Southern Hemisphere Tropical Cyclone Intensity Forecast Methods Used at the Joint Typhoon Warning Center, Part I: Control Forecasts Based on Climatology and Persistence

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Abstract

The development of a simple statistical tropical cyclone intensity forecast model is described. The primary purpose of this model, called Southern Hemisphere five-day statistical typhoon intensity forecast scheme (SH ST5D), is to provide a skill/no-skill control forecast for verifying other TC intensity forecasts, but it also provides useful and always-available forecasts of TC intensity in the Southern Hemisphere. The model is created by fitting an optimal combination of factors related to climatology and persistence (or CLIPER) using multiple linear regression. These CLIPER factors are determined from the best track tropical cyclone dataset produced by the United States of Americas' Joint Typhoon Warning Center (JTWC) in the years 1980-2002. In 2004 the SH ST5D model became part of the operational suite of tropical cyclone intensity guidance run at JTWC. The forecasts from the model since that time have outperformed both climatology (i.e., a constant 65 knots or 33 ms^{-1} forecast) and the persistence of initial conditions in a statistically significant manner in independent testing during 2004-2007.

1. Introduction

The Joint Typhoon Warning Center (JTWC) makes tactical tropical cyclone forecasts in the Southern Hemisphere to support the United States of America's military and civilian operations in this part of the world. These forecasts typically are made every 12 hours (h), extend through 48 h and consist of position intensity and significant (e.g., Hurricane-force, etc.) wind radii. Until recently the intensity forecast was based on very few objective forecast aids and heavily depended on trends in the satellite analysis. Table 1 shows the objective intensity guidance available in the Southern Hemisphere and when these became available.

In 2004 and 2005 new statistical models were developed to help forecast intensity in the Southern Hemisphere. These new models, one based on climatology and persistence (or CLIPER) and the other based on a statistical-dynamical approach where forecast fields from global models are used to statistically forecast intensity change (e.g., Knaff and Sampson 2008), were based on similar models operating in other basins. Most recently TC intensity forecasting in this region has been aided by consensus methods, discussed in Sampson and Knaff (2008).

The CLIPER model, called the Southern Hemisphere Statistical Typhoon Intensity Forecast (or SH ST5D) after its counterpart used in the western North Pacific, is based on the design documented in Knaff et al. (2003) and is the subject of this paper. As in other TC basins, the CLIPER models, including SH ST5D, are considered to have no skill by design as they are formulated by combining the optimum no-skill verification options of persistence and climatology. The SH ST5D model, while its forecast ability is somewhat limited and by design has no skill, is an important member of the JTWC forecast intensity guidance suite. First, since the model requires only a few routinely available inputs, SH ST5D is always available for forecasters. More importantly however, SH ST5D is used as a control model or baseline for other intensity forecasting methods. The development and use of CLIPER-based forecasts to provide operationally available control forecasts that are used to evaluate forecast skill is a common practice in tropical cyclone forecast verification (e.g., Neumann 1972; Jarvinen and Neumann 1979; Merrill 1980; Chu 1994; Aberson 1998; Knaff et al. 2003).

While implemented in JTWC operations in 2004, the SH ST5D has not been formally documented. With this documentation in mind, the following sections discuss the datasets used, the model's design and development and the past and expected performance of this model.

2. Datasets

The primary dataset used for both the development and the independent verification of SH ST5D is the tropical cyclone best track produced by JTWC following each season (JTWC, cited 2008). These "best tracks" represent the best post-season analysis available and made use of all observations available for each storm at each time. The years 1980-2002 were used to develop SH ST5D and the years 2004-2007 were used for independent verification. To remove the potential influence of land effects during development, all cases that came within 50 km of land were excluded from the dependent data. This resulted in 7231, 6622, 6027, 5461, 4919, 4404, 3912, 3460, 3047, and 2671 cases for the development of the 12-, 24-, 36-, 48-, 60-, 72-, 84-, 96-, 108-, and 120-h forecast models, respectively. Because the best track as well as forecasts of TC intensity are given in terms of knots (kt; nautical miles per hour, where 1 kt = 0.54 ms^{-1}), this unit will be used through the remainder of the text. Intensities are also considered maximum 1-minute sustained winds, which is the convention in the United States of America.

It is also important to note that the best track intensity record has many shortcomings. Some earlier tracks did not have intensity estimates associated with each track record, but by the mid 1980's all storms had intensity estimates every 6 hours. Errors in the track locations were corrected by Chu et al. (2002), but no attempt to reanalyze intensity was attempted. Shortcomings of the best track intensities were also the topic of recent literature as they relate to climate change (e.g., Landsea et al. 2006; Kossin et al. 2007). The authors, however, believe the data are of acceptable quality for the development of simple models of intensity change since the absolute accuracy of intensity estimates are less important and the sample size is very large. More important to this study is that all of the storms in the best track eventually reach an intensity of 35 kt (17 ms^{-1}) which biases the models developed here toward intensification.

3. Statistical Methodology

The methods used to develop the SH ST5D mirror those used to develop similar models in the Atlantic, East Pacific and western North Pacific as described in Knaff et al. (2003). The dependent variable, or predictand (DELV), is the change in intensity from the initial conditions. The independent variables, or predictors, are developed using 7 primary measurements as follows:

1) Date: (JDAY), is given as a Gaussian function about day 45 of the year as given by

$JDAY = e^{-\frac{(d-45)}{90}}$, where d is the day of the year.

2) Latitude (LAT), 0 – 90 S, south latitude is negative
3) Longitude (LON) in terms of degrees east (i.e., 0^o – 360^o)
4) Zonal speed of the storm (U) [kt] where motion toward the east is positive.
5) Meridional speed of the storm (V) [kt] where motion toward the north is positive
6) Current intensity (VMAX) [kt] as 1-minute sustained winds
7) 12-hour change in intensity (DVMX) [kt].

Twenty-eight additional predictors are constructed from the squares and cross products of the 7 primary predictors. This method results in a pool of 35 potential predictors from which the best predictor combinations can be selected.

Variable selection for multiple regression schemes can be accomplished through a number of methods. Three such methods are combined to select predictors in this study. The methods are forward selection, backward selection, and stepwise selection. In forward selection, predictors are added to a model (forward step). A predictor is retained in the model if the F-test p-value is less than a predefined value, PIN.   In backward selection, predictors are removed from the model (backward step) that is typically initialized with all the predictors. A predictor is removed if its p-value is greater than a predefined level, POUT. In stepwise selection, a backward step is attempted using POUT; if no variable is removed a forward step is attempted using PIN. The combination of a backward step followed by a forward step is referred to as a stepwise step. In stepwise selection only forced predictors enter the model initially and stepwise steps continue until no predictors can be removed from the model and no potential predictors that remain can be added. Forcing predictors into regression models refers to giving preference to a set of predictors by initializing the selection procedure with those predictors. If a set of predictors is forced into the model, those predictors must be evaluated before other potential predictors are allowed to enter the model (IMSL 1987). One can also combine various variable selection methods and the use of forced predictors to create regression models with desired properties. Such a procedure is used in this study.

The forecast equations are developed using multiple linear regression where the predictand is DELV and independent variables are the 35 members of the potential predictor pool. The predictors at each forecast interval are chosen using a procedure designed to improve the forecast continuity from one interval to the next, and to provide a preference for the selection of primary predictors over quadratic combinations for the first forecast interval (12-h). The first step is to choose from the primary variables (1-7) for the 12-h forecast in a forward selection process. For this first forecast time period PIN is set to 0.00001 and POUT is set to 0.00002 for this forward selection. Once primary predictors have been chosen they are then forced into the model and secondary predictors are then allowed to enter the model using a forward selection procedure with a PIN and POUT equal to 0.000001 and 0.000001. To remove primary predictors that have lost their statistical significance, a backward selection procedure is performed removing all predictors that have a probability of being by chance greater than 0.000001. Finally, the predictors in the model following the backward selection are forced into the model and a stepwise selection procedure passes through the remaining potential predictors one last time, using the same significance levels as the previous backward and forward steps, thus adding any remaining potential predictors made significant by the previous backward selection.

For forecast equations with lead times greater than 12 hours, the predictors chosen for the previous forecast time are given preference in the same way primary predictors are given preference for 12-hour forecast equations. This procedure was shown to provide more continuity among predictors and predictions with differing time lags than other variable selection procedures, and resulted in between 4 and 10 predictors being chosen for each forecast equation.

Table 2 lists the predictors used in the regression equation and the normalized coefficients associated with the predictors for forecast times 12-h through 120-h. Two predictors, LATxVMAX and UxVMAX, are used for all the forecast equations. The date, though in different forms, is also used at all forecast times. The quadratic terms involving LAT and LON are related to spatial variability of intensity change as shown in Knaff et al. (2003). Figure 1 shows the spatial pattern that results from the 48-h forecast equations using terms LON, LATxVMAX, LATxDVMAX and LON^2. For the creation of Fig. 1 VMAX is set to 50 kt and DVMAX is set to 0 kt, which makes the results comparable to the results show in Fig.3 of Knaff et al. (2003). Fig. 1 shows that a greater intensity change is associated with storms that are located further north with a slight east-to-west gradient favoring greater intensity change east of the Dateline and to a lesser degree near the African Coast. This spatial pattern appears to represent a combination of effects 1) the climatological location of warm (>25^{o}C) SSTs and the location of large land areas (i.e., Australia).

4. Model Evaluation

The resulting regression equations form the basis of the SH ST5D intensity prediction model. In this section, the SH ST5D model is evaluated. To assess how well this model describes the developmental data, the dependent forecast ability is discussed in terms of root mean square error (RMSE) and percent variance explained in terms of R^2. It is quite well known that statistical model performance typically degrades as a function of number of predictors and sample number when the model is applied to independent data (Knaff and Landsea 1997). To assess the real-time performance of the SH ST5D model, the independent performance is also examined. The performance will be evaluated versus persistence as well as other intensity forecast techniques available in the Southern Hemisphere.

Table 3 shows the statistics associated with SH ST5D's forecasts based on the dependent sample. Shown are RMSE, variance explained and the number of cases used to create each forecast. The regression fit to the data explains 45 - 55 % of the variance at all forecast periods with the percent variance increasing at the longer lead times. The RMSEs range from 4.8 kt for the 12-h forecast equation to 18.3 kt for the 108-h forecast equation with a saturation of errors occurring between 96-h and 120-h forecasts. The model fit is comparable to similar models developed in the North Atlantic, eastern North Pacific and western North Pacific in Knaff et al. (2003).

The SH ST5D model has been run in operations at JTWC since July of 2003 and independent verification statistics are available for the 2004 – 2007 Southern Hemisphere TC seasons. Statistics of the verification of SH ST5D, persistence of initial conditions (PER) and with a climatological value of intensity (CLIM) are presented in Table 4. The mean absolute errors

(MAEs) and biases are shown for the 12-, 24-, 36-,48-, 72-, 96-, and 120-h forecast periods. The intensity value of 65 kt is used for climatology as it closely approximates the mean values in the independent dataset at all forecast times indicated by the small biases for CLIM in Table 4. Biases for all of these methods are rather small and there is considerable variability in the MAEs with PER shown to have smaller (larger) MAEs than CLIM for shorter (longer) forecast periods. The MAEs produced by SH ST5D are statistically lower than MAEs produced by either CLIM or PER at all forecast times using a 99% confidence interval and adjusting the number of degrees of freedom to account for 30-h serial correlation. The SH ST5D model outperforms both climatology and persistence in this multiyear verification and is suitable for use as control forecast for TC intensity verification as well as a simple omnipresent operational TC intensity forecast tool.

5. Summary

The development of a simple statistical model for forecasting TC intensity change through five days in the Southern Hemisphere (SH ST5D) for use at the Joint Typhoon Warning Center has been documented. The model makes use of an optimal combination of factors related to climatology and persistence and is based on a multiple linear regression equation for each forecast time. The model was developed primarily as a verification tool, but the simplicity of the model also provides TC intensity forecasts that are both useful and always available. The statistics from both the dependent developmental data and from independent verification during 2004- 2007 indicate that the model provides forecasts superior to either climatology or persistence. Thus, since 2004 SH ST5D has become the skill/no-skill baseline for evaluating TC intensity change forecasts at JTWC.

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Figure Captions:

Figure 1. Example of the resulting spatial distribution of DELV [kt] calculated from the predictors containing LAT and LON in the Southern Hemisphere ST5D 48-h forecasts equations. To calculate these spatial distributions VMAX = 50 kt and DVMAX= 0 kt.   Note the contour intervals are 10 kt and negative DELV contours are dashed.

Table Captions:

Table 1. A list of objective tropical cyclone intensity guidance techniques available at the Joint Typhoon Warning Center, its interpolated aid, a brief description, and the year of first availability.

Table 2. Predictors and associated normalized coefficients for the five-day Southern Hemisphere ST5D model are listed for forecast times 12 to 120 hours. The number of individual predictors used for each forecast is given in parentheses.

Table 3. Dependent statistics for the Southern Hemisphere ST5D model are listed. Shown are the R^2 (variance explained), RMSE and the number of cases used to develop the regression equation for each forecast period.

Table 4. Verification statistics associated with forecasts of tropical cyclone intensity for the period 2004-2007. Shown are the mean absolute error (MAE) and bias (BIAS) in units of kt (1 kt =0.54 ms^{-1}) associated with the Southern Hemisphere ST5D model (ST5D), persistence of initial intensity (PER) and a climatological value of 65 kt (CLIM) for the 12-h, 24-h, 36-h, 48-h, 72-h, 96-h and 120-h forecasts. The number of forecasts for each time period is given in parentheses. Verification is based on JTWC best tracks for the 2004-2007 tropical cyclone seasons in the Southern Hemisphere.

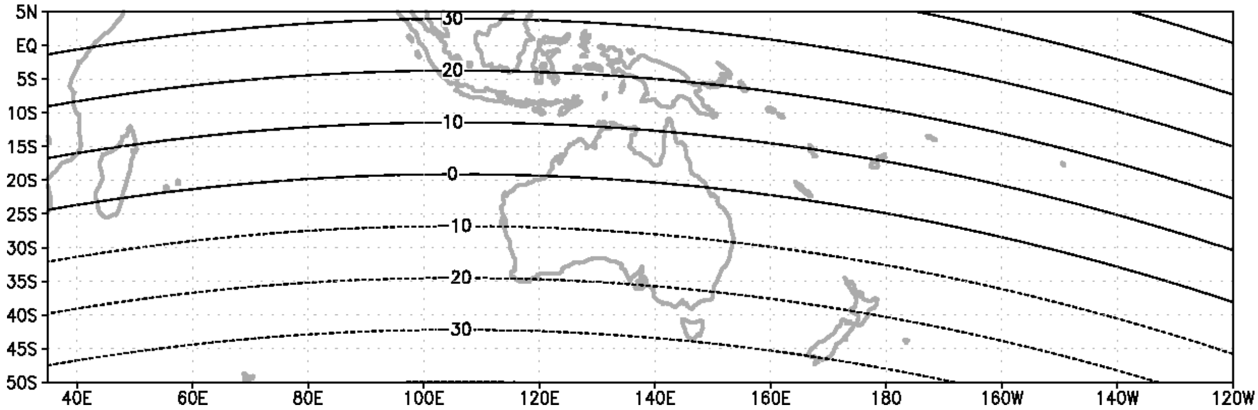

Figure 1. Example of the resulting spatial distribution of DELV [kt] calculated from the predictors containing LAT and LON in the Southern Hemisphere ST5D 48-h forecasts equations. To calculate these spatial distributions VMAX = 50 kt and DVMAX= 0 kt. Note the contour intervals are 10 kt and negative DELV contours are dashed.

Table 1. A list of objective tropical cyclone intensity guidance techniques available at the Joint Typhoon Warning Center, its interpolated aid, a brief description, and the year of first availability.

Model	Interpolated	Description	Year first available
NOGAPS	NGPI	U.S. Navy global model (Hogan and Rosmond 1991)	2004
UKM	UKMI	UK global model (Heming et al. 1995)	2003
GFS	AVNI	NWS global model (Lord 1993)	2002
GFDN	GFNI	Geophysical Fluid Dynamic Lab initialized by the Navy Operational Global Analysis and Prediction System model (Rennick 1999)	1998
TC-LAPS	TCLI	Australian TC-Limited Area Prediction System (Davidson and Weber 2000)	2002
TX-LAPS	TXLI	Australian Tropical eXtended Area Prediction System (Australian Bureau of Meteorology 2005)	2005
US. Air Force regional model	AFWI	Air Force mesoscale model (Grell et al. 1995)	2002
ST5D	None	Statistical model (Knaff and Sampson 2008)	2004
STIPS	None	Statistical-dynamical model based on JTWC forecast (Knaff and Sampson 2008)	Not available
S1xx	None	STIPS ensemble members	2006
ST10	None	STIPS ensemble	2006
ST11	None	Multi-model consensus that combines the ensemble members of ST10 and GFNI	2007
ST12	None	ST10 members, GFNI and CHII	Not available

ST13	None	ST10 members, GFNI, CHII and TCLI	Not available
ST14	None	ST10 members, GFNI, CHII, TCLI and UKMI	Not available
CHIPS	CHII	Coupled dynamical hurricane model (Emanuel et al. 2004)	2003

Table 2. Predictors and associated normalized coefficients for the five-day Southern Hemisphere ST5D model are listed for forecast times 12 to 120 hours. The number of individual predictors used for each forecast is given in parentheses.

Forecast (hr)	12	24	36	48	60	72	84	96	108	120
# of Predictors	(5)	(8)	(9)	(10)	(10)	(8)	(8)	(8)	(4)	(4)
JDAY	0.07	0.08	0.10							
LON			- 0.40	- 0.46	- 0.47	- 0.46	- 0.45	- 0.42		
V		- 0.17	- 0.16	- 0.13						
DVMAX	0.78	0.95	0.97	0.94	0.82	0.49	0.40	0.30		
$JDAY^2$				0.13	0.14	0.15	0.16	0.17	0.15	0.14
LATxV					0.10					
LATxVMAX	0.32	0.34	0.43	0.51	0.59	0.71	0.73	0.75	0.62	0.59
LATxDVMAX	0.22	0.33	 0.37	0.35	0.30					
LON^2		0.05	0.45	0.52	0.53	0.53	0.51	0.48		
UxVMAX	0.07	0.10	0.12	0.12	0.12	0.12	0.11	0.10	0.09	0.08

VxVMAX	0.25	0.25	0.24	0.19					
VxDVMAX					0.10	0.11	0.10		
VMAXxDVMAX	-0.16	-0.24	-0.32	-0.32	-0.29	-0.25	-0.19		
$VMAX^2$								-0.18	-0.21

Table 3. Dependent statistics for the Southern Hemisphere ST5D model are listed. Shown are the R^2 (variance explained), RMSE and the number of cases used to develop the regression equation for each forecast period.

Southern Hemisphere (1980-2002)										
	12-h	24-h	36-h	48-h	60-h	72-h	84-h	96-h	108-h	120-h
R^2	45.8	48.0	47.8	48.8	50.0	50.4	52.1	52.7	53.6	54.8
RMSE(kt)	4.8	8.3	11.5	13.8	15.6	17.2	17.7	18.1	18.3	18.1
Num	7231	6622	6027	5461	4919	4404	3912	3460	3047	2671

Table 4. Verification statistics associated with forecasts of tropical cyclone intensity for the period 2004-2007. Shown are the mean absolute error (MAE) and bias (BIAS) in units of kt (1 kt =0.54 ms^{-1}) associated with the Southern Hemisphere ST5D model (ST5D), persistence of initial intensity (PER) and a climatological value of 65 kt (CLIM) for the 12-h, 24-h, 36-h, 48-h, 72-h, 96-h and 120-h forecasts. The number of forecasts for each time period is given in parentheses. Verification is based on JTWC best tracks for the 2004-2007 tropical cyclone seasons in the Southern Hemisphere.

Forecast	**12-h**	**24-h**	**36-h**	**48-h**	**72-h**	**96-h**	**120-h**
Cases	**(1163)**	**(1049)**	**(930)**	**(818)**	**(611)**	**(451)**	**(318)**
			MAE (kt)				
SH ST5D	9.6	16.0	20.3	23.0	24.9	26.2	26.6
PER	10.7	19.5	26.3	31.0	36.0	37.6	40.8
CLIM	25.5	26.0	26.6	27.6	28.6	29.5	29.7
			BIAS (kt)				
SH ST5D	0.3	0.9	1.0	1.5	0.2	0.5	-5.1
PER	-0.2	-0.5	-1.0	-1.3	-2.5	-1.1	-0.4
CLIM	1.8	-0.2	-1.9	-2.7	-3.0	-0.6	0.3
			R^2				
SH ST5D	24.8	29.6	34.4	38.5	47.7	49.4	50.0