Improving QPE for Tropical Systems with Environmental Moisture Fields and Vertical Profiles of Reflectivity

Heather Moser[12]*, Kenneth Howard[2], Jian Zhang[2], and Steven Vasiloff[2]

[1]Cooperative Institute for Mesoscale Meteorological Studies, University of Oklahoma, Norman, OK
[2]National Severe Storms Laboratory, NOAA, Norman, OK

1. INTRODUCTION

Accurate estimation of rainfall has long been a pursuit of weather radar research. Initial studies focused on developing appropriate reflectivity to rain rate (Z-R) relationships for drop size distributions (DSDs) associated with different storm types. However, varying DSDs were observed even within single storms, making the definition of characteristic Z-R functions difficult (Marshall et al. 1947; Atlas and Chmela 1957; Battan 1973). Measuring DSDs and assigning Z-R relationships based on individual storm microphysics is difficult in a real-time, operational setting with single-polarization radar, so characteristic Z-R relationships were nevertheless selected for use in the National Weather Service's WSR-88D network. Current estimates of rainfall rate use only one default Z-R relationship ($Z=300R^{1.4}$) across the entire network of radars, but the option is available for additional Z-R functions to be added that are specific to the location of the radar, such as a tropical rain rate that is applied in coastal areas (Fulton et al. 1998).

Several case studies of landfalling tropical cyclones demonstrated that use of the tropical Z-R relationship ($Z=250R^{1.2}$) greatly reduced the underestimation bias of radar-based estimates of rainfall when compared with collocated rain gauges (Vieux and Bedient 1998; Davis 2004; Gates 1997; Wood 1997). However, Ulbrich and Lee (2002) also showed for landfall of the remnants of a tropical storm that the most appropriate Z-R relationship varied during different stages of the storm's passage over the radar. The initial rainfall rates from the outer bands of Tropical Storm Helene best resembled that of midlatitude continental convection while the tropical Z-R worked best for the center of the storm. While the *storm total* bias of the radar-based rainfall accumulation may have been small if a single Z-R relationship was used for the entire storm, large errors would be present when examining shorter time scales over the course of the storm's evolution (Ulbrich and Lee 2002). This result demonstrates the need for adaptable, spatially varied Z-R functions that reflect changing environmental conditions and storm mode.

The National Mosaic and Multisensor QPE Project (NMQ) is a testbed developed by the National Severe Storms Laboratory (NSSL) for both real-time, high-resolution precipitation estimation and short-term precipitation forecasts. The NMQ precipitation estimation product (Q2) has a 1-km spatial resolution over the continental United States, and hourly accumulations are updated every five minutes. It is a fully automated multisensor rainfall estimate that incorporates data from radar, rain gauges, and numerical weather prediction (NWP) model analyses. The various inputs are used to segregate different types of precipitation (stratiform and convective rain, hail, tropical rain, and snow) and assign different Z-R relationships at each grid point (Zhang et al. 2009).

Identification of tropical (i.e., warm rain) precipitation for Q2 is currently based on vertical profiles of reflectivity (VPR) calculated at each radar location (Xu et al. 2008). The radar's VPR is flagged as tropical if the reflectivity either monotonically decreases with height (i.e., no bright band is detected) or if the reflectivity below a detected bright band either remains approximately constant or increases with decreasing height. In other words, a non-tropical VPR is one in which reflectivity decreases below the bright band, implying that there is little if any increase of liquid water content below the freezing level (Fig. 1). If a VPR is identified as tropical, the tropical Z-R relationship is then applied to all locations within a distance from the radar where reflectivity exceeds a threshold (generally the value at which tropical rainfall rates begin to differ significantly from convective or stratiform rates in the Z-R functions). The distance and minimum reflectivity are both adjustable parameters in the tropical rainfall identification algorithm.

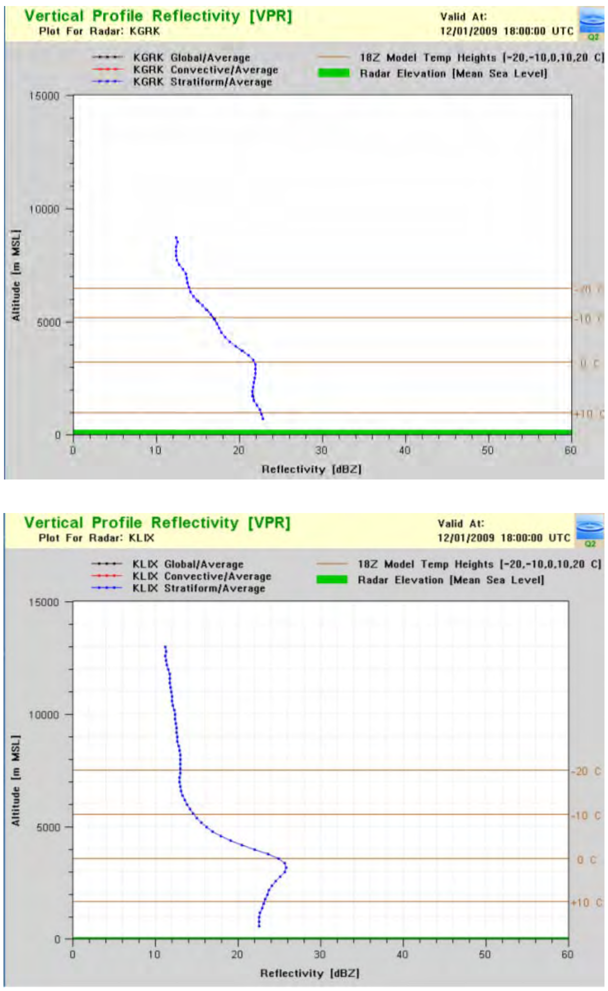

Figure 1. Vertical profiles of reflectivity classified as tropical (upper) and non-tropical (lower) in the Q2 system. Classifications are based on the slope of the profile below the freezing level.

Because the tropical rainfall identification is based only on a single, instantaneous VPR at each radar location, there is no way to determine in the current algorithm whether the tropical Z-R is appropriate for the entire umbrella of the radar. It is often the case that significant rainfall events occur along boundaries between different air masses, with precipitation on one side of the boundary having very different characteristics from precipitation on the other side. This is true for extratropical transition of tropical cyclones in the Mid-Atlantic region, as well as convection that develops along midlatitude fronts and troughs. Thus, to apply the tropical Z-R relationship precisely where we might expect warm rain to occur, we need more information about the environment from which the convection developed.

The goal of this study is to examine the Q2 rainfall estimates, hourly rain gauge accumulations, and environmental fields from the Rapid Update Cycle (RUC) model analyses for two tropical cyclone cases to determine if there are systematic relationships between the Q2 rainfall bias and the characteristics of the ambient environment that would indicate where application of the tropical Z-R is most appropriate.

2. DATA AND METHODOLOGY

The two rainfall cases analyzed for this study were both tropical cyclones that impacted North Carolina: Hurricane Isabel (2003) and Tropical Storm Alberto (2006). Hurricane Isabel made landfall near Cape Hatteras, NC, on September 18, 2003 at category 2 strength on the Saffir-Simpson scale (Gautam et al. 2005). It then weakened to a tropical storm over Virginia before becoming extratropical further north into Pennsylvania on September 19. The domain for this study only includes the region where Isabel was hurricane strength (Fig. 2), so it is considered to be a true tropical system with no extratropical characteristics.

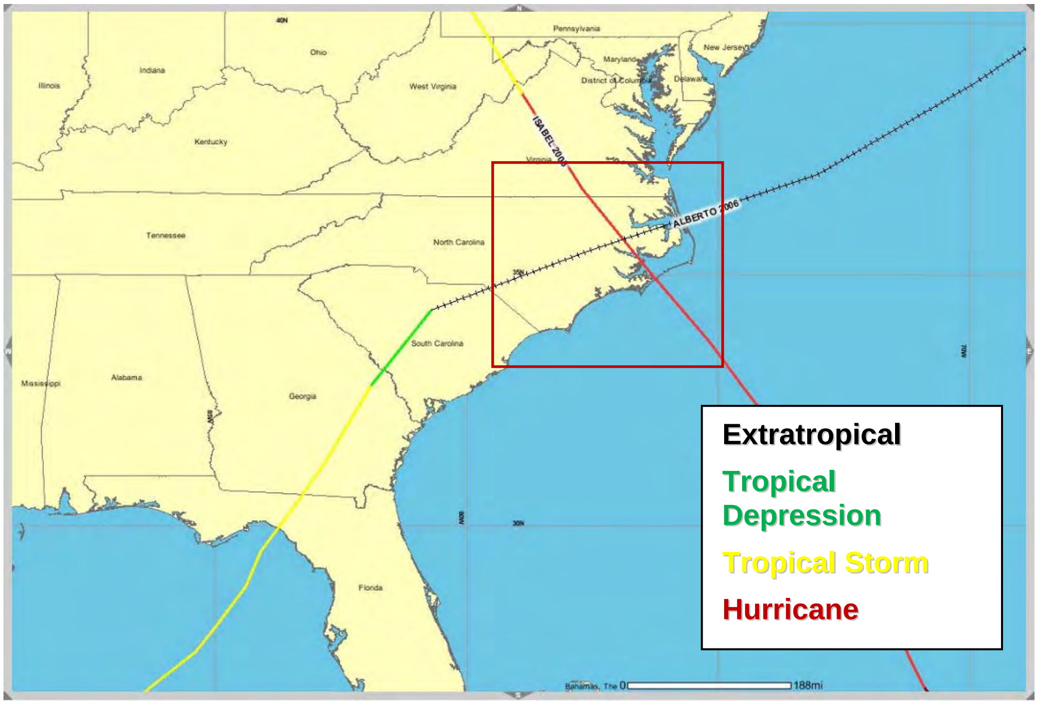

Figure 2. Tracks and intensities of Hurricane Isabel and Tropical Storm Alberto (source: Coastal Services Center). The red box represents the domain of this study.

Tropical Storm Alberto was quite different, however. Alberto developed in the western Caribbean and made landfall as a tropical storm over the Florida panhandle. The storm weakened to a tropical depression in Georgia as it moved northeast and was classified as extratropical by the time it reached eastern North Carolina (Franklin and Brown 2006). The remnants of Alberto left torrential rain and flooding in North Carolina, with some areas receiving 5-7 inches in 24 hours.

Hourly, 20 km, isobaric RUC analysis files were retrieved in GRIB format for the full duration of each rainfall event within the selected domain (Fig. 2). Individual variables were extracted and remapped to the Q2 cartesian 1km grid for direct comparison to the QPE fields. The variables analyzed for tropical rainfall classification were:

1) Precipitable water
2) Precipitable water * 1000-700 hPa mean Relative Humidity (an approximation of Precipitation Efficiency)
3) Equivalent Potential Temperature (Theta-E)
4) Cloud depth (difference between cloud base and cloud top fields)
5) 500 hPa Temperature

Additional variables were also extracted that were required for generation of Q2, such as 0 °C isotherm height (used for bright band detection for stratiform rain classification) and surface temperature (liquid vs. frozen precipitation classification).

Hourly Q2 rainfall fields without gauge bias correction were recreated for both events using the 20 km RUC fields and archived Level-II NEXRAD data from the National Climatic Data Center (NCDC). Data from three radars covering eastern North Carolina were used to generate the Q2 rainfall: Raleigh, NC (KRAX), Morehead City, NC (KMHX), and Wakefield, VA (KAKQ). The hourly Q2 accumulations are not based on single Z-R functions at each grid point for the entire hour. The best precipitation flag (stratiform, convective, tropical, or hail) is recalculated on the 5-minute update interval such that the one-hour accumulation can be a sum of different rainfall rates over the course of the storm evolution. While the hourly Q2 rainfall is updated every five minutes, only accumulations on the hour were retained for analysis in order to align with the times of the model fields and rain gauge data.

The collection of hourly rain gauge data for Hurricane Isabel and Tropical Storm Alberto included gauges from several different networks: ASOS, North Carolina ECONet, USGS, and RAWS. Any gauges that were more than 200 km from the nearest of the three radars were excluded from the analysis. Extensive quality control was performed on the gauge dataset for a previous study that examined the same two storms and associated Q2 rainfall fields (Kitzmiller et al. 2008).

For the calculation of Q2 bias, a nearest neighbor method was used to match the location of each rain gauge to the nearest grid point on the Q2 cartesian 1 km grid. The rain gauge hourly accumulation was then subtracted from the Q2 accumulation such that overestimates (underestimates) by Q2 would result in positive (negative) bias. Data values were not included in the analysis if both the Q2 and gauge accumulations were zero or if one of the two fields was flagged as missing. The bias was the value compared to the environmental fields in order to assess how well the Z-R selection for Q2 rainfall totals approximated the measured precipitation at varying intensities (reflectivity < 30 dBZ under a "tropical" radar was classified as stratiform).

3. RESULTS

A strong relationship was found for Hurricane Isabel between gradients in the environmental parameters and the gauge biases across the domain (Figs. 3, 4). Q2 tended to overestimate rainfall totals in environments with lower water vapor content and shallower convection and underestimate rainfall where convection was much deeper and water vapor content was higher (generally near the center of the storm). This tendency was not only true for the heaviest rainfall, however, but for lighter accumulations as well where precipitable water was high. Q2 underestimated rainfall at nearly all locations where the gauges exceeded 15 mm in one hour (denoted as yellow, green, and blue points in Fig. 4), and Q2 underestimates of more than 10 mm were all located in environments where precipitable water was greater than 40 kg m^{-2}. Large Q2 overestimates were only found where precipitable water was less than 40 kg m^{-2}. Similar trends were also evident in the equivalent potential temperature, 500 mb temperature, and cloud depth parameters (Fig. 4).

Because Alberto was extratropical as it passed over eastern North Carolina, its environment was much different from that of Hurricane Isabel. Precipitable water was generally lower across the domain, and the 500 mb temperature anomaly associated with the storm (i.e. mid-level diabatic warming) was generally lower. The trends between rainfall biases and environmental fields were not as clearly defined (Fig. 5), but the largest Q2 underestimates still occurred only where precipitable water was highest. The relative humidity modification of precipitable water did amplify the difference between the dry and moisture-rich environments and created a clearer separation between the largest Q2 high and low biases (Fig. 6).

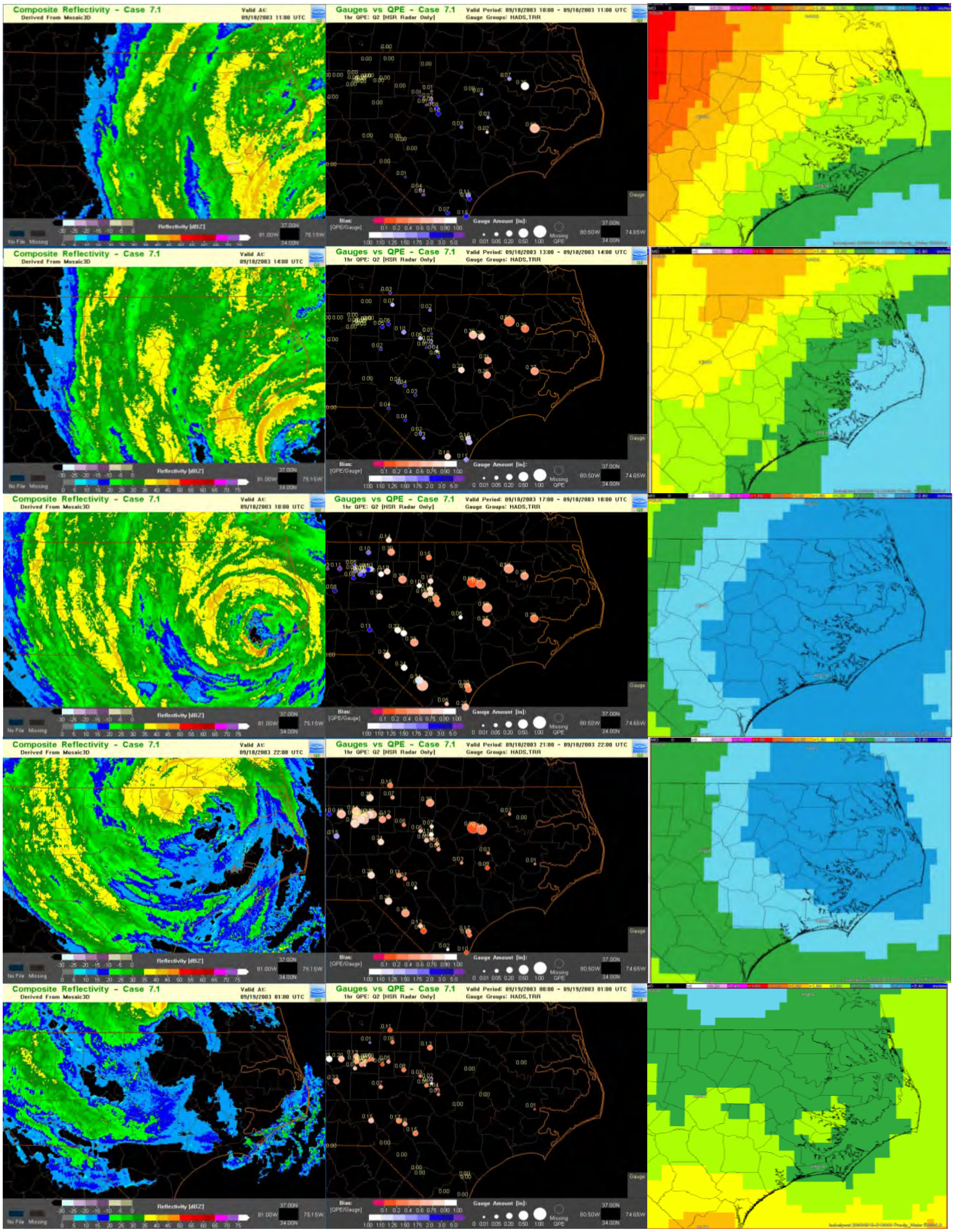

Figure 3. Evolution of reflectivity, gauge/Q2 bias, and precipitable water during the landfall of Hurricane Isabel. Blue (red) circles in the bias field represent Q2 overestimates (underestimates), and the dark green and blues in the precipitable water field indicate PW > 2 inches.

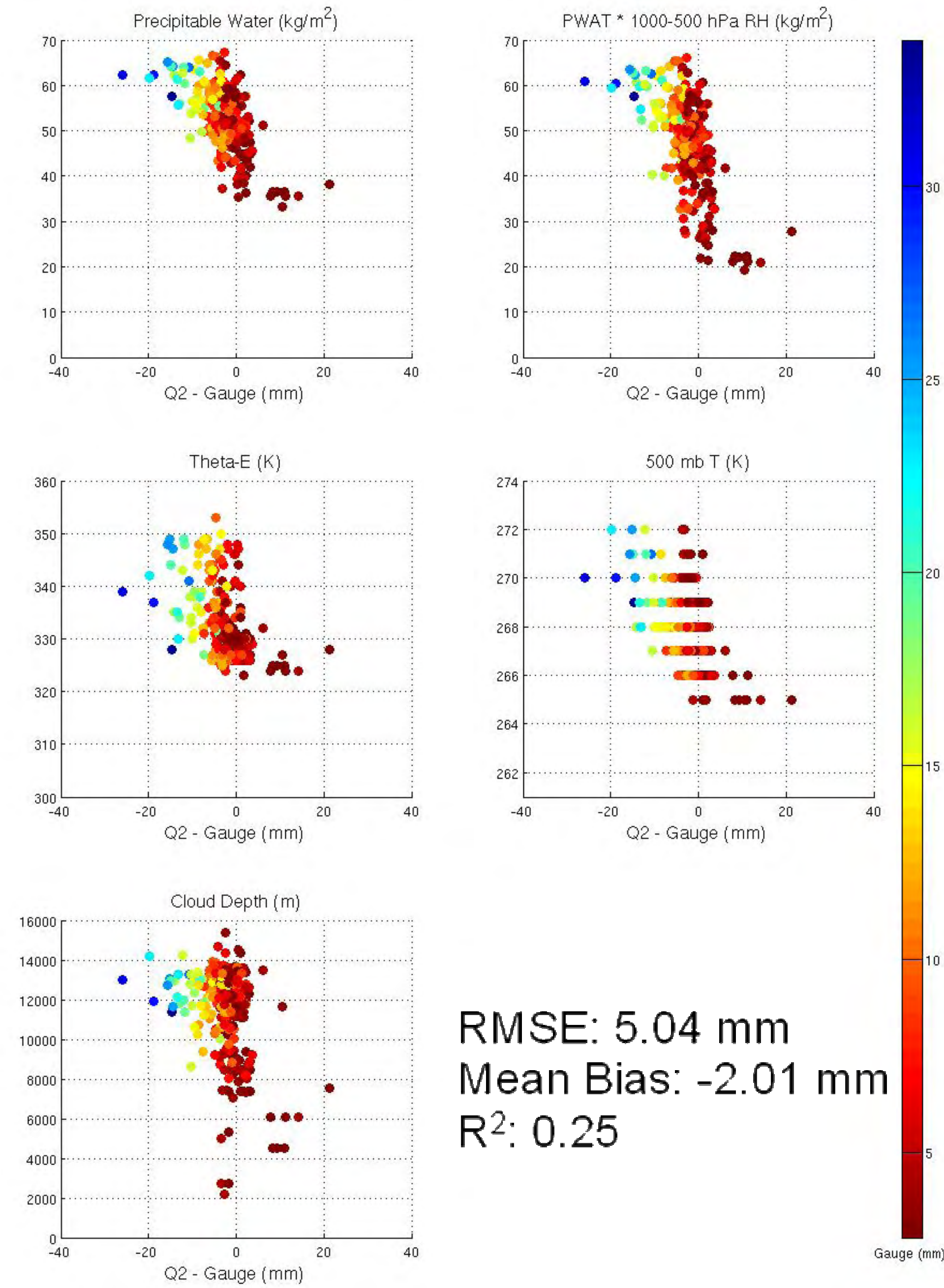

Figure 4. Comparison of RUC-derived environmental parameters and gauge/Q2 rainfall biases for Hurricane Isabel (all hourly gauge accumulations > 2.54 mm). Dot colors represent the hourly rain gauge accumulation.

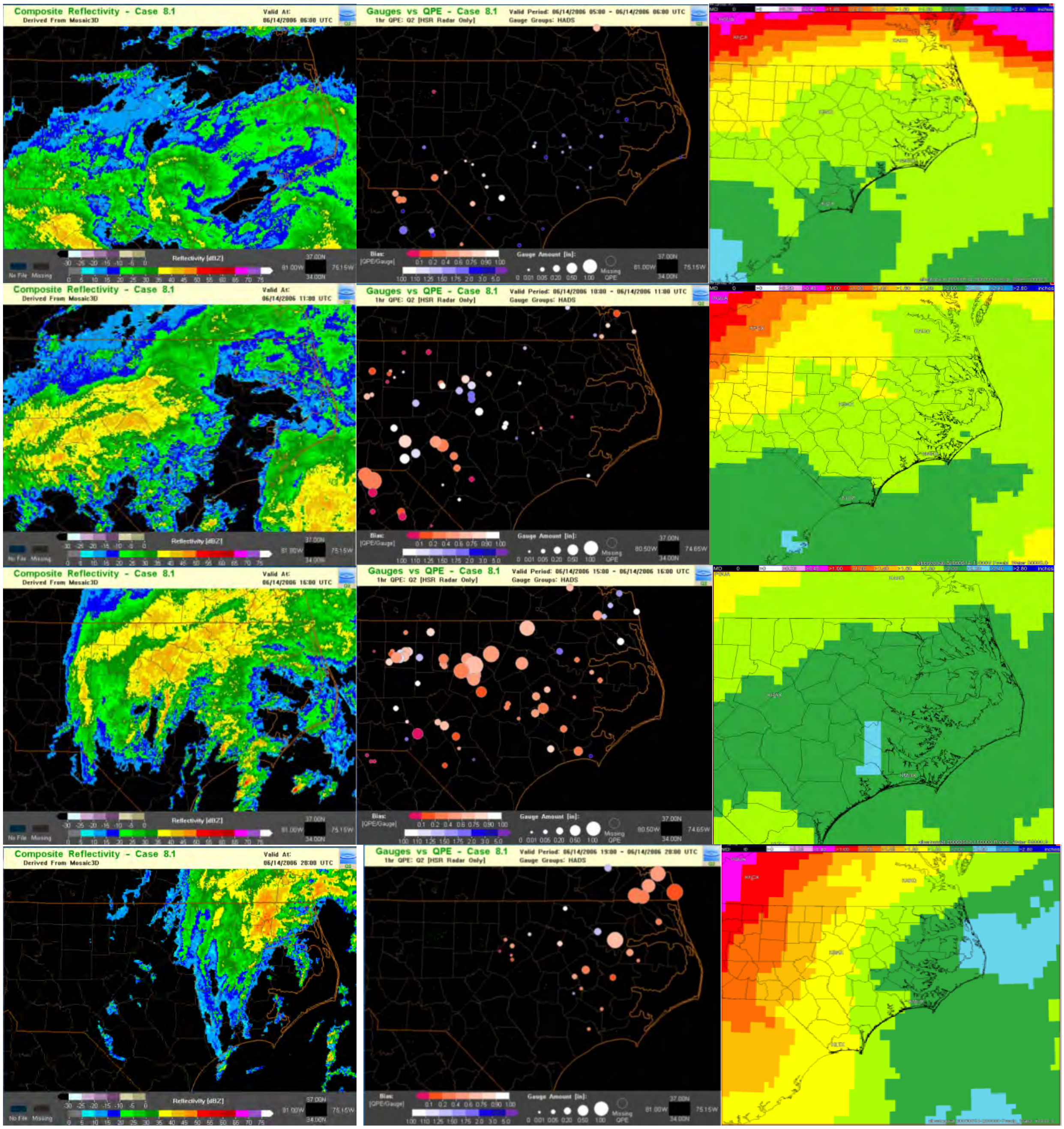

Figure 5. Evolution of reflectivity, gauge/Q2 bias, and precipitable water during the passage of the remnants of Tropical Storm Alberto. Blue (red) circles in the bias field represent Q2 overestimates (underestimates), and the dark green and blues in the precipitable water field indicate PW > 2 inches.

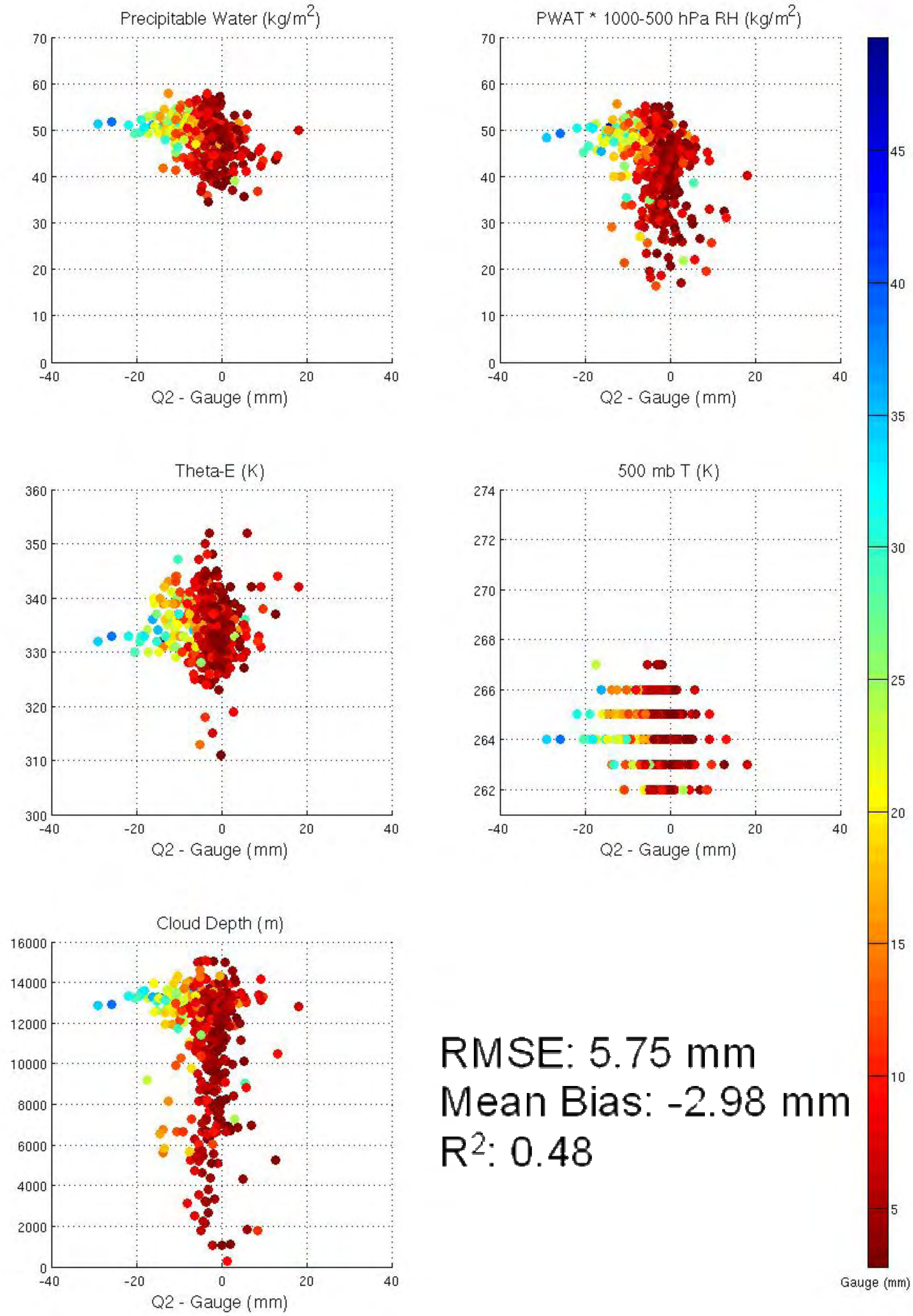

Figure 6. Comparison of RUC-derived environmental parameters and gauge/Q2 rainfall biases for the remnants of Tropical Storm Alberto (all hourly gauge accumulations > 2.54 mm). Dot colors represent the hourly rain gauge accumulation.

4. MODIFIED PRECIPITATION TYPE

Even if the nearest radar to a location is flagged as “tropical” by the Q2 algorithms, one would not expect the same tropical VPR shape in an environment containing much drier air below the cloud base. Evaporation would instead cause a reduction of liquid water content and drop size in the radar volume and thus reduce the reflectivity. This idea is supported by the relative humidity modified precipitable water field, because the 1000-700 hPa relative humidity only tended to reduce precipitable water where rainfall accumulations were very light and/or Q2 was significantly overestimating.

To eliminate the overestimation by Q2 in the vicinity of tropical rainfall, a modification was made to the precipitation typing algorithm to only allow the tropical Z-R function to be applied where precipitable water exceeded a threshold. The threshold was initially determined to be 48 kg m^{-2} (1.9 inches) based on the inflection points in Figs. 4 and 6 where the rainfall bias transitioned from positive to negative in both storms, but this value would likely vary by geographic location and season (an area of future research). Where the tropical rainfall rate was not allowed to be assigned, the precipitation types were assigned as either convective or stratiform as is typically done in Q2 where the radars are not flagged as tropical.

The modified precipitation typing greatly reduced the large overestimation by Q2 for Hurricane Isabel and led to a small improvement for Tropical Storm Alberto (Figs. 7, 8). Alberto differed from Isabel in that the areas affected by the restriction of the tropical precipitation type were confined to the westernmost part of the domain where few gauges are available. This caused the scatterplot of gauge rainfall to show only a minor improvement in the overestimation bias (Fig. 8).

Because Q2 has a tendency to systematically underestimate the heaviest rainfall amounts, the proposed explanation was that the Z-R relationship used for tropical rainfall is generally inadequate for capturing the rainfall rates in storms with high precipitation efficiency. An alternate tropical Z-R relationship was therefore tested for Isabel and Alberto that was derived from observations of convective storms over Taiwan ($Z=32.5R^{1.65}$). The use of the Taiwan Z-R function did improve the bias where water vapor content was high (Figs. 7, 8), but it also introduced some overestimation of lighter precipitation that was not present with the original tropical Z-R function.

Another idea proposed has been to use precipitable water or the relative humid ity-modified precipitable water as a scaling factor to enhance Q2 accumulations as a function of the environment’s water vapor content, which is a method currently employed for real-time satellite precipitation estimation algorithms such as the Hydroestimator (Scofield et al. 2003). Such an approach may have some value where the gauge-based bias correction is ineffective due to sparse gauge networks such as in the western U.S. Furthermore, a more linear approach to rainfall adjustment may not lead to the overestimation that was generated by changing the Z-R equation.

Precipitable water was the only parameter used in this study to modify the precipitation types, but the other parameters were analyzed for both events in order to determine if a combination of variables used together would be a more effective discriminator of tropical environments than using one parameter alone. Future work will examine these and other parameters on a larger scale to see how the criteria for tropical rainfall varies geographically. A fuzzy logic-type scheme using all the parameters (and the radar VPRs) with criteria specific to certain regions may be a much more robust way to apply the tropical rainfall rates in the Q2 system.

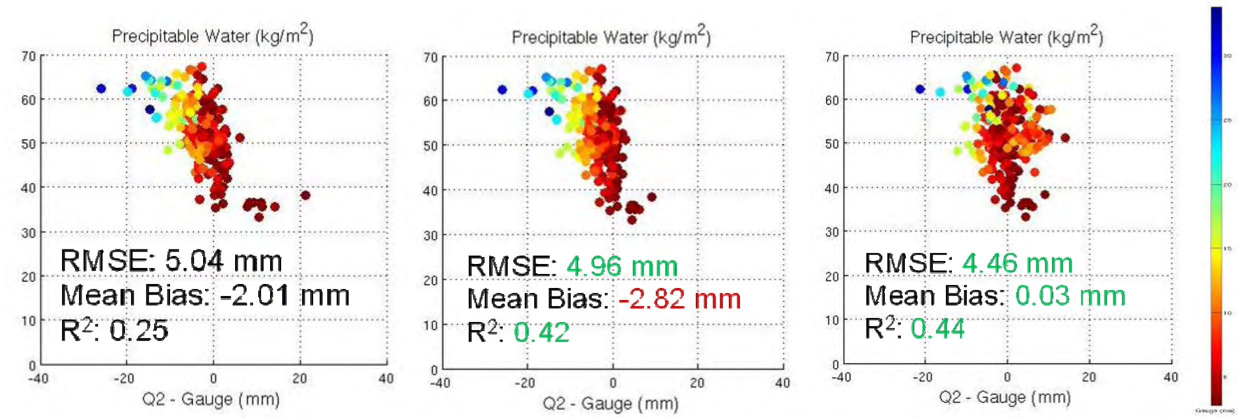

Figure 7. Comparison of RUC-derived environmental parameters and gauge/Q2 rainfall biases for Hurricane Isabel using the three different tropical rainfall algorithms: Q2 default (left), precipitable water modification (middle), and precipitable water modification with the Taiwan tropical Z-R function (right). Dot colors represent the hourly rain gauge accumulation.

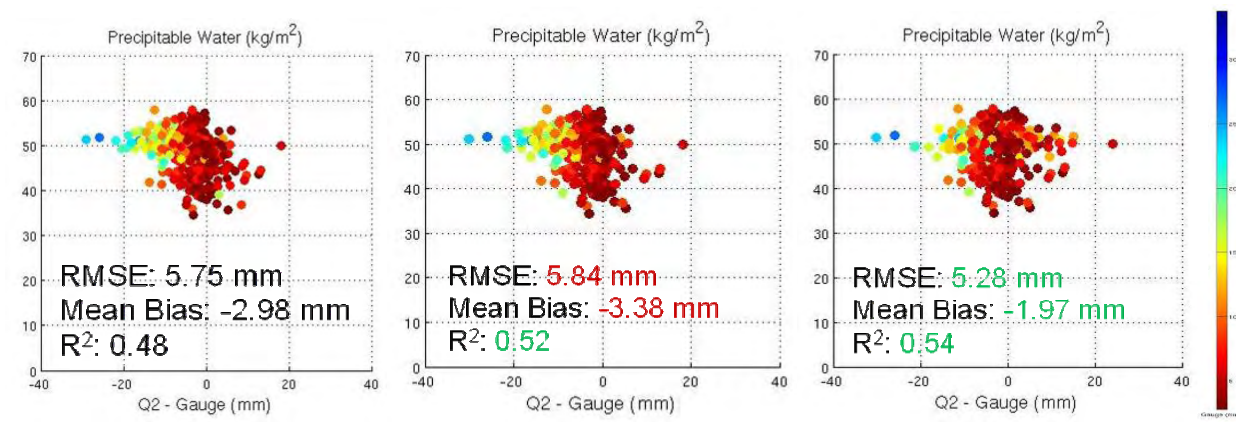

Figure 8. Comparison of RUC-derived environmental parameters and gauge/Q2 rainfall biases for Tropical Storm Alberto using the three different tropical rainfall algorithms: Q2 default (left), precipitable water modification (middle), and precipitable water modification with the Taiwan tropical Z-R function (right). Dot colors represent the hourly rain gauge accumulation.

5. ACKNOWLEDGEMENTS

We would like to thank Carrie Langston for her technical assistance with the Q2 data and algorithms.

6. REFERENCES

Atlas, D., and A. C. Chmela, 1957: Physical-synoptic variations of drop-size parameters. *Proceedings*, *6th Weather Radar Conference*, 21-30.

Battan, L. J., 1973: Radar Observation of the Atmosphere. Univ. of Chicago Press, Chicago, IL. 324 pp.

Davis, R. S., 2004: The impact of tropical rainfall rates on flash flood detection. *22nd Conf. on Severe Local Storms*, Am. Met. Soc., Hyannis, MA.

Franklin, J. L., and D. P. Brown, 2007: Atlantic hurricane season of 2006. *Mon. Wea. Rev.*, **136**, 1174-1200.

Fulton, R. A., J. P. Breidenbach, D.-J. Seo, D. A. Miller, and T. O'Bannon, 1998: The WSR-88D rainfall algorithm. *Wea. Forecasting*, **13**, 377-395.

Gates, C., 1997: Hurricane Bertha: Radar-gauge comparisons and changing the Z-R relationship. National Weather Service Tech. Report ER-98.

Gautam, R., G. Cervone, R. P. Singh, and M. Kafatos, 2005: Characteristics of meteorological parameters associated with Hurricane Isabel. *Geophys. Res. Letters*, **32**.

Kitzmiller, D. H., F. Ding, S. Van Cooten, K. W. Howard, C. Langston, J. Zhang, H. M. Moser, R. J. Kuligowski, D. Kim, Y. Zhang, and D. Riley, 2008: A comparison of evolving multisensory precipitation estimation methods based on impacts on flow prediction using a distributed hydrologic model. *22nd Conf. on Hydrology*, Am. Met. Soc., New Orleans, LA.

Marshall, J. S., R. C. Langille, and W. M. Palmer, 1947: Measurement of rainfall by radar. *J. Meteor.*, **4**, 186-192.

Scofield, R. A., and R. J. Kuligowski, 2003: Status and outlook of operational satellite precipitation algorithms for extreme-precipitation events. *Wea. Forecasting*, **18**, 1037-1051.

Ulbrich, C. W., and L. G. Lee, 2002: Rainfall characteristics associated with the remnants of Tropical Storm Helene in upstate South Carolina. *Wea. Forecasting*, **17**, 1257-1267.

Vieux, B. E., and P. B. Bedient, 1998: Estimation of rainfall for flood prediction from WSR-88D reflectivity: A case study, 17-18 October 1994. *Wea. Forecasting*, **13**, 407-415.

Wood, L. T., 1997: Using the tropical Z-R relationship to improve precipitation estimates during a heavy rain event in southeast Texas. *28th Conf. on Radar Meteorology*, Am. Met. Soc., Austin, TX.

Xu, X., K. Howard, and J. Zhang, 2008: An automated radar technique for the identification of tropical precipitation. *J. Hydromet.*, **9**, 885-902.

Zhang, J., K. Howard, S. Vasiloff, C. Langston, B. Kaney, A. Arthur, S. Van Cooten, K. Kelleher, D. Kitzmiller, F. Ding, D.-J. Seo, M. Mullusky, E. Wells, T. Schneider, and C. Dempsey, 2009: National Mosaic and QPE (NMQ) System – Description, results, and future plans. *34th Conf. on Radar Meteorology*, Am. Met. Soc., Williamsburg, VA.