J1.7 TOWARD INTEGRATION OF SATELLITE PRECIPITATION ESTIMATES INTO THE MULTI-SENSOR PRECIPITATION ESTIMATOR ALGORITHM

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1. INTRODUCTION

A multi-sensor Precipitation Estimator (MPE) has been deployed as part of the Advanced Weather Interactive Processing System (AWIPS) at National Weather Service (NWS) Weather Forecast Offices and River Forecast Centers throughout the nation. The NWS MPE combines radar rainfall estimates with rain gauge measurements and produces a suite of multi-sensor rainfall estimates. However, because of the limited effective radar coverage due to beam blockage and radar beam overshooting at far ranges of the radar, the radar-gauge multi-sensor estimates are of limited utility in the mountainous regions, especially in the western United States. Satellite based rainfall estimates, on the other hand, offer complete spatial coverage and provide often the only near real-time (15 minutes) precipitation estimates in many areas of the country. Therefore, Satellite Precipitation Estimates (SPE) produced by the National Environmental Satellite, Data and Information Service (NESDIS) have been made available for hydrological applications in AWIPS. Currently, MPE has the capability to display the SPE as a separate field for qualitative comparison. Also, if needed, this SPE field can be cut and pasted into any other MPE products through the Graphical User Interface known as HMAP_MPE (Lawrence et al, 2003). Such an operation, however, is subjective and time consuming, and does not amount to quantitative integration of SPE into MPE.

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In this paper, we report on the ongoing effort at NWS/Office of Hydrologic Development (OHD) toward development and implementation in the MPE of a methodology that objectively integrates SPE with radar and rain gauge data for quantitative multi-sensor precipitation estimation.

2. DATA

Data used in this study are rainfall measurements from the operational rain gauges and from the Co-operative rain gauge network and satellite precipitation estimates from The NESDIS HydroEstimator (formerly known as the Auto-Estimator) algorithm (Vicente et al, 1998). This product is based on infrared cloud top temperature measured by the Geostationary Operational Environmental Satellite (GOES), precipitable water and relative humidity, cloud top growth rate and temperature gradients. This product is also corrected for parallax dislocation and orographic effects (Vicente et al, 2002). The HydroEstimator product is made available to AWIPS at hourly time scale and approximately 4x4 km^2 Hydrologic Rainfall Analysis Project (HRAP) spatial scale.

For this study, California Nevada River Forecast Center (CNRFC) region was chosen because of the relatively poor effective radar coverage. The rain gauge network density was also sparse in the Nevada area. Hourly operational rain gauge data and hourly HydroEstimator products for the period November 2002 to March 2003 were analyzed. Daily co-operative rain gauge measurements were used to validate the results.

3. METHODOLOGY

The methodology in this work is similar to that of the MPE (Seo and Breidenbach, 2002) which combines radar and rain gauge data, except that in this study, radar rainfall estimates are replaced by satellite rainfall estimates. In order for satellite rainfall estimates to be merged with gauge data in the optimal estimation framework (Seo, 1996), however, they need to be unbiased. Hence, the first step toward quantitative integration is to correct for biases in the HydroEstimator product. A local bias correction algorithm, similar to the one used in MPE for radar rainfall data, was used to correct for biases in the HydroEstimator. For the details of the local bias correction algorithm, the reader is referred to Seo and Breidenbach (2002). The technique collects positive pairs of satellite and rain gauge data and calculates the bias as the ratio between the sum of rain gauge values and the satellite values within a circular window, the radius of which is an adaptable parameter. The local bias values are then interpolated to entire analysis domain (i.e. the RFC service area) to get the local bias field. To obtain the local bias-corrected estimates, the satellite rainfall estimates are multiplied, at each HRAP bin, by the corresponding local bias value. The second step is to merge the local bias corrected SPE field with the rain gauge data using an optimal interpolation technique (Seo 1996).

The original HydroEstimator, local bias corrected HydroEstimator, and gauge-Hydroestimator merged product were validated against the daily co-operative rain gauge network data. Note that, approximately 30% of the co-operative rain gauge network data may have contribution from the hourly gauge data. In other words, the validation is only 70% independent. The validation statistics calculated are bias, Root Mean Square Error (RMSE) and correlation coefficient. Since the validation data are daily accumulations, we have selected the days for which we have results for all 24 hours. After accounting for missing and incomplete days, 18 days in December 2002 and 12 days in March 2003 were used in the validation.

4. RESULTS AND DISCUSSION

Presented in Figure 1 are scattered plots between the HydroEstimator vs. co-operative rain gauge data, the local bias corrected HydroEstimator vs. co-operative rain gauge data and gauge-HydroEstimator merged product vs. the co-operative rain gauge data for December 2002. Figure 2 presents the same information as Figure 1, except for March 2003. Also presented in each scatter plot are the bias, RMSE value and correlation coefficient. The closer the bias to unity, the smaller the RMSE is, and the larger the correlation coefficient is, the better the performance of the methodology is. As one can see in Figs. 1a and 2a, the HydroEstimator values are significantly biased and have high RMSE values during December and March. While the local bias algorithm has improved RMSE and correlation coefficients during both months, bias value showed improvement only during December. Note that the number of data points used in validation is significantly smaller in March than in December (There were a total of 12513 data points during December compared to 8877 during March). Also, there is less rainfall in March than in December (Note the change in scale from Figure 1 to Figure 2). There is a marked improvement in bias value, RMSE and correlation coefficient in the gauge-HydroEstimator merged product during both months. Note that part of the improvement in the merged field may be attributed by the fact that the validation is not completely independent.

5. CONCLUSIONS AND FUTURE PLANS

The HydroEstimator product was bias- corrected and merged with the hourly rain gauge data to generate satellite based multi-sensor estimates. The gauge-HydroEstimator merged product is a significant improvement, in terms of accuracy, over the original HydroEstimator or the bias corrected HydroEstimator estimates.

The future plan is to fully integrate the Hydro-Estimator product with radar and rain gauge data into MPE. This can be carried out, e.g. by mosaicking the local bias corrected HydroEstimator product with local bias corrected radar rainfall field and merging the mosaicked field with rain gauge data to produce the gauge-radar-satellite merged multi-sensor estimates.

References

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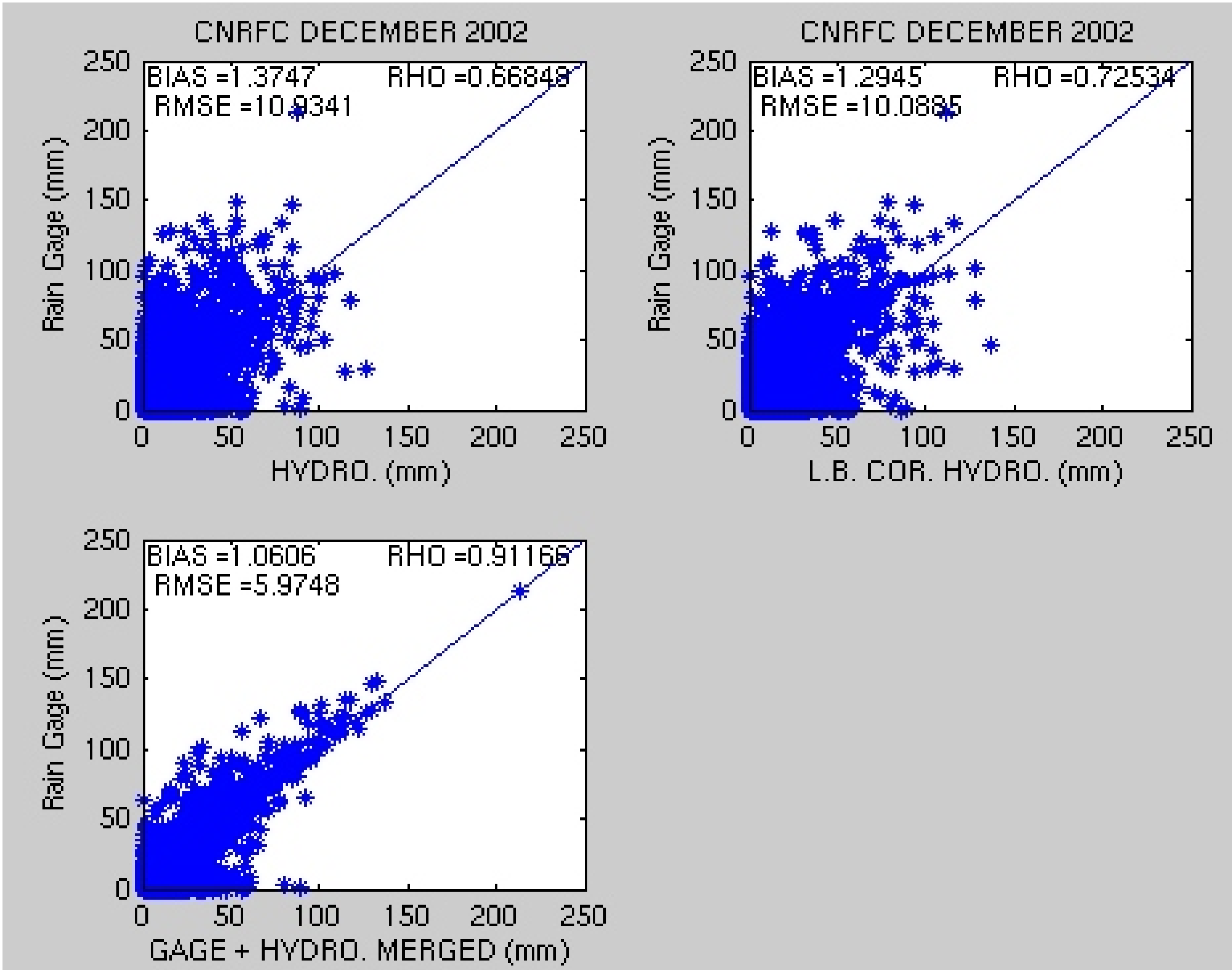

Figure 1. Scatter plots between (a) hydroestimator and co-op gauge data (top left) (b) local bias corrected hydroestimator and co-op gauge data (top right) and (c) gauge + hydro estimator merged product and co-op gauges (bottom) for the month of December 2002

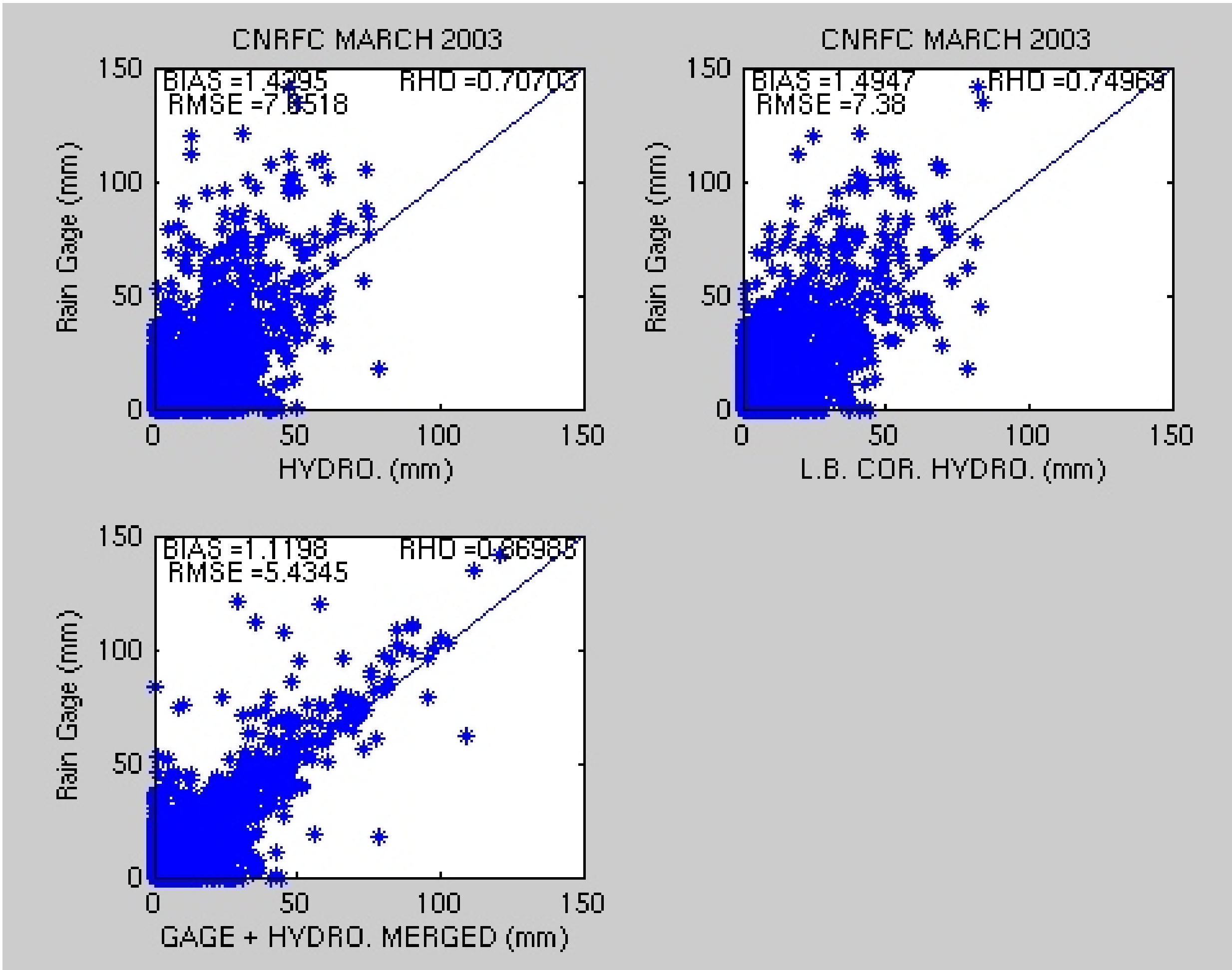

Figure 2. Same as figure 1, except for the month of March 2003