Hydrol. Earth Syst. Sci., 15, 2631–2647, 2011
www.hydrol-earth-syst-sci.net/15/2631/2011/
doi:10.5194/hess-15-2631-2011

Hydrology and Earth System Sciences

Bias correction of satellite rainfall estimates using a radar-gauge product – a case study in Oklahoma (USA)

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Received: 29 October 2010 – Published in Hydrol. Earth Syst. Sci. Discuss.: 16 November 2010
Revised: 20 July 2011 – Accepted: 16 August 2011 – Published: 25 August 2011

Abstract. Hourly Satellite Precipitation Estimates (SPEs) may be the only available source of information for operational hydrologic and flash flood prediction due to spatial limitations of radar and gauge products. SPEs are prone to larger systematic errors and more uncertainty sources in comparison with ground based radar and gauge precipitation products. The present work develops an approach to seamlessly blend satellite, radar and gauge products to fill gaps in ground-based data. To mix different rainfall products, the bias of any of the products relative to each other should be removed. The study presents and tests a proposed ensemble-based method which aims to estimate spatially varying multiplicative biases in hourly SPEs using a radar-gauge rainfall product and compare it with previously used bias correction methods. Bias factors were calculated for a randomly selected sample of rainy pixels in the study area. Spatial fields of estimated bias were generated taking into account spatial variation and random errors in the sampled values. Bias field parameters were determined on a daily basis using the shuffled complex evolution optimization algorithm. To include more error sources, ensembles of bias factors were generated and applied before bias field generation. We demonstrate this method using two satellite-based products, CPC Morphing (CMORPH) and Hydro-Estimator (HE), and a radar-gauge rainfall Stage-IV (ST-IV) dataset for several rain events in 2006 over Oklahoma. The method was compared with 3 simpler methods for bias correction: mean ratio, maximum ratio and spatial interpolation without ensembles. Bias ratio, correlation coefficient, root mean square error and mean absolute difference are used to evaluate the performance of the different methods. Results show that: (a) the methods of maximum ratio and mean ratio performed variably and did not improve the overall correlation with the ST-IV in any of the rainy events; (b) the method of interpolation was consistently able to improve all the performance criteria; (c) the method of ensembles outperformed the other 3 methods.

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1 Introduction

This study proposes and evaluates a method for improving hourly Satellite Precipitation Estimates (SPEs) by correcting biases with respect to a radar-gauge product. SPEs can provide the only available dense coverage of precipitation events, particularly over mountainous regions. Radar coverage includes gap areas with missing information due to various sources such as blockage, particularly over regions with heavier and more frequent storms. Rain gauges are not available everywhere and are very sparse over mountains and large water bodies. Two SPE products are considered here: Hydro-Estimator (HE) (Scofield and Kuligowski, 2003), which estimates precipitation using InfraRed (IR) imagery from Geostationary Operational Environmental Satellites (GOES), and CPC Morphing (CMORPH) (Joyce et al., 2004), which estimates precipitation using Passive MicroWave (PMW) based precipitation products.

Rainfall estimates based on IR imagery from GOES would be useful to weather forecasters and water managers because their high spatial (4 km) and time resolution facilitates hydrological prediction in comparison with the ones based on PMW from polar-orbiting satellites. Two GOES satellites, GOES-East and -West, cover the CONtinental United States (CONUS) at a temporal resolution of 15 min. PMW from a polar-orbiting satellite can provide for any given target twice daily images at coarser resolution (e.g., 15 km). Because of higher resolution of IR imagery, most of the satellite-based precipitation retrieval algorithms are still based on using IR at 10.7 micron wavelength from GOES. For instance, Hydro-Estimator and Auto-Estimator (AE) (Vicente et al., 1998) both use only GOES IR.

Although the time and space resolution of GOES IR imagery is higher than that of microwave instruments, IR only provides information about cloud-top brightness temperature, which is not information about inside or other cloud properties due to its shorter wavelength. To produce higher quality precipitation intensity, PMW has been also used for development of some satellite-based algorithms. CMORPH is a gridded precipitation product based on PMW data from instruments aboard low-orbiting satellites with a secondary use of IR cloud imagery. Though PMW precipitation products are generally higher in quality than IR based products, they have their own biases, for example in semi-arid climate where raindrops may evaporate before reaching the surface (Rosenfeld and Mintz, 1988). Besides, PMW products are available with some latency, which can restrict their usefulness for applications of flash flood forecasting. The estimated precipitation from the various satellite products, as well as their performance compared to independent measures of rainfall, can differ appreciably (Ebert et al., 2007).

In general, since satellite-based rainfall products are estimates from indirect measures (e.g., IR cloud-top temperature) they are prone to errors greater than the ones for radar-based rainfall measurements. Thus, more accurate high-resolution rainfall products could be obtained by combining satellite-based estimates with radar-based ones, using the satellite imagery to fill in precipitation in areas where radar is not available. In merging satellite with radar estimates of rainfall, any bias in the satellite-based rainfall estimation must be quantified and corrected so that the merged product is, as far as possible, consistent.

A simple and widespread approach to reduce the error in one rainfall product relative to another, reference product is to multiply the rainfall from the first product by a "bias factor" chosen to optimize the correspondence of the two products where they overlap. Authors such as Anagnostou et al. (1998), Smith and Krajewski (1990), Ahernet et al. (1986), and Seo et al. (1999) estimated constant bias factors that were applied to the entire estimated rainfall field to correct biases in radar precipitation products, as compared to point-based observations from rain gauges. Seo and Breidenbach (2002) used a spatially varying bias factor to reduce biases in radar precipitation products against rain gauge observations under the hypothesis that radar-gauge biases are variable, but spatially and temporally coherent. Efforts have also been made to quantify and correct biases in SPEs using rain gauge information (e.g. Boushaki et al., 2009 and Smith et al., 2006). McCollum et al. (2002) evaluated biases of SPEs using a gauge corrected radar rainfall product.

Most of the above-mentioned work assumed that the point-based observations of rainfall provided by rain gauges form the reference "true" measurements against which to evaluate and correct SPEs and radar-based rainfall products. However, the rain gauge network is not always dense enough to accurately represent a region's rainfall, and errors can arise in using point rain gauges to represent rainfall of a radar or satellite pixel (Chumchean et al., 2003). In contrast, radar provides pixel-based areal rainfall measurements with better spatial coverage that is more comparable to the scale of satellite imagery. The United States has more independent radar coverage pixels than point rain gauges. Hence, there are smaller sampling and random errors (Xie and Arkin, 1997) in using merged radar-gauge products rather than point-based rain gauges alone, particularly in areas where gauges are relatively sparse. We therefore will use a merged radar-gauge rainfall product as a reference to detect and correct biases in SPEs.

In this study, we consider bias adjustment via spatially variable bias factors, where the SPE field at a given time step is corrected through multiplying by a field of bias factors. The spatial field of bias factors is estimated from selected radar-gauge precipitation estimates divided by the SPEs for the same pixels to obtain a spatially distributed sample of bias factors. To reduce sampling errors, bias factors should be selected all over the study area (Smith et al., 2006). In the current study, pixel bias factors are sampled randomly over the study area. A bias factor spatial field is constructed based on the sampled values by weighting based on a negative power of the distance to the sample points. To reduce the effect of random error in the bias factors for individual pixels, our approach relies on pre-smoothing the sample values by averaging across an ensemble where they are perturbed with a spatially correlated noise component. We compare this procedure of estimating the bias factor field to (a) a spatially varying bias factor field constructed from the sample points without the pre-smoothing; and (b) a spatially uniform bias factor field based on either (1) the mean or (2) the maximum bias factor in the sample. We use two operational SPEs, HE and CMORPH, as the products to be corrected, and the NEXRAD Stage-IV (ST-IV) radar-gauge composite product as the reference. Our test site is Oklahoma state, in the south-central USA, and we consider 5 rainy days in 2006 that represent different seasons. The area is one with good rain gauge and radar coverage and is intended to provide a preliminary test of our method for correcting bias in satellite-based rainfall estimates. This study is intended to show the feasibility of bias correction for satellite rainfall products, which can be applied operationally even in areas and times where radar coverage is limited so that radar overlap with the satellite product is only partial.

This article is organized as follows. In Sect. 2, the satellite and radar-gauge data are described, including the study area. In Sect. 3, the overall approach to bias correction is described. This includes parameter estimation and generation of ensembles. Section 4 presents and discusses the results. The last section offers conclusions and recommendations for future work.

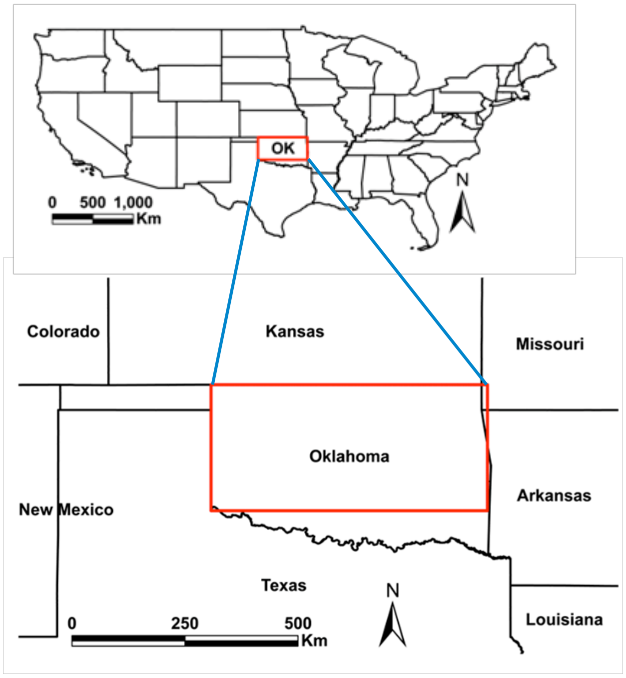

Fig. 1. Map of the conterminous US (top) and the study area (red box).

2 Study area and data used

A region geographically bounded by 34°–37° latitude north and 94.5°–100° longitude west, comprising most of Oklahoma State in the USA, was selected for this study (Fig. 1). The study location encompasses an area of about 136 000 km^2. The topographic elevation of the area ranges from 87 m near Little River to 1518 m above mean sea level on Black Mesa, and mean annual precipitation ranges from 432 mm in western high plains to 1296 mm in Ozark forest (see http://climate.ok.gov/index.php/site/page/climate_of_oklahoma).

Because of its rich meteorological network, the region and specific watersheds inside it have served as a test bed for many climatological and hydrological studies. Reliable radar rainfall estimates from a good distributed radar network over Oklahoma region make it well suited for investigating the capability of different approaches to correct bias errors from the selected SPEs (HE and CMORPH), against radar-gauge observations (ST-IV).

2.1 Hydro-Estimator (HE)

HE (Scofield and Kuligowski, 2003), which we adjust for bias in this study, is based on one of the cloud-top IR and rainfall relationships. High resolution hourly HE product at 4 km × 4 km pixel size, uses the GOES IR 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 AE, which was intended for deep, moist convective systems (http://satepsanone.nesdis.noaa.gov/PS/PCPN/HE.html). The HE algorithm identifies raining clouds based on both pixel brightness temperature (T_b) in GOES channel-4 and its value relative to its surroundings: pixels that are colder than their neighbors are presumed to be regions with updrafts and rainfall, while pixels warmer than the neighborhood average are associated with lower clouds and light or no rain. Rainfall rate is estimated as a function of pixel T_b, its surrounding values, precipitable water, relative humidity, convective equilibrium level, and lower-tropospheric winds, and terrain is used to diagnose regions of terrain-induced updrafts and downdrafts. At the NOAA National Environmental, Data, and Information Service (NESDIS), HE has been an operational rainfall product since 2002, and has been available at a spatial scale of 4 km by 4 km and hourly time scale for CONUS since 2004.

2.2 Climate Prediction Center Morphing (CMORPH)

CMORPH is a gridded precipitation product based on both passive microwave data from low orbiting satellites and IR data from GOES satellite (Joyce et al., 2004). CMORPH produces operational global (60° N–60° S) precipitation products at spatial resolution as high as 0.0728° (∼8 km at the equator) and half hourly time scale, which is the resolution we used. It combines the different existing microwave -based precipitation products from Special Sensor Microwave Imager (SSM/I) (Ferraro et al., 1997), Advanced Microwave Sounding Unit (AMSU)-B (Ferraro et al., 2000), and TRMM Microwave Imager (TMI) (Kummerow et al., 2001). The effective temporal resolutions of these products are on the order of hours, corresponding to the overpass frequency of most of the low orbiting satellites. In the CMORPH algorithm these microwave based precipitation products are propagated backwards and forwards in time to calculate precipitation at a finer time resolution. The IR data is used to determine cloud evolution to propagate rainy pixels from the microwave products (Joyce et al., 2004). CMORPH has been operational and data are available since 2002 from the Climate Prediction Center (CPC) of the National Centers for Environmental Prediction (NCEP).

2.3 Radar-gauge Stage-IV (ST-IV)

The NEXt generation RADar (NEXRAD) system is the network of more than 150 WSR-88 instruments in the United States operated by the NWS for weather prediction and precipitation estimation. Rainfall estimation from Doppler radars is based on converting the reflectivity (Z) of the radar signal, which records backscattering by rain drops, into rainfall estimates (R) through a nonlinear power function (Doviak and Zrnic, 1984).

At NWS, there are four stages of radar-based rainfall products. References such as Fulton et al. (1998) and Lin and

Mitchell (1999) contain details of how the different stages of radar products are produced. Briefly, Stage-I radar rainfall is produced for each radar scan at each radar site using the Z-R relationship. Hourly Stage-I products are 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 rainfall products. The bias adjusted Stage-II products are further optimally merged with point rain gauges (Smith and Krajewski, 1991; Fulton et al., 1998; Seo et al., 1999). In Stage-III, at each NWS River Forecast Center (RFC), the Stage-II (radar-gauge) products from multiple radars are stitched together to cover the area under the respective RFC. At this stage, overlapping Stage-II products are optimally combined. In addition, Stage-III products undergo routine manual quality control to make sure that products are free from any obvious error (Fulton et al., 1998). The regional Stage-III products obtained from the 12 RFCs are further mosaicked to a national 4 km stereographic NWS's Hydrologic Rainfall Analysis Project (HRAP) grid at NCEP, forming the ST-IV product. ST-IV is thus ultimately generated from more than 3000 automated hourly rain gauge observations and the WSR-88D radar based digital precipitation arrays (DPA) (Fulton et al., 1998). ST-IV precipitation product is available since 2001.

Radar based precipitation estimates are known to have problems including isolated targets and ground clutter, anomalous propagation, and partial beam reflection in mountainous regions (Fulton et al., 1998). Radar also suffers from range dependent attenuation (Young et al., 1999). However, composite products, such as ST-IV from NCEP, are manually quality controlled and corrected for these problems using direct rain gauge observations as one source of calibration. In this work, it is assumed that ST-IV can be used as a reference precipitation field over Oklahoma against which to correct systematic errors in SPEs.

3 Methodology

HE and ST-IV data are both in polar stereographic projection. They are converted to a regular grid of 4 km × 4 km resolution using a simple average of the data within a 4 km square grid cell.

In all the analysis involving CMORPH, ST-IV data at a 4 km spatial resolution is averaged to 8 km × 8 km to match up the resolution of CMORPH.

In the following, we describe the proposed approach for bias correction along with the simpler methods with which we compare our approach.

3.1 Bias factor

The bias factor is defined as the ratio of a true value to the corresponding biased value. Bias is adjusted by multiplying the values from the biased field by the bias factor.

According to Anagnostou et al. (1998), the area-mean bias ratio is defined as the ratio of the true mean area rainfall to the mean area of "biased" estimates. Thus, following the same definition, the maximum ratio bias factor will be the ratio of the area maximum of the true values to the maximum of the biased data field.

With the assumption that the rain gauge observation is the true and radar-based measurement is the biased rainfall information, the mean bias ratio is written as (Anagnostou et al., 1998):

$$B_{\mathrm{h}} = \frac{\sum_{i=1}^{n} G_{\mathrm{h}}(x_i)}{\sum_{i=1}^{n} R'_{\mathrm{h}}(x_i)} \tag{1}$$

where $G_{\mathrm{h}}(x_i)$ and R'_{h} are the gauge and radar measurements at location x_i and hour h. Therefore, the existing bias from the original SPE is corrected by multiplying each pixel value by the mean (or maximum) bias ratio.

3.2 Ensemble Bias Factor Field

Following the same definition, a bias factor or ratio between ST-IV and SPE products at a pixel level can be written as:

$$B(x_{\mathrm{k,h}}) = \frac{R_{\mathrm{h}}(x_{\mathrm{k}})}{S_{\mathrm{h}}(x_{\mathrm{k}})} \tag{2}$$

where $R_{\mathrm{h}}(x_{\mathrm{k}})$ and $S_{\mathrm{h}}(x_{\mathrm{k}})$ are the ST-IV (the "true" measurement in this study) and satellite measurements respectively, at location x_{k} and hour h.

From Eq. (2) bias factors can be:

- Zero if the radar pixel is not rainy and the corresponding satellite pixel is rainy.
- A positive real number if corresponding pixels from ST-IV and SPE are rainy.
- Infinity if the ST-IV pixel is raining and the corresponding satellite pixel is not rainy.
- Undefined if both pixels from ST-IV and SPEs are not raining.

We kept only pixels that were rainy in both precipitation fields; hence all our sample bias factors had positive values. A pixel is considered rainy if it registers a rainfall value of greater than 0.1 mm h^{-1} (Dai et al., 1999). A maximum of 150 (for HE) and 100 (for CMORPH, with its coarser resolution) bias factors were used for evaluation depending on the areal coverage of rain within the study area. The process of selecting pixels for the estimation of the bias factor field was as follows: (a) to ensure a fair spread of bias factors over the study area, 150 pixels for HE (100 in the case of CMORPH) are randomly picked regardless of their bias factor values;

(b) the non-positive bias factors are discarded; (c) the process of randomly picking pixels continues until a total of 150 for HE (100 for CMORPH) positive bias factors is obtained; and (d) any closely located pixels, which would tend to occur whenever rain covers only a small part of the study area, were thinned out, potentially reducing the number of pixels retained below 150 for HE and 100 for CMORPH.

The bias factors obtained for a sample of pixels can have large scatter compared to the underlying bias field because of, for example, random error in the satellite radiances or radar backscatter. Generating an ensemble of perturbed bias factors that represents variability based on their estimated small-scale scatter can be useful in visualizing these errors, and the sample can be pre-smoothed by averaging across the ensemble.

Following the acquisition of the required number of bias factors, the ensembles of bias factors were created by following a similar procedure to that of Mandel et al. (2009). That work used Cholesky decomposition of the state covariance matrix to generate posterior ensembles in an ensemble Kalman filter. Germann et al. (2006b) used Cholesky decomposition of the error covariance to generate ensembles of radar precipitation fields. The method was found to be flexible to the space-time dependence of mean, variance, and auto-covariance of error in radar rainfall estimates (Germann et al., 2006b). A similar approach was adopted here to perturb the bias factors at known locations before spatial interpolation to produce the bias factor field was carried out.

In our ensemble generation, let $\boldsymbol{b}$ be a known n by 1 vector of the randomly sampled known bias factors. $\mathbf{M}$ is the initial perturbation matrix of size n by N, where N is the required ensemble size (100); and $\mathbf{M}$ is assumed to have the form,

$$\mathbf{M} = \mathbf{O} + \mathbf{G} \tag{3}$$

$\mathbf{O}$ is a matrix of size n by N. The columns of $\mathbf{O}$ are replicates of $\boldsymbol{b}$. $\mathbf{G}$ is a matrix of independent random variables each drawn from $N(\mathbf{0}, \sigma^2)$, a normal distribution with mean zero and unknown variance σ^2.

The initial perturbation matrix $\mathbf{M}$ is multiplied by the Cholesky factor $\mathbf{Q}$ of the spatial covariance matrix $\mathbf{C}$ to produce ensembles, Eq. (4).

$$\hat{\mathbf{M}} = \mathbf{Q} \cdot \mathbf{M}; \mathbf{C} = \mathbf{Q} \cdot \mathbf{Q}^T \tag{4}$$

$$\mathbf{C} = \sigma^2 \cdot f\left(d_i - d_j\right) \tag{5}$$

where $\hat{\mathbf{M}}$ is the ensemble of perturbed bias factors, $\mathbf{C}$ is a positive definite matrix of dimension n by n with the error covariance of each pair of sample points, assumed to be only a function of their separation $\left(d_i - d_j\right)$. $\hat{\mathbf{M}}$ is thus a function of σ^2 as well as the parameters p and η introduced below.

Table 1. Optimized parameters for the five rainy events in 2006 for HE (CMORPH).

Rainy Event	Rainy Period (YYMMDDHH)	Parameter: Range (η [km])	Variance (σ^2 [mm^2])	Power (p)
1	06031818–06031918	6.87 (37.5)	0.75 (0.54)	4.44 (1.73)
2	06020605–06020705	4.43 (32.6)	0.75 (0.20)	4.07 (1.92)
3	06071021–06071121	6.58 (19.68)	0.85 (0.39)	3.23 (3.75)
4	06091008–06091108	6.59 (19.43)	1.19 (0.32)	4.09 (2.77)
5	06122902–06123002	8.55 (8.7)	0.50 (0.46)	2.70 (4.91)

A common correlation function, the exponential function without nugget effect (Kitanidis, 1986) with one unknown parameter was used as a spatial covariance estimator:

$$f\left(d_i - d_j\right) = \exp\left(-\frac{|d_i - d_j|}{\eta}\right) \tag{6}$$

where $|d_i - d_j|$ is the Euclidean separation distance in km between two bias factor sample pixels indexed at i and j, and η (km) is a range parameter.

The next step is to generate bias fields using each column of $\hat{\mathbf{M}}$. There are several spatial statistics approaches to generate spatial fields from point estimates of bias factors, including linear, kriging, spline, and Inverse Distance Weight (IDW) (Cressie, 1993). In this work, a multiplicative bias factor for the SPE was generated for each unknown pixel on an hourly basis using the IDW interpolation method given by (Shepard, 1968):

$$b(x_{i,\mathrm{h}}) = \sum_{k=0}^{n} \frac{W_{\mathrm{k,h}}(x)}{\sum_{k=0}^{n} W_{\mathrm{k,h}}(x)} b(x_{\mathrm{k,h}}) \tag{7}$$

$$W_{\mathrm{k,h}}(x) = \frac{1}{D\left(x_{i,\mathrm{h}}, x_{\mathrm{k,h}}\right)^p} \tag{8}$$

where $D(x_{i,\mathrm{h}}, x_{\mathrm{k,h}})$ is the distance from the unknown bias factor pixel $x_{i,\mathrm{h}}$ to all known bias factor calculated pixels $x_{\mathrm{k,h}}$. $p > 0$ is an exponent, and n is the number of sample bias factors at hour h. Finally the bias corrected SPE is calculated as:

$$S_{\mathrm{cor},i,\mathrm{h}} = \sum_{j=1}^{N} \frac{S_{i,\mathrm{h}} \cdot b_{i,\mathrm{h,j}}}{N} \tag{9}$$

where $S_{\mathrm{cor},i,\mathrm{h}}$ is the bias corrected HE at hour h, $S_{i,\mathrm{h}}$ is the HE at hour h and $b_{i,\mathrm{h},j}$ is the j-th member bias field at hour h. i is the pixel index in the rainfall field.

3.2.1 Parameter estimation

The parameters η, σ^2, and p have to be estimated to produce optimal bias correction. Parameter estimation was carried out separately for each day. Hourly ST-IV and SPE were aggregated to daily values before ratios of corresponding rainy pixels for parameter estimation were taken. In an operational setup, the parameters could be estimated using the previous 24 h. Parameters could also be estimated on hourly basis.

For parameter estimation, the shuffled complex evolution optimization algorithm (Duan et al., 1993), originally developed for hydrologic modeling, was used. Optimum values for parameters were determined based on minimizing an objective function given by the Root Mean Square Error (RMSE) between the ST-IV and mean ensemble bias corrected SPEs for a 24 h period (Eq. 10).

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{h}^{m}\sum_{j=1}^{n}\left(R_{i,\mathrm{h}} - S_{\mathrm{cor},i,\mathrm{h}}\right)^2}{n\cdot m}} \quad (10)$$

where n is the number of corresponding rainy pixels, and R is the ST-IV rainfall at each pixel, and m is the number of the rainy hours in the day.

3.3 Interpolation bias factor field

For comparison, a pixel-by-pixel spatial interpolation of bias factors in the interpolation method is carried out using Eq. (7), in addition to the mean and maximum ratio method bias factors. The interpolation method uses Eq. (7) on the original sample bias factors without generating an ensemble. Bias corrected SPE is obtained using Eq. (9) with $N=1$. We include the method of interpolation to show that improvements in bias and correlation coefficients are not only based on the results of accounting for spatial variation, but specifically on pre-smoothing the sampled bias factors through ensemble generation. Note that the only parameter involved in the method of interpolation is p.

The method of mean ratio works by multiplying the original satellite product by the mean of sampled bias factors. Similarly, the method of the ratio of maximums works by multiplying satellite products by the ratio of hourly maximum rain rates between the radar-gauge and the satellite estimates irrespective of their location.

4 Results and discussion

Four rainy representative days in 2006, one from each of the four seasons, were chosen for model evaluation. To better assess wintertime performance, which for SPE is generally poor, an additional winter case was chosen for overall evaluation of the model. The second and the last rainy events of the five events listed in Table 1 represent winter cases; event 1 is a spring case, event 3 is summer, and event 4 is a fall case.

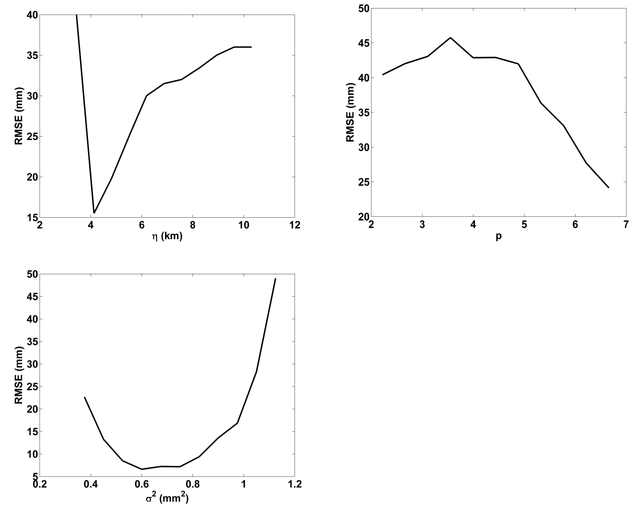

Fig. 2. Parameter sensitivity check for HE for the range (η [km]), the power (p) and the variance (σ^2 [mm^2]).

Bias adjustment using the ensembles method requires obtaining the optimized model parameters, namely the range (η), the power-law exponent (p), and the variance (σ^2), based on m-hour aggregates of SPEs and ST-IV as explained in the previous section (Eq. 10). Table 1 lists the optimal values of the three parameters for each of the rainy days. These varied from one rainy event to another. For HE the variance range was from 0.5 mm^2 for event 5 to 1.19 mm^2 for event 4. The lowest power parameter of 2.7 was observed for event 5 while a maximum value of 4.44 was observed for event 1. The range parameter varied from 4.43 km for event 2 to 8.55 km (approximately 2 grid cells) for event 5.

After obtaining the optimized model parameters, the impact of the parameters was examined by varying each parameter about their optimal values while keeping the other parameters fixed at their optimal values. To demonstrate the influence of the parameters in the bias correction model, the RMSE versus the respective parameter for rainy hour 06071022 (YYMMDDHH) was plotted. Figures 2 and 3 show the response of the RMSE to variation of each parameter around their optimal values for HE and CMORPH respectively. Figure 2 shows that the model was insensitive to the power parameter up to a power of 4.5. For p values greater than 5 the model was acutely sensitive and the value of RMSE decreased steadily. A high value of the power parameter of inverse distance weight implies sharp non smooth variation among the interpolated pixels (Shepard, 1968). The range parameter that influences the spatial correlation function shows an increase in RMSE for values less than 4 km (the grid spacing of HE) and less steep increase at larger values. A similar parameter check for CMORPH was carried out for the same rainy hour (Fig. 3).

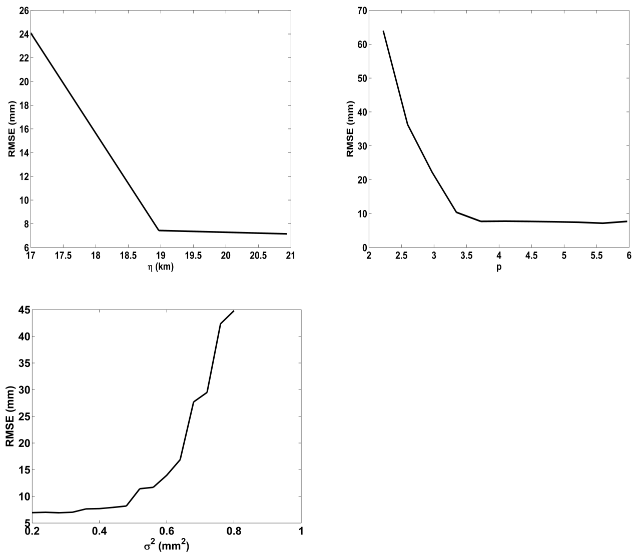

Fig. 3. Parameter sensitivity check for CMORPH for the range (η [km]), the power (p) and the variance (σ^2 [mm^2]).

The pattern of the parameters obtained for CMORPH has a similar nature to that of HE though with longer optimum η, which is of the order of 20 km. Figure 3 suggests that the optimal parameter set for CMORPH can be obtained from values $\eta > 19$ km, $p > 3$ and $\sigma^2 < 0.6\,\mathrm{mm}^2$.

Following optimization and sensitivity analysis of model parameters for each rainy event, the performance of SPEs adjusted using the method of ensembles was evaluated by comparing it with that of the SPEs adjusted with the other bias correction methods mentioned. Figure 4 shows the mapped precipitation fields from HE and CMORPH before and after adjustment of biases, using various bias correction methods, are compared with ST-IV at hour 06071022. In this figure, bias corrected satellite estimates (left side for HE and right side for CMORPH) using the methods of (c) Maximum ratio (d) Mean ratio (e) Interpolation and (f) Ensembles are depicted. Figure 4a is ST-IV (8 km resolution left and 4 km resolution right) and Fig. 4b is the original HE (left) and CMORPH (right). As shown in Fig. 4c, the SPE corrected using the maximum ratio and ensemble methods gave a better estimate than bias corrected rainfall amounts using the methods of mean-ratio and interpolation.

Quantitative statistical evaluation criteria were calculated using reference ST-IV pixels which were not used for bias correction. Recall that the maximum number of pixels used for bias correction were 150 and 100 for HE and CMORPH respectively. The statistical criteria used for evaluation are defined as:

Hourly Bias ratio,

$$\text{Bias ratio} = \frac{\sum_{j=1}^{n} R_j}{\sum_{j=1}^{n} S_{\mathrm{cor,j}}} \tag{11}$$

Hourly mean Absolute Difference (AD),

$$\mathrm{AD} = \frac{\sum_{j=1}^{n} |S_{\mathrm{cor}} - R|_j}{n} \tag{12}$$

The hourly RMSE,

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{j=1}^{n} (S_{\mathrm{cor}} - R)_j^2}{n-1}} \tag{13}$$

The hourly Correlation Coefficient (CC) between the bias corrected SPEs and ST-IV for corresponding rainy pixels,

$$\mathrm{CC} = \frac{\mathrm{COV}(S_{\mathrm{cor}}, R)}{\sqrt{\mathrm{VAR}(S_{\mathrm{cor}}) \cdot \mathrm{VAR}(R)}} \tag{14}$$

where j is the grid index and n is the number of all corresponding rainy pixels. COV(.) is the covariance between the ST-IV rainfall estimates and the bias corrected SPEs. VAR(.) is the variance of the rainfall field.

Figures 5 and 6 and Tables 2 and 3 compare the performances of the bias methods using these performance criteria. The figures demonstrate the performance of the individual methods for each rainy hour. Tables 2 and 3 summarize RMSE, correlation coefficient, and absolute difference for each event (from Table 1) for HE and CMORPH, respectively. In these tables, the hourly bias corrected products are aggregated to daily amounts for comparison. The relationship between ST-IV and the original SPEs before bias correction is also shown in these figures and denoted as "Original". Figures 5a–e and 6a–e, show Bias ratio, CC, RMSE and AD respectively. The two sets of figures 5a-e and 6a-e are for HE and CMORPH respectively. In most of Figs. 5 and 6, the original bias is below the red line. The red horizontal line in these figures represents the ideal (theoretical) value for the respective performance criteria. Thus, the satellite products overestimate the total areal precipitation (this doesn't mean the satellite products overestimate precipitation intensity at pixel level). From these figures, we note that the methods reduced biases variably. The method of maximum ratio effectively reduced biases in Figs. 5b, 6a, d and e. However the maximum ratio is not a reliable method for bias correction in all cases as it lacks consistency in the other bias plots. For instance, the method further degraded the satellite product in some cases (Figs. 5c, d and 6c). The classic mean-ratio (mean field bias correction) method effectively reduced bias in almost all cases except a few (for example Fig. 6a hour

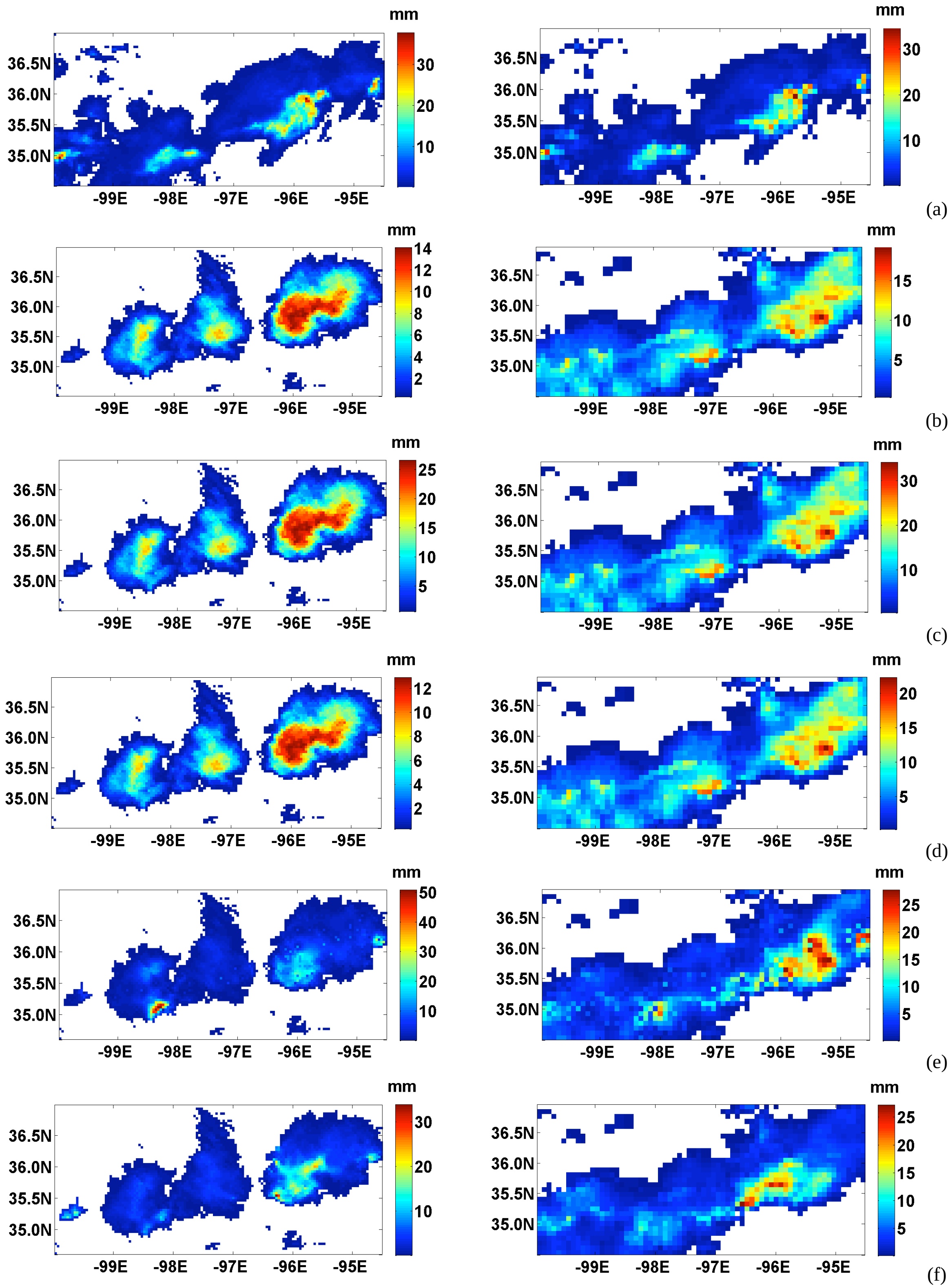

Fig. 4. Bias corrected satellite estimates (left side for HE and right side for CMORPH) at hour 06071022 using the methods of **(c)** Maximum ratio **(d)** Mean ratio **(e)** Interpolation and **(f)** Ensembles. **(a)** is ST-IV (4 km resolution left and 8 km resolution right) and **(b)** is the original HE (left) and CMORPH (right).

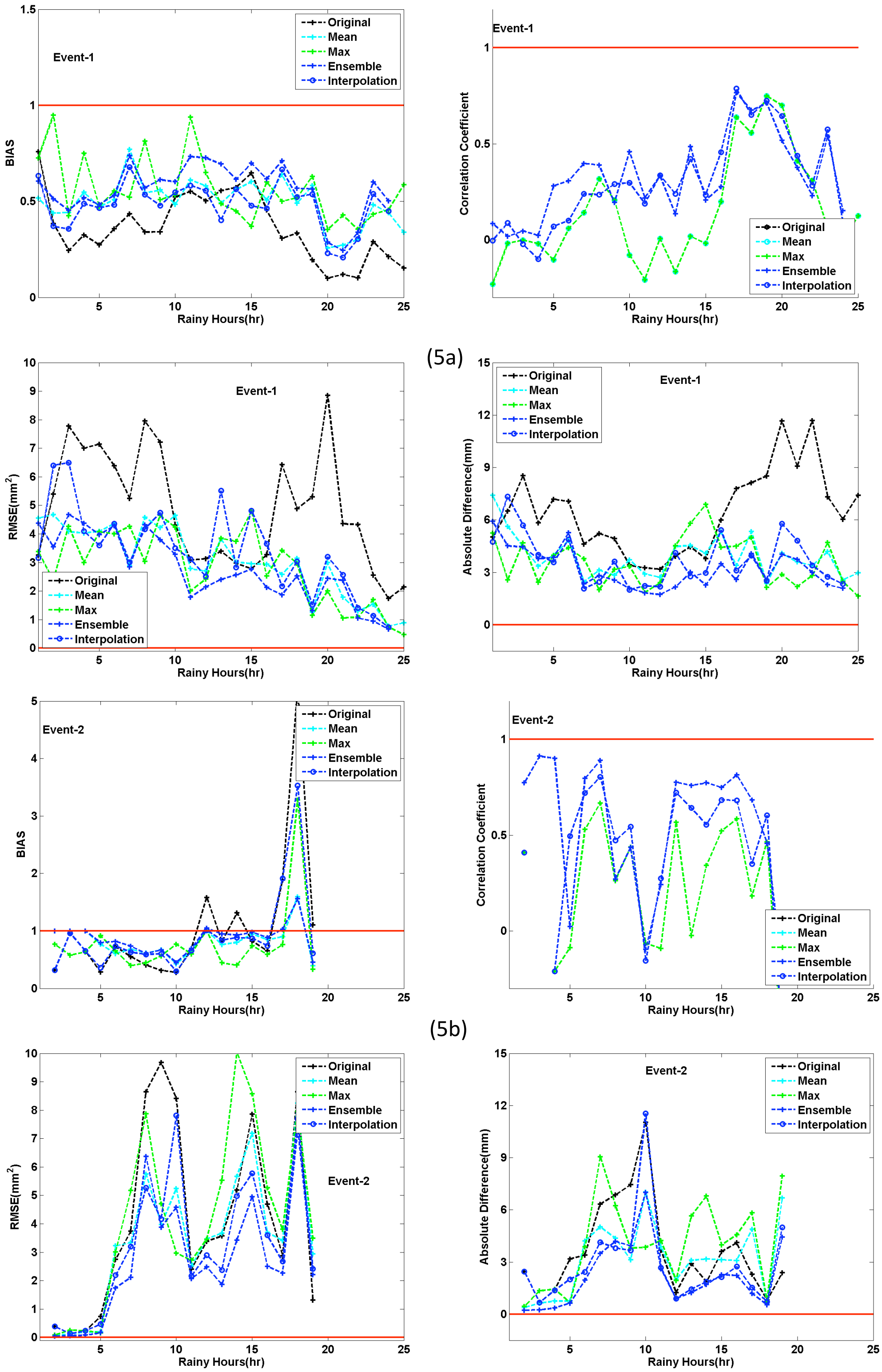

Fig. 5. Evaluation criteria BIAS, Correlation Coefficient, Root Mean Squared Error (RMSE) and mean Absolute Difference for HE against ST-IV. **(a)** Event 1, **(b)** Event 2, **(c)** Event 3, **(d)** Event 4 and **(e)** Event 5.

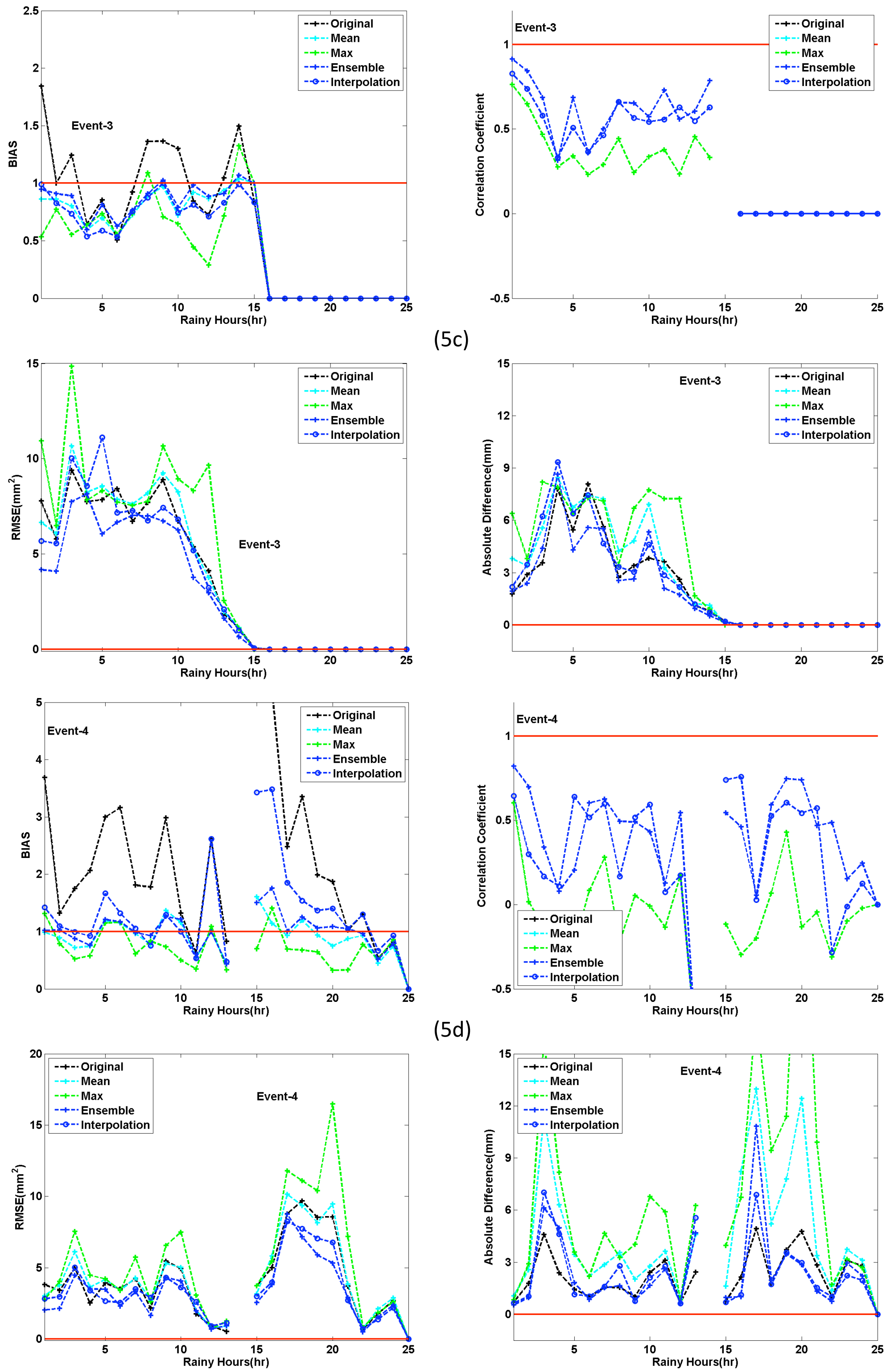

Fig. 5. Continued.

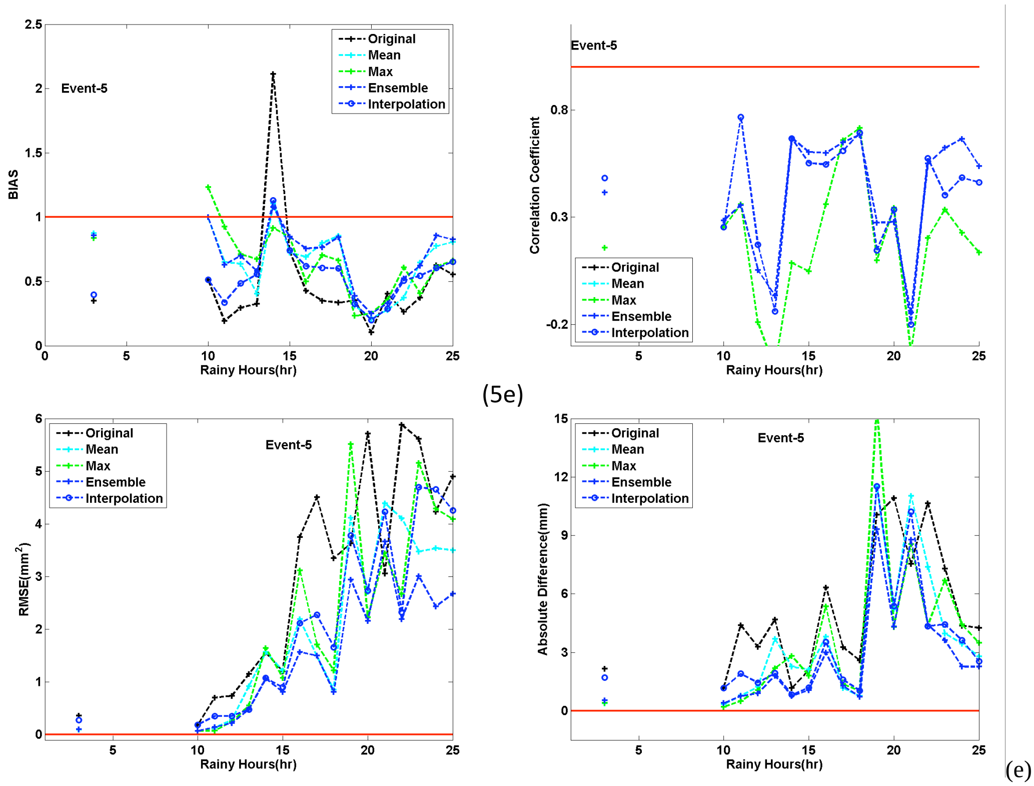

Fig. 5. Continued.

mark 14) when the sampled bias factors are not good representatives of the areal precipitation. In those cases bias ratios from the sample were mostly greater than 1 while the mean bias ratio for the whole region was less than 1. The methods of interpolation also effectively reduced bias in satellite precipitation products. But it was the method of ensembles which outperformed the rest. The performance of both the interpolation and ensembles methods is generally superior to the mean and maximum ratio methods, which use spatially constant bias factors.

Figures 5 and 6 also contain CC, RMSE and AD besides BIAS for each hour. Generally poorer correlation is observed in event 1 and event 5 (Winter cases) which reflects poor estimation of precipitation in satellite products in the winter time. The methods of maximum and mean ratio don't work well in terms of improving the correlation coefficient (CC). The method of ensembles tends to reduce AD and RMSE and improve CC better than interpolation without ensembles.

Figures 7a–e and 8a–e respectively are scatter plots for HE and CMORPH at rainy hours 06071107, 06020619, 06091015, 06122923, and 06031906. These selected hours from each rain event shown in Table 1. The right side of Figs. 7 and 8 represent the relationship after bias correction, and the left side represents values before bias correction. For each hour, the CC, RMSE and BIAS are shown as indicators of the overall performance of the ensemble bias correction method. The percentage improvement of the correlation coefficient varied from case to case. Both HE and CMORPH showed significant improvements after bias correction was made using the method of ensembles. For instance, for hour 06071107 the bias correction improved the correlation coefficient between the HE and ST-IV by 20 %. For cases with already higher correlation coefficient between the ST-IV and original SPEs a lower percentage of improvement was observed than with low correlation between the original SPEs and ST-IV. The scatter plots indicate that our method has effectively improved the SPE in randomly picked hours in every season.

In most rain events it is observed that even though significant improvements are obtained by our approach of interpolation with ensemble pre-smoothing, systematic biases remain in the satellite products.

In the US, radar and satellite products are available near real-time. This gives an advantage to radars to correct biases in satellite products over very sparse real time rain gauges. This work demonstrates that daily updates of parameters are sufficient to carry out bias correction in satellite products. The results showed that with only three parameters, the method of ensembles provides useful bias correction and should be further tested, particularly in rain gauge sparse areas.

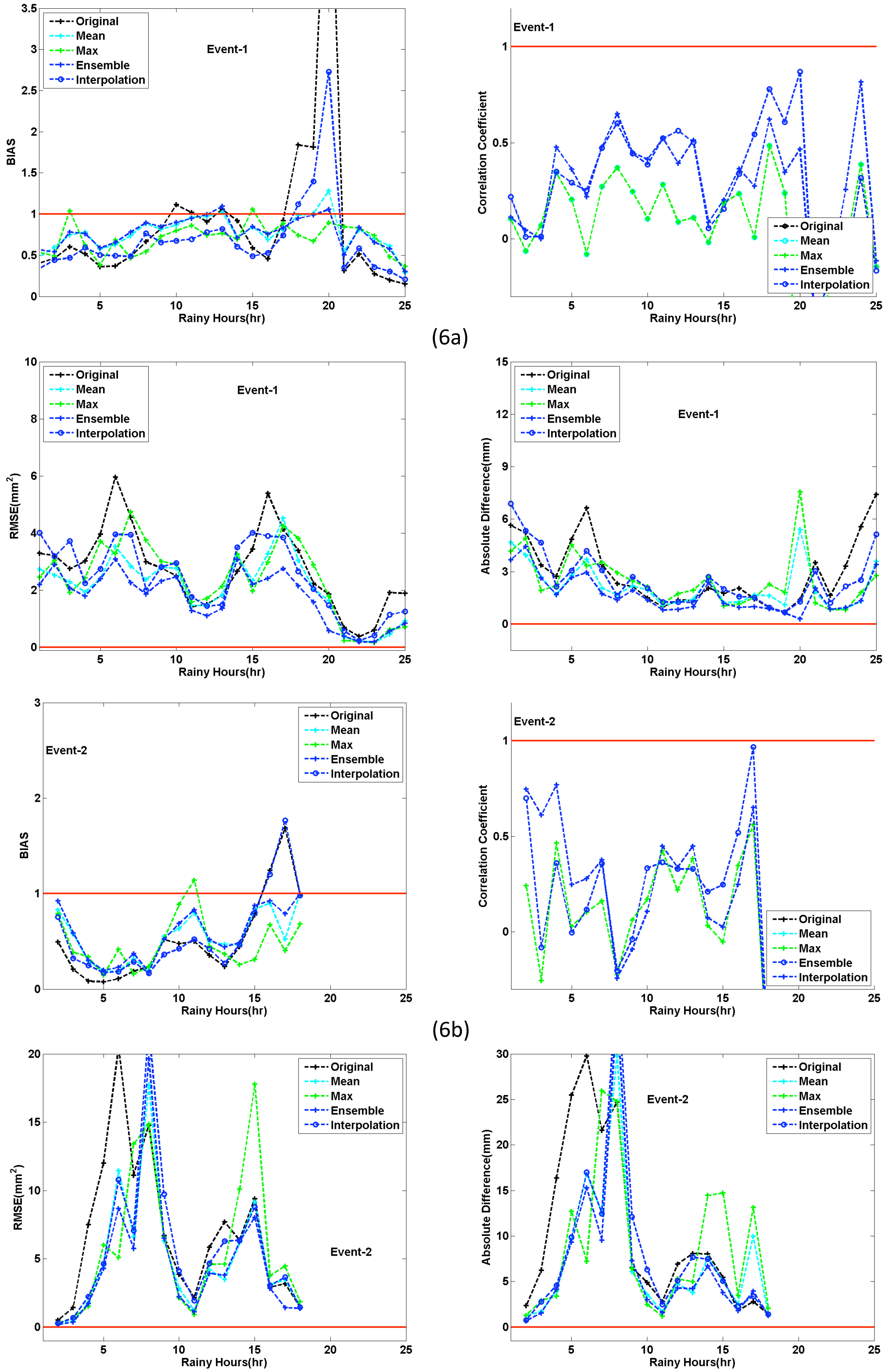

Fig. 6. Evaluation criteria BIAS, Correlation Coefficient, Root Mean Squared Error (RMSE) and Absolute Difference for CMORPH against ST-IV. **(a)** Event 1, **(b)** Event 2, **(c)** Event 3, **(d)** Event 4 and **(e)** Event 5.

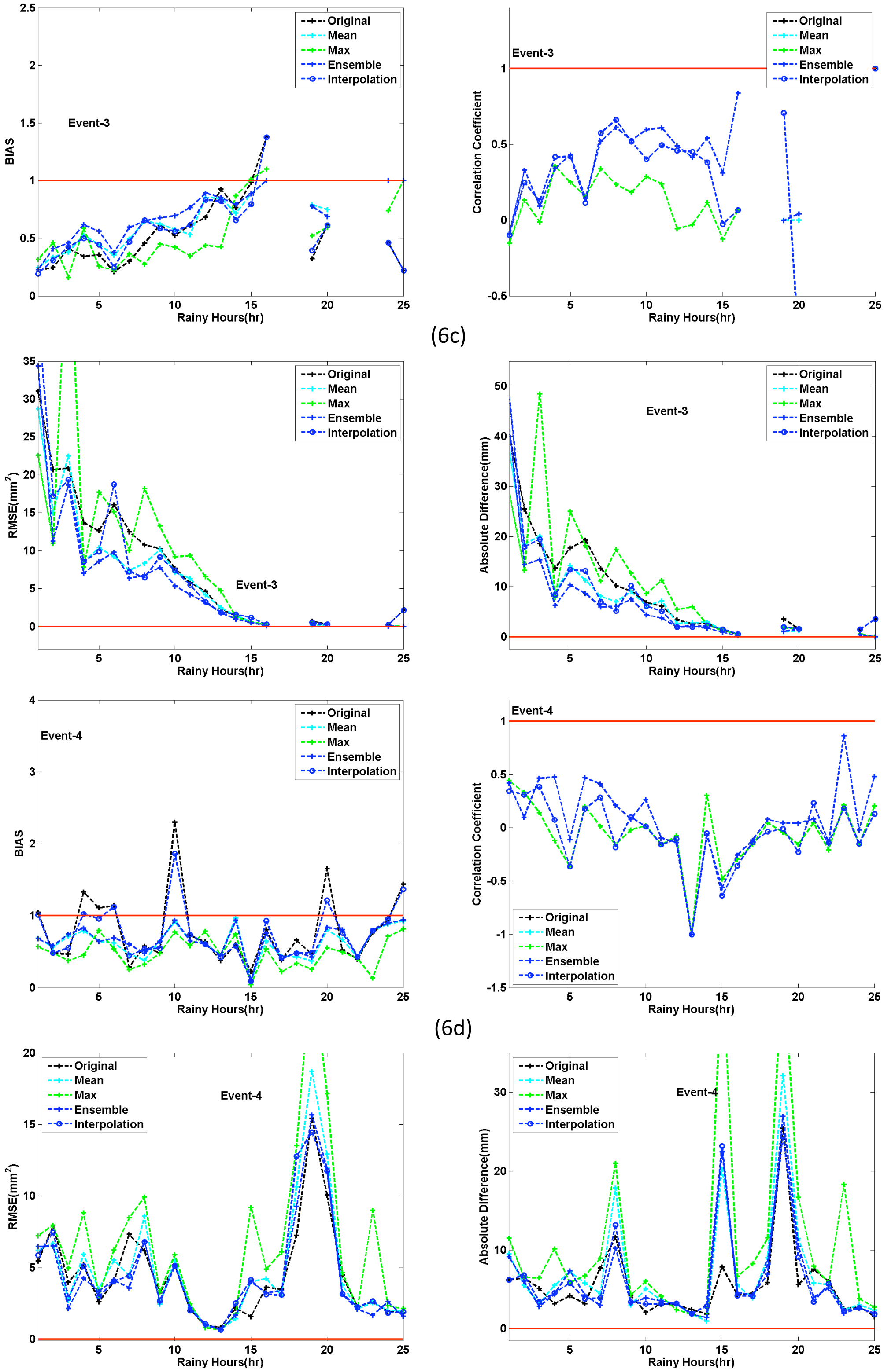

Fig. 6. Continued.

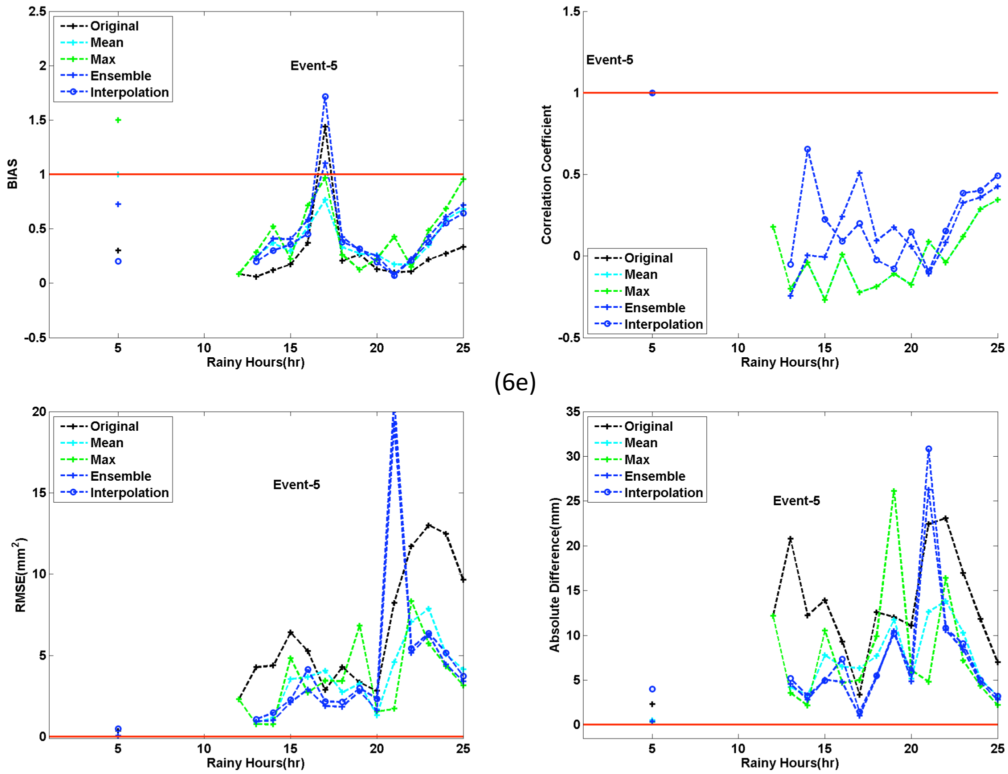

Fig. 6. Continued.

After further testing in more locations, the developed approach is intended to be implemented operationally along with existing operational satellite-based precipitation retrieval algorithms (such as HE and CMORPH) to correct biases and improve the resulting precipitation product. This is expected to improve the operational SPE products and reduce the differences between corresponding precipitation values produced by different algorithms, benefitting end users by providing improved quality precipitation information particularly over areas of sporadic or incomplete radar coverage.

The two SPE products selected for bias corrections are (1) Hydro-Estimator (HE), available in near real time (within ≈1 h) and (2) CPC Morphing (CMORPH) available at ≈18 h delay. Biases are computed and corrected against the operational merged radar-gauge rainfall product (Stage-IV), which also available within 1–2 h (in preliminary form) to 18 h (fully calibrated against gauge data). It is anticipated that the proposed method can be applied at 1 to 3 h windows to both the satellite and radar-gauge products, depending on the areal coverage of precipitation (which controls the amount of overlap between the satellite and radar fields). Hence, bias-corrected HE or CMORPH precipitation fields could be produced within <24 h.

5 Summary and conclusion

In this study, a bias correction approach with spatially varying bias factors pre-smoothed using an ensemble was proposed and compared to the mean field and maximum ratio approaches as well as to interpolation without pre-smoothing. For improved spatial coverage and sampling, instead of rain gauge measurements a radar-gauge mosaicked rainfall product (Stage-IV) was used to correct SPEs.

The sensitivity of spatial parameters was checked by varying each parameter around its optimal value while keeping the others constant. Results showed that all three parameters seem to have significant impacts on the bias correction quality. As one of the efficiencies of the method, it was shown that daily update of parameters was sufficient to adjust biases in hourly satellite products. Once the parameters were obtained, ensembles of bias factors were imposed to represent random errors in bias factors.

The performance of the proposed bias correction method was evaluated using root mean squared error, absolute bias, and correlation coefficient between the ST-IV and the corrected SPEs. Compared to the other methods tested, the proposed method of ensembles showed more improvement in bias ratio, correlation coefficient and RMSE. The method produced a correlation coefficient of 0.9 in one case while the other techniques did not show as much improvement over the original satellite product.

Table 2. Statistical outputs for the five rainy events of HE.

Statistics	Methods	Event 1	Event 2	Event 3	Event 4	Event 5
RMSE (mm)	Original	20.58	18.60	11.70	16.90	59.70
	Mean ratio	20.38	10.05	11.40	6.14	13.30
	Max ratio	21.10	8.26	11.10	9.06	21.60
	Interpolation	18.16	15.0	11.80	4.87	17.40
	Ensemble fields	17.70	7.90	9.30	4.30	10.61
Correlation Coefficient (CC)	Original	0.53	0.58	0.23	0.54	0.66
	Mean ratio	0.53	0.58	0.23	0.54	0.66
	Max ratio	0.53	0.58	0.23	0.54	0.66
	Interpolation	0.63	0.59	0.45	0.71	0.78
	Ensemble fields	0.65	0.59	0.47	0.79	0.81
Bias Ratio	Original	0.86	0.46	2.24	0.28	0.28
	Mean ratio	0.96	0.74	1.17	0.64	0.60
	Max ratio	0.93	1.50	1.10	0.69	0.55
	Interpolation	0.87	0.53	0.88	0.71	0.76
	Ensemble fields	0.98	1.20	0.94	0.82	0.78

Table 3. Statistical outputs for the five rainy events of CMORPH.

Statistics	Methods	Event 1	Event 2	Event 3	Event 4	Event 5
RMSE (mm)	Original	82.90	38.70	22.30	46.00	17.20
	Mean ratio	23.40	9.90	11.00	12.60	8.64
	Max ratio	18.10	11.3	10.20	10.00	8.70
	Interpolation	22.90	12.47	10.90	8.50	7.22
	Ensemble fields	16.70	6.80	7.30	7.50	6.27
Correlation Coefficient (CC)	Original	0.61	0.64	0.58	0.63	0.83
	Mean ratio	0.61	0.64	0.58	0.63	0.83
	Max ratio	0.61	0.64	0.58	0.63	0.83
	Interpolation	0.62	0.56	0.64	0.72	0.89
	Ensemble fields	0.67	0.71	0.67	0.76	0.89
Bias Ratio	Original	0.23	0.28	0.36	0.16	0.61
	Mean ratio	0.64	0.53	0.73	0.45	1.02
	Max ratio	0.78	0.34	0.64	0.53	1.05
	Interpolation	0.63	0.45	0.62	0.53	1.01
	Ensemble fields	0.80	0.96	1.08	0.60	1.01

By adjusting biases in satellite products, radar-like satellite rainfall products can be produced. This is highly desirable in many operational settings where radar and satellite products being merged can differ sharply in terms of bias even though both undergo gauge-based bias adjustments before merging. It has also a considerable advantage in producing radar-like products in radar gap areas and during radar outages. During radar outages, the approach can provide radar-like products using bias factors determined from radar data from the previous hour and satellite products from the present hour. This method can complement the existing operational bias corrections which are rain gauge based.

Acknowledgements. This study was partially supported and monitored by the National Oceanic and Atmospheric Administration (NOAA) under grant number NA06OAR4810162. The statements contained within this paper are not the opinions of the funding agency or the US government, but reflect the authors' opinions.

We would like to thank Robert Kuligowski, Robert Joyce and Yelena Yarosh for providing all the necessary data. Thanks are due to Ademe Mekonnen and Yu Zhang for editing the original version of the paper. Thanks to Jan Mandel and Cecilia Hernandez for their cooperation and help.

Edited by: H. Cloke

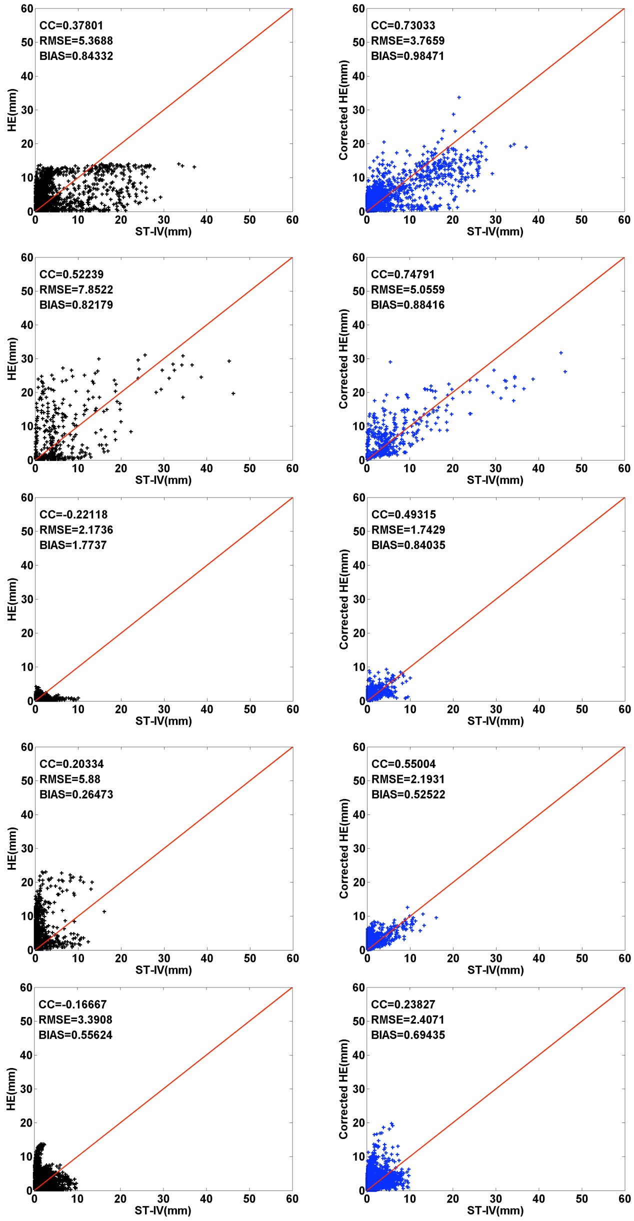

Fig. 7. Scatter plot of radar-gauge (ST-IV) and satellite estimate (HE) before (left side) and after (right side) bias correction for 06071107, 06020619, 06091015, 06122923 and 06031906 (from top to bottom respectively). CC, RMSE and BIAS are the correlation coefficient, Root Mean Squared Error and Bias.

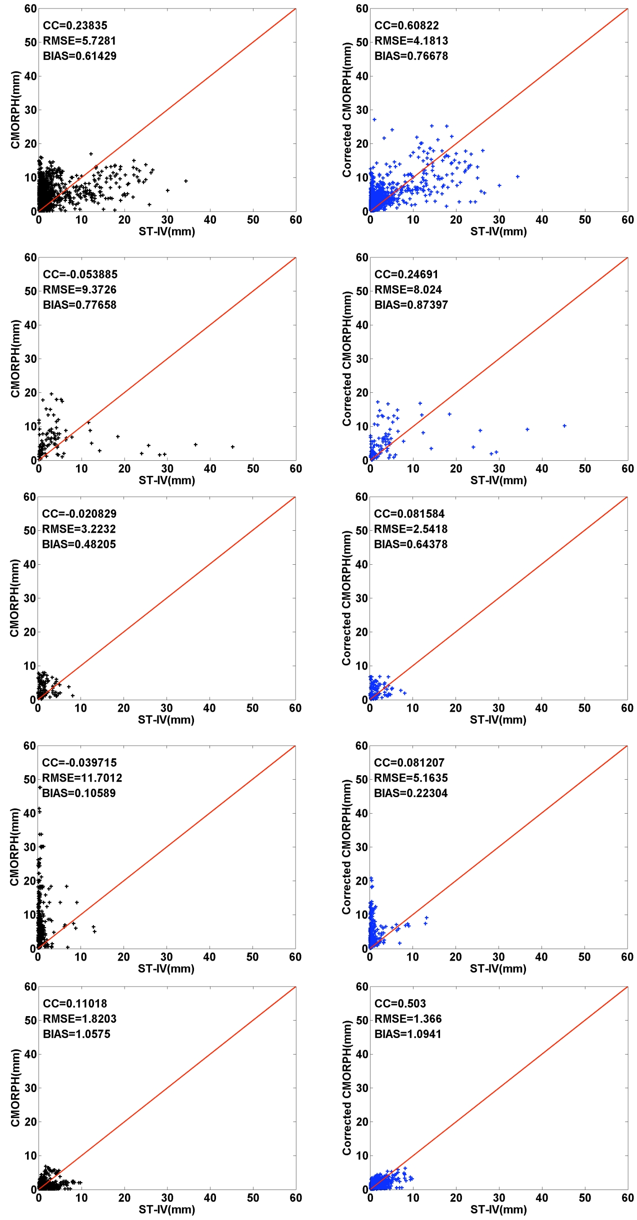

Fig. 8. Scatter plot of radar-gauge (ST-IV) and satellite estimate (CMORPH) before (left side) and after (right side) bias correction for 06071107, 06020619, 06091015, 06122923 and 06031906 (from top to bottom respectively). CC, RMSE and BIAS are the correlation coefficient, Root Mean Squared Error and Bias.

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