Incorporate Satellite Precipitation Product into Radar-Gage Multi-sensor Precipitation Estimation Algorithm

Yuxiang He[1,2], Yu Zhang[1], Robert Kuligowski[3], Robert Cifelli[4]
[1]National Water Center (NWC), NWS, NOAA, Silver Spring, Maryland 20910; [2]UCAR, Boulder, Colorado 80307;
[3]NOAA/NESDIS/Center for Satellite Applications and Research, College Park, Maryland 20740; [4]Physical Sciences Division, NOAA/Earth System Research Laboratory, Boulder, Colorado 80305

Abstract

The purpose of this work is to develop and test a new and enhanced fusion module in the Multisensor Precipitation Estimator (MPE) that would more effectively integrate real-time satellite quantitative precipitation estimates (SQPE). This module consists of a preprocessor that mitigates systematic bias in SQPE, and a two-way blending routine that statistically fuses adjusted SQPE with radar estimates. Systematic bias and false alarms are reduced through a simple quantile matching algorithm with bias-corrected radar estimates as the reference. The products of this module are validated using independent gauge data. Preliminary validation confirm that the method not only correct the satellite systematic bias and enhance the quality of satellite precipitation quality, but also improve the similarity of geographical distribution patterns between satellite and radar products. The effectiveness of the blending module is also tested through a data denial experiment, and the results of the experiment show that the blending helps reduce the discontinuities along the boundaries of effective radar coverage and improves the root mean square error.

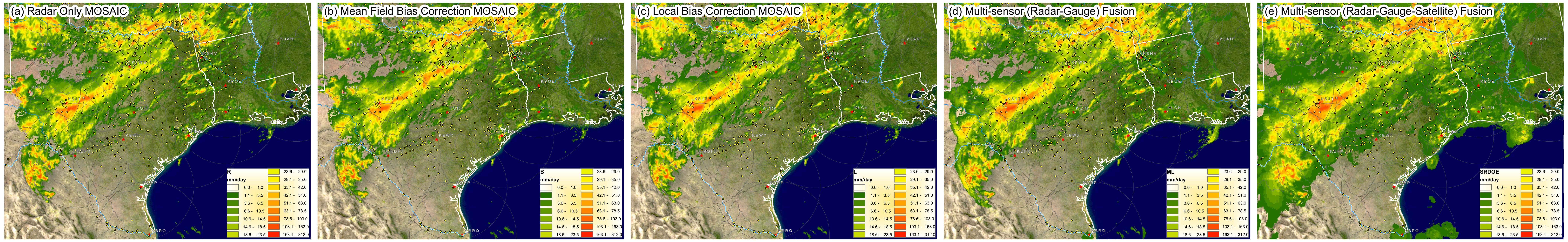


Fig. 3. Example results of radar only, radar-gauge, radar-gauge-satellite fusion for August 28, 2006, processed by the offline MPE system with enhancement of integrating satellite data algorithm. (a) radar only mosaic, (b) Mean field bias correction, (c) local bias correction, (d) Multi-sensor (Radar-Gauge) fusion, (e) Multi-sensor (radar-gauge-satellite) fusion.

Software Architecture

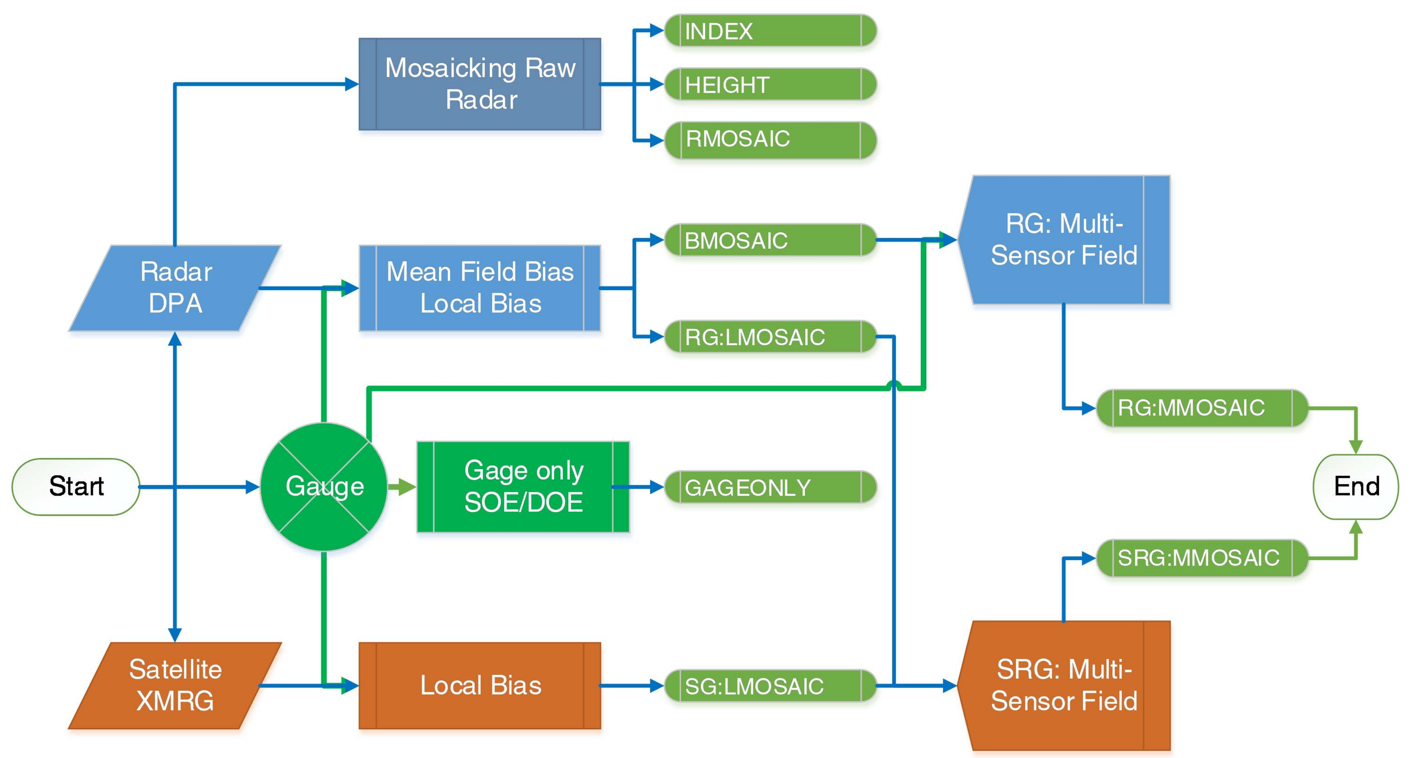


Fig. 1. Flow-chart of multi-sensor precipitation estimation system.

MPE contains a suite of algorithms for single and multisensory precipitation estimation, including gage-based estimation, multi-radar mosaicking, and gauge-radar multisensor blending.

Multi-radar mosaic:
Combining estimates from multiple radars into a single gridded product. This mosaicking of radar coverage maps results in a field known as the INDEX field. The actual height of coverage for each bin is stored as HEIGHT field. Its product is known as RMOAIC.

Mean Field Bias (MFB) Correction:
Estimating a spatially uniform, but temporally varying bias for each radar. Its product is known as BMOAIC.

Local bias (LB):
Estimating spatially varying bias. It has been shown to be effective in gage rich areas for uniform and widespread precipitation. Its products is known as LMOAIC.

Multi-Sensor blending:
A variant of Kriging technique called single optimal estimation (SOE) is used for objectively blending radar and gauge products. Its products is known as MLMOAIC.

Satellite module:
MPE fills the radar gaps using bias-corrected satellite product, and blends the result product with radar and gauge data by double optimal estimation (DOE) algorithm. Its product is named as SRDOEMOAIC.

DOE Algorithm improvement for radar and satellite

The DOE algorithm devised by Seo (1998) is adopted for objectively blending radar, satellite and gauge data. Because the errors in the satellite rain rates are generally larger than those in the radar data, its contributions should vary in space depending on the distribution of radar data quality.

In order to generate the optimal merged precipitation field, the weight coefficients allocating the contribution from each dataset in the overlapping areas are determined by the ratio of root-mean-square error (RMSE) σ_R and σ_S. This weight coefficient just impacts the conditional expectation; it does not impact conditional probability estimation.

Satellite rain rates may have systematic bias relative to bias corrected radar data, so the quartile mapping technique was introduced into this study to address this problem.

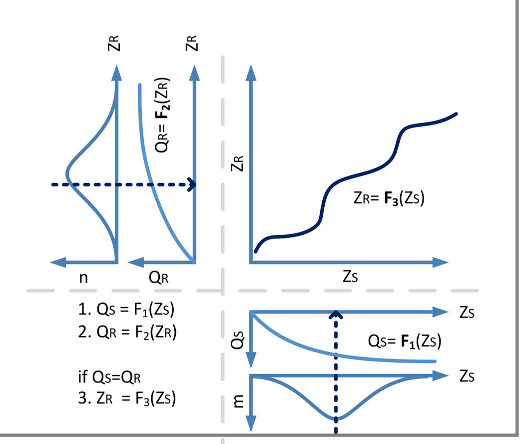


Fig.2. Quartile mapping Schematic diagram

Validation and verification

Rain gauge observations are assumed to be the ground truth for validating MPE result. The rain gauges on the HRAP grid were averaged to compare with MPE results, the available pairs of rain gauge averages and MPE values were compared for daily intervals. Several metrics were selected in this study.

1) Radar precipitation has limitations and defects by virtue of its principle, e.g. beam tilting and expanding. Mosaicked precipitation values were examined by range categorization from radar center. They were classified into 6 regions using radar beam height $0\sim1km, 1\sim2km, 2\sim3km, 3\sim4km, 4\sim5km$ and $>5km$. The distribution of radar data quality will be extracted and incorporated into radar–satellite fusion. The classification results on the 28th August 2006 is shown in the Fig 4.

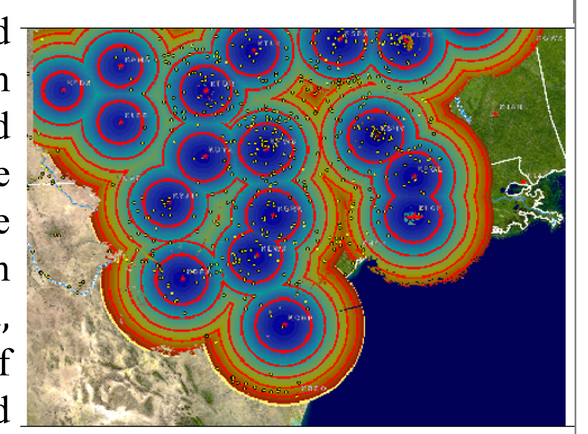
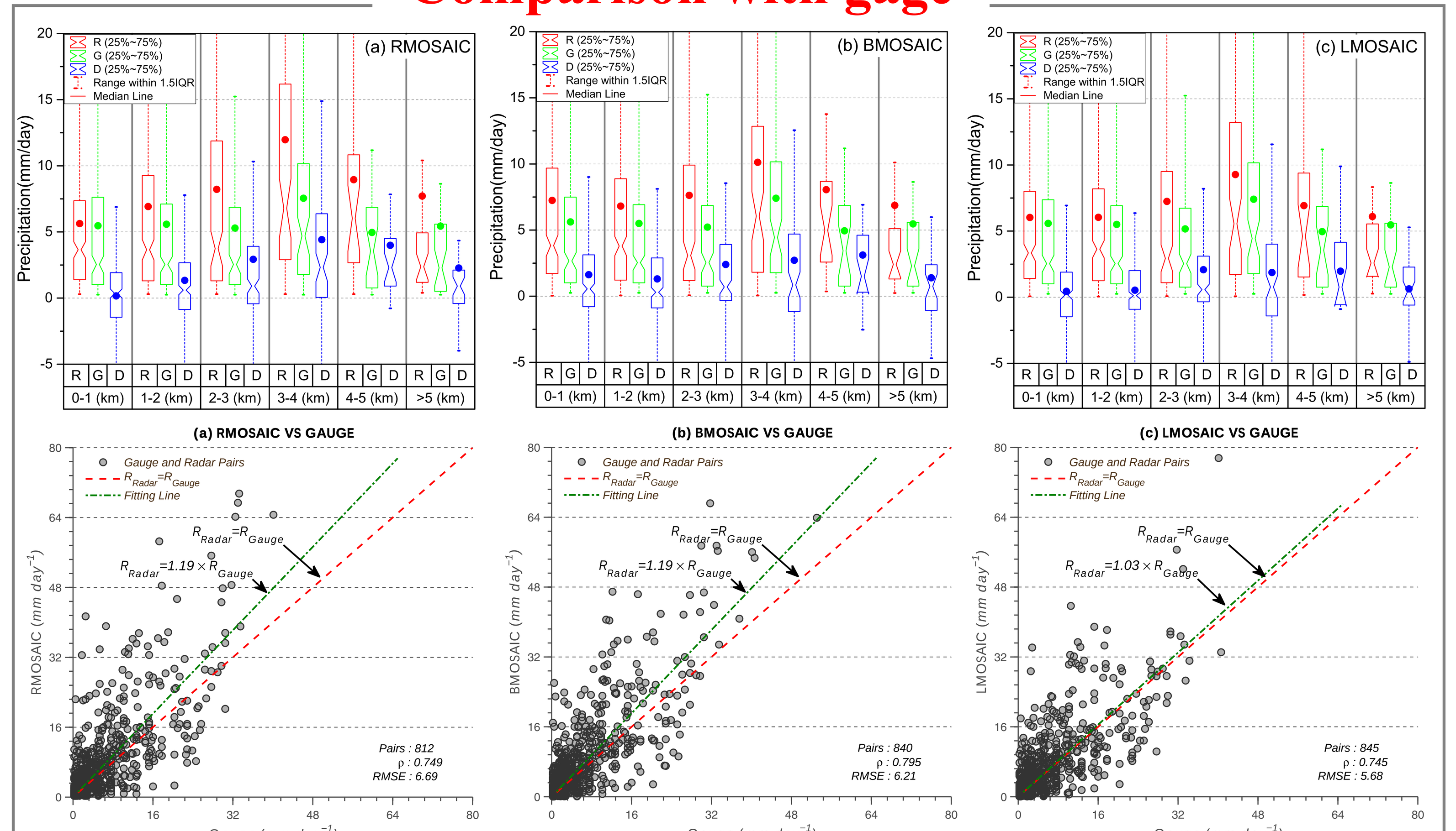


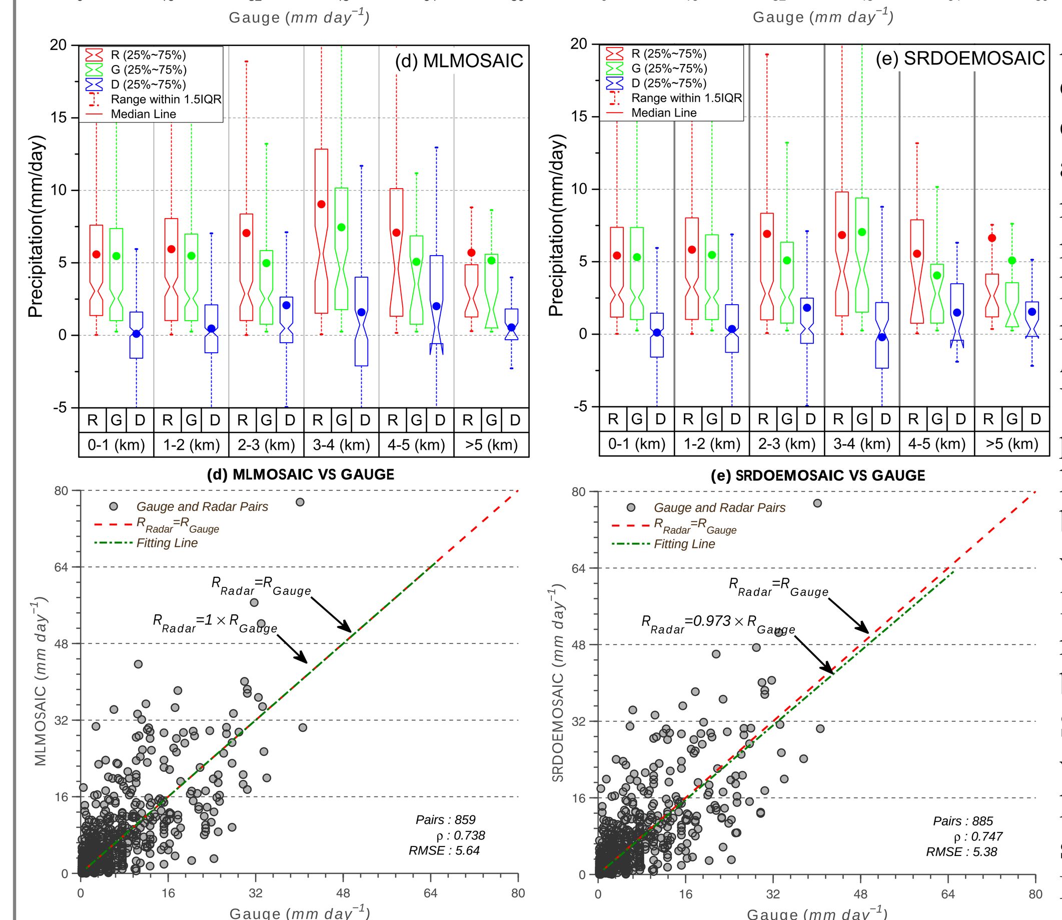
Figure 4: area classification with distance to radar center

2) In order to determine which estimation in radar-gauge fusion is the best product to further blend with satellite precipitation. Part of the metrics were shown in the Figure 3,and 5. they indicate that the performance of those algorithms have following relationship:

$$RMOSAIC < BMOSAIC < LMOSAIC < MLMOSAIC$$

Comparison with gage





A sensitivity analysis was done on daily basis for August 2006, and compared the validation results for about 200 stations in Texas. The results indicate that their average root-mean-square error (RMSE) have the following relationship: *RMOSAIC > BMOSAIC > LMOSAIC > MLMOSAIC > SRDOEMOSAIC.* While almost all of the MPE products have positive bias, RMOSAIC has a conspicuous positive bias at beam heights of from 3 to 4km which may be caused by melting-layer. Radar data quality can't better represent ground precipitation beyond the beam height over 3km. So satellite was introduced to blend with radar data exceeding 3km height. The estimation has a very significant improvement as shown in Fig.5 (e).

Fig.5. Comparison between MPE estimates and gauge observed data in each distance regions; the red, green and blue box are distribution characters of MPE product, gauge data, and their difference, respectively. Scatter plots are correlation coefficient and root-mean-square error between MPE estimations and gauge pairs.

Conclusion and Future Work

The Offline MPE end-to-end system has been initially set up and preliminarily evaluated, including an enhanced capability to integrate satellite data information. The main conclusion is **1)** Quartile mapping is useful to correct bias in the satellite rain rates. **2)** radar data errors exhibit a very clear range dependent distribution. The errors increase as large as satellite have when beam height over 3km. **3)** Radar-gauge-satellite fusion module DOES improve the rain estimation quality in the region where radar beam height over 3km. Future work will be aimed at its optimization, fine-tuning and stress-testing with long time series and application on the feeding to hydrological model over different watershed. The following tasks are planned: **1)** Optimize and validate MPE with enhanced DOE algorithm for satellite algorithm in conjunction with Robert Kuligowski and Robert Cifelli. **2)** Calibrate/Validate MPE against *in-situ* gauge data, SCaMPR and CMORPH precipitation. **3)** Setup the NWC hydrologic model to evaluate multi-sensor precipitation products. **4)** Develop a MPE system to cover the CONUS with 1-km resolution

Literature

- Zhang, Y., Reed, S., Kitzmiller, D., 2010. Effects of Retrospective Gauge-Based Readjustment of Multisensor Precipitation Estimates on Hydrologic Simulations. Journal of Hydrometeorology, 12(3): 429-443
- Zhang, Y. et al., 2012. Comparative Strengths of SCaMPR Satellite QPEs with and without TRMM Ingest versus Gridded Gauge-Only Analyses. Journal of Hydrometeorology, 14(1).
- Seo, D.J., 1998. Real-time estimation of rainfall fields using radar rainfall and rain gage data. Journal of Hydrology, 208(1–2).
- Kitzmiller, D. et al., 2011. Evolving Multisensor Precipitation Estimation Methods: Their Impacts on Flow Prediction Using a Distributed Hydrologic Model. Journal of Hydrometeorology, 12(6): 1414-1431

Disclaimer

Correspondence: Yuxiang.he@noaa.gov, Tel.: 301-427-9519