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Use of JPSS ATMS and VIIRS data to Improve Tropical Cyclone Track and Intensity Forecasting

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Introduction

The JPSS instruments, namely the Advanced Technology Microwave Sounder (ATMS) and the Visible Infrared Imaging Radiometer Suite (VIIRS), carried by the Suomi National Polar-Orbiting Partnership satellite (SNPP), provide unique information that could be critical for the forecasting of tropical cyclone (TC) track and intensity and is currently underutilized. Our group is developing several new TC applications using data from JPSS instruments. The MPI application uses ATMS data to improve the Statistical Hurricane Intensity Prediction Scheme (SHIPS) and the Logistic Growth Equation Model (LGEM), that have generally outperformed dynamical models in intensity prediction in the last 5 years. In the future, the results from all applications will be combined to improve the forecasts of rapid changes in tropical cyclone intensity, which is one of the highest priorities within NOAA.

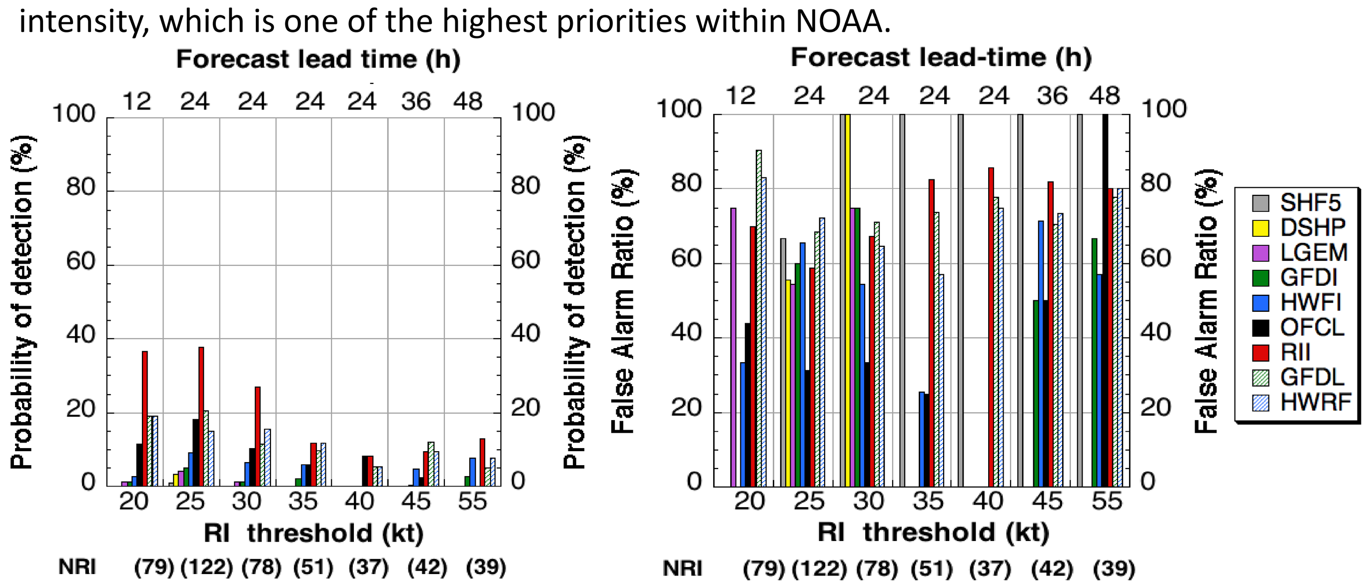
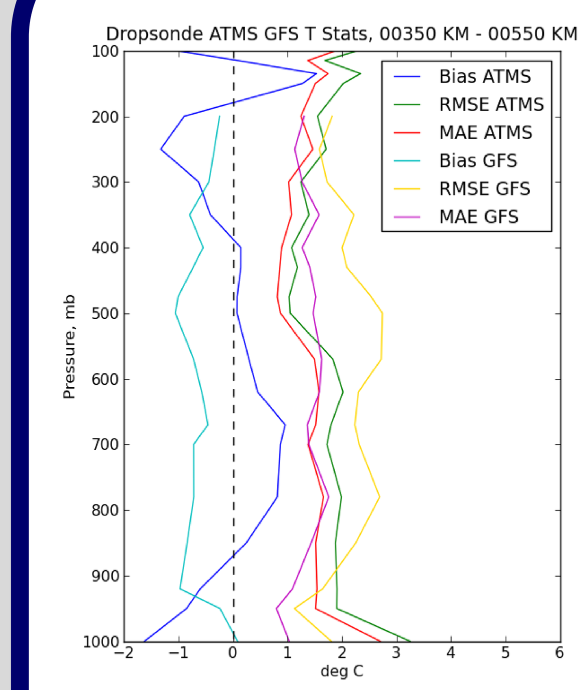
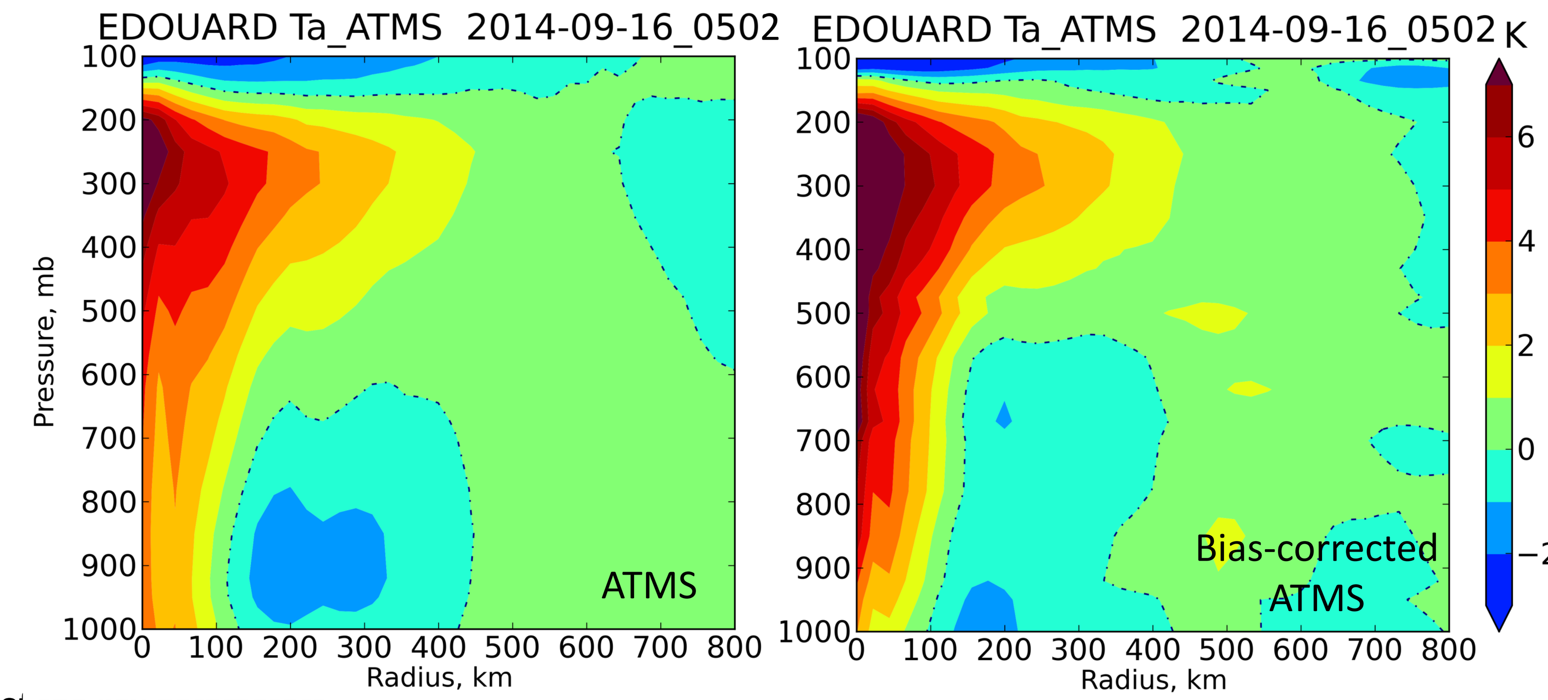


Figure from DeMaria 2015 (see https://ams.confex.com/ams/95Annual/webprogram/Paper261741.html)

- The Rapid Intensification Index (RII) is a statistical-dynamical tool for forecasting TC RI events (at least 25 kt intensity increase in 24 hours)
- RII is operational at NHC but has considerable room for improvement

Maximum Potential Intensity (MPI) Estimates from ATMS





- **SHIPS and LGEM use MPI as one of the key parameters**
- Operational versions of SHIPS, LGEM, and RII use statistical MPI based on SST
- **Use ATMS-MIRS T, q, SLP retrievals** and SST **to estimate MPI** using algorithm by Emanuel (1988), Bister and Emanuel (1998):

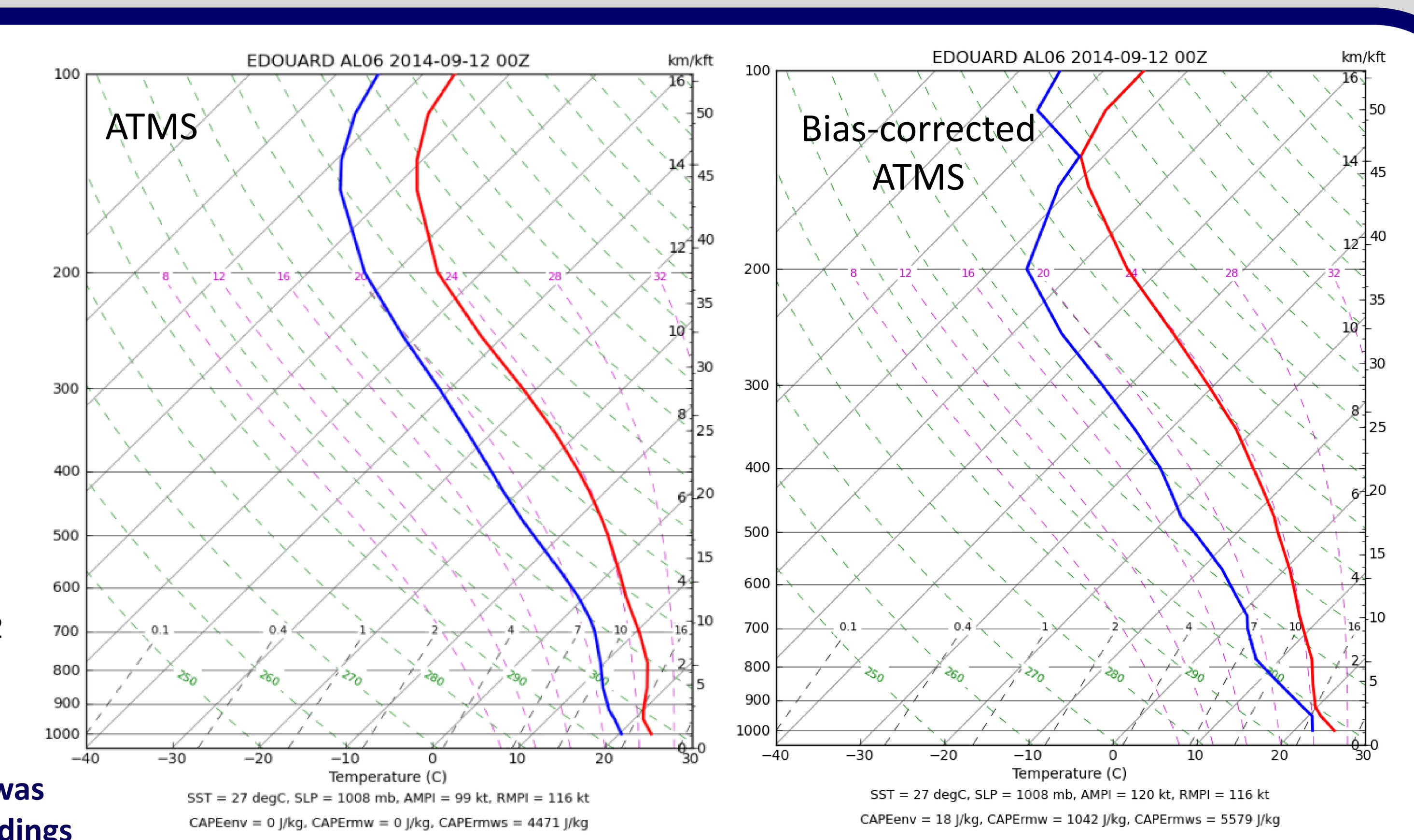
$$(MPI)^2 = \frac{T_s - T_o}{T_o}\frac{C_k}{C_D}(k^* - k)$$

•T_s, T_o, k^*, k: estimated from SST, sounding •C_k/C_D: ratio of surface exchange coefficients

- **MPI calculation from ATMS:**
  1. Average T, RH between r = 200 to 800 km to get $\overline{T}(p), \overline{RH}(p)$
  2. Input $\overline{T}(p), \overline{RH}(p)$ environmental profiles to Emanuel (1988) MPI algorithm
  3. Replace empirical MPI with ATMS MPI in RII and models

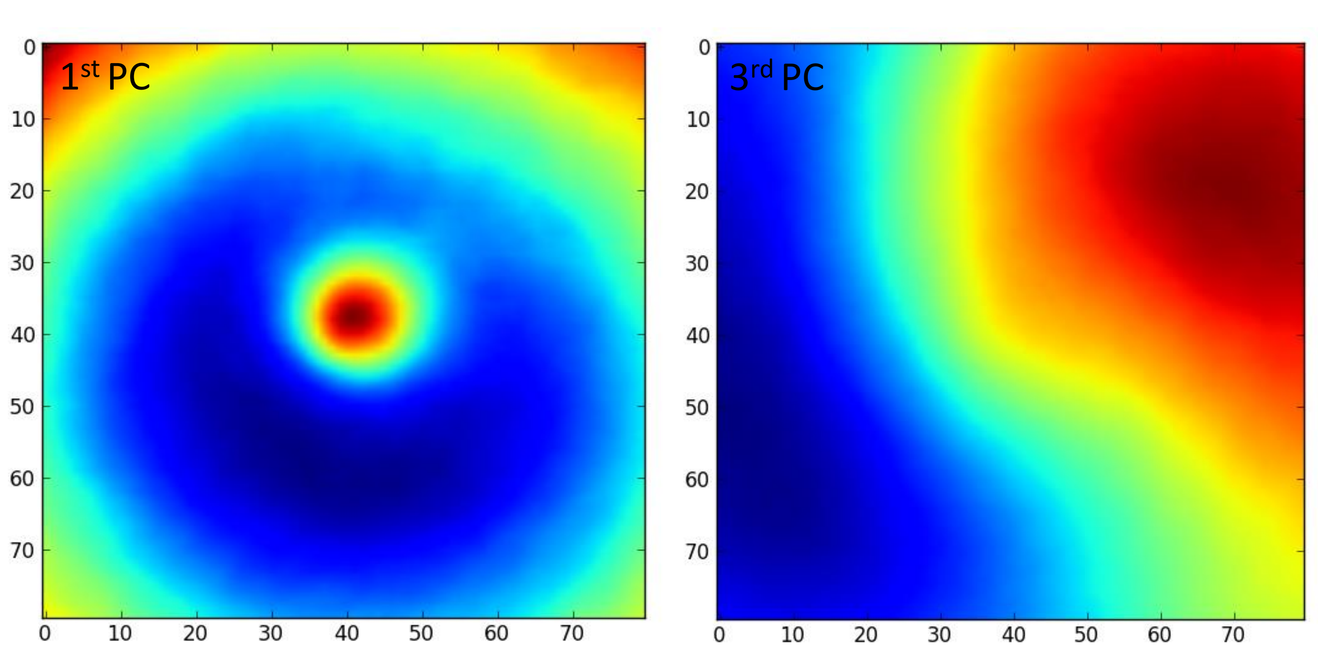
Statistical comparison of ATMS soundings to dropsondes was conducted, and bias correction was applied to ATMS soundings as a function of p, and distance from the storm center

- **TC warm core from bias-corrected ATMS profiles**
  - extends further to the surface
  - more pronounced warm anomaly at 250 hPa
- **Cold anomalies from bias-corrected ATMS profiles**
  - reduced cold air anomaly at 1000-700 hPa, 100-300 km from the storm center
  - reduced cold anomaly at the storm center at 1000-500 hPa

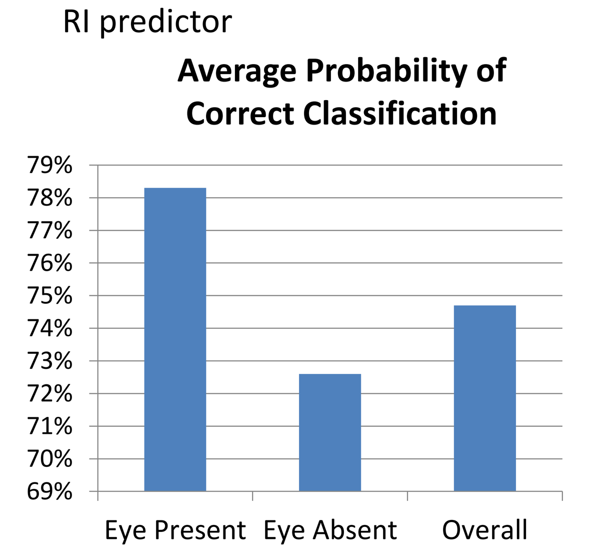


- **Bias-corrected ATMS profiles and corresponding MPI estimates:**
  - ATMS MPI increases after applying bias, and is usually larger than GFS MPI
  - The dry/cold bias at the surface is at least partially corrected
  - Environmental CAPE value are above zero for the developing storms. Largest CAPE values on bias-corrected plots with averaging between 300-800 km
  - More pronounced boundary layer
  - T profile follows more closely moist adiabat, for example, removed "bump" at 900-700mb
  - RH profiles for bias-corrected ATMS look smoother for 300-600 km averaging. "Bump" at 500 hPa removed.

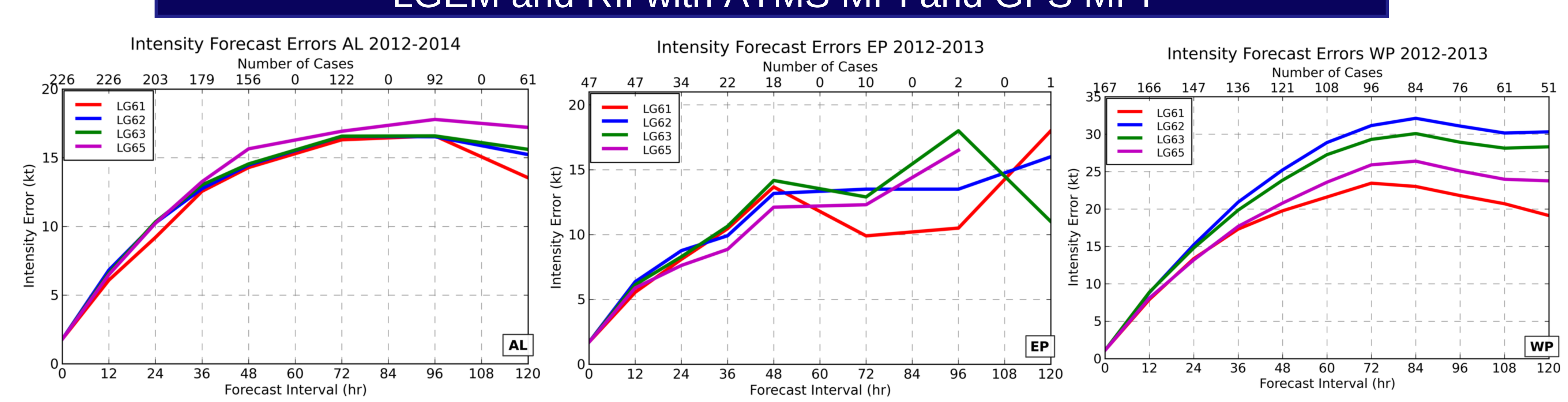
Objective Automated Eye-Detection



- **Automated objective eye-detection algorithm has been developed:**
- The algorithm was developed using training/testing sets of IR images with "Eye-Present", "Eye-Absent" classifications derived from TAFB Dvorak Intensity Fixes. (Velden et al., 2006)
- Training set was fed into Principal Component Analysis to find basis vectors (Above) and projected onto basis vectors to reduce dimension.
- Reduced dimension training set and associated TAFB classifications fed into Quadratic Discriminant Analysis (QDA) implementation to train machine learning algorithm.
- Testing set projected on to same basis vectors then classified by QDA.
- Automated algorithm overall eye-detection accuracy is 75%.
- Algorithm output can be further converted to probabilistic and used as additional RI predictor



LGEM and RII with ATMS MPI and GFS MPI

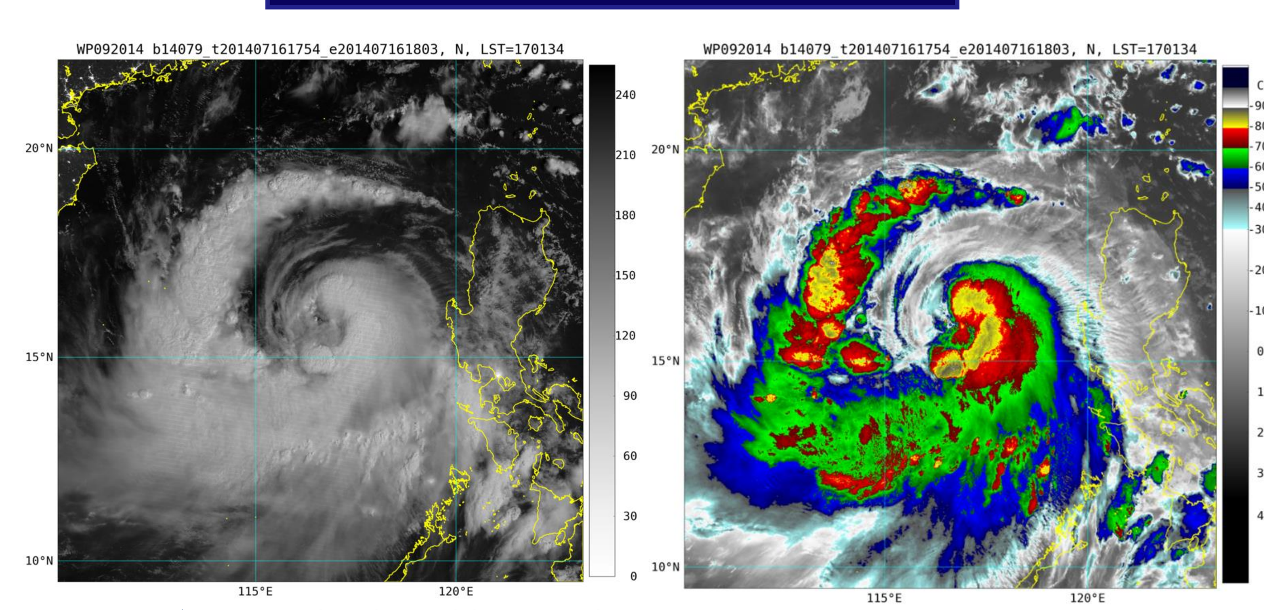


- **LGEM** is first rerun with the same settings as operational version (LG61)
- LGEM is then rerun with empirical MPI replaced by a) GFS MPI (LG62) b) ATMS MPI (LG65), and c) bias-corrected ATMS MPI (LG63)
- **AL, bias-corrected ATMS MPI:** same errors as operational version for 36-96 hr forecast, better than non-corrected ATMS MPI
- **EP, ATMS MPI:** better than both operational and GFS runs for 12-48 hr forecast. More data are needed.
- **WP, ATMS MPI:** better than GFS and same errors as operational version for 12-36 hr forecast
- **RII:** Statistics are preliminary: based on very small number of cases
- **AL:**
  - Use of bias-corrected ATMS profiles to estimate MPI reduces Brier Score for RII
  - ATMS-based estimates slightly worse than new GFS
- **EP:** only one RI case available, unable to calculate statistics
- **WP:**
  - Brier Score: ATMS < GFS
  - Brier Skill Score: ATMS/GFS > 0
  - Bias: ATMS slightly higher than GFS

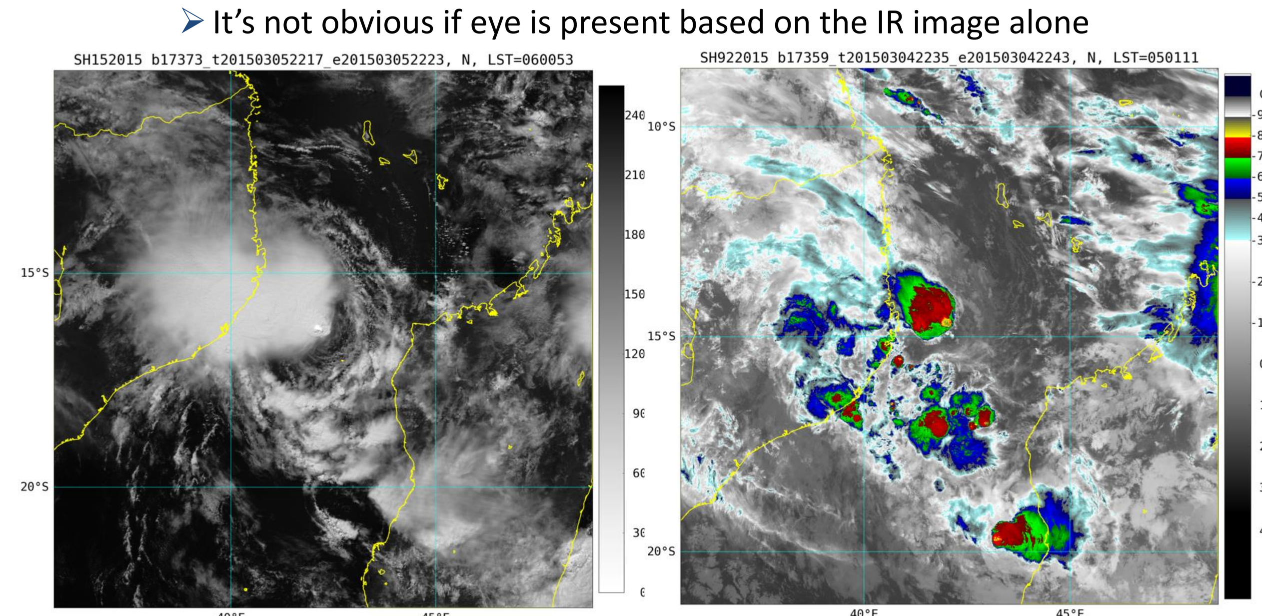
Basin	RI	BS GFS (G) 2014	BS GFS (G) 2013*	BS Bias-Corrected ATMS	BS ATMS (A)	BS Mean (M)	BSS A/G	BSS G/M	BSS A/M	Bias GFS	Bias ATMS	#Cases ALL	RII
AL	25 kt	845.31	964.55	788.87	879.54	788.87	-2.98	-7.16	-10.35	1.79	1.92	248	22
AL	30 kt	493.73	723.53	483.40	499.92	483.40	-1.66	-2.14	-3.83	1.84	1.94	248	13
AL	35 kt	312.07	477.11	301.62	311.08	301.62	-1.05	-3.46	-4.55	1.68	1.76	248	8
AL	40 kt	172.52	248.40	154.17	170.87	154.17	-2.07	-11.90	-14.21	2.21	2.37	248	4
WP	30 kt	1026.92	1044.39	1007.02	969.85	1560.0	1.94	34.17	35.45	0.56	0.58	179	31

* The 2013 numbers for GFS were obtained using 2012-2013 data sample

VIIRS DNB for TCs



- Eye is clearly visible on night-time DNB image
- It's not obvious if eye is present based on the IR image alone



- Low level circulation center visible only on DNB image
- Hard to see the center location from the IR image alone

Conclusions

- AL: applying to ATMS profiles bias correction based on statistical comparison with dropsondes produces more realistic TC structure
- LGEM and RII with ATMS MPI estimates:
  - AL: use of bias-corrected ATMS profiles produces better forecasts than use of uncorrected profiles
  - EP, WP: biases developed for AL do not work well for other basins, use of uncorrected ATMS profiles slightly improves RII and short-term LGEM forecasts for some forecast times (more data is needed for reliable statistics)
- Further focus will be on use of other parameters from ATMS for the RII, rather than just the MPI, since use of ATMS MPI does not produce significant improvement
- The overall accuracy of the objective automated eye-detection algorithm is 75%. Algorithm is being further improved by using high-resolution VIIRS data. Its output can be further used as RII predictor.
- VIIRS DNB imagery provides unique information that could be used for eye-detection and center-fixing

References

Bister, M., and K. A. Emanuel, 1998: Dissipative heating and hurricane intensity. *Meteor. Atmos. Phys.*, **65**, 233–240. doi:10.1007/BF01030791

DeMaria, M., 2009: A Simplified Dynamical System for Tropical Cyclone Intensity Prediction. *Mon. Wea. Rev.*, **137**, 68–82. doi: http://dx.doi.org/10.1175/2008MWR2513.1

Velden C. and Coauthors, 2006: The Dvorak tropical cyclone intensity estimation technique. *Bull. Amer. Meteor. Soc.*, **87**, 1195–1210.

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