A User's Guide to the UW-CIMSS Tropical Cyclone Intensity Estimation (TIE) Model

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1. Introduction

Infrared (IR) imagery from geostationary satellites is a fundamental tool for diagnosing and forecasting tropical cyclones (TC) because the temporal and spatial regularity of sampling allows for continuous and timely global monitoring of TCs. However, 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 frequent sampling (half hourly or better with present day GOES) and long history of IR data collection has resulted in large-volume archival data sets that allow for calculation of *indirect* relationships between IR-measured temperatures and intensity.

The first widely disseminated method that correlates IR imagery with TC intensity was the Dvorak Enhanced IR (EIR) technique (Dvorak and Wright 1977, Dvorak 1984). The correlations that the Dvorak EIR technique are based on were determined informally by means of human experience (empirically). The Dvorak EIR technique is still in use today and serves as a global benchmark method for estimating TC intensity using remote sensing data. The method does, however, suffer from subjectivity – that is, different forecasters will typically estimate different TC intensities based on the same IR imagery (Velden et al. 1998). The differences are often large. Another pitfall of the Dvorak technique is that it requires measurable operator training. This can be a significant problem in forecast offices that experience a large volume of forecaster transience (Engel 2002).

Similar to the Dvorak technique, the Tropical cyclone Intensity Estimation (TIE) model provides estimates of TC intensity based in part on features of the temperature field measured from geostationary infrared satellite imagery. The TIE-model was developed at UW-CIMSS to take advantage of large volume data sets that are presently available, by considering more *statistically formal* relationships between IR derived variables and TC intensity. The TIE-model is a multivariate linear model (multiple regression) and is thus completely objective. The model is applicable throughout the entire TC lifetime and its application requires no training.

2. TIE-model construction

The TIE-model is defined in the multiple linear regression framework

$$y = a_0 + a_1 x_1 + \ldots + a_n x_n$$

where y is the predictand (estimated value) based on the values of the known input parameters (predictors) $x_1, \ldots, x_n$. The constant coefficients $a_0, \ldots, a_n$ are determined using a large developmental data set and a statistical software package.

The TIE-model estimates TC central pressure (P_c) using five predictors $T_{\text{warm}}, T_{\text{cold}}$, SYM, LAT, and MPI. The IR-derived predictors $T_{\text{warm}}, T_{\text{cold}}$, and SYM are described in section 2 of Velden et al. (1998) but are also redefined here:

1. T_{warm} = temperature (°C) of the warmest pixel found within 40 km of TC center. This value is the **eye temperature** (when an eye exists).

2. T_{cold} = average temperature (°C) within an annulus surrounding the TC center. The annulus is defined by $24 \leq r \leq 136$ km. T_{cold} represents an average **eyewall cloud-top temperature**.

3. SYM = temperature (°C) of the coldest pixel from a set of 28 warm pixels found along a set of 28 circles centered at TC center. The 28 circles lie within the annulus used to calculate T_{cold}. The warmest pixel temperature along each circle is computed and SYM is the temperature of the coldest of those temperatures. SYM gives a measure of how **symmetric and "closed" the eyewall area is**.

4. LAT = latitude (°N or S) of the TC center. LAT should always be positive.

5. MPI = exp(0.1813 SST) where SST is the sea surface temperature (°C) at TC center. MPI represents TC maximum potential intensity based on SST (DeMaria and Kaplan 1994).

The UW-CIMSS TIE-model is specifically defined by

$$P_c = a_0 + a_1\, T_{\text{warm}} + a_2\, T_{\text{cold}} + a_3\, \text{SYM} + a_4\, \text{LAT} + a_5\, \text{MPI}, \tag{1}$$

where P_c has units of mb, and

$$\begin{array}{lll} a_0 = 1003.1324076 & a_1 = -0.3980090 & a_2 = 0.6746796 \\ a_3 = 0.4220070 & a_4 = -0.5440850 & a_5 = 0.1780407. \end{array}$$

The coefficients $a_0, \ldots, a_5$ were determined using a developmental data sample that contains 1688 data points from 26 TCs that occurred in the Atlantic basin during the period 1995 to 2002. The 26 TCs in the sample are Bertha (1996), Bonnie (1998), Bret (1999), Danielle (1998), Danny (1997), Dennis (1999), Edouard (1996), Erika (1997), Felix (1995), Floyd (1999), Fran (1996), Georges (1998), Gert (1999), Hortense (1996), Irene (1996), Iris (1995), Iris (2001), Keith (2000), Lenny (1999), Lili (2002), Luis (1995), Marilyn (1995), Michelle (2001), Mitch (1998), Opal (1995), and Roxanne (1995).

Each data point in the developmental data sample comprises:

1. An aircraft reconnaissance fix. Each aircraft fix contains the maximum tangential wind encountered along the flight-level radial leg (toward or away from the TC center, typically along the 700 mb pressure level), and the TC central pressure extrapolated from flight-level to the sea surface. Although the maximum tangential wind is a more

important indicator of TC intensity, it can be strongly dependent on TC azimuth (measured around the TC center) and thus can be highly variable between consecutive flight-level radial legs. The TIE-model uses TC central pressure as an indicator of intensity since it has no spatial dependence, and only varies in time.

2. Values of $T_{\text{warm}}, T_{\text{cold}}$, and SYM calculated from GOES IR imagery captured within 1 hour of the reconnaissance fix.

3. LAT.

4. MPI. The SST at TC center is from NOAA Optimal Interpolation (OI) fields.

The linear regression given by (1) explains 63% of the variance of aircraft-measured TC central pressure in the developmental sample.

The relative importance of each of the five predictors of the TIE-model can be assessed by normalizing the model and comparing the magnitudes of the five normalized (correlation) coefficients (Table 1). The most important predictor is the central eye region parameter T_{warm}, and its coefficient is negative in sign. The coefficients of the eyewall region predictors, T_{cold} and SYM, are the next two largest and both are positive in sign. Thus, as expected, warmer eye temperatures and colder eyewall cloud-top temperatures correlate with greater

Table 1: Correlation coefficients (sorted by amplitude) for the five predictors used in the multivariate TIE-model. All coefficients are significant at greater than the 99.9% confidence level. The regression explains 63% of the variance of aircraft-measured TC central pressure.

predictor	correlation coefficient
T_{warm}	-0.64
T_{cold}	$+0.43$
SYM	$+0.34$
MPI	$+0.26$
LAT	-0.16

intensity (lower pressure). The remaining two predictors, MPI and LAT act to modulate the relationship between the IR-derived predictors and TC intensity. For example, the coefficient of LAT is negative because the height of the tropopause typically lowers, and the tropopause temperature consequently increases, with increasing latitude. Since the tropopause acts as a lid on TC eyewall convection, the minimum achievable cloud-top temperature above the eyewall region increases with increasing latitude. However, this latitude-dependent limitation on the minimum achievable eyewall cloud-top temperatures apparently does not represent a strong enough limitation on intensity to negate this effect (Kossin and Velden 2003). In other words, imposing a lower lid on eyewall convection does not impede the intensity enough to

counteract the relationship between cold eyewall clouds and intensity. Thus, for example, a TC with some fixed mean eyewall cloud-top temperature will be more intense at higher latitudes, all other parameters being equal.

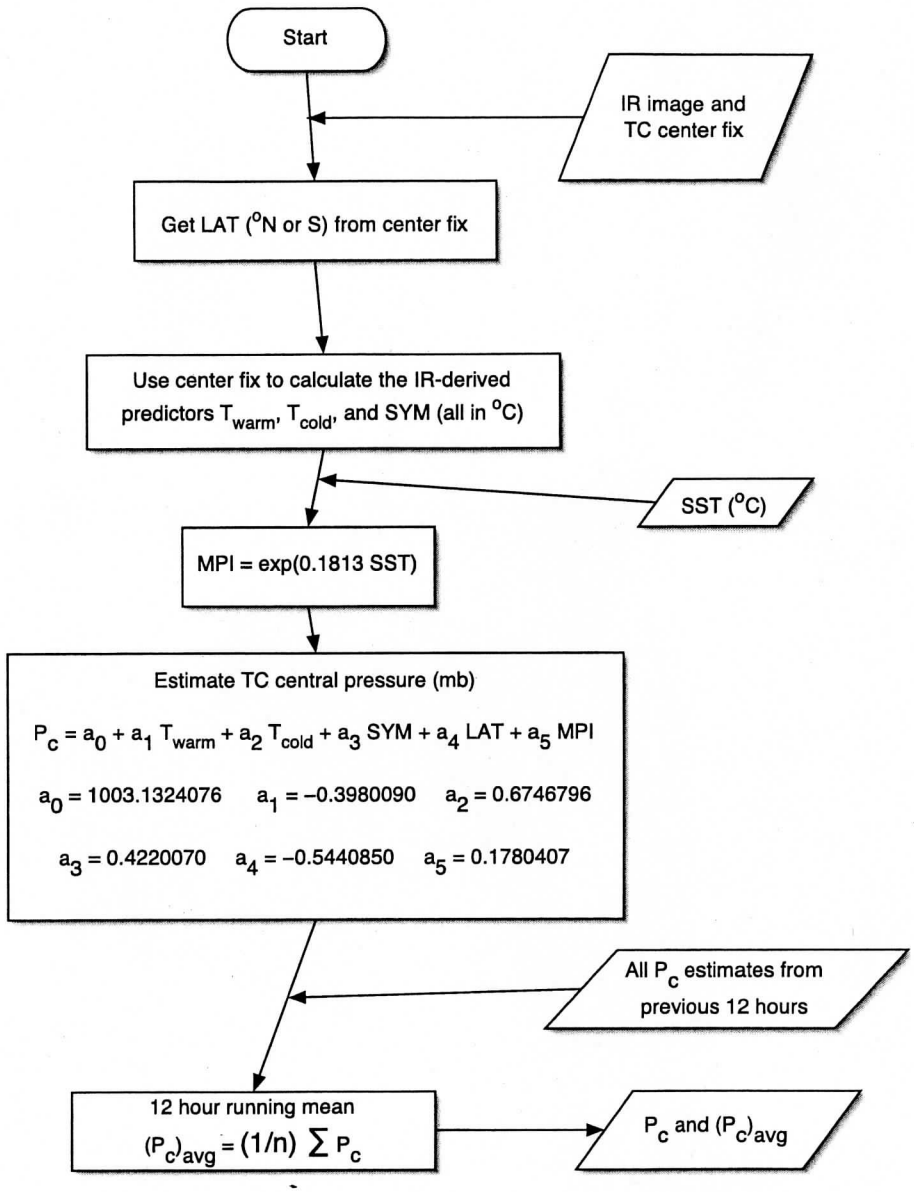

Figure 1: The UW-CIMSS TIE-model.

The time variability of the IR-derived predictors T_{warm}, T_{cold}, and SYM can exhibit short period oscillations in addition to the more physically meaningful longer period tendencies. These short period variations don't typically correlate well with associated short period variations of TC intensity and can lead to spurious indications of rapid intensity change. Although accurate prediction or measurement of rapid intensity change is highly desirable,

it is necessary to filter the TIE-model output using a simple time average to remove the recurring problem of "false alarms". This is achieved with a 12h running mean of the P_c estimates. The complete sequence of steps that define the TIE-model are outlined explicitly in Fig. 1.

3. TIE-model performance

The TIE-model was tested using a jackknife approach in which each TC in the 26 TC sample was individually removed from the sample and the coefficients of the regression were rederived using the remaining 25 TCs. The resulting regression was then used to estimate P_c in the omitted TC. The errors between the TIE-model P_c and the aircraft-measured central pressure for the omitted TC were then calculated. These steps were repeated for each TC and the accumulated errors were tallied to form an overall error. This method gives a good indication of how the TIE-model will perform, *on average*, in an operational real-time environment. The overall error distribution from the jackknife procedure is shown in Fig. 2.

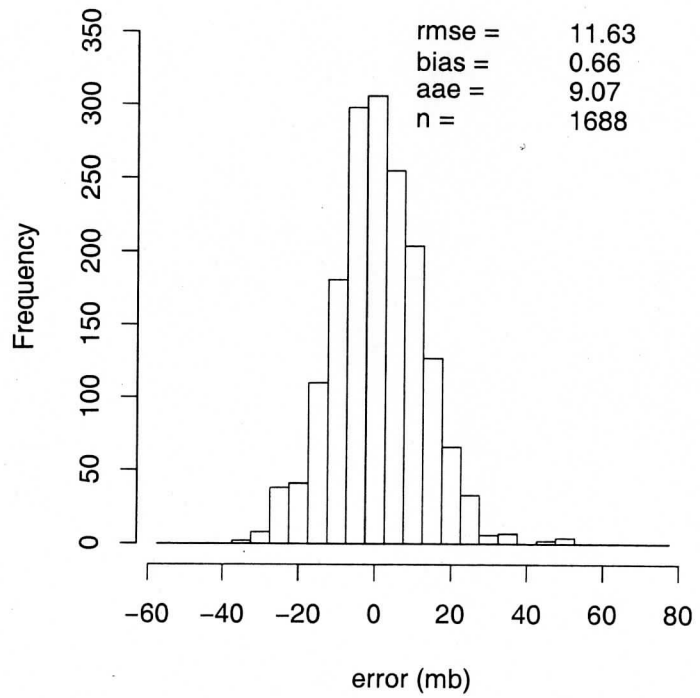

Figure 2: Distribution of TIE-model errors. Negative (positive) error indicates that the TIE-model overestimated (underestimated) intensity compared to aircraft measurements. The root mean square error (rmse), bias, and average absolute error (aae) are shown in mb.

The largest errors (+45 to +50mb) and a substantial majority of the errors between +30 and +35mb are due entirely to poor performance in estimating the intensity over the lifetimes of Opal (1995) and Mitch (1998) (Fig. 3). Consequently, removal of these two TCs from the testing sample results in significantly better performance. This may be justified in the case of

Opal (1995) because the poor performance of the TIE-model was caused by instrumentation problems – the pinhole eye that emerged during Opal's rapid intensification was too small to be adequately resolved by the GOES IR sensor. If a warm eye temperature is *artificially* introduced into the TIE-model predictor T_{warm}, the intensity estimate errors are reduced nearly to zero during Opal's maximum intensity.

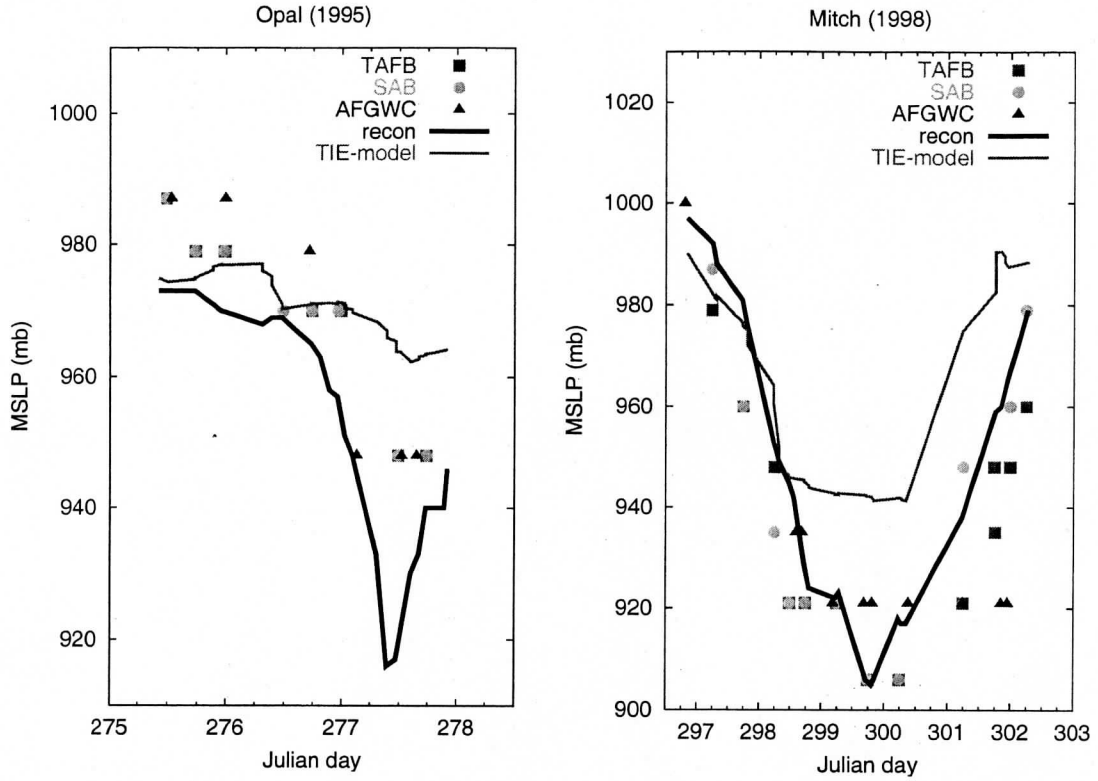

Figure 3: Time evolution of central pressure in Hurricanes Opal (1995) and Mitch (1998); aircraft-measured central pressure (black curve), TIE-model estimates (red curve), and operational Dvorak technique estimates from the Tropical Analysis and Forecasting Branch (TAFB, red squares), Satellite Applications Branch (SAB, green circles), and Air Force Global Weather Center (AFGWC, blue triangles).

Unfortunately, it is not presently clear what is responsible for the poor performance in Mitch (1998). The values of aircraft-measured central pressure during maximum intensity lie at the extreme range of the sample, and thus lie outside the range of the training sample when Mitch is omitted in the jackknife procedure. This situation can be problematic for statistical methods such as linear regression and neural networks because the method is forced to extrapolate beyond its training range, and this usually results in significant loss of accuracy. It is hoped that future inclusion of additional very intense TCs into the training sample will improve this weakness. If expanding the sample does not improve performance in the strongest TCs, then the need for additional predictors that can identify the important features missed by the five present predictors must be addressed.

Examples of good TIE-model performance are shown in Fig. 4. For the case of Hortense (1996), there is some noise in the TIE-model during the developing stages (Julian days 251–255) that was not entirely removed by time averaging. Nevertheless, the TIE-model does a good job of capturing the development, maximum intensity, and weakening of Hortense. The initial weak tropical storm stage was also well estimated.

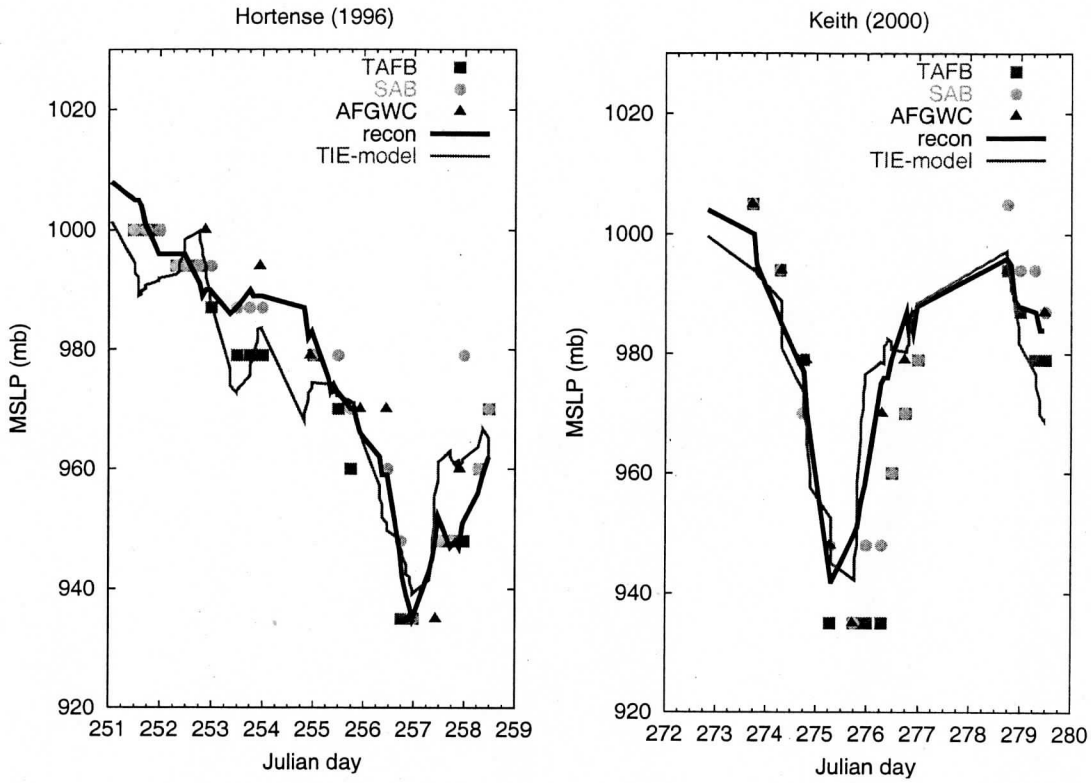

Figure 4: Same as Fig. 3, but for Hurricanes Hortense (1996) and Keith (2000).

Also shown in Fig. 4, the entire life-cycle of Hurricane Keith (2000) was well estimated by the TIE-model. The maximum intensity was estimated slightly late, and the reintensification that occurred as Keith emerged from land and moved over the Bay of Campeche (Julian day 279) was overestimated, but the overall TIE-model error was small. The TIE-model captured the rapid intensification and subsequent weakening very well.

4. Summary

The UW-CIMSS TIE-model is a multivariate linear model that estimates TC intensity in terms of central pressure. The input parameters (predictors) of the model are derived from geostationary satellite IR imagery and sea surface temperature. The latitudinal dependence of IR-derived cloud-top temperatures is accounted for explicitly by including latitude as a predictor. The IR-derived predictors give information about TC eye temperature, eyewall cloud-top temperature, and eyewall symmetry. The TIE-model is completely objective and is applicable to all stages of TC lifecycle.

In quasi-independent (jackknife) testing, the TIE-model was found to perform well in a variety of situations. Overall rmse within the developmental sample is less than 12mb. Two TCs in the 26 TC sample were found to be problematic for the TIE-model – Opal (1995) and Mitch (1998) – and are responsible for a a significant portion of the sample rmse. In the case of Opal, the problem was not a model problem, but was caused by the inability of the GOES-IR sensor to resolve Opal's pinhole eye. For the case of Mitch, it is not so clear where the problem lies, but it may be due to the fact that Mitch is the most intense TC in the developmental sample, and thus lies outside the training range in the jackknife testing. Future expansion of the sample to include more very intense TCs will hopefully mitigate this problem. At the end of each TC season, the developmental sample will be expanded and the TIE-model coefficients will be rederived.

The TIE-model is expected to evolve considerably in the near future. The multiple regression framework offers an excellent platform for testing a wide variety of predictors. These may include parameters derived from synoptic fields or satellite microwave imagery or soundings.

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References

DeMaria, M. and J. Kaplan, 1994: Sea surface temperature and the maximum intensity of Atlantic tropical cyclones. *J. Climate*, **7**, 1324–1334.

Dvorak V. F., and S. Wright, 1977: Tropical cyclone intensity analysis using enhanced infrared satellite data. Proceedings of the 11th Technical Conference on Hurricanes and Tropical Meteorology. Amer. Meteor. Soc. 268–273.

Dvorak, V. F., 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.]

Engel, G. T., 2002: Satellite applications at the Joint Typhoon Warning Center. Rapporteur Report, Topic 0.1e, 5th WMO International Workshop on Tropical Cyclones, Tech. Doc. WMO/TD No. 1136, WMO, Geneva, Switzerland.

Kossin, J. P., and C. S. Velden, 2003: A pronounced bias in tropical cyclone intensity estimation based on the Dvorak technique. *Mon. Wea. Rev.*, submitted.

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.