

Improvements in the Probabilistic Prediction of Tropical Cyclone Rapid Intensification with Passive Microwave Observations

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ABSTRACT

The probabilistic prediction of tropical cyclone (TC) rapid intensification (RI) in the Atlantic and eastern Pacific Ocean basins is examined here using a series of logistic regression models trained on environmental and infrared satellite-derived features. The environmental predictors are based on averaged values over a 24-h period following the forecast time. These models are compared against equivalent models enhanced with additional TC predictors created from passive satellite microwave imagery (MI). Leave-one-year-out cross validation on the developmental dataset shows that the inclusion of MI-based predictors yields more skillful RI models for a variety of RI and intensity thresholds. Compared with the baseline forecast skill of the non-MI-based RI models, the relative skill improvements from including MI-based predictors range from 10.6% to 44.9%. Using archived real-time data during the period 2004–13, evaluation of simulated real-time models is also carried out. Unlike in the model development stage, the simulated real-time setting involves using Global Forecast System forecasts for the non-satellite-based predictors instead of “perfect” observational-based predictors in the developmental data. In this case, the MI-based RI models still generate superior skill to the baseline RI models lacking MI-based predictors. The relative improvements gained in adding MI-based predictors are most notable in the Atlantic, where the non-MI versions of the models suffer acutely from the use of imperfect real-time data. In the Atlantic, relative skill improvements provided from the inclusion of MI-based predictors range from 53.5% to 103.0%. The eastern Pacific relative improvements are less impressive but are still uniformly positive.

1. Introduction

Recent innovations in operational numerical weather prediction (NWP) bear promise in the longstanding challenge of improving tropical cyclone (TC) intensity prediction (e.g., Tallapragada 2014; DeMaria et al. 2014). Even so, rapid intensification (RI) events in TCs continue to present a significant hurdle for TC intensity

forecasting (Gall et al. 2013). Part of the difficulty stems from the fact that RI, by definition (e.g., Kaplan et al. 2010, hereafter KDK10), is a rare event, which challenges statistical RI forecasting schemes designed with a finite climatology. Contemporary studies on RI, such as KDK10, define an RI event as a TC experiencing an increase in the 1-min maximum sustained surface wind speed beyond some threshold representing the 90th–95th percentiles of 24-h intensity change, typically 25–35 knots (kt; $1 \text{ kt} = 0.51 \text{ m s}^{-1}$) per 24-h period. Observational analysis suggests that favorable environmental conditions such as high ocean heat content, lower

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vertical wind shear, and higher low-level humidity are typically more favorable for RI (Kaplan and DeMaria 2003; KDK10; Hendricks et al. 2010). Yet, favorable environmental conditions do not guarantee RI and it is widely believed that the internal dynamics distinguish which storms in favorable environments will undergo RI (e.g., Hendricks et al. 2010). Therefore, insufficient grid resolution, initialization errors, and imperfect parameterization of various physical processes in NWP models likely prevent the accurate prediction of internal dynamics associated with RI. Nonetheless, ongoing improvements in NWP hint at a brighter future in RI prediction. Like NWP models, statistical RI forecast models likely suffer, in part, because they also lack sufficient information about the internal storm structure and dynamics.

With the exception of Atlantic TCs routinely monitored by radar-equipped NOAA research aircraft, detailed three-dimensional depictions of kinematic and thermodynamic storm structure are rarely available. However, satellite data can offer proxies with which to estimate these aspects of TC structure. For example, probabilistic forecasts of RI that derive a significant amount of skill by accounting for environmental factors have been further improved by including TC structure information from 10.7- μm infrared (IR) satellite data (KDK10; Rozoff and Kossin 2011, hereafter RK11; Monette et al. 2012). Satellite IR data indicate that storms undergoing RI tend to present more symmetric and vigorous cold cloud tops near the center of circulation when compared against other storms. Lightning analyses by DeMaria et al. (2012) show that rainband regions are more electrically active prior to RI events, which is consistent with the recent Tropical Rainfall Measuring Mission (TRMM)-based study of Jiang and Ramirez (2013). DeMaria et al. demonstrate that the inclusion of lightning-based predictors into the linear discriminant analysis-based Statistical Hurricane Prediction Scheme (SHIPS) rapid intensification index (RII; KDK10) shows potential to improve probabilistic RI forecasting. The benefits of satellite-derived information quantifying cloud and convective properties are unsurprising given the significant body of research indicating the important ties between latent heating processes and RI, including efficient intensification when latent heating is located within a region of high inertial stability (Shapiro and Willoughby 1982; Schubert and Hack 1982; Hack and Schubert 1986; Nolan et al. 2007; Vigh and Schubert 2009; Pendergrass and Willoughby 2009; Molinari and Vollaro 2010; Nguyen and Molinari 2012; Rogers et al. 2013) and the potential relationship between convective bursts and RI (McFarquhar et al. 2012; Rogers et al. 2013; Wang and Wang 2014).

In spite of the benefits attained by using IR-satellite imagery in RI forecasting techniques, IR imagery is

somewhat limited in its depiction of the precipitation structure since it primarily shows only the topmost region of clouds, which are often widespread, thick cirrus that obscure views of the more detailed structure of latent heating processes beneath. On the other hand, passive microwave imagery (MI) observed by low-Earth-orbiting satellites peers through the cirrus cloud canopy but is attenuated by larger liquid and ice hydrometeors and can, therefore, more effectively capture the TC precipitation structure (Hawkins and Velden 2011). While the sampling of a TC by microwave sensors is more irregular and limited in time than geostationary IR data, the information contained in MI appears to be quite relevant to the prediction of RI. Kieper and Jiang (2012, hereafter KJ12) found that a ring pattern observed in the 37.0-GHz composite color product provided in the Naval Research Laboratory TC MI dataset (Lee et al. 2002) is often concurrent with storms undergoing RI and therefore improves SHIPS RII (KDK10). The 37.0-GHz channel of MI depicts both emission from liquid hydrometeors and the scattering of radiation from cloud ice (Weng and Grody 1994). In the 37.0-GHz composite color products, the symmetry in total precipitation (which includes both “warm rain” associated with shallower convection and cloud ice aloft) is fundamental to the findings of KJ12. The MI-aided study of Jiang and Ramirez (2013) shows that RI is accompanied by greater spatial coverage of rain in the inner core, and they further provide empirically determined necessary conditions for RI. These results are also consistent with the TRMM Precipitation Radar (PR) study of Zagrodnik and Jiang (2014), which shows that precipitation frequency and the coverage of rainfall increases in the inner core and becomes more symmetric in rapidly intensifying TCs over time. Their results further concur with the significant contribution of warm-rain precipitation to the 37.0-GHz ring described in KJ12 in that Zagrodnik and Jiang show relatively shallow, weaker convection and stratiform precipitation are the most important parameters for RI, although deeper convection does become more prevalent as RI continues.

The goal of the current study is to improve the probabilistic prediction of RI using a variety of predictors derived from passive MI. To this end, we exploit information from MI to design physically based parameters that describe the distribution, organization, and intensity of precipitation signatures (caused by the attenuation due to warm rain and ice hydrometeors) in the inner core of developing and maturing TCs. It will be shown that optimally selected MI-based predictors can enhance the skill of a probabilistic RI model. The remainder of the paper is organized as follows. In section 2, we describe the data and methodology of this study. Section 3 provides an

TABLE 1. The SHIPS developmental dataset-based predictors used for the LR RI models in the Atlantic (ATL) and eastern Pacific (EPAC).

Predictor	Model	Definition
PER	ATL, EPAC	Previous 12-h intensity change (i.e., persistence)
RSST	ATL	Reynolds SST
ENSS	EPAC	Vertical average of the negative differences between the equivalent potential temperature of an air parcel lifted pseudoadiabatically from the surface and the environmental saturation equivalent potential temperature ($r = 200\text{--}800$ km)
D200	ATL	200-hPa divergence ($r = 0\text{--}1000$ km)
SHDC	ATL, EPAC	850–200-hPa vertical wind shear magnitude calculated with the vortex removed relative to the 850-hPa center ($r = 0\text{--}500$ km)
POT	ATL, EPAC	Departure from the TC's max potential intensity
BTA1	ATL	Mean IR cloud-top T_b ($r = 0\text{--}30$ km)
BTA2	EPAC	Mean IR cloud-top T_b ($r = 100\text{--}300$ km)
BTM	EPAC	Max IR cloud-top T_b ($r = 0\text{--}30$ km)
SDBT1	EPAC	Std dev of IR cloud-top T_b ($r = 50\text{--}200$ km)
SDBT2	ATL	Std dev of IR cloud-top T_b ($r = 100\text{--}300$ km)

overview of the performance of the newly developed microwave-based RI model using leave-one-year-out cross validation with developmental data and includes an evaluation of simulated real-time performance. Concluding thoughts are presented in [section 4](#).

2. Methodology

Aspects of TC structure are quantified here in an attempt to improve the probabilistic prediction of RI. In particular, passive MI is used to create predictors describing the structure of precipitation in TCs for a probabilistic RI model. The particular model chosen for this study is the logistic regression (LR) model ([Wilks 2006](#)) developed without MI for RI prediction in [RK11](#). MI-enhanced versions of this LR model are developed for both the Atlantic and eastern Pacific Ocean basins using data from the National Hurricane Center's (NHC) North Atlantic hurricane database (HURDAT; [Jarvinen et al. 1984](#)), the SHIPS developmental dataset based on gridded operational global analyses data ([DeMaria et al. 2005](#)), and passive MI data described below.

a. Probabilistic model

In both the Atlantic and eastern Pacific, MI-enhanced LR models are formulated around the LR-based RI model described in [RK11](#). The LR model's probability of an RI event occurring, specifically an event in which the increase in maximum wind $\Delta v_{\max}$ over a time period of Δt meets an RI threshold denoted by a , is represented as

$$p_L(\Delta v_{\max}/\Delta t \geq a) = \frac{1}{1 + \exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_N x_N)}, \quad (1)$$

where the $x_n = (x_1, x_2, \dots, x_N)$ represent N environmental or storm-structure-related predictors and the β_n

are fitted coefficients. These models are specifically designed to predict the probability of RI occurring at the synoptic times of 0000, 0600, 1200, and 1800 UTC, where RI is defined as an intensification event of sufficient magnitude over the following 24-h period. Three RI thresholds, including $a = 25, 30$, and $35 \text{ kt (24 h)}^{-1}$, are considered. To test whether the models possess improved skill when considering only more mature storms, two sets of models are developed around certain intensity thresholds. One set of LR models considers retrospective developmental data from any storm with intensities of at least 25 kt, which includes all of the developmental data, while a second set of models are constructed considering only data from storms with an intensity of at least 45 kt. The latter threshold, which represents moderate-strength tropical storms, screens out a large number of weaker storms while retaining a relatively larger proportion of the strongest intensification cases. The 45-kt intensity threshold is somewhat arbitrary, but it is worth noting that using an aircraft-reconnaissance-based climatology of Atlantic TCs during 1989–2008, [Vigh et al. \(2012\)](#) found a median TC intensity of 50 kt accompanies the beginning stages of eye banding and a median intensity of 58 kt is found for the first aircraft detection of an eye. Therefore, the 45-kt intensity threshold includes TCs in crucial stages of intensification.

The models' non-MI predictors are obtained from HURDAT and the SHIPS developmental dataset ([Table 1](#); see also [RK11](#)). In the Atlantic, the LR model uses the previous 12-h intensity change PER, the [Reynolds and Smith \(1994\)](#) sea surface temperature RSST, the 200-hPa divergence averaged within 1000-km radius r from the TC's center D200, the 850–200-hPa vertical wind shear magnitude over an annulus of 0–500-km radius from storm center after the vortex was removed relative to the 850-hPa center SHDC, the departure from the TC's maximum potential

TABLE 2. Footprint sizes for each passive microwave sensor at the low-, medium-, and high-frequency channels used in this study.

Sensor	Low-frequency channel		Medium-frequency channel		High-frequency channel	
	Frequency (GHz)	Footprint (km $\times$ km)	Frequency (GHz)	Footprint (km $\times$ km)	Frequency (GHz)	Footprint (km $\times$ km)
SSM/I	19.35	69 $\times$ 43	37.0	37 $\times$ 28	85.5	15 $\times$ 13
SSMIS	19.35	73 $\times$ 47	37.0	41 $\times$ 31	91.655	14 $\times$ 13
TMI level 1B	19.35	30 $\times$ 18	37.0	16 $\times$ 9	85.5	7 $\times$ 5
AMSR-E level 2A	18.7	27 $\times$ 16	36.5	14 $\times$ 8	89.0	6 $\times$ 4

intensity POT, the mean IR cloud-top brightness temperature T_b averaged within 30-km radius from storm center BTA1, and the standard deviation of IR cloud-top T_b averaged within 100–300-km radius from storm center SDBT2. The environmental predictors RSST, D200, SHDC, and POT are averaged from the 0-h time of the RI forecast through the following 24 h. Atlantic TCs that undergo RI tend to have larger PER, higher RSST, stronger D200, lower SHDC, and/or higher POT than storms that do not experience RI. In addition, IR-based predictors show RI cases produce colder inner-core cloud tops, more widespread, cold cloud tops, and more axially symmetric cloud structure with respect to the TC's center.

The SHIPS developmental dataset predictors used in the eastern Pacific LR model include PER, SHDC, POT, a measure of tropospheric static stability ENSS, the mean IR cloud-top T_b over the region of 100–300-km radius from storm center BTA2, the maximum IR cloud-top T_b within 30-km radius from storm center BTM, and the standard deviation of IR cloud-top T_b averaged over the region with a 50–200-km radius from storm center SDBT1. Like the environmental predictors in the Atlantic, ENSS is based on a 24-h time average beginning at the time of the forecast. As described in RK11, eastern Pacific TCs that undergo RI have higher PER, lower SHDC, higher POT, and lower ENSS. Also, like Atlantic storms, RI cases in the eastern Pacific have colder cloud tops, more widespread cold cloud tops, and the cloud structure is more azimuthally symmetric with respect to the TC center.

b. Microwave imagery-based predictors

1) DATASETS

The MI-based predictors are derived from a variety of satellite datasets, including the Special Sensor Microwave Imager (SSM/I), the Special Sensor Microwave Imager/Sounder (SSMIS), TRMM Microwave Imager (TMI), and the Advanced Microwave Scanning Radiometer for Earth Observing System (AMSR-E). This study incorporates the vertical and horizontal polarizations (V pol and H pol, respectively) of the SSM/I and TMI sensor T_b at 19.35, 37.0, and 85.5 GHz; SSMIS T_b at 19.35, 37.0, and 91.655 GHz; and AMSR-E T_b at 18.7,

36.5, and 89.0 GHz. Each sensor has distinct spatial resolutions, with AMSR-E and TMI providing the highest resolution. The retrospective developmental MI dataset in this study includes SSM/I and TMI T_b from 1998 to 2012, SSMIS data from 2005 to 2012, and AMSR-E data from 2002 to 2011. Table 2 shows more details on the datasets used in this study.

The various microwave spectral channels depict distinct aspects of hydrometeor attenuation and thereby precipitation processes, which is why three channels are considered in the MI-based RI models. As an example, Fig. 1 shows a variety of TMI channels for Hurricane Dean (2007) in its tropical storm stage at 1314 UTC 15 August. At the time of this imagery, the storm was in the early stages of RI prior to eventually becoming a major hurricane on 17 August. In the 19.35-GHz (V pol) and 37.0-GHz (V pol) T_b channels, which are most sensitive to emission by liquid water hydrometeors, a loosely organized ring of hydrometeors surrounds the storm center and an extensive spiral rainband exists to the south (Figs. 1a,b). The ring structure is azimuthally asymmetric, with the strongest precipitation occurring to the east-southeast in the 19.35-GHz channel and in the southwest quadrant of the 37.0-GHz channel. Nonetheless, the symmetric 19.35- and 37.0-GHz (V pol) precipitation structure resembles a nascent eyewall structure, consistent with the 37.0-GHz pattern that often precedes RI as discovered by KJ12. Now, the 37.0- and 85.5-GHz polarization-corrected temperature PCT of Figs. 1c and 1d, which show features associated with the scattering of upwelling microwave radiation from ice higher up in the atmosphere (Spencer et al. 1989; McGaughey et al. 1996), similarly identify hydrometeors likely associated with convection placed in roughly the same regions as shown in Figs. 1a and 1b. However, the detailed structure is a bit different. A ring pattern is not apparent and the azimuthal wavenumber-1 asymmetry with respect to the TC center is a bit more drastic aloft, with the maximum ice scattering signatures to the east of the storm center. Including all channels for consideration as predictors can aid in determining which aspects of storm structure are most relevant to forecasting RI with the LR model, and may even help identify which aspects of the structure are key to RI in a dynamical sense.

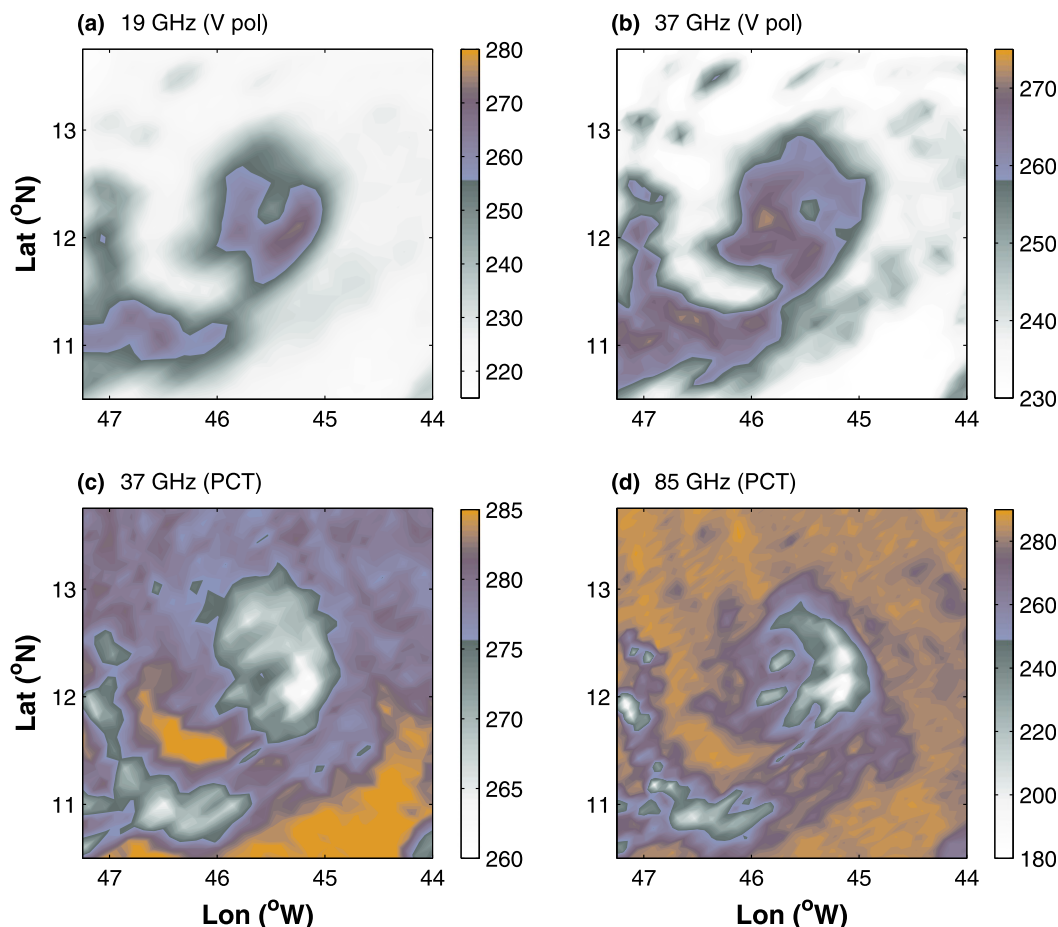


FIG. 1. TMI T_b (K) of Hurricane Dean at 1314 UTC 15 Aug 2007 for (a) 19.35 GHz (V pol), (b) 37.0 GHz (V pol), (c) 37.0 GHz (PCT), and (d) 85.5 GHz (PCT).

For comparison, Fig. 2 shows *GOES-11* IR imagery from about the same time as the MI in Fig. 1. Clearly, there are some similarities between the different satellite views of Hurricane Dean, particularly in the ice scattering signature in the PCT imagery and the cold cloud tops in the IR imagery. Both show a distinct azimuthally asymmetric structure, with the most intense cold cloud tops and ice scattering to the north and east of the center, along with a spiral rainband that extends toward the southwest portion of the image. The clouds in the IR imagery, however, are much more expansive than either the ice scattering or warm-rain features in the MI. Moreover, the nascent eyewall structure in the 19.35-GHz, and 37.0-GHz (V pol) MI is not as clear-cut in the IR data, although an IR warm spot is found in the general vicinity of the MI-indicated incipient eyewall.

2) SENSOR CALIBRATION

Before creating MI-based predictors, calibration of AMSR-E and SSMIS T_b to be compatible with TMI and

SSM/I T_b is carried out. As noted above, the AMSR-E sensor uses 18.7-, 36.5-, and 89.0-GHz channels as opposed to the 19.35-, 37.0-, and 85.5-GHz channels of the TMI and SSM/I sensors. Also, SSMIS uses a 91.655-GHz channel instead of the 85.5-GHz channel. While the physical interpretations of the low-, mid-, and high-frequency channels are similar for each sensor, the T_b differences from sensor to sensor for a given scene in space and time can be significant (as high as 10 K) (Jones and Cecil 2006, hereafter JC06; Hawkins et al. 2008). One way to calibrate different sensors involves applying radiative transfer models over a range of environmental conditions (e.g., Hong 2008), a rigorous but involved process. To facilitate potential operational updates of this model, a much simpler yet effective calibration approach is chosen. Specifically, the histogram matching technique of JC06 is applied to all AMSR-E channels and the 91.655-GHz SSMIS channel to make them more compatible with the TMI and SSM/I channels. These adjustments are carried out for both the H pol and V pol.

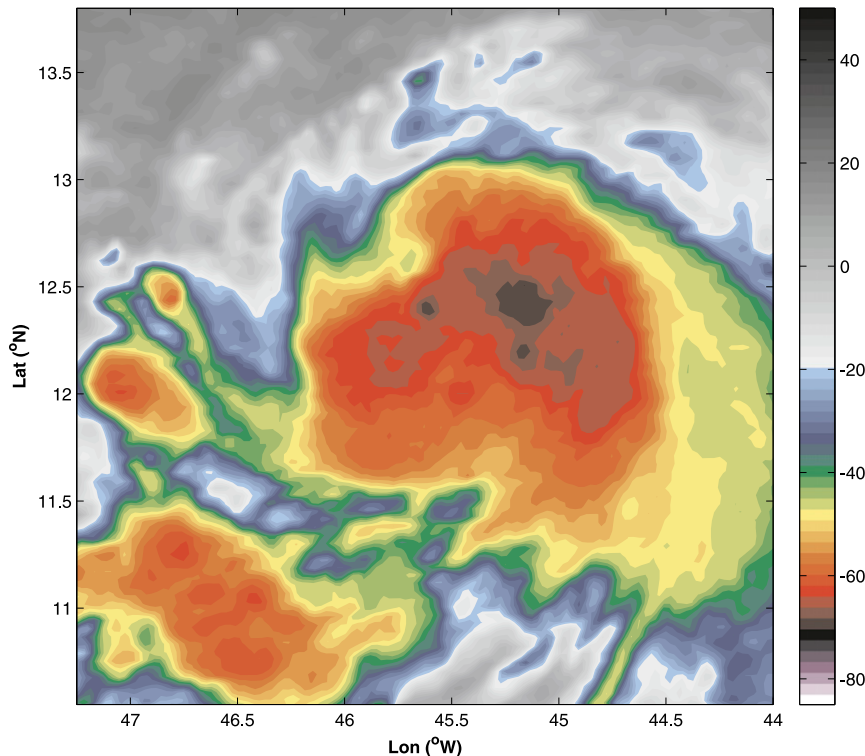


FIG. 2. GOES-11 IR ($10.7\ \mu\text{m}$) T_b ($^{\circ}\text{C}$) of Hurricane Dean at 1315 UTC 15 Aug 2007.

The higher spatial resolution TMI is used to develop calibrations for both AMSR-E and SSMIS.

To carry out the JC06 histogram matching adjustments for a given sensor, there must be a number of instances where a given TC is observed by that sensor and the TMI instrument at nearly the same time. The frequency of such a coincidence is relatively low. Tables 3 and 4 show a number of cases found where AMSR-E and SSMIS sensors observed Atlantic TCs within 45 min or less of a TMI overpass of the same TCs. These coinciding overpasses are used to calibrate all AMSR-E and the 91.655-GHz SSMIS channels to the reference TMI channels. Only data in which TMI and AMSR-E or SSMIS overlap and that fall within 10° of the TC center are considered. Furthermore, only data from over the ocean are used since land data are not considered in the model development either.

It should be noted that the storm center is determined using the objective TC center finding algorithm of Wimmers and Velden (2010), known as the Automated Rotational Center Hurricane Eye Retrieval (ARCHER). Given the sensor parallax issues associated with lower- and higher-frequency channels that measure precipitation at different altitudes, along with the vertical tilt of the TC that is often present from factors such as vertical wind shear, the TC centers associated with 19.35- and 37.0-GHz imagery are based on applying ARCHER to the 37.0-GHz

channel (H pol) while the 85.5-GHz-based centers are derived from the 85.5-GHz (H pol) channel. The data from each truncated AMSR-E and SSMIS swath is then interpolated onto the latitude-longitude grid of the matching reference TMI case.

The scatter diagrams in Fig. 3 imply matching specific coinciding satellite overpasses poses some challenges. Specifically, there is considerable spread. There are a number of factors that can cause such data spread, including a sensor's look angle and center point (e.g., Wiebe et al. 2008), as well as changes in precipitation features in the relatively small amount of time between satellite overpasses, which include both advection of precipitation features and changes in their intensities. These kinds of factors can exacerbate the spread in the scatterplots in Fig. 3 since precipitation features often have very sharp horizontal T_b gradients. Overall, as can be seen in Fig. 3, the median and the majority of the spread (25th and 75th percentiles) suggest most of the data fall within a relatively small range. Histogram matching will reduce the overall bias between sensors but will not improve the spread caused by the various aforementioned artifacts.

Once AMSR-E data are interpolated onto TMI grids, the histogram matching technique can be carried out. Cumulative distribution functions (CDFs) of T_b are

TABLE 3. Atlantic TC cases used in the AMSR-E and TMI histogram matching.

TC	Intensity (kt)	AMSR-E TC overpass time and date	TMI TC overpass time and date
Ivan	115	0445 UTC 6 Sep 2004	0530 UTC 6 Sep 2004
Jeanne	50	0632 UTC 20 Sep 2004	0707 UTC 20 Sep 2004
Jeanne	80	0619 UTC 22 Sep 2004	0655 UTC 22 Sep 2004
Dennis	75	0620 UTC 7 Jul 2005	0542 UTC 7 Jul 2005
Emily	30	1645 UTC 11 Jul 2005	1658 UTC 11 Jul 2005
Ophelia	70	1842 UTC 11 Sep 2005	1826 UTC 11 Sep 2005
Rita	100	0726 UTC 22 Sep 2005	0810 UTC 22 Sep 2005
Bertha	80	1701 UTC 10 Jul 2008	1728 UTC 10 Jul 2008
Bertha	50	1709 UTC 17 Jul 2008	1732 UTC 17 Jul 2008
Bertha	55	1614 UTC 18 Jul 2008	1637 UTC 18 Jul 2008
Ike	115	1820 UTC 7 Sep 2008	1833 UTC 7 Sep 2008

computed for the 18.7–19.35-, 36.5–37.0-, and 85.5–89.0-GHz channels of the matching TMI and AMSR-E cases and for the 85.5–91.566-GHz channels of the adjoined TMI and SSMIS cases. As in JC06, cumulative probabilities for each polarization and channel from the sensor to be adjusted (AMSR-E or SSMIS) are paired with their corresponding reference CDF values from the equivalent polarization and channel of TMI. Linear regression is then used on these paired data to adjust the AMSR-E or SSMIS T_b results to the corresponding TMI channels. Here, the adjustment equation is

$$T_{b,\text{adj}} = T_0 + \alpha T_b, \quad (2)$$

where α and T_0 are the linear regression coefficients to be determined. In some cases, as will be noted below, the overall quality of the fit can be improved by only developing and applying the calibration for a limited range

of T_b . The best-fit coefficients in Eq. (2) are shown in Table 5 for each channel and polarization for both AMSR-E and SSMIS. Table 5 also provides the lower threshold for the range of data considered in the histogram matching process (no upper bound was necessary). The fit for the coefficients of Eq. (2) benefited from applying a lower bound in the case of the 85.5-GHz channel (both AMSR-E and SSMIS) and the 37.0-GHz (H Pol only) AMSR-E channel. It is worth noting that in the case of 85.5-GHz data, the 85.5-GHz TMI data can become considerably colder than the matching 89.0-GHz AMSR-E and 91.655-GHz SSMIS data at the cold end of the T_b spectrum (Hawkins et al. 2008), but there are relatively few data composing the cold extremes and the overall quality of the calibration would be hindered by including these data in the calibration.

The AMSR-E (raw and adjusted) and TMI CDFs for all channels are plotted in Fig. 4 (top). As in JC06, for

TABLE 4. Atlantic TC cases used in the SSMIS and TMI histogram matching.

TC	Intensity (kt)	SSMIS TC overpass time and date	TMI TC overpass time and date
Bertha	90	2331 UTC 9 Jul 2008	2318 UTC 9 Jul 2008
Gustav	60	0044 UTC 29 Aug 2008	0032 UTC 29 Aug 2008
Ike	125	1200 UTC 4 Sep 2008	1136 UTC 4 Sep 2008
Paloma	85	1042 UTC 9 Nov 2008	1055 UTC 9 Nov 2008
Alex	60	1346 UTC 29 Jun 2010	1350 UTC 29 Jun 2010
Danielle	80	0950 UTC 29 Aug 2010	0948 UTC 29 Aug 2010
Igor	70	2255 UTC 19 Sep 2010	2310 UTC 19 Sep 2010
Otto	50	1004 UTC 7 Oct 2010	0946 UTC 7 Oct 2010
Otto	75	0937 UTC 9 Oct 2010	0935 UTC 9 Oct 2010
Shary	30	2306 UTC 28 Oct 2010	2310 UTC 28 Oct 2010
Bret	35	1114 UTC 21 Jul 2011	1105 UTC 21 Jul 2011
Don	30	1342 UTC 27 Jul 2011	1337 UTC 27 Jul 2011
Emily	45	0112 UTC 4 Aug 2011	0121 UTC 4 Aug 2011
Franklin	30	2329 UTC 12 Aug 2011	2336 UTC 12 Aug 2011
Gert	50	2058 UTC 15 Aug 2011	2050 UTC 15 Aug 2011
Gert	50	2221 UTC 15 Aug 2011	2221 UTC 15 Aug 2011
Katia	60	0913 UTC 2 Sep 2011	0906 UTC 2 Sep 2011
Katia	80	1326 UTC 8 Sep 2011	1316 UTC 8 Sep 2011
Katia	75	1045 UTC 9 Sep 2011	1041 UTC 9 Sep 2011

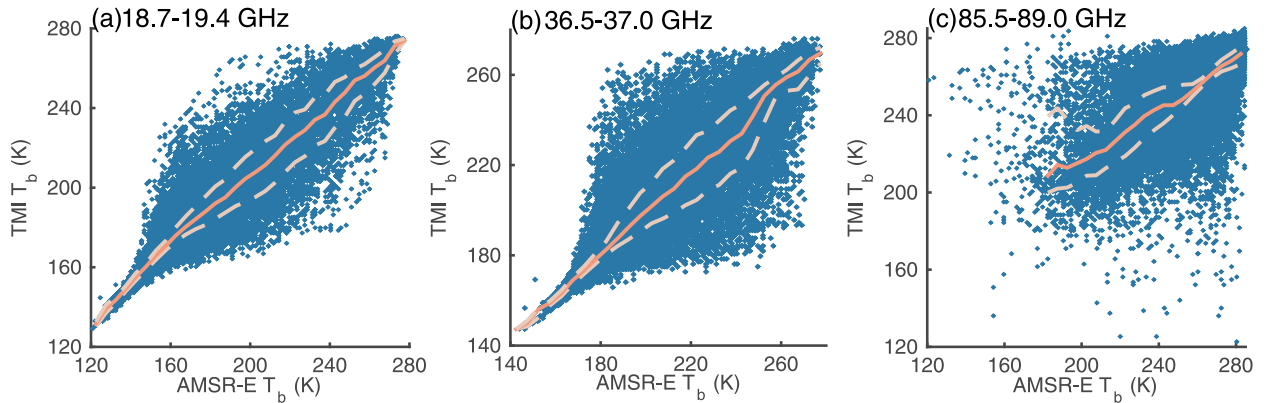


FIG. 3. Scatter diagrams of TMI T_b (K) vs AMSR-E T_b (K) for the (a) 18.7–19.35-, (b) 36.5–37.0-, and (c) 85.5–89.0-GHz channels (blue dots), along with the 25th, 50th, and 75th percentiles of the spread as a function of AMSR-E T_b .

each CDF, data are paired along lines of equal cumulative probability. These pairs are then plotted in Fig. 4 (bottom). The linear regression then adjusts the AMSR-E temperature toward the 1:1 line of the TMI T_b [also plotted in Fig. 4 (bottom)]. Overall, the AMSR-E calibration improves the agreement between the AMSR-E and TMI CDFs. The 91.655-GHz SSMIS to 85.5-GHz TMI calibration follows similarly to those shown in Fig. 4, but the SSMIS–TMI CDFs are even closer in value (Fig. 5), so the adjustments (as seen in Table 5) are relatively minor.

One challenge to contend with is the loss of AMSR-E in 2011 and TMI in 2015, and the eventual losses of current SSM/I and SSMIS instruments. However, these losses are mitigated by SSMIS replacements (e.g., DMSP *F19* and *F20*) and the recent arrival of the Advanced Microwave Scanning Radiometer 2 (AMSR2) on board the *Global Change Observation Mission–Water (GCOM-W1)* satellite and the Global Precipitation Measurement (GPM) Microwave Imager (GMI). Given the 18.7-, 36.5-, and 89.0-GHz frequencies of GMI and AMSR2 and 91.655-GHz frequency of current and future SSMIS sensors, future revisions of this algorithm should calibrate the channels of all satellite data to the GMI–AMSR2 or the SSMIS frequencies instead of calibrating all data to the TMI and SSM/I channels, as is done here.

3) PREDICTOR CREATION

After all data are collected and AMSR-E and SSMIS data are calibrated, a variety of procedures are carried out to create MI-based structural predictors describing the state of a TC’s inner core. First, before creating predictors, a best-track TC location estimate is used to construct a smaller storm-centered initial microwave data grid from the complete swath of data from a given microwave sensor. If the TC center estimate does not geographically fall within the swath at the time of the

satellite image, then the data are discarded. Second, data points falling over land (including islands) are set to missing values since land values of T_b under clear conditions can be similar in magnitude to intense precipitation, creating ambiguity in the structural features of the TC. Third, since PCTs for 37.0 and 85.5 GHz are often used to detect strong convection (e.g., Cecil 2011), PCTs are derived for both channels, where the 37.0-GHz PCT = $2.18 T_b$ (V pol) – $1.18 T_b$ (H pol) and the 85.5-GHz PCT = $1.818 T_b$ (V pol) – $0.818 T_b$ (H pol) (Spencer et al. 1989). At this stage, ARCHER (Wimmers and Velden 2010) is used to improve upon the best-track centers. As in the AMSR-E calibration process, the 37.0-GHz T_b (H pol) are used for the lower-frequency channels (19.35 and 37.0 GHz) to align with the center at lower altitudes and the 85.5-GHz T_b (H pol) are used for the 85.5-GHz channels to align with the center at higher levels of the atmosphere.

Once the best center estimates are determined from ARCHER, all data are bilinearly interpolated onto 65×65 grids with ~ 5.6 -km grid spacing. Next, for each microwave channel, two sets of predictors are designed for consideration in the LR model development. Inspired

TABLE 5. Lower-end T_b thresholds for the histogram matching and linear regression coefficients for the T_b adjustments applied to each sensor, channel, and polarization.

Sensor/frequency/polarization	T_b -adjusted threshold (K)	T_0	α
AMSR-E/19.35 GHz/H pol	0	27.3962	0.9043
AMSR-E/19.35 GHz/V pol	0	17.9857	0.9415
AMSR-E/37.0 GHz/H pol	205	–1.4223	0.9996
AMSR-E/37.0 GHz/V pol	0	–10.4180	1.0331
AMSR-E/85.5 GHz/H pol	240	10.1912	0.9417
AMSR-E/85.5 GHz/V pol	245	39.0850	0.8434
SSMIS/85.5 GHz/H pol	100	–5.5971	1.0226
SSMIS/85.5 GHz/V pol	100	8.8109	0.9681

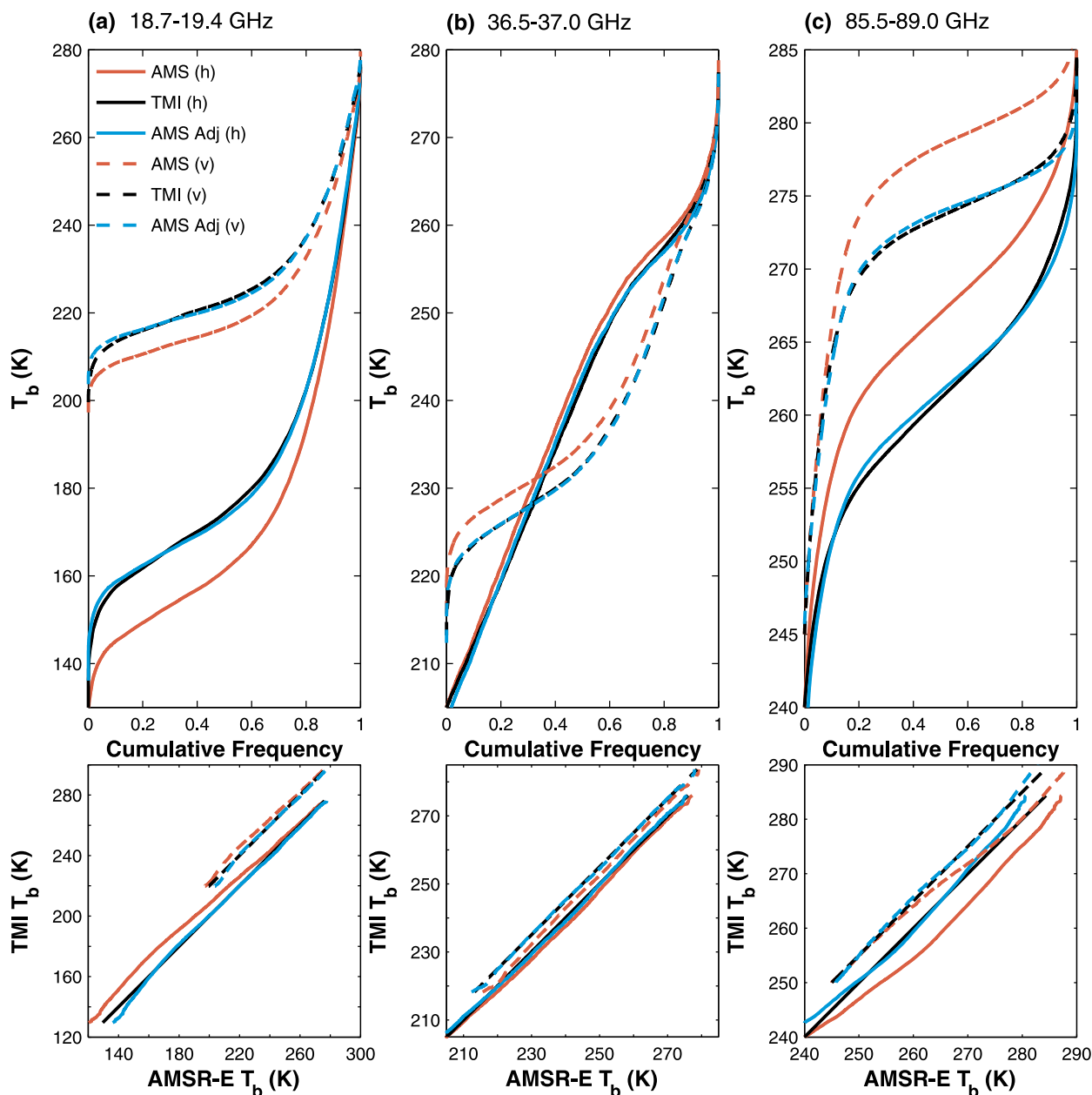


FIG. 4. (top) CDFs for both H pol and V pol and (bottom) matched pair plots of AMSR-E (raw, red; adjusted, light blue) and TMI (black) for (a) 18.7–19.35-, (b) 36.5–37.0-, and (c) 85.5–89.0-GHz T_b (K) from the 11 satellite passes summarized in Table 3. In (bottom), the vertical polarization is offset by 20, 5, and 5 K in (a), (b), and (c), respectively, to improve visualization of the different polarizations in the same plot. In addition, the TMI 1:1 line is included for reference.

by the association of increasing precipitation symmetry and its emergent ring structure (KJ12) to RI, the first set of MI-based predictors is defined from an objective maximum inner-core precipitation annulus (MIPA) detection technique. The idea is, for sufficiently organized storms, an MIPA will detect the eyewall. However, an eye and eyewall are often not present, particularly in weaker storms. In this situation, an MIPA is placed in the region of most intense precipitation near the inner core

anyway, with the idea that, were the storm to intensify (or reintensify), this precipitation activity would likely become associated with an eyewall. Specific details on this objective technique are described below. In addition to a storm-specific MIPA, a second set of simpler MI-based predictors uses fixed geometry to define more general characteristics of the storm inner core.

MIPA-based predictors are obtained from each satellite image to estimate the structure and characteristics

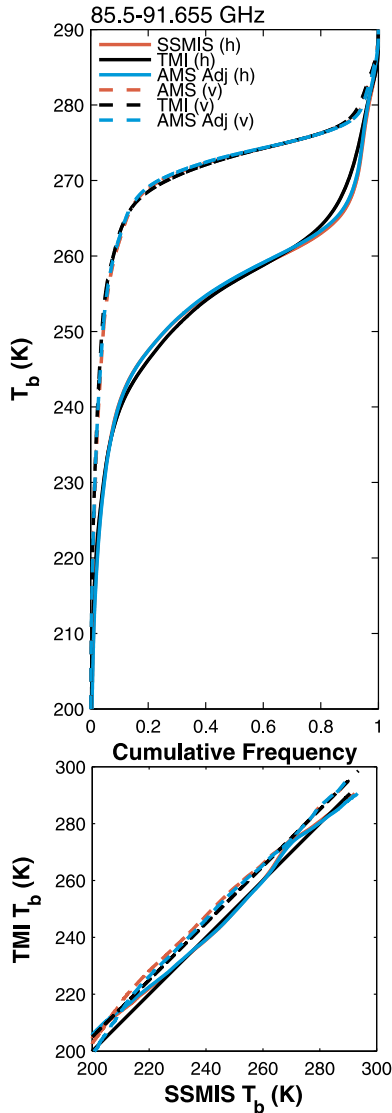


FIG. 5. (top) CDFs for both H pol and V pol and (bottom) matched pair plot of SSMIS (raw, red; adjusted, light blue) and TMI (black) for 85.5–91.655-GHz T_b (K) from the 19 satellite passes in Table 4. In (bottom), the vertical polarization is offset by 5 K to improve visualization of the different polarizations. Also, the TMI 1:1 line is included for reference.

of inner-core organization, particularly the degree to which a storm has acquired eye and eyewall-like structures. To objectively define an MIPA, a large variety of annular regions are considered, with the outer radius varied from 80 down to 10 km, while the inner radius is allowed to vary from 0% to 75% of the radius of the outer edge of the annulus. For each channel, the parameters used to search for the best MIPA per satellite image have been subjectively determined after looking at a large number of storm cases over a variety of intensities. For 19.35 GHz, an annulus that contains the

greatest proportion of its geometric area having T_b (V pol) > 245 K and T_b (H pol) > 215 K is selected as an MIPA. If no candidate MIPA contains any points satisfying these criteria, the annulus with the maximum radius and skinniest width [i.e., the inner and outer MIPA radii are $0.75 (80 \text{ km}) = 60$ and 80 km , respectively] is assigned as an MIPA, a subjective decision motivated by the very rough tendency for weaker storms to more likely have an incipient eyewall (and likely its radius of maximum wind) at a greater radius from its center. Obviously, there are exceptions to this rule, but this choice allowed for an MIPA to be defined for every TC case in the developmental dataset. For the 37.0-GHz channel, an MIPA is selected based on the greatest proportion of area covered by $PCT < 270 \text{ K}$ or where both T_b (V pol) $\geq 265 \text{ K}$ and $PCT \geq 270 \text{ K}$. These thresholds are chosen according to the findings of Jiang et al. (2011). Finally, the 85.5-GHz MIPAs are chosen based on the greatest proportion of a candidate MIPA containing 85.5-GHz $PCT < 250 \text{ K}$. This threshold is similar to the 85.5-GHz T_b 255-K threshold identified in Spencer et al. (1989) for rainfall rates of $1\text{--}3 \text{ mm h}^{-1}$ and is also consistent with the 250-K 85.5-GHz PCT threshold Cecil et al. (2002) and Cecil and Zipser (2002) found to signify significant precipitation features. In Cecil et al. (2002), this 250-K PCT threshold was most commonly exceeded in TC eyewalls and comparatively much less so in TC rainbands and other general oceanic tropical precipitation structures. Like in the 19.35-GHz channel, the 37.0- and 85.5-GHz MIPAs default to an annulus with the widest radius and skinniest width ($r = 60\text{--}80 \text{ km}$) when no annulus data points satisfy the subjective criteria defined above. In the case of concentric eyewalls (Sitkowski et al. 2011), it is worth noting that this methodology typically detects an outer eyewall as an MIPA in lieu of an inner eyewall as the eyewall replacement cycle evolves, since the eventual decay of an inner eyewall will no longer satisfy the objective search criteria listed above as effectively as the outer eyewall will.

Figure 6 provides several examples of the objectively determined MIPA for the 19.35-, 37.0-, and 85.5-GHz channels of TMI at various stages in the development of Hurricane Rita (2005). Rita offers a wide spectrum of scenarios to help describe typical behaviors of the MIPA detection, illustrating both the weaknesses and strengths of the current algorithm. At 0842 UTC 18 September, TMI indicates warm-rain and ice scattering features to the east of the center of the storm. At this point, Rita is weak and has an intensity of 25 kt. The 19.35-GHz MIPA latches onto this precipitation region, as the T_b are sufficiently warm [i.e., T_b (H pol) > 215 K and T_b (V pol) > 245 K] in this region to satisfy the MIPA criteria, although the MIPA is extended to its largest possible radius from storm center (i.e., 80 km) anyway. The

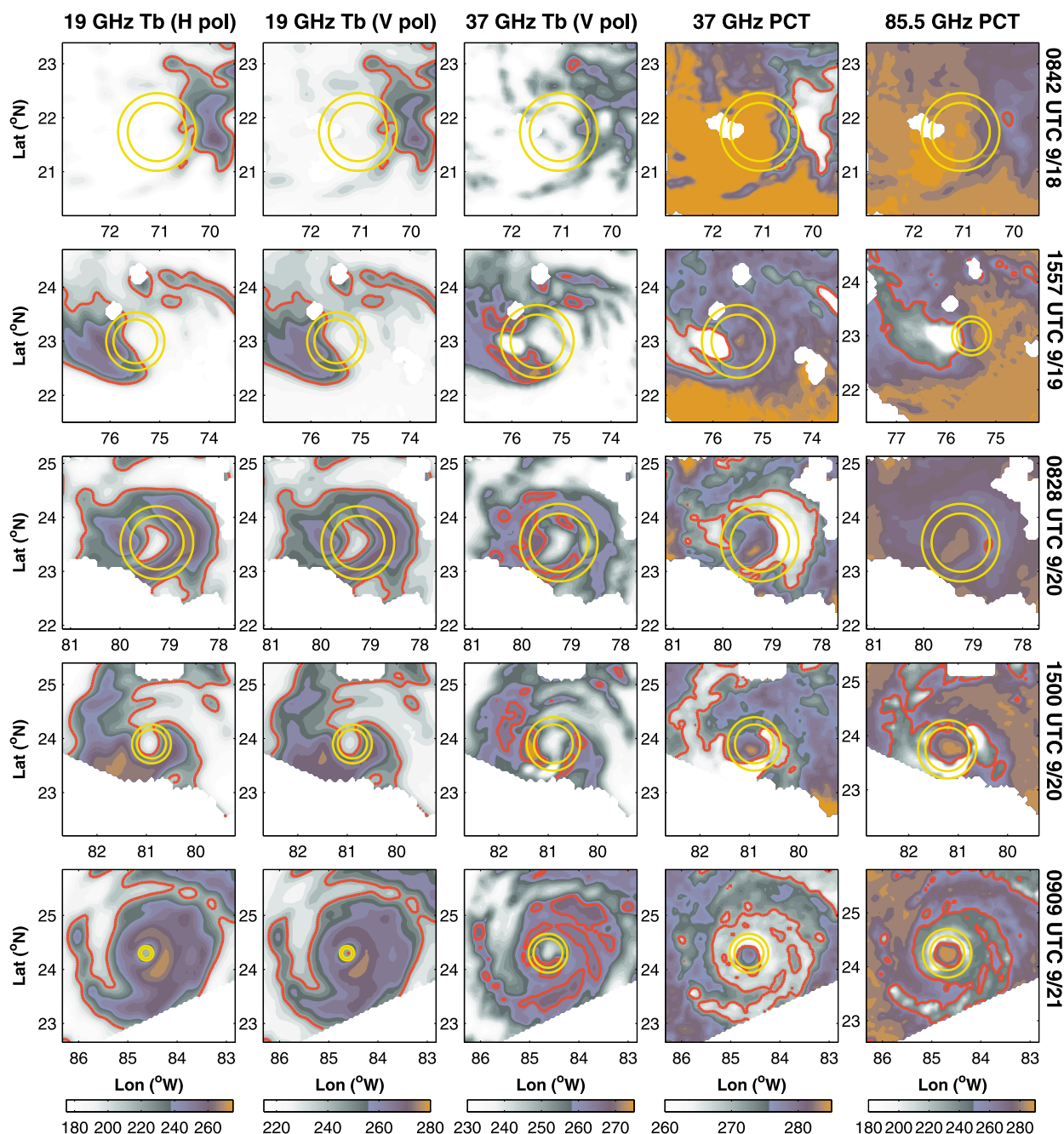


FIG. 6. TMI imagery of Hurricane Rita (2005) at various stages of its development (time descending downward), including (from left to right) 19.35-GHz T_b (H pol), 19.35-GHz T_b (V pol), 37.0-GHz T_b (V pol), 37.0-GHz PCT, and 85.5-GHz PCT. The yellow circles denote the MIPA objectively determined for each channel. The boldface red contours denote (from left to right) 215-, 245-, 265-, 270-, and 250-K T_b isolines related to the objective MIPA search algorithm. Hurricane Rita's intensity was (from top to bottom) 25 kt at 0842 UTC 18 Sep, 55 kt at 1557 UTC 19 Sep, 60 kt at 0828 UTC 20 Sep, 75 kt at 1500 UTC 20 Sep, and 105 kt at 0909 UTC 21 Sep. After the final image, Hurricane Rita intensified another 45 kt in the following 24 h.

37.0-GHz T_b are not warm enough anywhere for an MIPA to be defined, but the largest possible MIPA is able to extend into a region of sufficiently cold PCT ($PCT < 270$ K). The 85.5-GHz PCT are not cold enough for the MIPA criteria to be met anywhere within the

search radius, so the MIPA defaults to the thinnest, largest-radius annulus, which turns out to be consistent with the other channels anyway. By 1557 UTC 19 September, when Rita is now intensifying into a strong tropical storm (with an intensity of 55 kt), an intense, but

very asymmetric region of precipitation has moved closer to the west of Rita's center. The presence of intense precipitation closer to the inner core leads to the MIPA criteria being satisfied for all channels at various radii. In fact, the analyzed MIPAs attain much smaller sizes at this time, particularly for the 85.5-GHz channel. By 0828 UTC 20 September, with an intensity of 60 kt, Rita's inner-core precipitation has become much more symmetric (although the precipitation now does not extend as close to the TC center), with MIPA criteria being easily met for the 19.35- and 37.0-GHz channels, while the criteria are only marginally satisfied in the 85.5-GHz channel at a fairly large radius from the center. The MIPA size increases from the previous time at 19.35 and 85.5 GHz. By 1500 UTC 20 September, Rita has now become a hurricane (75-kt intensity) and all MIPAs are therefore defined at smaller radii. This trend continues at 0909 UTC 21 September, when Rita has intensified to 105 kt. In fact, the 19.35-GHz MIPA shrinks to the smallest size possible because of intense warm-rain precipitation being detected all the way at the center. The MIPA size trend is not perfect (one should expect a more monotonic decrease of MIPAs in time if they truly represent the region near the radius of maximum winds and the nascent eyewall in the case of an intensifying TC).

Figure 6 shows the overall MIPA trend of contraction is consistent with what is expected in an intensifying TC. This algorithm behavior is typical of many TC cases examined in the developmental dataset. However, there are still a number of cases (figure not shown) where the current MIPA detection can be less reliable, especially in the case of highly sheared TCs, where convection pulses off and on, typically downshear of the TC center, which can cause the MIPA size to be too oscillatory in time (compared to what is likely a more stable radius of maximum winds and radius of maximum boundary layer convergence). Future work should seek to improve the algorithm to have the MIPA more faithfully follow nascent and developed eyewalls and not be as volatile in the case of strong vertical wind shear. Some ideas for future improvements include using supplemental information such as radius of maximum wind information or having physically motivated constraints on trends that decrease some of the sensitivity of the MIPA to rapid changes in precipitation structure.

Once an MIPA is detected, defining predictors is straightforward. For each channel and polarization, the minimum, maximum, mean, and variance of the MIPA T_b are computed. In addition, similar statistics are defined for the region interior to the MIPA (which can represent the degree to which a storm may have attained an eye). Other parameters are retained for testing as well, including the size and width of the MIPA, and the relative difference in mean T_b between the MIPA and interior region.

The second set of structural MI-based predictors is based on fixed spatial geometry around a TC center. Similar to the MIPA-based predictors, the minimum, maximum, mean, and variance of T_b are calculated for a variety of radial regions relative to the TC center, including the radial regions of $r = 0$ –30, 30–130, 0–100, and 100–300 km. These radial regions are chosen to concur with the radial regions used to define satellite IR-based predictors in the SHIPS developmental dataset and ostensibly represent the central region that may contain an eye ($r = 0$ –30 km), the remainder of the inner core ($r = 30$ –130 km), the total inner core ($r = 0$ –100 km), and the outer rainband region ($r = 100$ –300 km). Other predictors defined for these radial regions include the radial location of T_b extrema, motivated by the observation that intensifying storms contain more concentrated precipitation near the core of the storm.

Once storm-centered MI-based predictors are calculated for all satellite images in the developmental dataset, optimal predictors are chosen such that they are statistically independent from other model predictors in Table 1 and from other MI-based predictors. First, in the case of MIPA-based and fixed-geometry predictors, if there are any missing data inside the region defining the predictor (e.g., data outside the MI swath or land), the developmental data from that time are not considered in the model development. Then, using leave-one-year-out cross validation, predictors are selected that maximize the Brier skill score (BSS; Wilks 2006) defined with respect to the training data's baseline climatological probability of RI. Furthermore, for each MI predictor chosen for the models, the differences in their composite mean values in the RI and non-RI samples must be statistically significant at the 95% level according to a two-sided Student's t test. All model MI predictors and attendant LR model coefficients are developed using 1998–2012 data and are only considered for TCs that exist over the ocean. The MI-enhanced models retain all of the SHIPS-based predictors shown in Table 1, but also include a set of optimally determined MI-based predictors. To properly compare the forecast skill of the MI-enhanced LR models with the basic LR models lacking MI, each model is trained and evaluated on only forecast times in which all of the SHIPS-based and optimal MI-based predictors are available. Despite the uneven temporal coverage of low-Earth-orbiting satellite passes over a storm, the models are developed to make forecasts at the synoptic times of 0000, 0600, 1200, and 1800 UTC.¹ To deal with the irregular times of TC

¹ Synoptic times were chosen for these models to conform to the standard operational forecast times at the NHC.

TABLE 6. The MI-based predictors used for the LR RI models in the Atlantic (ATL) and eastern Pacific (EPAC).

Model	Definition	Mean value of RI cases vs non-RI cases
ATL	Mean 37.0-GHz T_b (H pol) within the MIPA	Higher
ATL	Max 85.5-GHz PCT in region interior to the MIPA	Lower
ATL	Radius of max 37.0-GHz T_b (V pol) found within $r = 30$ – 130 km	Smaller
ATL	Radius of min 85.5-GHz T_b (H pol) found within $r = 30$ – 130 km	Smaller
EPAC	Mean 37.0-GHz T_b (V pol) within the MIPA	Higher
EPAC	Min 37.0-GHz PCT in region interior to the MIPA	Lower
EPAC	Max 85.5-GHz T_b (H pol) in region interior to the MIPA	Lower
EPAC	Percent of MIPA containing 85.5-GHz PCT < 250 K	Higher
EPAC	Radius of min 85.5-GHz PCT found within $r = 30$ – 130 km	Smaller
EPAC	Mean 37.0-GHz T_b (H pol) within $r = 100$ – 300 km	Higher

overpasses, the MI-based schemes are only developed for forecasts when the MI is 6 h old or less. Based on the sample considered here, 6 h old or less MI are available for about 75% of the synoptic times associated with TCs in the SHIPS developmental dataset. In an operational setting, data latency may reduce the availability of the most recent satellite overpasses. For the sake of argument, if a 2-h data latency is assumed, then MI data 6 h old or less are available about 60% of the synoptic times. However, data latency is not assumed in the current model development. It is also important to reiterate that missing or incomplete data coverage for a geometric area defining various MI predictors leads to further reduction of the MI used in this study, so that ultimately 55% of the synoptic times during the 1998–2012 period of the developmental dataset are used to develop the LR models.

Table 6 shows the optimal MI-based predictors that are added to the Atlantic and eastern Pacific MI-based versions of the LR models. In addition to the predictors listed in Table 1, the Atlantic MI-based LR models incorporate four MI-based predictors. These predictors include the mean 37.0-GHz T_b (H pol) in the MIPA, the maximum 85.5-GHz PCT in the region interior to the MIPA, and the radii of the maximum 37.0-GHz T_b (V pol) and minimum 85.5-GHz T_b (H pol) for the $r = 30$ – 130 -km region. Unlike the study of Jones et al. (2006), which showed 19.35-GHz-based MI predictors were most useful in a statistical predictive model of general

TC intensity change, 19.35-GHz predictors are rejected in the predictor search procedure for the probabilistic RI models developed here. When comparing the mean values of the optimal Atlantic predictors for RI versus non-RI cases in our developmental dataset, the predictors show a consistent picture of RI storms containing more vigorous precipitation in the inner core, with a tendency for the strongest latent heating activity to be more concentrated near the center of the storm. The eastern Pacific MI-based models differ somewhat from the Atlantic versions. In addition to the predictors in Table 1, the eastern Pacific LR models benefit most from including six optimally chosen MI-based predictors, including the mean 37.0-GHz T_b (V pol), the minimum 37.0-GHz PCT and maximum 85.5-GHz T_b (H pol) in the region interior to the MIPA, a predictor describing the percentage of the MIPA containing 85.5-GHz PCT below 250 K, the radius of the minimum 85.5-GHz PCT found within $r = 30$ – 130 km, and the mean 37.0-GHz T_b (H pol) within $r = 100$ – 300 km. Although the eastern Pacific models use slightly different predictors than the Atlantic models,² the mean values of the predictors for the RI and non-RI cases are physically consistent between basins, in that the inner cores of storms undergoing RI contain greater precipitation coverage and intensity. Also like the Atlantic, the most intense precipitation also occurs closer to storm center in eastern Pacific RI cases.

3. Model evaluation

a. Model skill based on developmental data

When compared against the climatological probability of RI, each model considered in this study possesses positive forecast skill in the prediction of RI. Here, skill is evaluated through the BSS with a baseline of climatology, computed from leave-one-year-out cross validation on the developmental data. The BSS values for each model are provided in Fig. 7. Overall, and consistent with other studies (KDK10; RK11), all LR models in the eastern Pacific (Fig. 7b) achieve greater forecast skill compared to the Atlantic models (Fig. 7a). For the

² Note, the objective search for optimal predictors chooses the mean MIPA 37.0-GHz T_b for both the Atlantic and eastern Pacific, but the H pol T_b for the Atlantic and V pol T_b for the eastern Pacific. It turns out one could interchange either polarization in either ocean basin with only a 0.2% cost to the BSS, which is rather insignificant. Similar minor differences in skill are evident when exchanging the polarizations of two other predictors that are similar between basins, including the max 85.5-GHz T_b in the region interior to the MIPA and the radius of min 85.5-GHz T_b found within $r = 30$ – 130 km.

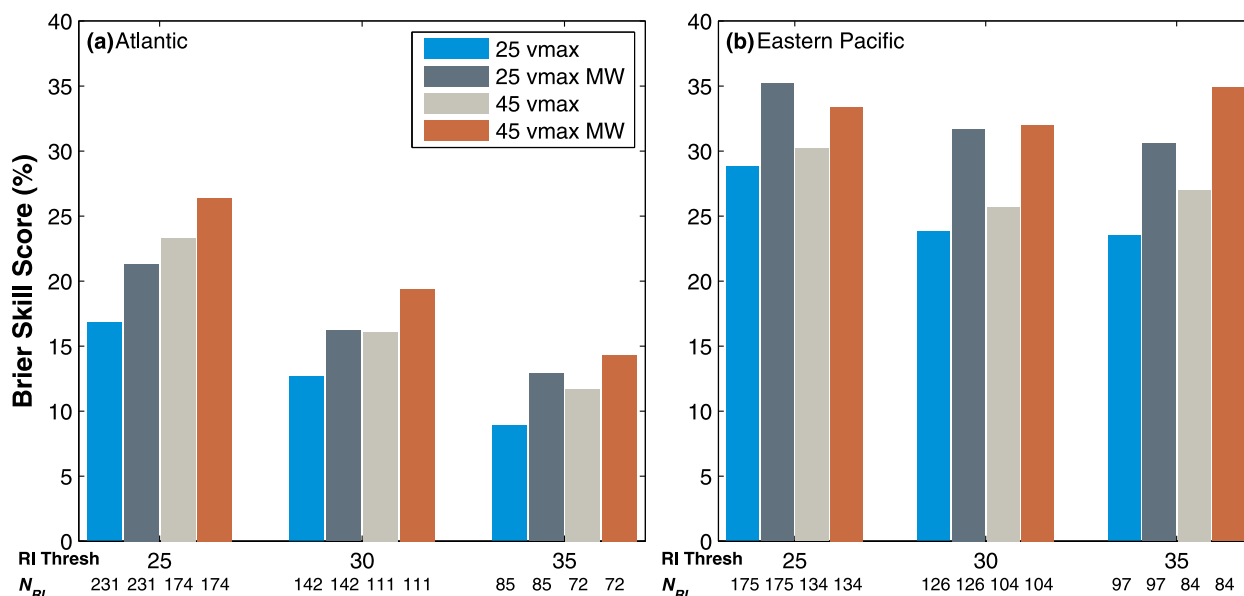


FIG. 7. BSS values for the LR model at 25, 30, and 35 kt $(24 \text{ h})^{-1}$ RI thresholds without MI-based predictors (light blue and gray for TCs of at least 25- and 45-kt intensity, respectively) and with MI-based predictors (dark blue and red for TCs of at least 25- and 45-kt intensity, respectively) for the (a) Atlantic and (b) eastern Pacific. These results are for the technique of leave-one-year-out cross validation over the years 1998–2012. In the Atlantic, the sample sizes for the 25- and 45-kt storm intensity thresholds are 1993 and 1484, respectively. In the eastern Pacific, the sample sizes for these two storm intensity thresholds are 1554 and 1074. The number of RI cases for each RI and intensity threshold is shown along the x axis below each bar.

most part, the skill of the LR models decreases in both the Atlantic and eastern Pacific as the RI threshold is set to higher values. This is expected for an empirically derived probabilistic model since a higher RI threshold makes RI an even rarer event. The exception to this rule is the 35 kt $(24 \text{ h})^{-1}$ RI threshold in the eastern Pacific (Fig. 7b), in which the BSS is higher than in the 30 kt $(24 \text{ h})^{-1}$ RI threshold.

Most importantly, Fig. 7 shows the impact MI-based predictors have on the performance of the LR models. Inclusion of MI-based predictors yields more skillful LR-based RI models in their respective RI threshold bins. On average, the MI-based predictors improve the BSS of the RI models by 3.5% in the Atlantic, with a range of 2.6%–4.5%, depending on RI threshold and initial TC intensity ranges considered. The relative improvements from including MI-based predictors in the Atlantic range from 13.3% to 44.9%. In the eastern Pacific, the average BSS improvement is 6.5% over their non-MI counterparts, with a range of 3.2%–7.9%. This yields relative improvements in the range from 10.6% to 33.2%.

b. Simulated real-time performance

The model skill provided in Fig. 7 is based on reanalysis data from the developmental data and the best-track data. The environmental predictors listed in Table 1 (i.e., RSST, ENSS, D200, SHDC, and POT) are averaged over the 24-h period following the forecast time. In the

real-time environment, however, these environmental predictors must be created from NWP model forecast fields after the initial time, which will produce additional forecast error associated with the NWP model. Moreover, storm data such as the storm center location and estimated intensity may not agree with the more accurate best-track data that are produced after the hurricane season. Therefore, to obtain a more robust evaluation of the MI-based models in a simulated real-time environment, all models are rerun for the period 2004–13 using archived forecast fields from the Global Operational System (GFS) NWP model and also storm data that were available in real time during Atlantic and eastern Pacific TC events. To accomplish this, each LR-based RI model was rederived for each of the years during the period of 2004–12 by excluding data from a given year when evaluating the model’s “real time” performance over that year. This ensures that the reforecast results are independent from the training data in the developmental dataset. As before, to ensure a fair comparison of model performance, evaluation of each model is only carried out at forecast times in which both non-MI and MI-based predictors are available.

1) CASE STUDIES

Before examining the overall performance of the simulated real-time models developed for the Atlantic and eastern Pacific, a couple of case studies are now

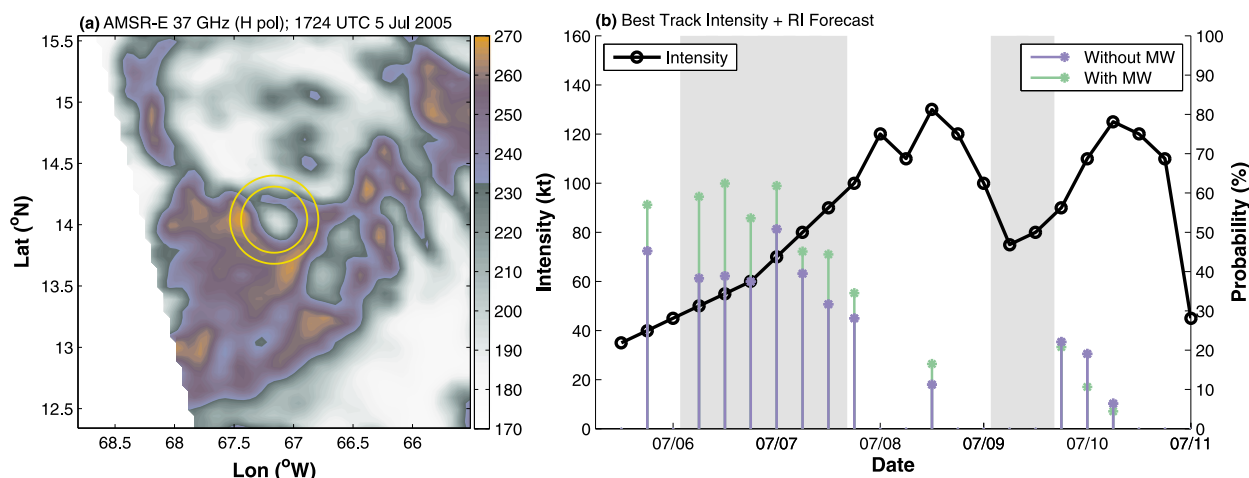


FIG. 8. (a) AMSR-E T_b (K) for 37.0 GHz (H pol) of Atlantic TC Dennis at 1724 UTC 5 Jul 2005, along with the objectively determined MIPA. (b) The time evolution of TC Dennis's (2005) observed best-track intensity (kt; solid black line) and the probability (%) of 25 kt $(24 \text{ h})^{-1}$ or greater intensification rates as predicted by the LR model without (purple) and with (green) MI-based predictors. The gray-shaded regions demarcate forecast times when RI was observed over the subsequent 24 h. Forecast probabilities are only plotted at the synoptic times of 0000, 0600, 1200, and 1800 UTC when microwave data are available within the previous 6 h (i.e., if a green/purple dot is missing at a synoptic time, then no forecast is made).

presented to show how MI-based predictors impact LR models. The first example shows how MI can increase the probabilities of detecting RI prior to actual RI events, while the second example shows how MI may reduce the false alarm rate of RI forecasts.

Using the 25 kt $(24 \text{ h})^{-1}$ RI threshold, the performance of the LR model for Atlantic Hurricane Dennis (2005) is now presented. Dennis had two RI events. A lengthy period of RI transpired between 0600 UTC 6 July and 1200 UTC 8 July as the TC intensified to a Saffir–Simpson category 4 hurricane and traveled northwestward over the Caribbean toward its landfall in Cuba. After returning to sea en route to the United States' Gulf of Mexico coast between 0600 UTC 9 July and 1200 UTC 10 July, Dennis once again rapidly intensified into a category 4 hurricane. Prior to the first RI period, MI showed signs of a well-organized TC. For example, Fig. 8a shows the AMSR-E 37.0-GHz T_b (H pol) of Dennis at 1724 UTC 5 July. Warm T_b associated with more intense precipitation and ice scattering is organized into an asymmetric ring structure around the TC-estimated center. The objective MIPA is consistent with the visual presentation of the T_b .

Forecasts are made for only some of the synoptic times during Dennis's lifetime when there are sufficiently recent satellite overpasses that produce quality-controlled MI. Both versions of the LR model produce elevated probabilities of RI during the first period of RI. No forecasts are made for the second period of RI because of the lack of MI. Each model version incorrectly produces heightened probabilities just prior to and immediately following the times associated with RI in the

subsequent 24 h. The MI version of the LR model produces even higher probabilities of RI during this time period, reflecting the impressive storm organization in the AMSR-E imagery. This situation points out a relative weakness of the MI-based model that has been observed in a number of other cases (not shown). Namely, it is not uncommon for the MI-based model to incorrectly enhance RI probabilities (i.e., add to the false alarm rate) too early before RI begins, exactly as seen in Fig. 8b. Also, when a storm intensifies at a robust rate, but not quite at a rate qualifying as RI, the MI-based model can suffer from the same overly aggressive RI forecasts. Figure 8b also shows that at later times, while the model did not make forecasts during the second RI period, the two versions of the LR model produce relatively similar results, with the MI LR model producing slightly lower RI probabilities on 9 and 10 July. In these cases, forecast probabilities are correctly low since RI does not occur.

The eastern Pacific's Hurricane Raymond (2013) is another storm with two periods of RI. This example provides a case where the MI can actually reduce RI probabilities when a TC's environment seems quite favorable to RI. On 25 October 2013, Raymond was in a compromised state after previously experiencing enhanced vertical wind shear and likely suffering from cool ocean upwelling resulting from the slow movement of the storm immediately following its peak intensity on 22 October. The SSMIS 85.5-GHz PCT at 1307 UTC 25 October (Fig. 9a) showed a highly asymmetric ice scattering signature with respect to the estimated storm center. The storm center can be inferred in Fig. 9a by the

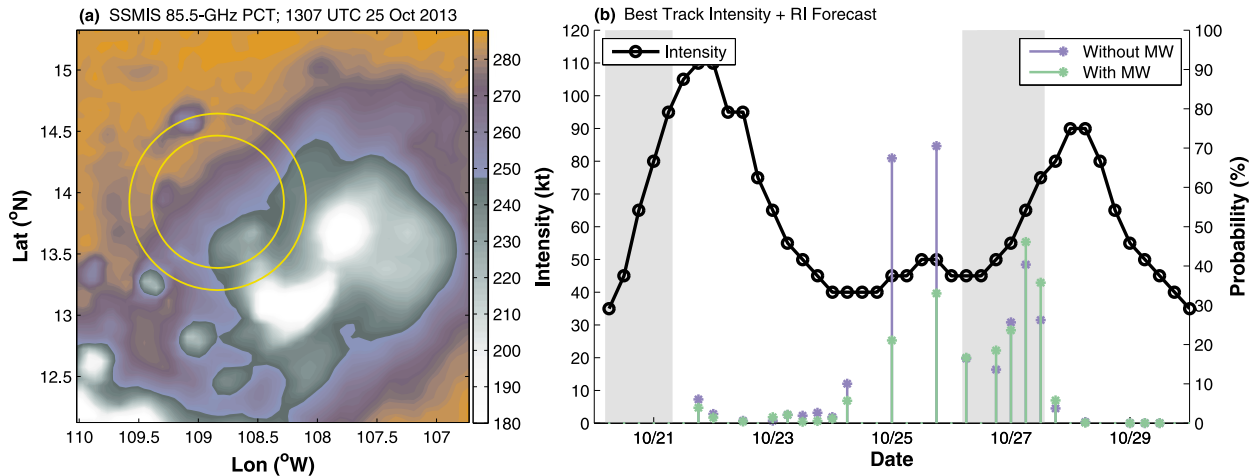


FIG. 9. (a) SSMIS PCT (K) for 85.5 GHz (H pol) of eastern Pacific Hurricane Raymond at 1307 UTC 25 Oct 2013, along with the objectively determined MIPA. (b) The time evolution of Hurricane Raymond's (2013) observed best-track intensity (kt; solid black line) and the probability (%) of 25 kt (24 h)⁻¹ or greater intensification rates as predicted by the LR model without (purple) and with (green) MI-based predictors. The gray-shaded regions demarcate forecast times when RI was observed over the subsequent 24 h. Forecast probabilities are only plotted at the synoptic times of 0000, 0600, 1200, and 1800 UTC when microwave data are available within the previous 6 h (i.e., if a green/purple dot is missing at a synoptic time, then no forecast is made).

objective MIPA fit to the 85.5-GHz imagery for Raymond at this time. Most of the deep convection appears in the southeast quadrant of the storm. In Fig. 9b, RI probabilities are erroneously high on 25 October in the baseline LR model. The environment was quite favorable for RI on 25 October, featuring an enhanced maximum potential intensity and low vertical wind shear. This is why the baseline LR model suggests RI during the period. However, the MI-based version of the LR model correctly reduces the probabilities of RI significantly on 25 October. Taking into consideration the poor presentation of the MI helps improve the forecast in this instance. Otherwise, at forecast times in which MI was available, both models performed in a similar manner for the remainder of Raymond's lifetime. MI data were unfortunately not available for the first period of RI. However, both versions of the eastern Pacific LR model correctly forecast low probabilities of RI between 1800 UTC 21 October and 0600 UTC 24 October. The second period of RI coincides with a time of plentiful MI coverage for Raymond. Both models produce low to moderate probabilities of RI, with the MI-based version performing only slightly better.

2) GENERAL MODEL PERFORMANCE

Figure 10 shows the overall performance of the simulated real-time models (2004–13) according to the BSS defined relative to climatology. In both the Atlantic (Fig. 10a) and eastern Pacific (Fig. 10b), all models suffer a degradation in forecast skill at all RI thresholds when compared to the BSS associated with leave-one-year-out

cross validation on the developmental data (Fig. 7). This is not unexpected, and is likely due, in part, to the added errors introduced from using operational GFS forecast data and archived real-time initial storm estimates rather than the reanalysis data. Nonetheless, all models are still skillful relative to a baseline of climatology and, once again, the eastern Pacific produces more skillful models in most cases.

The simulated real-time skill evaluation shows that MI-based predictors continue to benefit the LR models. In fact, given the errors intrinsic to using real-time data, it is illuminating that the MI-based predictors provide even greater relative benefits to the models at all RI thresholds in the Atlantic when compared against the relative BSS improvements in Fig. 7. The mean improvement offered by MI-based predictors in BSS for the Atlantic models is now 5.7% instead of the 3.5% seen in the leave-one-year-out cross validation using “perfect forecast” data. In terms of relative improvement to a baseline skill defined by the simulated real-time, non-MI version of the LR models, skill improves by 53.5%–103.0% in the Atlantic, depending on RI thresholds and intensity ranges considered. On the other hand, the relative improvements in the eastern Pacific are quite a bit more modest, with a mean increase in BSS by only 1.6%, with relative skill increases ranging from 4.9% to 25.5% relative to the non-MI-based LR models.

Another way to assess the RI models' performance is through deterministic verification. Following KDK10 (and their Fig. 17), probability thresholds are derived to determine whether a forecast indicates RI or not. First, a climatological probability of false detection (POFD) is computed for each RI threshold and intensity threshold

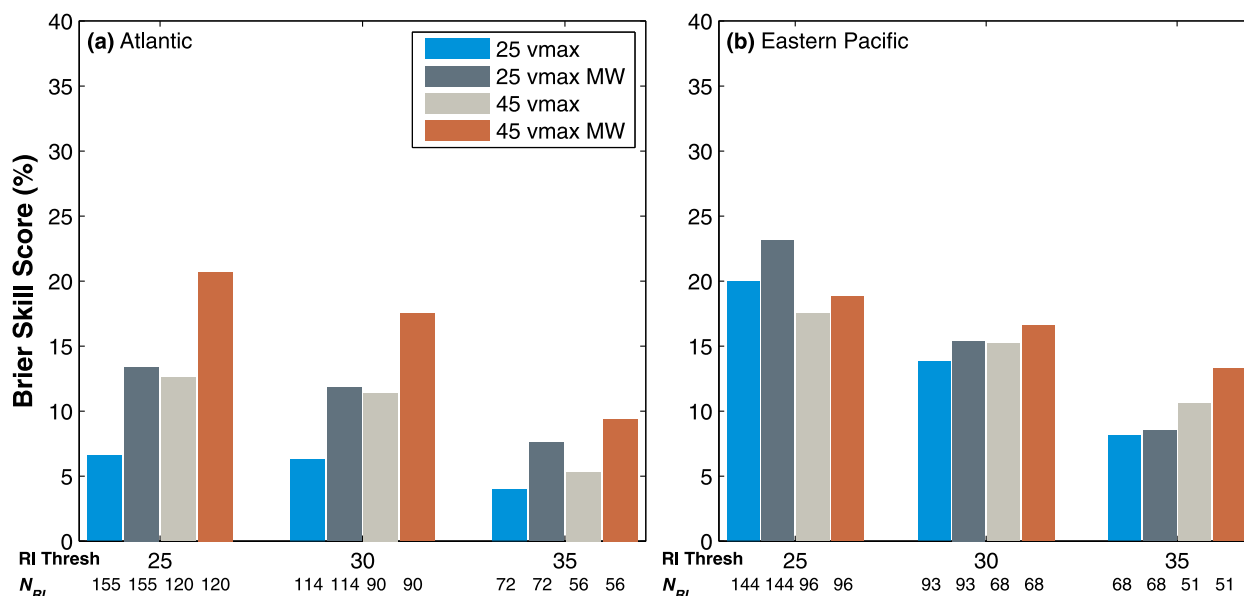


FIG. 10. BSS values for the simulated real-time LR model at 25, 30, and 35 kt $(24 \text{ h})^{-1}$ RI thresholds without MI-based predictors (light blue and gray for TCs of at least 25- and 45-kt intensity, respectively) and with MI-based predictors (dark blue and red for TCs of at least 25- and 45-kt intensity, respectively) for the (a) Atlantic and (b) eastern Pacific. These results are for the 2004–13 reforecasts. In the Atlantic, the sample sizes for the 25- and 45-kt storm intensity thresholds are 1417 and 1024, respectively. In the eastern Pacific, the sample sizes for these two storm intensity thresholds are 1231 and 818. The numbers of RI cases for each RI and intensity threshold are shown along the x axis below each bar.

in the Atlantic and eastern Pacific. These climatological POFDs are obtained from 2004 to 2012. From there, a model POFD for each RI threshold is computed for each RI and intensity threshold over the entire 2004–13 period. The model POFD is specifically computed as the number of false alarms when the RI-model-predicted probabilities exceeds the climatological POFDs divided by the total number of forecasts made. These model POFDs then serve as the probability thresholds of whether RI occurs or not according to the forecasted probability. Figure 11 shows the probability of detection (POD), false alarm ratio (FAR), and Pierce skill score (PSS; Wilks 2006). The POD provides the percentage of RI cases that are correctly predicted by the LR and the FAR is the percentage of times that RI does not occur when the LR model predicts RI. The PSS is a bulk skill score that measures how the POD compares to the model's POFD, where a score of 1 is a perfect forecast, a positive score between 0 and 1 is skillful, and a negative score suggests a model with worse than random forecasts. Similar to the BSS plots, the MW-based models improve the POD, FAR, and PSS in almost all cases, with the exception of FAR for some of the RI models in the eastern Pacific, where the FAR is fairly comparable for MI- and non-MI-based models. Nonetheless, eastern Pacific PSS values show uniform improvements for all MI-based models thanks to higher POD rates at all

thresholds/intensities. Similar to KDK10, the LR-based models (with and without MI-based predictors) suffer from high FARs.

To better interpret forecast model probabilities, reliability diagrams (Wilks 2006) are now presented. Reliability diagrams show how well the forecast probabilities of an RI event correspond to the observed frequency of those same events. Figure 12 shows reliability diagrams and accompanying sharpness diagrams for all of the Atlantic-based real-time models developed for each of the RI thresholds. In the reliability diagrams (Figs. 12a,c,e), the 45° diagonal line represents perfect reliability for all forecast probabilities and the horizontal and vertical dashed lines show the climatological probability of RI computed from the 2008–12 developmental dataset. The shaded regions show where forecasted probabilities contribute to positive Brier skill scores [see Wilks (2006) for the relationship between reliability diagrams and Brier skill score]. By and large, MI-enhanced models improve reliability for most predicted probabilities, but there are some probabilities in which MI degrades the model [e.g., the forecasted probabilities in the 0.4–0.5 probability range at the RI threshold of 35 kt $(24 \text{ h})^{-1}$]. Consistent with Fig. 11, there is a tendency for each model to overpredict RI, as many of the curves dip below the 45° diagonal line. The sharpness diagrams (Figs. 12b,d,f) show that MI-based predictors allow the models to achieve higher-end

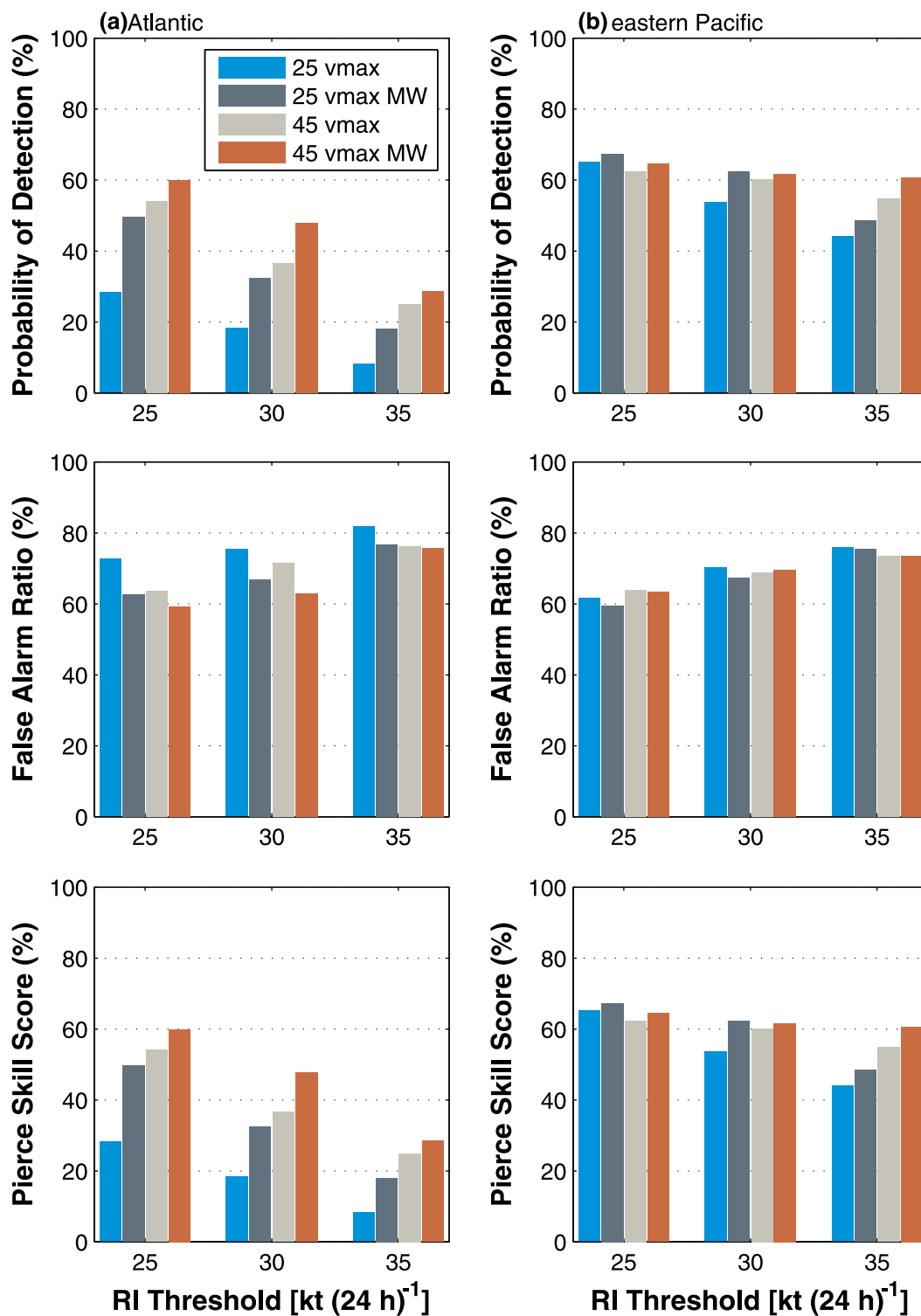


FIG. 11. (top) POD, (middle) FAR, and (bottom) PSS for the (a) Atlantic and (b) eastern Pacific simulated real-time deterministic RI forecasts. Results are provided at the RI thresholds of 25, 30, and 35 kt (24 h)^{-1} . The numbers of samples are the same as in Fig. 10.

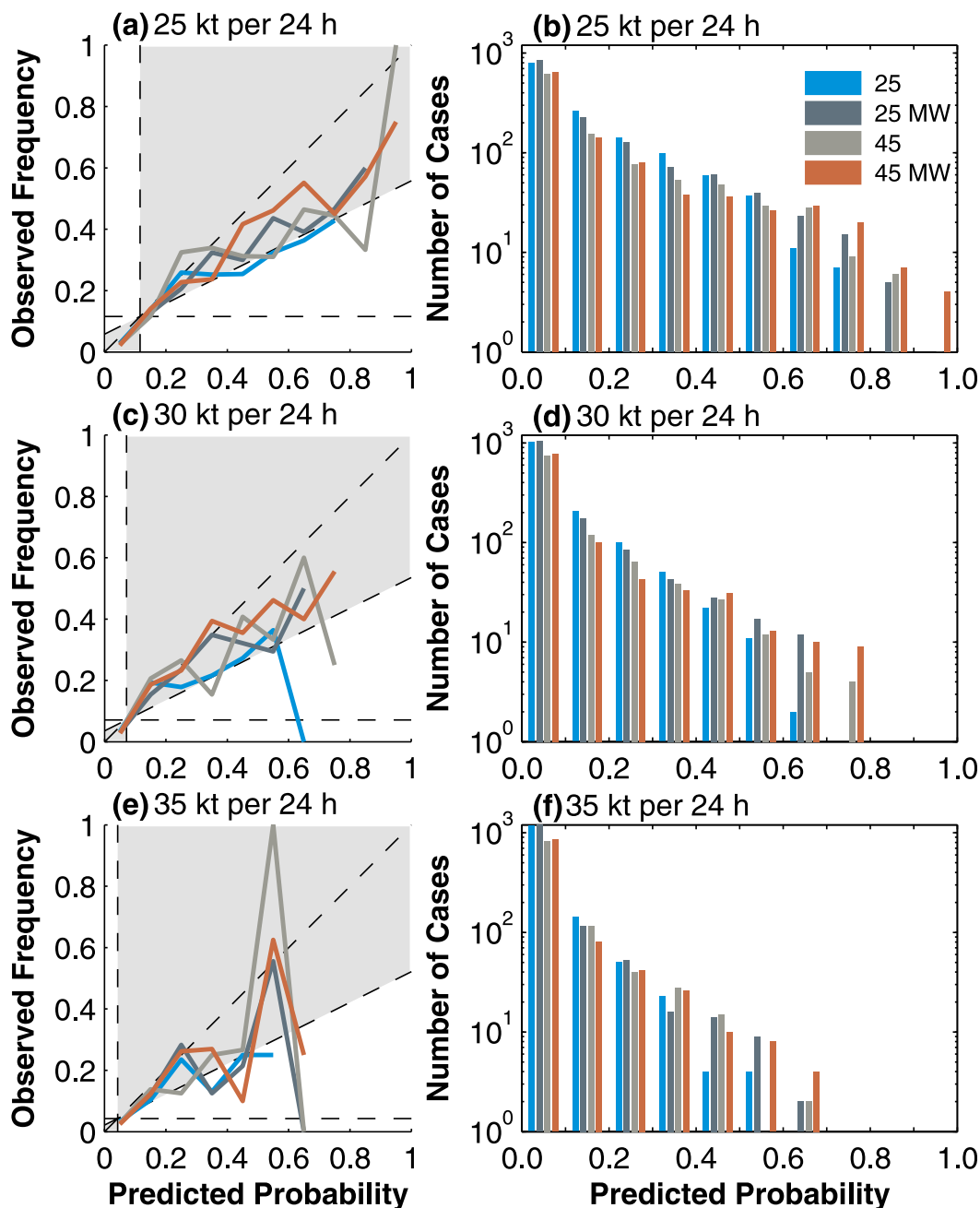


FIG. 12. Reliability diagrams for the simulated real-time LR models without (light blue and gray for TCs of at least 25- and 45-kt intensity, respectively) and with (dark blue and red for TCs of at least 25- and 45-kt intensity, respectively) MI-based predictors for RI thresholds of (a) 25, (c) 30, and (e) 35 kt $(24 \text{ h})^{-1}$, and corresponding figures showing the numbers of forecasted probabilities falling between 0 and 0.1, 0.1 and 0.2, ..., and 0.9 and 1.0 for the RI thresholds of (b) 25, (d) 30, and (f) 35 kt $(24 \text{ h})^{-1}$. The horizontal and vertical dashed lines in (a), (c), and (e) represent the climatological rates of RI for the respective RI thresholds.

probability RI forecasts, which contributes to an overall improvement in model skill.

When comparing the reliability and sharpness attributes of the Atlantic-based real-time models (Fig. 12) with the eastern Pacific models (Fig. 13), the story is

consistent with the BSS comparison shown in Fig. 10b. Overall, the eastern Pacific models show greater reliability than do the Atlantic models, particularly because eastern Pacific models possess greater sharpness, meaning the models are able to forecast higher

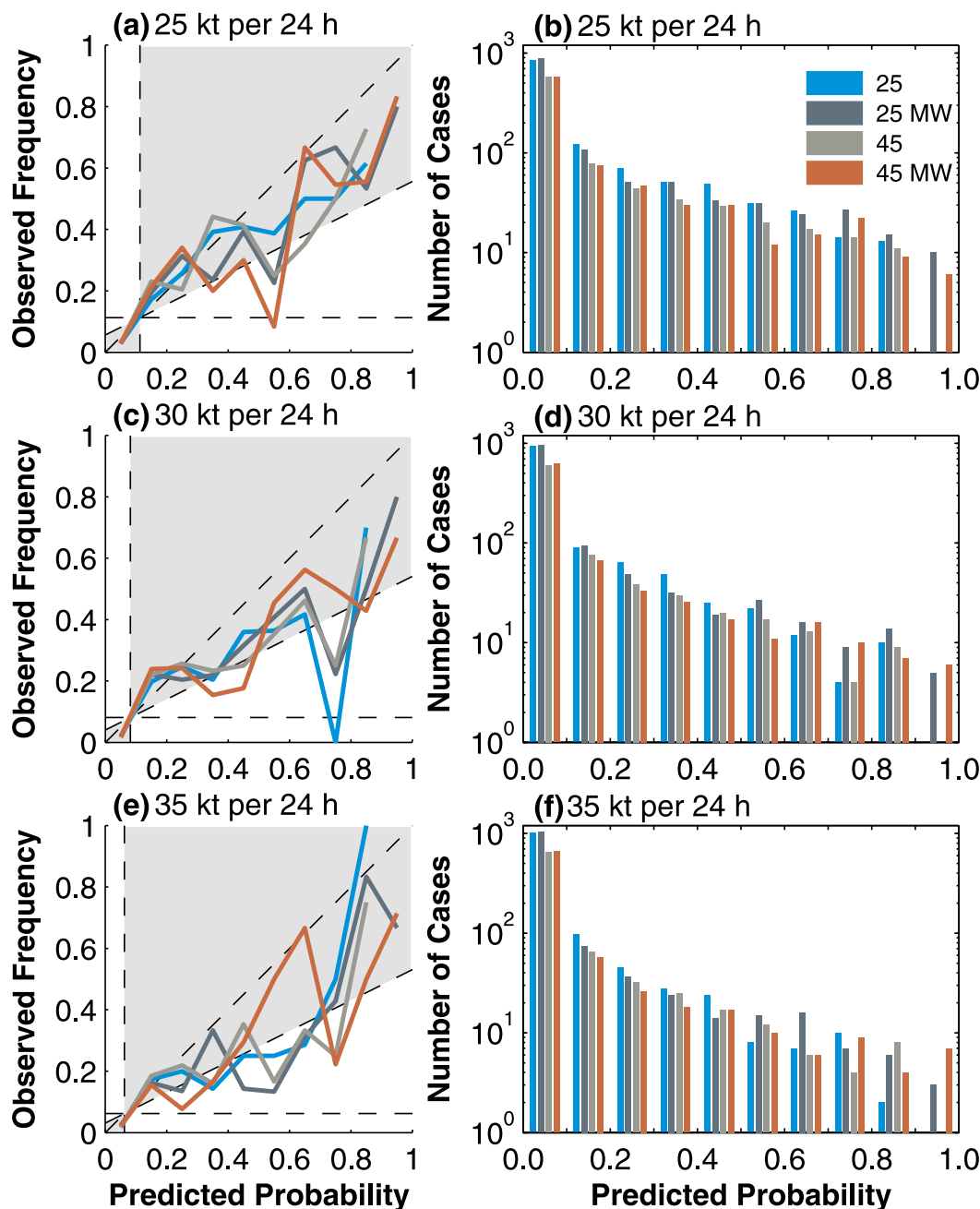


FIG. 13. As in Fig. 12, but for the eastern Pacific.

probabilities of RI (Figs. 13b,d,f). Congruent with the BSS values, the relative improvement achieved in reliability from adding MI to the models is not as notable in the eastern Pacific as in the Atlantic basin.

4. Conclusions

This study shows the inclusion of tropical cyclone (TC) structure information as depicted by passive

microwave imagery (MI) in probabilistic models of rapid intensification (RI) is advantageous. In particular, MI from a variety of spectral channels can provide detailed information about the organization of precipitation and convection in a TC that is often not available in other conventional observational datasets. Considering the likely relevance of a TC's precipitation and related latent heating structure to RI, this paper revisits a probabilistic logistic regression (LR) model for RI developed in RK11,

which is based on predictors derived from both observational/model analysis and geostationary satellite IR imagery. This baseline LR model is adapted to include predictors derived from passive MI.

In this study, LR models incorporating MI are developed in the Atlantic and eastern Pacific Ocean basins. These updated models also include the original environmental and IR-satellite predictors from the [RK11](#) LR models. Leave-one-year-out cross validation on the developmental retrospective dataset shows the MI-based models produce improved skill over the models not including MI. In the Atlantic, the Brier skill score (BSS) improves, on average, by 3.5% after adding MI-based predictors, yielding relative improvements in forecast skill from 13.3% to 44.9%, depending on the RI threshold and initial TC intensity ranges considered. In the eastern Pacific, the improvement in BSS is, on average, 6.5%, with relative improvements over the non-MI-based models ranging from 10.6% to 33.2%. Within the context of the baseline skill of the models presented in [KDK10](#) and [RK11](#), these improvements are quite notable and are therefore likely to impart a measureable impact on operational forecasting.

To gain a more reliable estimate of model performance in an operational environment, simulated real-time testing is conducted for both the Atlantic and eastern Pacific models using archived real-time forecast data from 2004 to 2013. In this case, environmental predictors are no longer based on “perfect” model analyses for the 24-h forecast periods, but on forecasted values of the environmental predictors. Therefore, one can expect the skill of the LR models to decrease. This is indeed the case. However, in the simulated real-time environment, the MI can be even more valuable since the model degradation is due solely to imperfect forecast values of environmental predictors. This is particularly true in the Atlantic Ocean, where the inclusion of MI causes skill to improve relative to a baseline skill by anywhere from 53.5% to 103.0% depending on the RI thresholds and intensity ranges considered. The relative improvements in the eastern Pacific are quite a bit more modest, with relative skill increases from 4.9% to 25.5%. Part of the reason for this is that the baseline LR possesses higher skill in the eastern Pacific than the Atlantic, even in the simulated real-time setting. As such, the MI-based predictors offer relatively fewer improvements. It is possible that the eastern Pacific ceiling of predictability is closer to being reached by the baseline, non-MI-based models than in the Atlantic. This may explain why the Atlantic benefits more from the inclusion of additional storm structure information. These skill-ceiling differences between basins, which have been indicated in previous studies as well (e.g., [KDK10](#); [RK11](#)), have yet to be thoroughly explained.

The results of this study suggest that the operational implementation of the objective, automated MI-based empirical RI models would be a worthwhile venture. While low-Earth-orbiting satellites do not always capture a TC in a timely manner, MI-based predictors less than 6 h old were available for roughly half of the synoptic time forecasts considered in this study. To maintain the operational use of these models, periodic updates will be needed to incorporate new satellite data as old satellites expire and new ones replace them. However, the temporal coverage could become a severe issue if these limited-term satellites are not fully replaced in the future. Assuming the continuing availability of passive microwave satellites, updates of these potentially operational models should be straightforward. These updates will simply require updating data feeds and, if necessary, sensor calibration. The histogram matching technique is simple enough that the calibration update should be relatively automatic.

Given the very simple nature of the structural predictors used in this study, further improvements to the MI-based probabilistic schemes are likely. The predictors used here are based on simple geometry and basic statistical properties of the T_b in these geometrically defined regions. More sophisticated predictors describing key asymmetries in hydrometeor features or physically relevant thresholds of structures relevant to RI could be developed to improve the ability of predictors to signal whether RI processes are taking place. Another approach that may prove profitable is to better discern predictor behavior in various stages of TC development. For example, using the TRMM PR, [Zagrodnik and Jiang \(2014\)](#) showed that storms just beginning RI have less latent heating coverage and symmetry than rapidly intensifying storms that have been undergoing RI in the previous 12 h or more. The temporal trends in precipitation structures relevant to RI in TCs are somewhat overlooked by the simple binary classifier approach used here and therefore the current design of the model is likely washing out some temporal signals that could be beneficial to the probabilistic prediction of RI.

While improving predictors and accounting for temporal trends are certainly avenues of future research that will likely benefit probabilistic RI prediction, future work should also include other types of satellite data as well. For example, future innovations may consider looking at additional passive MI channels, such as the ASMR2 23.8-GHz channel that is well suited for depicting integrated water vapor, or using derived products such as precipitation rates. Additional types of microwave satellite sensors may also provide unique information that can be incorporated into future adaptations of probabilistic RI models, such as the Advanced Microwave Sounding Unit (AMSU) or Advanced Technology Microwave Sounder (ATMS) instruments.

As another direction of future research, other statistical models such as the Bayesian model described in RK11 and the SHIPS RII model of KDK10 could be enhanced with MI-based predictors. Enhancing additional models will help produce an even more skillful consensus probabilistic RI forecast, which has proven to be more reliable than any individual probabilistic model in the RK11 study. Finally, forecasting RI in other ocean basins will likely benefit from probabilistic MI-based models as well.

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