18B.3 TESTING CAPABILITY OF SUCCESSIVE CORRECTION METHOD AND BAYESIAN SPATIAL MODEL TO FILL GAPS OVER THE RADAR NETWORK

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1. INTRODUCTION

Radar rainfall estimates are critical input products in a distributed hydrologic prediction and flash flood forecast models. However, in mountainous regions, rainfall measurements from ground-based radar observations has of particular difficulty in terms of eliminating ground echoes caused by shielding of radar beams by high mountains. Since such regions are hydrologically important, the need for a rainfall product of better accuracy is critical for hydrological prediction.

To improve estimates over radar-gap, studies on multi-source precipitation estimates have been pivotal. Most such research efforts on multi-source data are about calibrating or merging radar- and/or satellite-based rainfall with rain gauge observation to improve quantitative precipitation estimation (QPE) (e.g. Seo (1998b)) assuming that rain gauge observations can reliably account for the true values of point-based rainfall. Kondragunta et al., (2005) integrated bias corrected Satellite Precipitation Eastimates (SPE) with respect to the rain gauge data to fill the radar-gap and create a radar mosaic algorithm implemented in the quantitative Multi-sensor Precipitation Estimation (MPE).

In this study, capability of using the Successive Correction Method (SCM) in conjunctioin with a Bayesian spatial model to produce a multi-source rainfall data by combining radar, satellite, rain-gauge and PRISM (Parameter-elevation Regressions on Independent Slopes Model) products over an artificially created radar gap in Oklahoma, geographically bounded by 34^{o} – 37^{o} latitude north and 94.5^{o} – 100^{o} longitude west is evaluated. Real gap areas over radar network cannot be used as a test-bed due to lack of availability of radar rainfall required for validation of generated multi-sources product. Several daily and 4 km×4 km satellite, radar, rain-gauge, and monthly PRISM precipitation products for the year 2006 were used for this study.

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Rainfall products from satellite InfraRed (IR) based Hydro-Estimator (HE) and radar Stage-II are selected to be merged using the SCM so that the artificially created gap over the radar network could be filled. The satellite-radar product from SCM is further combined with rain gauge and climatological PRISM precipitation products using a Bayesian spatial model. The satellite-radar-gauge-PRISM combined precipitation product is evaluated using three evaluation criteria: coefficient of correlation, bias and Nash-Sutcliffe efficiency. Generated multi-source rainfall product using this method is a better product than HE when it is evaluated against independent rain-gauges. The present study implies that by using the available radar pixels surrounding the gap area, rain-gauge, PRISM and satellite products, radar like product is achievable over radar gap areas that benefits and has huge impacts on hydrological simulations and prediction purposes.

2. DATA

2.1. Hydro-Estimtor (HE):

One of the approaches, HE (Scofield and Kuligowski, 2003) uses GOES Infrared window channel-4 (10.7 μm wavelength) as the main input data to estimate the rate of surface rainfall. HE was developed as an improvement to the original Auto-Estimator (AE) which was developed for deep, moist convective systems (http://satepsanone.nesdis.noaa.gov/PS/PCPN/HE.html) . At the (NOAA)/National Environmental, Data, and Information Service (NESDIS), HE has been one of the operational satellite-based rainfall product since 2002, and has been available for use at a spatial scale of 4 km by 4 km and time scale of 1 hour for the US (CONUS) since 2004.

2.2. Radar Stage II (ST-II)

At NWS, there are four stages of radar based rainfall products. References such as Fulton et al., 1998, http://www.emc.ncep.noaa.gov/mmb/ylin/pcpanl/QandA/#STAGEX contain details of how the different stages of radar products are produced. Stage-I radar rainfall product is produced for each radar scan at each radar site using the Z-R relationship. Hourly Stage-I products are then generated by summing up the scan-wise accumulations. In the next step, the Stage-I products are adjusted for mean field bias using all the available rain-gauges to produce bias-adjusted Stage-II. The bias adjusted Stage-II products are further optimally merged with point rain-gauges. The original WSR-88D algorithm has considered quality control and corrections for isolated targets and ground clutter, tilt test and anomalous propagation, and partial beam correction (Fulton et al., 1998).

Hourly radar ST-II, a mosaicked radar product over the CONUS with a spatial resolution of 4 x 4 km^2 for the year 2006 has been used in this study.

2.3. Rain gauges

Rain gauge data are obtained from NCDC's Cooperatives rain gauge stations and Oklahoma Mesonet. Under the National Weather Service (NWS), thousands of precipitation data are recorded manually everyday across the United States by the COoperative Observer Program (COOP) which is a public based rainfall reporting platform. Measurements from rain-guages are considered as the true measurements. For this study there are more than 40 COOP rian-gauges reporting hourly precipitations have been used for model calibration. Measurements from these gauges are in hundreds of inches. The measurements are converted to mm by multiplying (25.4/100). For validation and variogram parameter estimation, we used daily independent rainfall measurements from the Oklahoma mesonet. The Oklahoma Mesonet is a network of 120 automated environmental monitoring stations. The network provides a quality controlled precipitation and more than 5 other environmental parameters at these locations.

2.4. PRISM

One of the dataset used in this study is Parameter-elevation Regressions on Independent Slopes Model (PRISM). It is a climatological data including temperature, dew-point and precipitation average for the conterminous United States at a spatial scale of 4 km. For this study, monthly PRISM precipitation data was used as one of the covariates.

3. METHODOLOGY

3.1. Covariate preparation

In a Bayesian spatial model, covariates are supplemental data which are known at each grid point with the required temporal and spatial resolutions which are daily and 4 km. Hence, the radar data with missing pixels and monthly PRISM cannot be used directly as covariates. The only data that can be directly used in the analysis is HE, the rest of the covariates need modifications and are developed as follows.

a) ST-II as a covariate

The HE product is merged with that of the ST-II to fill gaps over ST-II (Figure 4). We implemented the Successive Correction Method (SCM), originally developed for data assimilation to calculate missing pixels. The SCM uses the information from available ST-II pixels surrounding the gap area and satellite rainfall to fill the gap pixels (Mahani et al., 2009).

Assume a selected moving window size m×m with its center at u_0, the merged precipitation for any missing pixel centered at u_0 in the gap area is calculated based on information from satellite pixels and known available radar pixels with in the window.

Starting from a missing pixel surrounded by the maximum number of available radar pixels, the method continues calculating other missing pixels by moving the m×m window successively.

For this study, the Brandes' scheme of SCM has been adopted (Brandes 1975). In addition, we implemeted the method of Double Optimization Estimation (DOE) (Seo 1998b) in the SCM frame-work to fill gaps over the radar network (Figure 4).

b) PRISM as a covariate

One of the covariates for this study was the mean PRISM climatological monthly precipitation. For this study, monthly precipitations from PRISM are averaged for past 10 years prior to the year considered in the study before they are used as a covariate for this study. The averaged monthly PRISM products are disaggregated into daily by calculating percentage partial fractions using the daily gauge measurements (Schaake et al., 2004). Percentage partial fractions are calculated for the monthly averaged data using the method explained as in (Schaake et al., 2004). The percentage partial fractions are multiplied by the monthly averaged PRISM products to calculate the required daily PRISM covariate.

3.2. Bias correction

Before merging ST-II with HE to fill gaps in the radar network, the HE is bias corrected against the radar and rain gauges using the method of ensembles (Tesfagiorgis et. al, 2011).

3.3. Bayesian Spatial Model

Assuming a spatial Gaussian process in a linear spatial regression model, the random rainfall field *Z* can be given as:

$$Z(\beta_i, X_i) = \beta_1 X_1(s) + \ldots + \beta_p X_p(s) + \varepsilon(s) \quad (1)$$

Where X_i is a covariate and β_i is model parameter; $\varepsilon(s) \sim N(0, cov(Z(s), Z(u)))$.

In a Gaussian process the covariance matrix can be modeled as

$$Cov(Z(s), Z(u)) = \begin{cases} \delta^2 & \text{if } |s-u| = 0 \\ \sigma^2 \kappa_\theta(s,u) & \text{if } |s-u| > 0 \end{cases} \quad (2)$$

$|s-u|$ is a Euclidean distance between two locations *s and u*. δ^2 is the nugget.

Assuming an exponential variogram function, the correlation function can be given as:

$$\kappa_\theta(s,u) = \exp(-|s-u|/\eta) \quad (3)$$

3.2.1 Parameters and Priors

The next step is to assign priors for the parameters. The parameters, βs, σ^2, δ^2, τ^2 and η should be assigned. It is assumed that priors are conjugate with posteriors.

We used an independent prior distribution for β and σ^2. Where β is a Normal distribution; where as σ^2 and δ^2 follow the inverse gamma function with some shape and rate parameters.

To model the spatial model we used 'bayesGeostatExact' in R (Finley et al., 2007). It is a Bayesian spatial linear model with fixed semivariogram parameters. The fixed parameters to model the spatial field in 'bayesGeostatExact' are (spatial range) and the ratio between δ^2 and partial-sill. We calculated the fixed parameters from the experimental variogram using rain gaguges. For our choice of the experimental variogram, we employed the exponential experimental variogram as shown in Figure 1.

We assumed an isotropic one dimensional variogram which represents the spatial roughness of a spatial data set quantitatively for fixed parameters estimation. The variograms are produced using the daily mesonet datasets. Out of the total 120 Mesonet raingauges, we have picked 60 of them to develop the variogram.

The most ideal condition is to calculate the parameters for each rainy day. But from feasibilty and efficieny point of view, it is better to determine this parameter using all rainy days using the mesonet rain gauge points. Instead we consider the mean of all the daily variograms. The red line in Figure 1 is the mean of the individual blue semi-variograms.

Referring Figure 1, a more conservative choice of η (spatial range) 5 km was used. The parameter indicating the ratio between the nugget (30 mm^2) and sill (150 mm^2) 1/5 was used (Figure 1). The numbers in this figure represent selected rainy days.

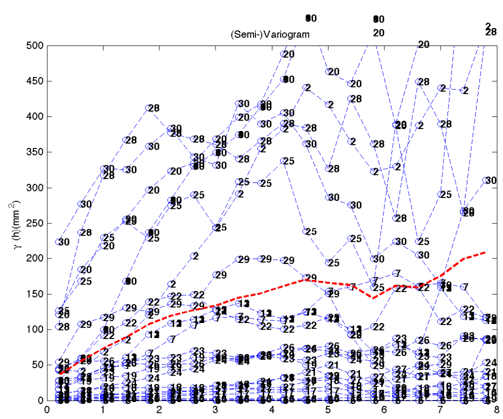


Figure 1 Experimental semivariogram using Mesonet rain gauges.

A prior of an inverse gamma function with shape 1 and rate 1 was used for the σ^2.

10000 posterior samples were collected for each daily simulation. The βs multivariate normal mean vector hyper prior is (1,1,1). β multivariate normal precision matrix hyperprior is diag(1,1,1). We have applied an exponential covariance model.

The function spPredict is used to make predictions at unknwon locations. The function collects the posterior predictive samples of the new locations given by the bayesGeostatExact. We have applied 1000 chain burn-in.

4. RESULTS

9 daily rainy days in 2006 (0110, 0128, 0319, 0320, 0323, 0504, 0508, 0509 and 0617) considered for model calibration and validation. In the Bayesian model, the posterior of the parameters are collected from the model based on 10,000 samples. In some cases, the number of rain-gauges is relatively small; however satisfactory results are obtained in such cases. A sample multi-source product is shown for 20060504 (Figure 5).

Quantitative statistical evaluation criteria (Correlation coefficient, Bias and Nash-Sutcliff Efficiency) were calculated using reference gauges which were not used for model calibration. Figures 8 and Table 1 compare the performances of the multi-source method using these performance criteria. Table 1 summarizes these statistical criteria. In this table, the daily statistical criteria are averaged for the study period. The figure demonstrates the performance of the merged product, ST-II and HE for each rainy day.

5. CONCLUSION AND FUTURE WORK

The multi-source rainfall products produced by combining different existing rainfall estimates have shown better accuracy and correlation than the individual rainfall fields (the radar-only product (ST-II) and Satellite product (HE)) against independent mesonet gauges (Figure 8 and Table 1). The correlations obtained for this multi-source product ranged from 0.4 to 0.86. In some cases a correlation value of 0.4 was obtained. The merged product can effectively be used to fill gaps of up to a size of $1.5^o \times 1.5^o$. This occurs because the orginal inputs, ST-II, HE and PRISM are highly biased at the calibration gauge spots. The Nash-Sutcliffe Efficiency (NSE) and Bias for the model is much better than the individual rainfall products.

The results are further validated in real gap areas. Further results will be reported in the future.

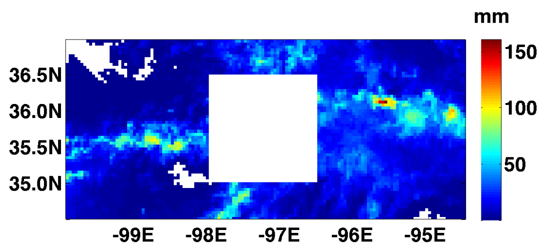


Figure 2 Radar product Stage-II with the artificially created gap for 20060504

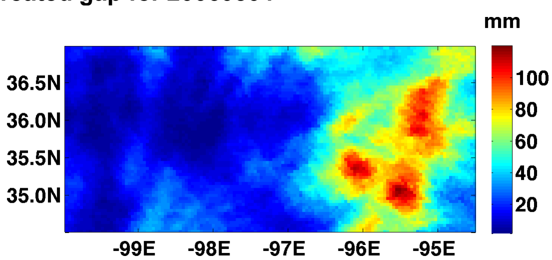


Figure 3 Satellite Precipitation product Hydro-Estimator for 20060504

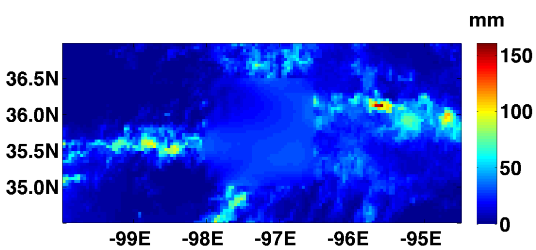


Figure 4 ST-II merged with HE to fill gaps

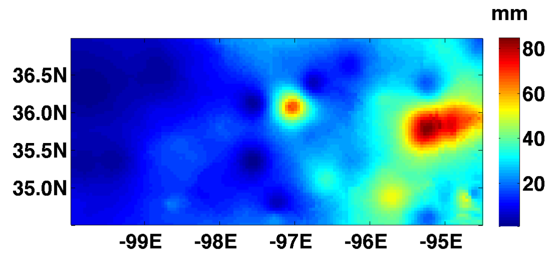


Figure 5 A merged product for 20060504.

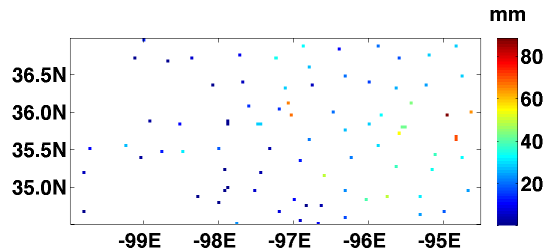


Figure 6 Mesonet Rain gauge network and their measurements for parameterization and validation for 20060504

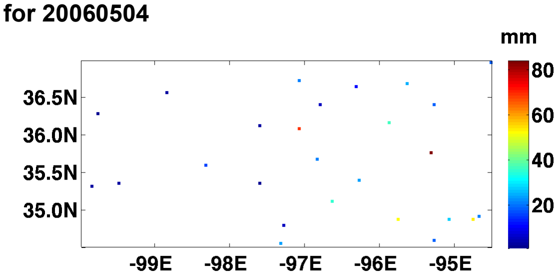
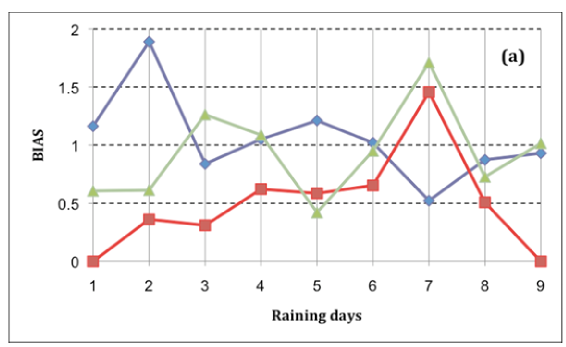


Figure 7 COOP rain gauges used for calibration for 20060504



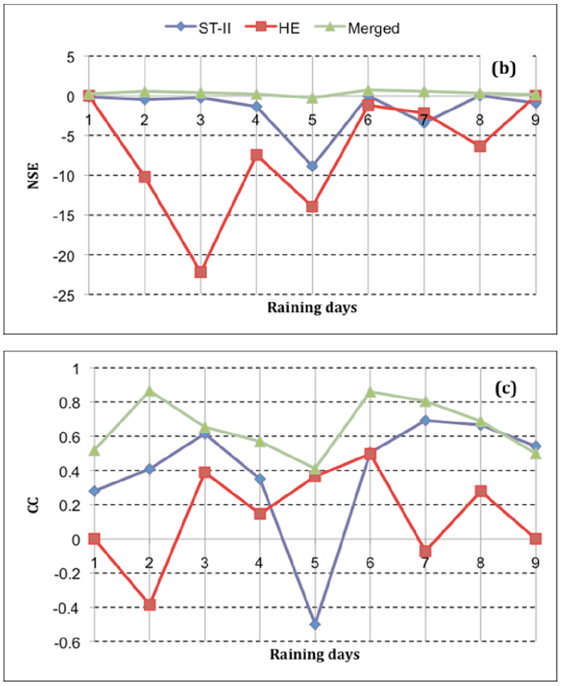


Figure 8 A time series of the three statistical criteria (Bias, Nash-Sutcliff Efficiency (NSE) and Correlation Coefficient (CC))

Table 1 Summary of statistics of ST-II, HE and Merged product compared with Mesonet gauges. CC(correlation Coefficient), NSE (Nash-Sutcliff Efficiency). Values are mean of the 9 rainy days considered.

Data source	CC	Bias	NSE
ST-II	0.40	1.06	-1.70
HE	0.36	0.64	-9.07
Merged product	0.65	0.94	0.33

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