P2.18 A NEW STATISTICAL METHOD FOR ESTIMATING TROPICAL CYCLONE INTENSITY FROM GOES-IR IMAGERY

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1. INTRODUCTION

Infrared (IR) imagery from geostationary satellites is a crucial tool in diagnosing and forecasting tropical cyclones (TC's) because the temporal and spatial regularity of sampling allows for continuous global monitoring of TC's. On the less positive side, IR imagery is often severely limited at giving *direct* information about TC inner core structure and evolution because upper level cirrus clouds are opaque at typical IR wavelengths. This is especially problematic in TC scenes which often display a central dense overcast (CDO) aloft, and much of the structure of the eyewall and surrounding rainbands becomes obscured.

Although TC diagnosis and forecasting is challenged by the presence of upperlevel cirrus, the regularity of IR data and the volume of images that currently exist in archival data sets allow for calculation of *indirect* relationships between cloud top temperatures (T_b) and intensity. The first widely applied method for estimating TC intensity using geostationary data was the Dvorak technique (Dvorak 1975, 1984). In response to the inherent subjectivity of the Dvorak technique, Zehr (1989) and Velden et al. (1998) developed the objective Dvorak technique (ODT) which is currently employed by various forecast centers and provides an objective method that is competitive with the subjective Dvorak technique. At present, various ways to improve the performance of the ODT are being explored under the umbrella of the advanced ODT (AODT, Olander et al. 2002). In particular, improvement of the ODT in the case of weaker systems (below Category 1) is being addressed using various scene typing schemes and objective curved band analyses. All three of these methods (the subjective, objective, and advanced objective Dvorak technique) relate particular IR derived parameters to current TC intensity. To put it another way, these methods are based on *correlations* between IR imagery features and TC intensity. For example, it is accepted that colder cloud tops (i.e., deeper convection) in the TC eyewall region correlate well with greater intensity. These correlations have historically been determined by means of human experience, that is, empiricism.

This paper introduces a new approach that builds on empirical foundations, and considers more formal statistical relationships between IR derived variables and TC intensity. A multivariate linear model (multiple regression) is formed and tested. At the writing of this paper, only a handful of independent error tests have been performed to establish the accuracy and consistency of the method, but all results thus far have been very encouraging, and suggest that the linear model is competitive with the existing AODT while streamlining the process considerably and reducing the number of decisions (e.g., scene type identification) that are made within the framework of the AODT. Much more thorough testing will be presented at the meeting.

2. RESULTS

As a first step, the IR predictors applied to the model are the same as those used by the AODT. Mean sea level pressure (MSLP) measured by aircraft reconnaissance (recon) is the predictand. The IR parameters that we found to be highly significant (above 99%) in their correlation with TC central MSLP comprise almost the entire set of IR parameters currently employed by the AODT in addition to latitude and longitude[1] (Table 1). This is an encouraging result because it formally confirms that the input parameters to the current AODT do indeed relate well statistically to intensity. Results of a dependent test of the new regression based

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[1]The correlation of longitude and TC intensity may be due to Atlantic SST climatology, and while the significance is high, the amplitude is very small and has little effect on the intensity estimate.

Table 1: Normalized coefficients (sorted by amplitude) for the predictors used in the multivariate linear model. ERT = temperature of warmest pixel in eye region, CWCRT = coldest pixel from a set of warm pixels along a set of cold rings (Zehr 1989), MCRT = mean cloud region temperature, LAT = latitude, ERFTV, CRFTV = eye, cloud region Fourier transform value, CRSV = cloud region symmetry value, LON = longitude. The variance of aircraft measured MSLP explained by the regression is 57%.

predictor	norm. coeff.	conf. level
ERT	-0.7705	99.9–100%
CWCRT	0.3952	99.9–100%
MCRT	0.3842	99.9–100%
LAT	-0.2799	99.9–100%
ERFTV	0.1259	99.9–100%
CRFTV	0.0958	99–99.9%
CRSV	-0.0896	99–99.9%
LON	0.0591	99.9–100%

method applied to a sample of 1624 IR images for which we have corresponding aircraft reconnaissance MSLP data is shown in Fig. 1.

Comparison of the first (top) and third panels in Fig. 1 shows that when estimating MSLP based on a single image (i.e., with no information about previous IR scenes or intensities), the linear model outperforms the AODT. The root mean square error (RMSE) of MSLP estimated by the linear model is 13 mb while the RMSE of the AODT raw T-number MSLP is 17 mb. The linear model has reduced the outliers and distributes the errors more normally. Comparison of the second and fourth (bottom) panels shows that when MSLP estimated by the linear model (denoted as r-MSLP) is time averaged[2], the linear model is competitive with the CI-number based MSLP of the AODT. The RMSE for both methods are essentially equal, and the errors of the averaged r-MSLP are more normally distributed. The AODT CI-number is formed using a combination of time averaging and application of rules, some of which are based on identification of scene types (the rules and scene types are employed

[2]Time averaging was performed using the same 12 h weighted mean that is used in the ODT and AODT. We plan on testing different averaging schemes, and may find that a shorter averaging period will perform just as well or better.

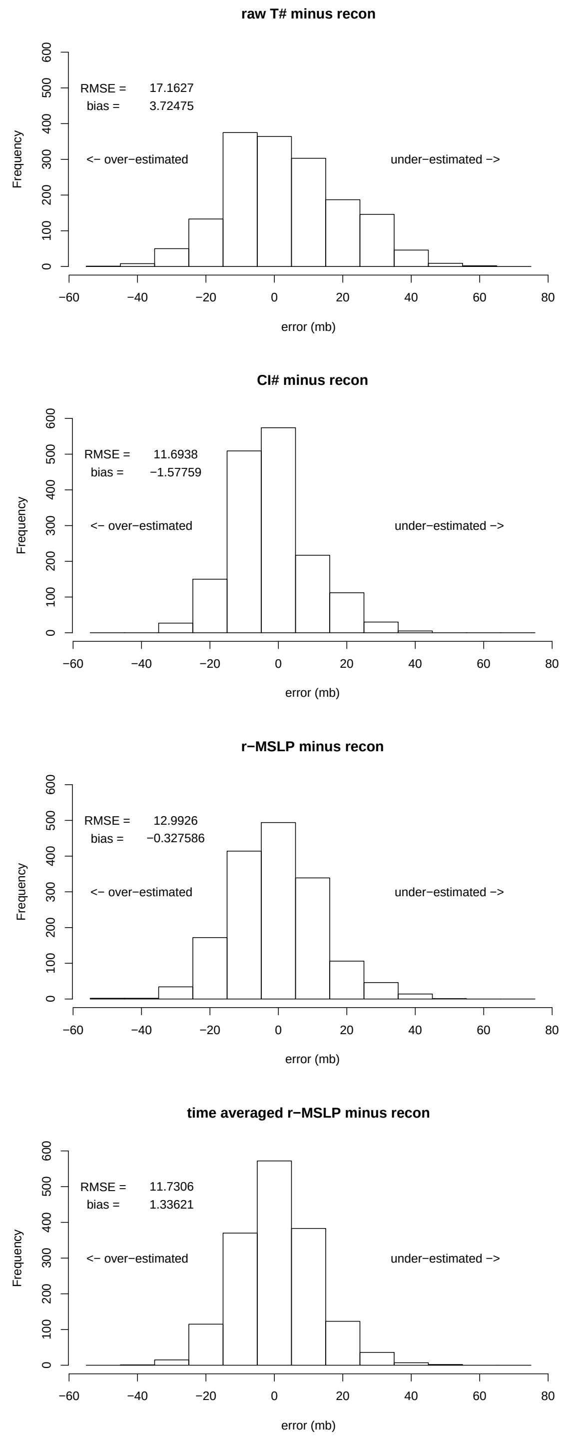

Figure 1: Error analysis of MSLP estimated from the AODT raw T-number and CI-number versus reconnaissance (top two panels), and the regression based MSLP (r-MSLP) before and after time averaging (bottom two panels).

within the AODT in order to mirror the rules set out in the subjective Dvorak technique). Scene type identification is one of the more difficult challenges that research on the AODT is actively addressing, but is *not required by the linear model*.

The results shown in Fig. 1 are based on dependent testing of the entire sample of images that are concurrent with recon. An independent test of two TC's is presented here. For each TC, we rederived the regression coefficients for the entire sample minus that particular TC, and then tested the isolated storm (jackknife procedure). The results are shown in Fig. 2 [Fran (1996)], and Fig. 3 [Edouard (1996)]. As seen in Fig. 2, the linear model (based on a *single* image, i.e., with with no time averaging) again gives a better estimate of MSLP than the raw T-number derived from the AODT. The RMSE is reduced from 13 mb to 8 mb. The bias is comparable, but of opposite sign (negative error implies an overestimation of intensity). The bottom panel shows the evolution of MSLP as measured by recon (black curve), and as estimated by the linear model (red) and the AODT (blue and green). Presently, we are performing time averages of r-MSLP but they are not yet available at the time of this writing. It is clear however that a time average performed on the red r-MSLP curve in Fig. 2 will result in greater accuracy. The formal results will be presented at the meeting.

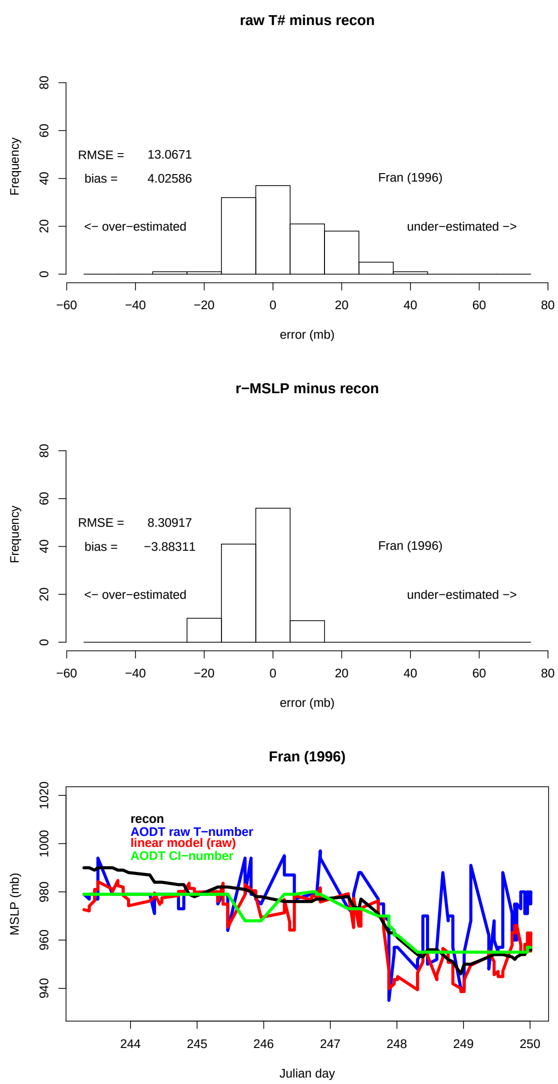

Figure 2: Independent (jackknife) MSLP error analysis of the linear model applied to Hurricane Fran (1996), and comparison with the AODT.

Figure 3 demonstrates the performance of the linear model applied to Hurricane Edouard (1996). The RMSE is again significantly lower than the AODT (based on raw T-number), as is the bias, but the systematic underestimation of MSLP is evident in both the linear model and the AODT. As seen in the bottom panel, the calculation of CI-number from the AODT raw T-number does a good job of forcing the MSLP closer to the recon curve, and the linear model is fairly competitive overall. Again, a reduction of error can be expected when time averaging of r-MSLP is performed.

It should be noted that the results shown in Figs. 2 and 3 do not constitute a thorough examination of the performance of the linear model. Further testing is needed, and it is possible that the model will be significantly outperformed by the AODT on particular individual cases. Again, results of this thorough testing will be provided at the meeting.

3. DISCUSSION

A new model for estimating TC intensity using IR imagery was introduced. The model is a simple linear regression of aircraft reconnaissance MSLP onto a set of IR derived parameters, and information about TC position. When compared in a dependent test using a large sample of images, the MSLP estimated by the linear model (r-MSLP) has significantly smaller errors than the MSLP estimated from the AODT raw T-number. When time averaging was performed on r-MSLP, the linear model was competitive with the AODT CI-number, while the calculation of r-MSLP requires less steps and decisions than the AODT. At the time of this writing, a very limited amount of independent testing has been performed, and it is not yet clear how well the linear model will perform in a variety of cases, but the independent testing results using Hurricanes Fran and Edouard (1996) are very encouraging.

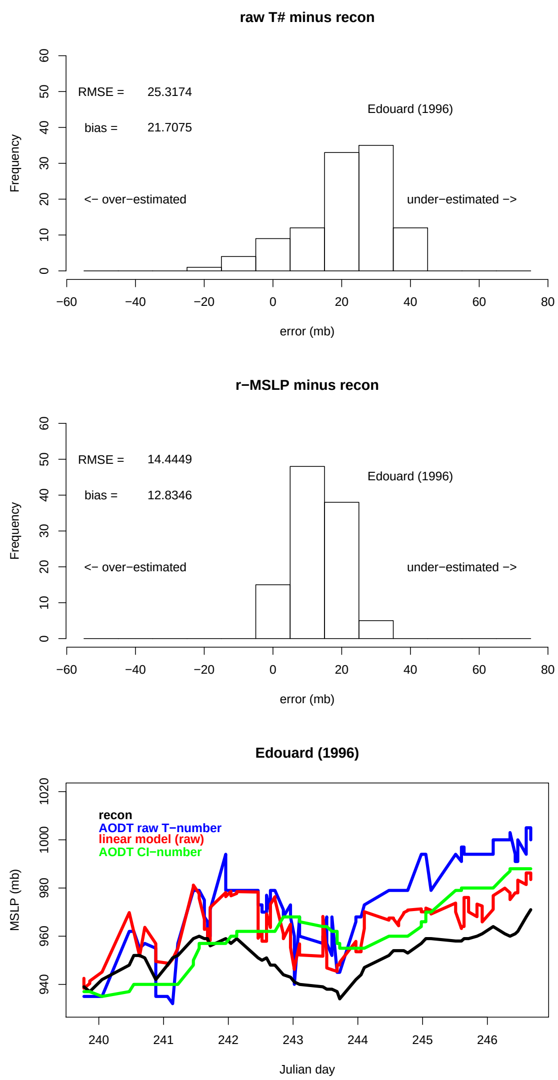

Figure 3: Same as Fig. 2, but for Hurricane Edouard (1996).

In closing, we note that the construct of the multivariate linear model also allows for the easy future inclusion of a broad variety of additional parameters. In particular, inclusion of microwave derived parameters (e.g., Bankert and Tag 1997, 2002; May et al. 1997; Hawkins et al. 1998) seems a logical next step in the evolution of a hybrid model that incorporates multi-satellite sensor information to estimate TC intensity. Additional IR derived parameters can also be easily tested within the model. Information regarding climatology, persistence, and synoptic scale environmental factors similar to those used in SHIPS (Statistical Hurricane Intensity Prediction Scheme; DeMaria and Kaplan 1999; DeMaria et al. 2002, 2003) may form significant parameters for estimating current intensity as well as forecasted intensity, and can be readily included in the linear model.

Acknowledgement: This work is supported by NRL-MRY Satellite Applications Grant N00173-01-C-2024.

4. REFERENCES

Bankert, R. L., and P. M. Tag, 1997: Automating the subjective analyses of satellite observed tropical cyclone intensity. Preprints, 22nd Conference on Hurricanes and Tropical Meteorology. Amer. Meteor. Soc. 37–38.

Bankert, R. L., and P. M. Tag, 2002: An Automated Method to Estimate Tropical Cyclone Intensity Using SSM/I Imagery. *J. Appl. Meteor.*, **41**, 461–472.

DeMaria, M., and J. Kaplan, 1999: An Updated Statistical Hurricane Intensity Prediction Scheme (SHIPS) for the Atlantic and Eastern North Pacific Basins. *Wea. Forecasting*, **14**, 326–337.

DeMaria, M., R. M. Zehr, J. P. Kossin, and J. A. Knaff, 2002: The use of GOES imagery in statistical hurricane intensity prediction. Preprints, 25th Conference on Hurricanes and Tropical Meteorology. Amer. Meteor. Soc. 120–121.

DeMaria, M., M. Mainelli, L. K. Shay, J. A. Knaff, and J. P. Kossin, 2003: Improvements in real-time statistical tropical cyclone intensity forecasts using satellite data. Preprints, 12th Conference on Satellite Meteorology and Oceanography. Amer. Meteor. Soc.

Dvorak, V., 1975: Tropical cyclone intensity analysis and forecasting from satellite imagery. *Mon. Wea. Rev.*, **103**, 420–430.

Dvorak, V., 1984: Tropical cyclone intensity analysis using satellite data. NOAA Tech. Rep. NESDIS 11, 47 pp. [Available from NOAA/NESDIS, 5200 Auth Rd., Washington, DC 20233.]

Hawkins, J. D., D. A. May, J. Sandidge, R. Holyer, and M. J. Helveston, 1998: SSM/I-based tropical cyclone structural observations. Preprints, 9th Conf. on Satellite Meteorology and Oceanography. Amer. Meteor. Soc., 230-233.

May, D. A., J. Sandidge, R. Holyer, and J. D. Hawkins, 1997: SSM/I derived tropical cyclone intensities. Preprints, 22nd Conference on Hurricanes and Tropical Meteorology. Amer. Meteor. Soc. 27–28.

Olander, T. L., C. S. Velden, and M. A. Turk, 2002: Development of the advanced objective Dvorak technique (AODT) - current progress and future directions. Preprints, 25th Conference on Hurricanes and Tropical Meteorology. Amer. Meteor. Soc. 585–586.

Velden, C. S., T. L. Olander, and R. M. Zehr, 1998: Development of an Objective Scheme to Estimate

Tropical Cyclone Intensity from Digital Geostationary Satellite Infrared Imagery. *Wea. Forecasting*, **13**, 172–186.

Zehr, R. M., 1989: Improving objective satellite estimates of tropical cyclone intensity. Preprints, 18th Conf. on Hurricanes and Tropical Meteorology. San Diego, CA, Amer. Meteor. Soc. J25–J28.