7A.2 Multi-sensor Precipitation Reanalysis

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1. INTRODUCTION

Accurate historical precipitation analysis is needed for various hydrologic, hydrometeorological, hydroclimatological applications. Increasingly, many of these applications require analysis at high spatio-temporal resolutions. Since the implementation in the early to mid-1990's the network of Weather Surveillance Radar – 1988 Doppler (WSR-88D), commonly known as the Next Generation Weather Radar (NEXRAD), real-time precipitation analysis in the U.S. has been heavily relying on radar data for high-resolution precipitation information. In the continental U.S., the WSR-88D network consists of approximately 140 sites, most of which have been operational for well over a decade now. The WSR-88Ds provide radar reflectivity estimates for the NEXRAD Precipitation Processing Subsystem (PPS, Fulton et al. 1998) which produces radar-derived precipitation products in real time in support of the National Weather Service's mission and external users. Quantitative precipitation estimates (QPE) from radar, however, are subject to various sources of error (Wilson and Brandes 1979, Vasiloff et al. 2007) and, by themselves, are generally not suitable for quantitative hydroclimatological applications. To produce precipitation estimates that are more accuate than those obtainable from radar or rain gauges alone, multisensor estimation is necessary, consisting usually of bias correction of radar QPE and multivariate analysis, or merging, of bias-corrected radar QPE and rain gauge data. In NWS, such multisensor precipitation estimation applications produce precipitation estimates at different spatial scales and in stages (Hudlow 1988, Vasiloff et al. 2007). For example, the so-called Stage III products are generated at the River Forecast Centers (RFC), which are nationally mosaicked at the National Centers for Environmental Prediction (NCEP) to produce the Stage IV products (Fulton et al, 1998, Vasiloff et al. 2007). In the early 2000's, the Multisensor Precipitation Estimation (MPE) algorithm replaced the Stage III algorithm at most RFCs (Breidenbach et al. 1998, 2001b, 2002). At the Arkansas-Red Basin River Forecast Center (ABRFC) and in the Western Region, the P1 algorithm (see Appendix A of Seo and Breidenbach 2002) and the Mountain Mapper (see Section 2 of Schaake et al. 2004) are used, respectively, Instead of the MPE.

Since they were first implemented, both the radar and multisensor QPE algorithms in PPS and MPE, respectively, have undergone a number of significant changes for improvement, resulting in significant changes in the error characteristics of the respective precipitation products. Being a real-time operation, Stage III analysis can only make use of the real-time data that are available by the time of the analysis. The objective of this work is to produce temporally-consistent high-quality high-resolution multisensor precipitation reanalysis products for a wide range of climatological and hydroclimatological applications. Development of such products should capitalize on the additional data that may not be available in real time, and the retrospective nature of the analysis that allows identification, correction and quantification of the errors, which are generally not possible in real time due to insufficient data and computing power. Toward that end, the National Climatic Data Center (NCDC) in collaboration with the National Weather Service (NWS) has redeveloped the MPE algorithm (Seo and Breidenbach 2002) into the Multisensor Precipitation Reanalysis (MPR) algorithm over the pilot domain (Figure 1). MPR inputs the historical Digital Precipitation Array (DPA) products from the WSR-88D network and the rain gauge data from the the Cooperative Observers Program (COOP) and the Hydrometeorological Automated Data System (HADS) networks and outputs a suite of reanalysis products similar to that of MPE products (see Figure 2). As a pilot project, the reanalysis is set up for the regional domain over North and South Carolinas which includes six WSR-88D sites (see Figure 1). The goal of the pilot project is to demonstrate improvement of experimental MPR products over the operational QPE products. The main sources of improvement include additional rain gauge

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data, systematic quality control of rain gauge data, correction of systematic biases in radar QPE and parameter optimization for radar-gauge merging. In this paper, we describe the data and the reanalysis procedure used for the pilot project, and summarize the results, including comparative evaluation with the Stage IV products.

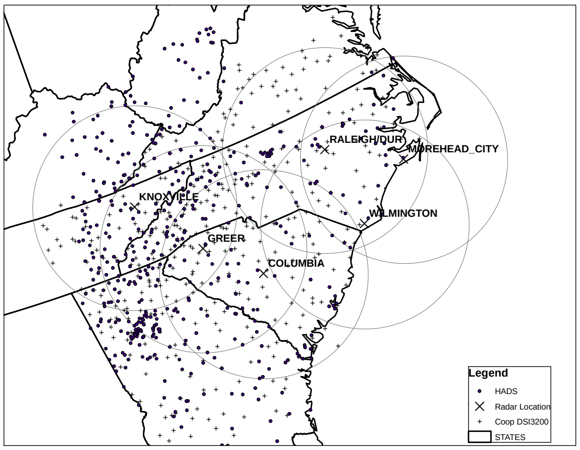

Figure 1: Study location including radar range rings of 230km and rain gauge locations used in the study.

2. DATA AND QUALITY CONTROL

The radar data source is the WSR-88D Digital Precipitation array (DPA) and the rain gauge data sources are the HADS and COOP data. In this section we provide an overview of the data used and the quality control steps taken to screen out bad data and gauges.

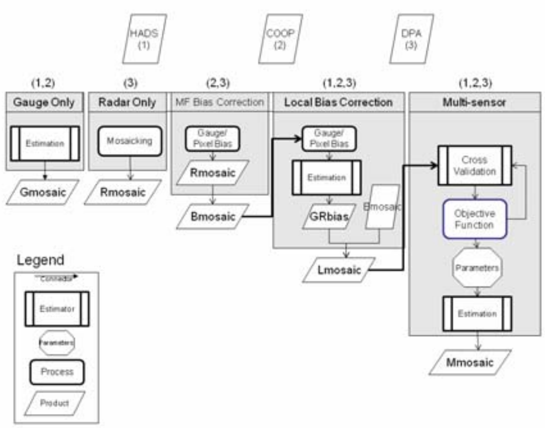

Figure 2: Workflow of the multi-sensor precipitation reanalysis.

2.1 Digital Precipitation Array (DPA)

The DPA is one of approximately 20 products in the WSR-88D Level III data suite that are derived from the Level II data (Klazura and Imy, 1993). The DPA product is an hourly running precipitation total on the HRAP grid (approximately 4x4 km^2) out to a range of 230 km from the radar. The estimates are produced by the WSR-88D Precipitation Processing Subsystem (PPS, Fulton et al. 1998) by combining radar reflectivity estimates from multiple elevation angles using a hybrid scan strategy, converting reflectivity (Z) to rainfall (R) using the Z-R relation and then mapping them onto the HRAP grid. Currently, five sets of parameters are used operationally for the Z-R relation for five different precipitation regimes, a=300,b=1.4; a=200,b=1.6; a=250,b=1.2; a=130,b=2.5; a=75,b=2.5, for convective, stratiform, tropical, stratiform-east, and stratiform-west precipitation events, respectively. The major sources of errors in the DPA include, but are not limited to, radar calibration (Ulbrich and Lee 1999, Smith et al. 1996), anomalous propagation (Krajewski and Vignal 2001), bright band enhancement (Smith et al. 1996), radar beam blockage (Young et al. 1999), nonuniform vertical profile of reflectivity (Seo et al. 2000), uncertain microphysical parameters such as the Z-R coefficients (Smith et al. 1996, Vasiloff et al. 2007). These errors vary in space and time and accumulate nonlinearly in time. As such, it is extremely difficult, if not practically impossible, to isolate individual errors from the DPA products and correct them a posteriori. In this work, we make no attempt to improve the intrinsic quality of the DPA products as, in our view, such an effort is more cost-effective by reprocessing the Level II data. As such, we rely solely on the operationally produced DPA products for radar QPE in this work.

To screen out obviously bad DPA data from the reanalysis process, we developed an ad hoc procedure. It consisted of first calculating the fractional coverage and conditional mean of radar precipitation for each of the hourly rainfall maps associated with each of the six radars in the pilot domain. Next we defined a subjective threshold value for each of the statistics and identified the hours for which the statistics exceeded this threshold. We then created an animation of these hours and visually identified the obviously bad DPA precipitation maps that could be attributed to ground returns from AP, bright band, or other non-precipitating events like birds and insects. These hours were then added to a list which was used as a database for exclusion during the follow-on processing of the MPR algorithm.

2.2 Hydrometeorological Automated Data System (HADS)

The primary source of hourly rain gauge data is the reprocessed Hydrometeorological Automated Data System (HADS) data of Kim et al. (2009), which are based on the historical archive of the real-time data collected and distributed by the HADS Program in the NWS Office of Hydrologic Development (OHD). The period of record of the reprocessed data is 2002 – present. To the best of the authors' knowledge, the HADS data are the only hourly precipitation data set available for the entire U.S. as a single product. Kim et al. (2009) have investigated data loss and quality issues with the HADS, including possible biases with respect to neighboring COOP gauges. Through reprocessing, they addressed a number of these issues, which resulted in an increase in the number of hourly HADS precipitation data (particularly those ending at the top of the hour) and improved quality. In many instances the reprocessed data resulted in the recovery of storm events and other hourly observations that may be critical to MPR. For further details, the reader is referred to Kim et al. (2009).

In addition to the rain gauge data-based quality control steps used in reprocessing the HADS data (see Kim et al. 2009 for details), we have implemented a simple procedure to identify bad rain gauges using radar data. We screened out bad gauges by comparing seasonal accumulations of rain gauge precipitation and the corresponding radar pixel values in the DPA products. We removed suspect rain gages by visual inspection as well as examining a set of summary statistics for individual gauges for the given season. The statistics include the indicator and conditional correlation coefficients to check the strength of association in precipitation detection and estimation of precipitation amount given detection, respectively, between the rain gauge observation and the collocated radar estimate within the effective coverage of the radar (Breidenbach et al. 1999, 2001a), and conditional coefficient of variation of precipitation amount to check the reasonableness of its seasonal statistics against climatology. For visual inspection we also examined the scatter plots of rain gauge values versus the corresponding radar pixel values of hourly precipitation at the seasonal scale. This additional quality control results in screening out about an additional 20 percent of the reprocessed HADS data.

2.3 Cooperative Observers Program

The Cooperative Observers Program provides thousands of meteorological and hydrometeorological observations daily in the U.S. (NCDC 2000). These data include both hourly and daily gauge precipitation observations that can be used in MPR. The spatial density of the daily stations is much larger than that of the hourly stations. As such, it is important that MPR utilize the daily COOP observations to the maximum possible extent. Because the analysis in MPR is currently carried out only at the hourly scale, it is necessary to disaggregate the daily gauge observations into hourly estimates of gauge precipitation. Subsection 3.3 describes the disaggregation procedure used in MPR.

We have applied the DPA-based quality-control procedure described in section 2.2 to identify suspect gauges that may have survived the gauge data-based quality control steps. As with the HADS data, the procedure was carried out for each season of the analysis period. This additional quality control screens out about 10 percent of the COOP data. Table 2 summarizes the availability of the HADS and COOP rain gauge data in the pilot domain.

3. REANALYSIS PROCEDURE

Here we give a brief overview of the MPR procedure.

1. <u>Mosaicking of radar QPE</u>. The procedure used is the same as that in MPE (Breidenbach et al. 1999, 2001a), which involves identifying the effective coverage of the radar based on the long-term seasonal radar climatology and knowing the height of the radar beam. The mosaicking process consists of the following steps. For each HRAP bin in the analysis domain, determine if the bin falls within the effective coverage of any radar. If it does not, radar QPE is not available for that bin. If it falls within the effective coverage of two or more radars, identify the bin with the lowest unobstructed sampling height and assign the radar precipitation estimate from that radar to that bin. For further details, the reader is referred to Breidenbach et al. (1999, 2001a).
2. <u>Mean field bias correction</u>. We correct for inter-radar calibration differences by comparing, radar site by radar site, DPA estimates to rain gauge observations in the long term. This correction is conceptually similar to the mean field bias correction in MPE at a large time scale (Seo et al. 1999). We define the mean field bias as the ratio of the long term accumulation between the COOP data within the effective coverage of the radar (Breidenbach et al. 1999, 2001a) and the collocating DPA estimates from that radar.

3. Time disaggregation of daily COOP data. To utilize all available rain gauge data in the pilot domain in hourly analysis, we disaggregate daily rain gauge observations to hourly rain gauge estimates. The procedure used in this work is based on a similar procedure used for MPE in NWS operations (NWS 2005). The procedure involves pairing daily rain gauge observations with collocated DPA estimates. Then the daily rain gauge estimates are time-distributed proportionally according to the hourly DPA estimates over that 24-hr period, which produces hourly estimates of rain gauge precipitation at the COOP locations. Our experience is that using radar precipitation estimates to distribute the COOP data works better for the warm season than the cool season due likely to larger errors in radar QPE in the cool season. For this reason, we extended the time disaggregation procedure to use the gauge-only analysis using hourly HADS gauge data to time-distribute the daily COOP observations in the cool season.
4. Local bias correction. The Bmosaic field, which is obtained from mosaicking the mean field bias-corrected DPA products from multiple sites as described above may have spatially-varying biases that may be correctable by rain gauges, depending on the quality of the radar QPE and the density of the available rain gauges. The sources of such "local" biases include partial beam blockages due to structures and terrain (Young et al. 1999), returns from anomalous propagation (AP) of the radar beam, and non-uniform vertical profile of reflectivity including bright band enhancement (Baeck and Smith 1998, Smith et al. 1996, Young et al. 1999). The local bias correction procedure used in MPR is conceptually similar to that used in MPE (Seo and Breidenbach 2002) applied at a seasonal time scale.
5. Radar-gauge merging. The bias correction steps described above are intended to reduce mean error but not necessarily error variance. The primary purpose of radar-gauge merging is to reduce error variance. The merging algorithm used for MPR is a variant of the operational procedure used in MPE by the NWS referred to as single optimal estimation (SOE, Seo 1998). The algorithm has many adaptable parameters. For MPR, we have identified the following 4 parameters to be optimized for each month: the multiplicative bias factor, the indicator and conditional correlation coefficients between radar and rain gauge precipitation, and the coefficient of variation of precipitation. Optimization consists of four steps: find the a priori parameters; evaluate the hour-by-hour, via cross validation, the merged estimate at each gauge location using the variant of SOE; Evaluate the gradient of the objective function with respect to the four parameters to be optimized. Then repeat steps 2-4 until convergence.

4. EVALUATION

Fig 3 and 4 show the cross validation results for warm and cool seasons, respectively, in the form of scatter and quantile-quantile (QQ) plots. The figures show the verifying gauge observation vs. the estimate (Gmosaic, Mmosaic, or Stage IV) for daily amounts for warm or cool seasons from 2002 through 2007. The QQ plots show how closely the marginal distribution of the estimated precipitation matches that of the observed. The figures show that Mmosaic has somewhat smaller scatters than Stage IV for both warm and cool seasons, but slightly larger scatter than Gmosaic for the cool season. The QQ plots show that Mmosaic most closely follows the marginal distribution of observed precipitation for larger precipitation amounts. The small number of highly overestimated Stage IV values in the cool season is probably due to bad HADS data that could not be quality-controlled in real time.

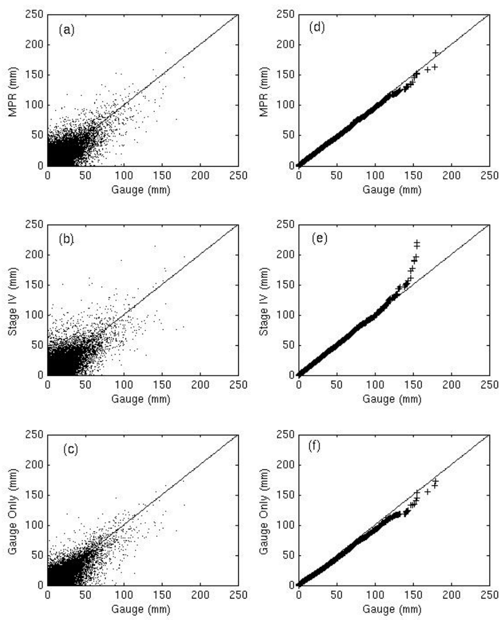

Figure 3: Scatter plots of the rain gauge estimates versus the product estimates (a) MPR product, (b) stage IV product, (c) gauge-only product and the corresponding quantile-quantile plots, (d),(e),(f) for all warm season daily scale estimates from 2002 – 2007.

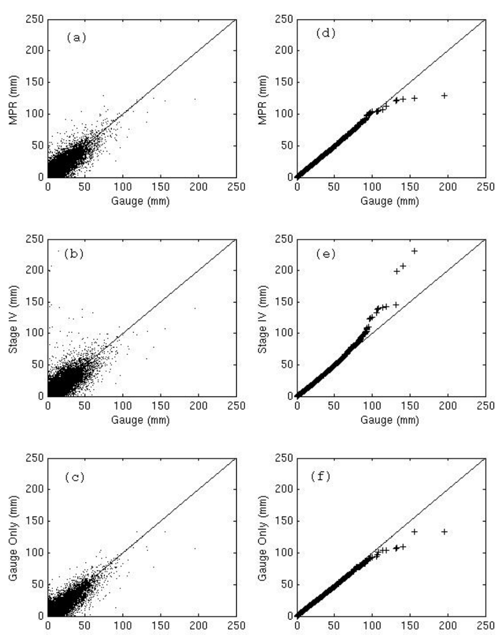

Figure 4: Scatter plots of the rain gauge estimates versus the product estimates (a) MPR product, (b) stage IV product, (c) gauge-only product and the corresponding quantile-quantile plots, (d),(e),(f) for all cool season daily scale estimates from 2002 – 2007.

Figure 5 shows the bar graph of the bias (Gauge-to-Radar ratio) for each MPR product alongside that of the Stage IV product. In the figure, the Gmosaic is the gauge-only estimate (see Fig 2). Fig 5 shows that the biases are reduced in each step of the MPR process, from Bmosaic to Lmosaic to Mmosaic. The Stage IV product has little bias in the warm season in the pilot domain, but has a significant bias in the cool season. This cool-season bias is due to the large low bias (i.e. underestimation) in Rmosaic, and reflects the difficulty of completely correcting it in real time using limited rain gauge data. Mmosaic, on the other hand, is essentially bias-free for both warm and cool seasons.

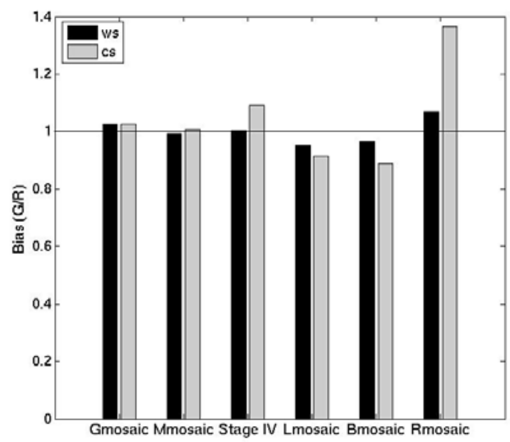

Figure 5: Long term bias between the rain gauge values and the algorithm products gmosaic (gauge-only product), mmosaic (MPR product), Stage IV (stage IV product), lmosaic (local bias adjustment), bmosaic (inter-radar bias adjustment), and rmosaic (radar-only product).

5. CONCLUSIONS

The major findings from the experiments are:

- Using both the hourly HADS gauge data and the hourly estimates of time-distributed daily COOP data provides very significant improvement in radar-gauge and gauge-only analysis of daily precipitation over using only either one of the two networks.
- In the warm season, the radar-gauge merged estimate from MPR, Mmosaic, is consistently superior to Stage IV, and Stage IV is consistently superior to the gauge-only estimate from MPR, Gmosaic. For daily amounts greater than 25.4 mm,

the marginal improvement of Mmosaic over Gmosaic is much greater.

- In the cool season, Gmosaic is consistently superior to both Mmosaic and Stage IV, and both Gmosaic and Mmosaic very significantly outperform Stage IV. That Mmosaic is inferior to Gmosaic is an indication that the quality of cool-season radar QPE (i.e. the DPA products) needs to be improved significantly in order to provide value to radar-gauge estimation. That Mmosaic very significantly improves over Stage IV reflects the value of utilizing all available rain gauge data and the benefits of reanalysis for more effective bias correction and multisensor estimation.

The MPR pilot project described in this paper provides a first step toward reanalysis over the U.S. While the value of MPR has been demonstrated for the pilot domain, reanalysis at the national scale faces a number of large challenges, many of which are shared also by real-time analysis. To foster a community-wide effort for MPR and to develop and capitalize on the synergism with real-time analysis, we have formed the MPR Working Group. We welcome any comments or suggestions toward realizing MPR at the national scale and participation in the Working Group.

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