity Prediction System (STIPS) developed by Knaff et al. (2005). All of the environmental predictors are obtained using a "perfect prog" Approach (Kalnay, 2003). Both the NCEP GFS FNL analysis and the actual TC best track (by the RSMC Tokyo) are used to develop the models. The predictors that are evaluated at the beginning of the forecast period are static, such as those predictors related to climatology and persistence; and predictors that are averaged along the track

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Table 1. Potential climatological, environmental, and satellite-based predictors. The predictors that are evaluated at the beginning of the forecast period are static (S), and the predictors that are averaged along storm track from the initial time to the forecast time are time dependent (T).

Predictor	Description	Static (S) or time dependent (T)
Climatology and persistence		
MWS0	Initial maximum wind speed	S
DMWS	Maximum wind speed during the past 12 h	S
JDAY	Absolute value of (Julian day – 248)	S
SPD	Strom translational speed	S
LAT	Latitude of storm center	S
LON	Longitude of storm center	S
Environmental		
POT	Maximum potential intensity based on Eq. (1) minus initial maximum wind speed	T
RHLO	Area-averaged (200–800 km) relative humidity at 850–700 hPa	T
RHHI	Area-averaged (200–800 km) relative humidity at 500–300 hPa	T
U200	Area-averaged (200–800 km) zonal wind at 200 hPa	T
T200	Area-averaged (200–800 km) temperature at 200 hPa	T
$\delta200$	Area-averaged (0–1000 km) divergence at 200 hPa	T
REFC	Relative eddy flux convergence within 600 km at 200 hPa	T
SHR	Area-averaged (200–800 km) 200–850-hPa wind shear	T
USHR	Area-averaged (200–800 km) 200–850-hPa zonal wind shear	T
$\zeta850$	Area-averaged (0–1000 km) 850-hPa relative vorticity	T
Satellite-based		
SLHF	Area-averaged (5° × 5° box) surface latent heat flux	S
IRR	Area-averaged (0-100 km) inner-core rain rate	S

Table 2. Model and verification. STIPER predictor normalized regression coefficients with explained variances (R^2) statistics at the bottom in different verification years. The predictors are listed on the left side of the table and the verification years are listed at the top. N is the number of dependent samples used to develop the equation shown in parentheses. The lower four rows show the verification results for these models in intensity change (kt over 24 hours) for the year. M is the number of samples for verification.

Year (N) Predictor	2000 (1063)	2001 (1040)	2002 (1005)	2003 (1041)	2004 (977)	2005 (1047)	2006 (1053)	2007 (1083)	2008 (1115)
1) MWS0	–0.05	–0.07	–0.08	–0.02	–0.06	–0.05	–0.02	–0.07	–0.04
2) DMWS	0.28	0.31	0.30	0.30	0.29	0.30	0.29	0.28	0.28
3) JDAY	–0.12	–0.10	–0.12	–0.11	–0.12	–0.10	–0.11	–0.12	–0.11
4) LAT	–0.11	–0.09	–0.10	–0.09	–0.13	–0.09	–0.09	–0.13	–0.11
5) POT	0.40	0.37	0.37	0.42	0.38	0.38	0.41	0.37	0.40
6) RHLO	0.07	0.04	0.05	0.04	0.05	0.04	0.05	0.06	0.06
7) RHHI	–0.01	0.01	0.02	0.03	0.00	0.04	0.00	–0.01	–0.01
8) SHR	–0.17	–0.18	–0.17	–0.18	–0.18	–0.16	–0.17	–0.18	–0.18
9) SLHF	0.06	0.06	0.05	0.03	0.04	0.05	0.06	0.05	0.05
10) IRR	0.06	0.08	0.07	0.08	0.05	0.08	0.07	0.07	0.06
R^2	54%	53%	54%	53%	55%	53%	53%	53%	53%
M	115	138	173	137	201	131	125	95	63
CLIPER	7.0(38%)	6.6(46%)	7.5(40%)	7.1(51%)	8.1(38%)	7.7(49%)	7.6(51%)	9.9(44%)	8.7(56%)
BASE	6.6(44%)	6.4(53%)	6.8(46%)	6.9(54%)	7.6(44%)	7.6(55%)	7.2(55%)	8.6(56%)	8.2(60%)
STIPER	6.5(44%)	6.5(52%)	6.9(47%)	6.8(54%)	7.4(46%)	7.7(54%)	7.2(55%)	8.5(56%)	8.1(62%)

of the storm from the initial observation to the forecast time are time dependent, providing the mean conditions for the storm, such as those predictors related to SST, moisture and wind fields.

The MPI is defined as the upper bound of TC intensity for a given atmospheric and oceanic thermal conditions (Camp and Montgomery 2001). We use the MWSST in each 0.5°C SST interval to fit this exponential MPI function described in Eq. (1) and determine the coefficients. The coefficients are given by A = 23.75 kt, B = 91.9 kt, C = 0.09 °C^{-1} and T_0 = 30.0 °C.

$$MPI = A + Be^{C(T-T_0)} \tag{1}$$

SLHF and IRR predictors are computed as the average within a box of 5° × 5° and within a radius of 100 km centered at TC position, respectively. The averaging areas optimize their correlation coefficients with intensity and intensity changes, as also suggested in previous studies (Chang et al., 1994; Rodgers et al., 1994). For the operational purpose, SLHF and RR are deemed to be static predictors, since it is impossible to acquire remote sensed information in "future".

A linear stepwise regression procedure is used to select parameters from the potential predictor pool. A 99% statistical significance level based on an F test (e.g., Wilks 2006) is the threshold for an individual predictor to be added initially in the model. Once selected, a predictor can only be removed if its

significance level becomes less than 98% after the addition/removal of another predictor.

Three regression models are developed: a) control (BASE), which uses the 16 STIPS original predictors to select significant predictors and create a base regression model, b) STIPER which is STIPS plus SLHF and IRR, and c) CLIPER, which is generally a baseline to evaluate the skill of operational models. A model can be considered to produce skilful intensity forecast if it has smaller error than CLIPER.

Assuming the independence of annual statistics, the samples in one year are used for verification and the samples in the other years are used for model development. As a result, for each CLIPER, BASE and STIPER model there are totally nine regression equations, which may contain different sets of significant predictors due to different training samples. All of the predictors identified for any regression equation are included in the final group of predictors. The final CLIPER, BASE and STIPER models are created using the final group of predictors. The predictand as well as the predictors are normalized by subtracting their means and dividing by their standard deviations before regression, the resulting coefficients can be used to compare the relative contribution of each predictor directly.
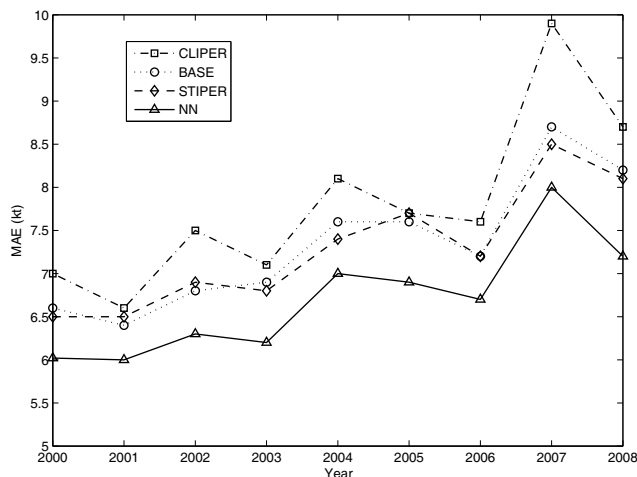

Figure 1. The mean absolute errors (MAE, kt) of four regression models (CLIPER, BASE, STIPER, and NN) for different verification years.

3.2 Model results

Table 2 lists the normalized coefficients associated with each predictor for each STIPER forecast equation. N is the number of samples used to develop the regression equations. The STIPER models contain 10 important predictors: initial intensity (MWS0), previous 12-h intensity change (DMWS), absolute value of Julian day minus 248 (JDAY), initial latitude of the storm (LAT), potential (POT), 850–700-hPa average relative humidity (RHLO), 500–300-hPa average relative humidity (RHHI), 200 – 850 hPa wind shear (SHR), SLHF and IRR.

The lower rows in Table 2 shows mean absolute errors with explained variances (R^2) of CLIPER, BASE and STIPER forecasts for different verification years. Both the BASE and STIPER models perform better than CLIPER. Among the nine verification cases, STIPER has the lowest mean absolute error and the highest R^2 for 6 cases, with a MAE 1%–3% smaller than the STIPS models. Hence, STIPER show moderate skill for TC intensity forecast and the inclusion of satellite-based

predictors SLHF and IRR provides 1%–3% improvement compared with the model without satellite information.

4. NEURAL NETWORK MODEL

The nonlinear response of the linear regression model suggests the use of non-linear models can be beneficial. A neural network (NN) model using back-propagation algorithm (Rumelhart et al. 1986) is developed using the same predictors from the linear regression model STIPER.

Figure 1 shows the mean absolute errors of the NN model as well as three linear regression models (i.e., CLIPER, BASE, and STIPER). The mean absolute error reduction of NN models is from 5% to 11% compared to STIPER models for different years. The NN model is clearly better than the STIPER model in predicting varying intensity changes.

5. SUMMARY AND DISCUSSION

A new maximum potential intensity equation is derived using remote-sensed sea surface temperature data with high temporal and spatial resolution. The inclusion of satellite-based SLHF and IRR in a linear regression model (STIPER) provides a 1%–3% improvement in 24-h typhoon intensity forecasting compared to a multiple linear regression model (BASE). Analysis of the intensity forecast categories shows the largest improvement of the STIPER model occurs for those rapidly intensifying storms. Verifications of the model results show non-linear responses of the linear regression model. To account for the non-linear response, a NN model is developed using the same predictors as the STIPER model. The NN show a 5%–11% reduction in mean absolute error relative to the STIPER model. The forecast errors with rapid intensifying cases of the NN model are reduced further relative to the STIPER model.

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