JOBNAME: JHM 00#0 2011 PAGE: 1 SESS: 8 OUTPUT: Fri Sep 2 14:29:46 2011 Total No. of Pages: 12
/ams/jhm/0/jhmD1005023

Journal of Hydrometeorology (Proof Only)

How Much Can a priori Hydrologic Model Predictability Help in Optimal Merging of Satellite Precipitation Products?

ABEBE GEBREGIORGIS AND FAISAL HOSSAIN

Department of Civil and Environmental Engineering, Tennessee Technological University, Cookeville, Tennessee

(Manuscript received 2 November 2010, in final form 8 June 2011)

ABSTRACT

AU1 In this study, the authors ask the question can a more superior precipitation product be developed by merging individual products according to their a priori hydrologic predictability? The performance of three widely used high-resolution satellite precipitation products [Tropical Rainfall Measuring Mission (TRMM) real-time precipitation product 3B42 (3B42-RT), the NOAA/Climate Prediction Center morphing technique (CMORPH), and Precipitation Estimation from Remotely Sensed Information using Artificial Neural AU2 Networks-Cloud Classification System (PERSIANN-CCS)] was evaluated in terms streamflow predictability for the entire Mississippi River basin using the Variable Infiltration Capacity (VIC) macroscale hydrologic model. A merging concept that was not based on a single universal merging formula for the whole basin but rather used a ''localized'' (gridbox by gridbox) approach for merging precipitation products was then explored. In this merging technique, the a priori (historical) hydrologic predictive skill of each product for each grid box was first identified. Prior to streamflow routing, the corresponding accuracy of the spatially distributed simulations of soil moisture and runoff were used as proxy for weights in merging the precipitation products. It was found that the merged product derived on the basis of runoff predictability outperformed its counterpart merged product derived on the basis of soil moisture simulation. Results indicate that such a gridbox by gridbox merging concept that leverages a priori information on predictability of individual products has the potential to yield a more superior product for streamflow prediction than what the individual products can deliver for hydrologic prediction.

1. Introduction

Satellite precipitation (hereafter interchanged with ''rainfall'') has witnessed considerable improvement in scale over the last two decades from degree daily resolutions in Global Precipitation Climatology Project (GPCP; Huffman et al. 2001) to 0.25° 3-hourly resolution during the Tropical Rainfall Measurement Mission (TRMM) era (Huffman et al. 2010). TRMM has been designed to monitor and study the tropical rainfall for the first time with the help of both active and passive microwave sensors. Before TRMM, rainfall estimates were mostly obtained from satellites with visible, infrared, and passive microwave sensors, which were typically affected by cloud covers and resulted in less accurate rainfall estimation. TRMM's collection of instruments, such as a microwave imager, a visible and infrared scanner, and lightning imaging sensors, now provide finescale observations of precipitation and its vertical distribution. The success of TRMM mission has paved the road for the Global Precipitation Measurement (GPM) mission. With a newer set of instruments added to the existing constellation, the GPM mission will usher in a new era in precipitation estimation from space in terms of higher spatial resolution, global extent, and frequency of sampling of rainfall (Hou et al. 2008).

Despite the progress in developing finer-scale products, obtaining precipitation information at the required accuracy level for hydrology still remains a challenge (Hossain and Huffman 2008). Because satellite rainfall estimation is not a direct observation, the uncertainty that is inherent in the satellite estimates originate from sampling and retrieval algorithm error. Satellite rainfall data can also have large uncertainties depending on the type of sensors and their resolution (Kidd et al. 2003; Hong et al. 2006; Gebremichael et al. 2003). Although there have been several studies that have assessed the impact of using pre-GPM satellite precipitation datasets (such as TRMM-based multisatellite products) for hydrologic

Corresponding author address: Dr. Faisal Hossain, Department of Civil and Environmental Engineering, Tennessee Technological University 1020 Stadium Drive, Boc 5015, Cookeville, TN 38505.
E-mail: fhossain@tntech.edu

DOI: 10.1175/JHM-D-10-05023.1

AU3 modeling (see, e.g., Su et al. 2008; Nijssen and Lettenmaier 2004, among many others), the utilization of such ''performance'' information of each product toward optimal merging for a more superior product has received virtually no treatment in literature. In this study, our goal is therefore to investigate a fundamental paradigm shift in improving the accuracy of satellite rainfall products, which is to leverage a priori knowledge on how each product typically performs in hydrologic modeling as a guide toward a single ''universal'' product with more superior predictability.

So far, most of the merging application has been carried out based on rainfall but not on hydrologic features to the best of our knowledge. For example, Huffman et al. (1995) have used linear optimal coefficients that are inversely proportional to the square of the error to merge gauge rainfall data with satellite estimates by assuming all the rainfall products free of bias. Xie and Arkin (1996) have developed a merging algorithm for model prediction and satellite rainfall products based on the assumption of random and unbiased observation error that are normally distributed. To the best of our knowledge, such merging technique is based on one universal (i.e., for the entire application region) merging algorithm/formula rather than recognizing that a spatially varying merging approach might be more appropriate.

Recently, work has been reported on estimation of the statistical error properties of satellite rainfall products by Kalman filtering method using spaceborne surface soil moisture retrievals (Crow and Bolten 2007). This leveraging of remotely sensed surface soil moisture data has shown that robust information about the relative error of satellite rainfall product is possible. Consequently, this appears to indicate that predicted soil moisture, using a hydrologic model, may also hold similar promise in estimating relative errors of a rainfall product.

Because there are large numbers of high-resolution precipitation products (HRPP) that are derived from various algorithms, we are now faced with issues related to uncertainty of these various satellite rainfall products. The general question we ask herein is, how does merging of satellite rainfall products based on individual hydrologic predictability improve the accuracy of simulated hydrologic variables? More specifically, we seek an answer to the question, does merging based on spatially varying features (grid box by grid box) advance the predictive ability of hydrologic model from satellite rainfall compared to the more common but spatially uniform merging approach? From the recent work of Crow and Bolten (2007), it appears that soil moisture predictability can be a useful proxy for identifying the uncertainties associated with satellite rainfall products. Thus, merging diverse satellite rainfall products based on hydrologic predictability may lead to a superior satellite rainfall product if the spatial error signatures of individual products are properly leveraged.

For example, if product A is historically more consistent in yielding more accurate soil moisture estimates at valley regions over product B, then, in place of using a universal merging formula (i.e., one merging algorithm for the whole basin), it makes more sense to merge the two products over valley regions with higher weight for A. Therefore, it is our hypothesis that leveraging the spatial signatures of hydrologic variable predictability can be a more useful guide in merging products for better hydrologic prediction. Because of a plethora of satellite rainfall products, this hypothesis should now be tested in a scientific and systematic approach in the lead up to GPM. As a broader impact, the outcome of our research will act as a pathfinder to optimal use of emerging satellite rainfall products in operational hydrology in the near future (i.e., the GPM era).

2. Study area, model description, and data

The study was conducted in Mississippi River basin (MRB), which is one of the biggest and most important basins in the United States, with major contributions to the physical and economic growth of the nation (Fig. 1). F1
It has four major tributary rivers, which include the Missouri, Ohio, Arkansas–Red, and Tennessee Rivers. The basin has a total area of 3 224 535 km^2 (1 245 000 mi^2) and it encompasses more than 32% of the U.S. land area. The basin covers wide range of topographic regimes from low land, such as 1 m above mean sea level (MSL) to mountainous area (above 4300 m MSL). Higher-elevation regions mostly dominate the western part of the basin and the extreme edges of the eastern border. The land use of the western part of the basin is characterized by forest, shrub land, and savanna/grassland. The eastern and southern parts are described by forest and central, whereas the northern parts are dominated by cropland and natural vegetation. Average annual precipitation increases from approximately 200 mm in the west to 1800 mm in the east. The diverse climate, land use, topography, and hydrologic features make the MRB an ideal test bed to explore concepts on leveraging spatial characteristics of satellite rainfall outlined earlier.

In this study, the Variable Infiltration Capacity (VIC) macroscale hydrological model (Liang et al. 1994; Liang and Xie 2001; Liang et al. 1996; Liang et al. 1999) was implemented for estimation of runoff and soil moisture of the basin. A unique feature of VIC is its capability to carry out complete water and energy balance on a grid-cell basis at subdaily time steps. VIC can simulate the

JOBNAME: JHM 00#0 2011 PAGE: 3 SESS: 8 OUTPUT: Fri Sep 2 14:29:46 2011 Total No. of Pages: 12
/ams/jhm/0/jhmD1005023

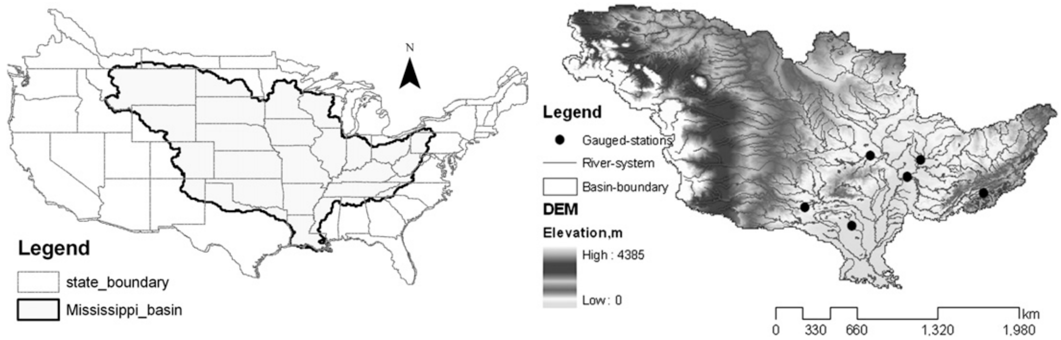

FIG. 1. (left) The location of MRB in the United States. (right) Elevation of the study basin, river system, and river gauging stations where simulation was performed.

partitioning of incoming energy and moisture at the land surface into separate components of energy and water balance (Su et al. 2008). The model also considers the spatial variability of soil moisture, precipitation, vegetation cover, and topography, and the subgrid variability in soil properties is represented by a spatially varying infiltration capacity (Liang 1994; Cherkauer and Lettenmaier AU4 1999; Su et al. 2008). Therefore, this feature makes the model ideal for understanding the spatial features of runoff and soil moisture simulation.

The VIC model inputs include meteorological forcing data (daily precipitation, maximum temperature, minimum temperature, and wind speed), soil data, vegetation cover, gridcell elevation, and snowband elevation. The VIC model was set up for ingestion of three high-resolution satellite rainfall products. In addition, the merged satellite rainfall and gridded ground rainfall data, which were considered as ground validation (GV), were also ingested in VIC. VIC simulated runoff and base flow of grid cells were then routed to the outlet points using the Horizontal Routing Model (HRM; Lohmann et al. 1998). Streamflow simulation was assessed at six internal gauging stations (Fig. 1). Model parameters, such as variable infiltration curve parameter, maximum velocity of base flow, fraction of velocity of base flow, fraction of maximum soil moisture, and depth of soil layers that control infiltration and subsurface moisture storage, were calibrated to maximize the agreement between predicted and observed streamflow AU5 F3 at the gauging stations as indicated in Fig. 3a,b.

The ground observation of rainfall data was available from Washington University Surface Hydrology Group. In their native format, the data originate from a point gauge network. For application in VIC, the gauge data AU6 were gridded for the entire nation based on the SYMAP interpolation algorithm (Bowling et al. 2004) at a spatial resolution of 0.125° and a temporal resolution of a day. During the preparation of input dataset for the VIC model, the only varying aspect for different scenarios was the precipitation, which was obtained from different satellite products. These satellite products were research-graded satellite rainfall product [TRMM real-time precipitation product 3B42 (3B42-RT); Huffman et al. 2007]; passive microwave (PMW)-derived rainfall estimate [the National Oceanic and Atmospheric Administration (NOAA)/Climate Prediction Center morphing technique (CMORPH); Joyce et al. 2004]; and neural network algorithm-based generated rainfall product [Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks-Cloud Classification System (PERSIANN-CCS); Hong et al. 2004; Hsu et al. 2010].

3. Methodology

As mentioned earlier, the core science question addressed was related to the merging of satellite

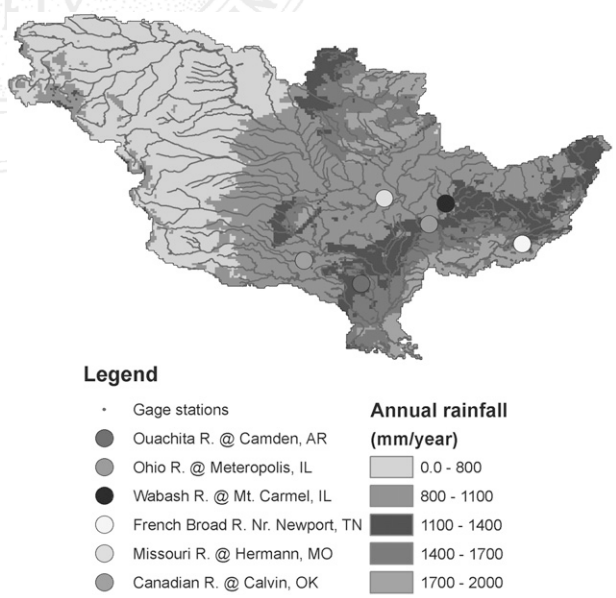

FIG. 2. Mean annual rainfall in MRB (mm yr^{-1}).

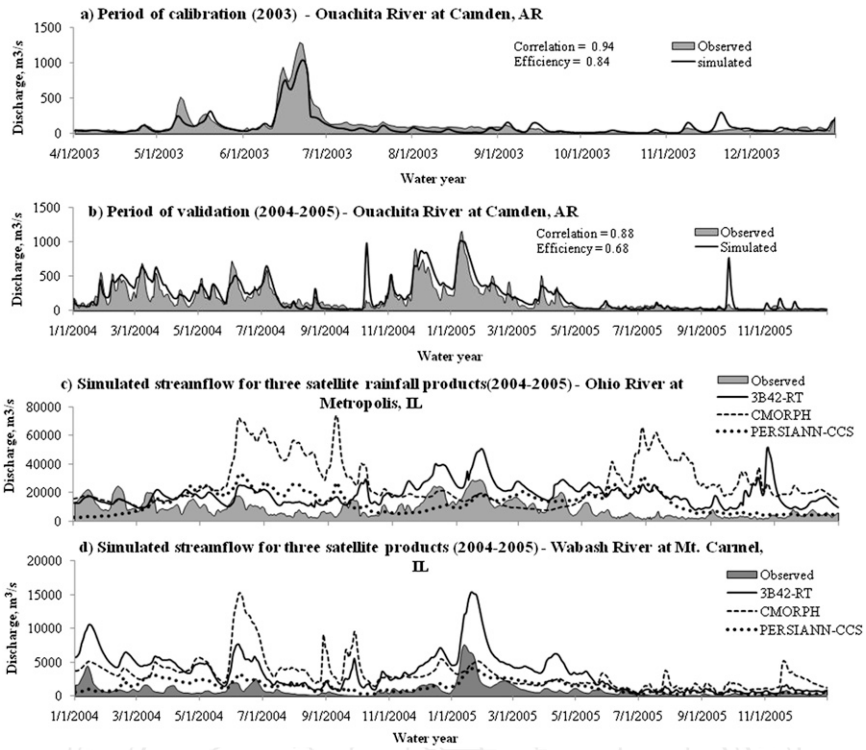

FIG. 3. Streamflow simulation performance of various rainfall products. (a) Calibration and (b) validation sample results for the VIC model using GV rainfall data on the Ouachita River at Camden, Arkansas. (c),(d) Simulated streamflow from three satellite rainfall products (3B42-RT, CMORPH, and PERSIANN-CCS) on the Ohio and Wabash Rivers, Illinois.

precipitation product to improve the simulation accuracy of hydrological variables: namely, streamflow in this case. In this study, a linear combination of weight factors that are inversely proportional to error variance [i.e., mean squared error (MSE)] of soil moisture and runoff were applied to merge the satellite rainfall products. First, the a priori MSE [Eq. (1)] in soil moisture and runoff simulation for each grid box was calculated using as reference, the simulation obtained from gauge precipitation. Next, the MSEs were inverted and used as weights according to Eq. (2). The weights were relative and unbiased and hence they added up to one. Finally, the merged rainfall product for each grid box was a linear weighted combination of the weights per Eq. (3),

$$\mathrm{MSE}(i,j) = \frac{\sum_{k=1}^{m}[P_{\mathrm{sat}}(i,j)_k - P_{\mathrm{grd}}(i,j)_k]^2}{m}, \quad (1)$$

$$w(i,j)_r = \frac{1/\mathrm{MSE}(i,j)_r}{\sum_{r=1}^{n} 1/\mathrm{MSE}(i,j)_r}, \quad (2)$$

$$P_{\mathrm{mgd}}(i,j)_r = \sum_{r=1}^{n} w(i,j)_r P(i,j)_r, \quad \text{and} \quad (3)$$

$$\sum_{r=1}^{n} w(i,j)_r = 1, \quad (4)$$

where P_{sat} is prediction from satellite rainfall data; P_{grd} is prediction from ground data; P_{mgd} is merged satellite rainfall; i, j is the location of the grid cell; m is the total number of data used; n is the number of satellite products in the merging; and w is the weight factor for individual grid cell for particular satellite product. Although the focus of our study was not on the development of a mathematical theory for merging, it should be remembered that the use of a linear combination of weights implies the following three assumptions for theoretical validity: (i) the input/output response is linear; (ii) the errors are unbiased and normal; and (iii) the measurements in the individual satellite products are statistically independent. Although our study does not make these assumptions explicitly [i.e., clearly assumption (i) does not hold for the case of rainfall–runoff transformation, whereas assumptions (ii) and (iii) cannot be completely

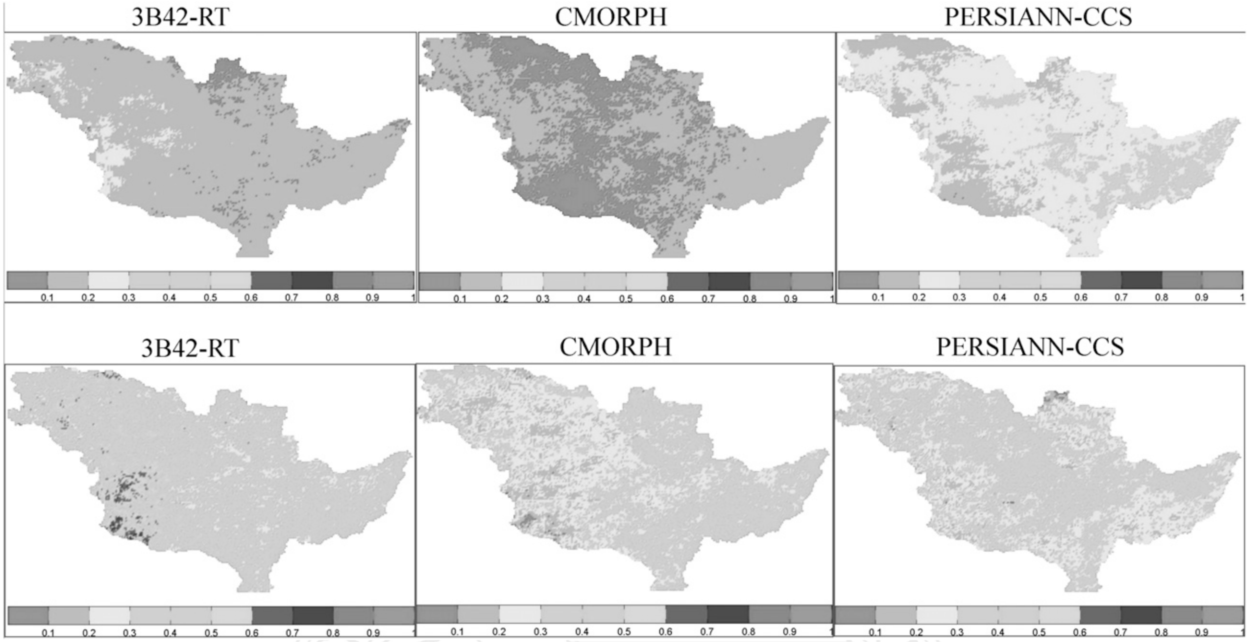

FIG. 4. Plot of spatially distributed average merging weight factors generated for MRB for the calibration period (2003). The merging weight factors are derived based on (top) runoff error and (bottom) soil moisture error for three satellite rainfall products (3B42-RT, CMORPH, and PERSIANN-CCS).

proved or disproved for satellite data), we recognize that any generalizable mathematical theory of hydrologically relevant merging of satellite precipitation products based on the linear combination of weights will need to address these assumptions at some point.

The VIC model was calibrated for GV rainfall data using measured streamflow as shown in Figs. 3a,b. The periods of calibration and validation were 2003 (1 yr) and 2004–05 (2 yr), respectively. The soil moisture and runoff were predicted for all satellite rainfall datasets for

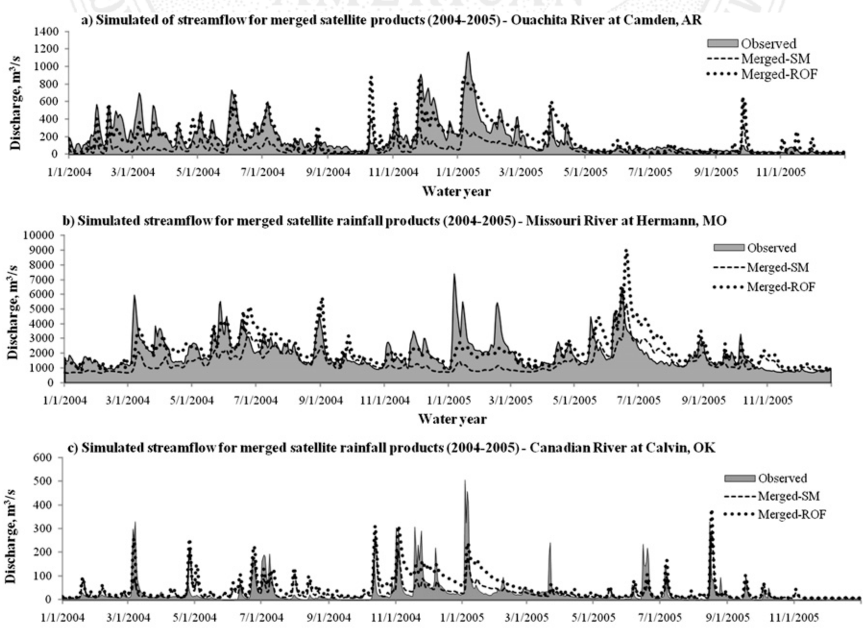

FIG. 5. Comparison of observed and simulated streamflow from two merged satellite products at three streamflow gauging stations.

TABLE 1. Evaluation of performance of various rainfall products in simulating streamflow at six gauging stations in MRB for the period of 2004–05. Note that, in this study, error is defined as satellite rainfall estimate minus GV rainfall.

Stations	Drainage area (mi^2)	Performance measures	Rainfall products for streamflow simulation: Gridded GV rainfall data	3B42-RT	CMORPH	PERSIANN-CCS	M_SM	M_ROF
Ouachita River at Camden, AR	5510	Relative BIAS (%)	14	−2	21	−77	−66	−2
		Relative RMSE (%)	41	38	90	85	73	42
		Correlation coef	0.9	0.9	0.6	0.4	0.7	0.8
		Nash–Sutcliff efficiency	−0.4	0.0	−1.4	0.3	0.4	0.1
Ohio River at Metropolis, IL	241 000	Relative BIAS (%)	67	141	191	44	−53	14
		Relative RMSE (%)	89	112	230	95	71	56
		Correlation coef	0.7	0.2	−0.4	0.0	0.1	0.3
		Nash–Sutcliff efficiency	0.0	0.1	−9.1	−0.4	−1.2	0.6
Wabash River at Mt. Carmel, IL	28 932	Relative BIAS (%)	157	261	238	44	−30	44
		Relative RMSE (%)	132	227	223	71	68	66
		Correlation coef	0.7	0.8	0.3	0.6	0.6	0.6
		Nash–Sutcliff efficiency	−1.9	−8.6	−5.6	0.3	0.0	0.3
French Broad River near Newport, TN	1972	Relative BIAS (%)	70	84	41	−50	−62	−16
		Relative RMSE (%)	94	141	98	75	74	60
		Correlation coef	0.6	0.2	0.2	0.3	0.5	0.5
		Nash–Sutcliff efficiency	−1.0	−3.6	−0.9	0.6	0.6	0.6
Missouri River at Hermann, MO	570 650	Relative BIAS (%)	12	100	708	284	−29	10
		Relative RMSE (%)	56	117	813	321	51	42
		Correlation coef	0.4	0.5	0.3	0.5	0.4	0.6
		Nash–Sutcliff efficiency	−0.4	−6.8	−304	−50.9	0.5	−0.3
Canadian River at Calvin, OK	28 900	Relative BIAS (%)	134	138	646	233	−5	59
		Relative RMSE (%)	89	80	276	132	34	53
		Correlation coef	128	128	511	230	72	81
		Nash–Sutcliff efficiency	0.6	0.5	0.3	0.2	0.6	0.6

the calibration period. Using this period, the a priori (historical) weights for each product were derived from soil moisture and runoff error (relative to that simulated by GV rainfall data). The MSE at each grid box was used as the proxy for weight of each product at that specific grid box according to Eqs. (1)–(4). The merging concept was tested on independent satellite rainfall data (i.e., not used for calibration or deriving merging weights) and period set that extended beyond the calibration period from 2004 to 2005 (2 yr).

4. Results

In this study, we analyzed the performance of three satellite rainfall products in hydrologic modeling and employed merging methodology that leveraged a priori hydrologic predictability to yield a more accurate merged product. A comparison of streamflow simulation based on various satellite rainfall products with observed flow revealed clear differences. During the validation period (2004–05), satellite products (except for the merged products) were mostly found to overestimate the streamflow at the selected gauging stations. In Figs. 3c,d, the CMORPH rainfall product overpredicted the streamflow much more compared to the other satellite products. The PERSIANN-CCS product yielded better flow simulation during the recession stages of a flooding event, and it also captured the low-flow regime realistically. When compared to CMORPH and PERSIANN-CCS, the 3B42-RT satellite product seemed to yield better simulation of streamflow. Because of the spatial and temporal variation in performance among satellite rainfall products, it seems logical to use of more than one product (combined products). By using a gridbox by gridbox merging algorithm, such a combined product can potentially account for the space–time performance limitations (and complement the strength) of each individual product.

Figure 4 illustrates the spatially distributed merging weight factors of the basin which is generated based on the error variance (MSE) of runoff and soil moisture (top and bottom panels, respectively). Large differences and distinct patterns are seen across the whole basin for all products and for both scenarios (runoff and soil moisture). A higher the weight factor indicates greater accuracy in prediction by the rainfall product. From Fig. 4 (top), the values of the weighting factors for 3B42-RT lie between 0.2 and 0.3 at the western edge of the basin (Missouri subbasin). This area is mainly characterized by high mountains (Fig. 1). It also receives an average F4

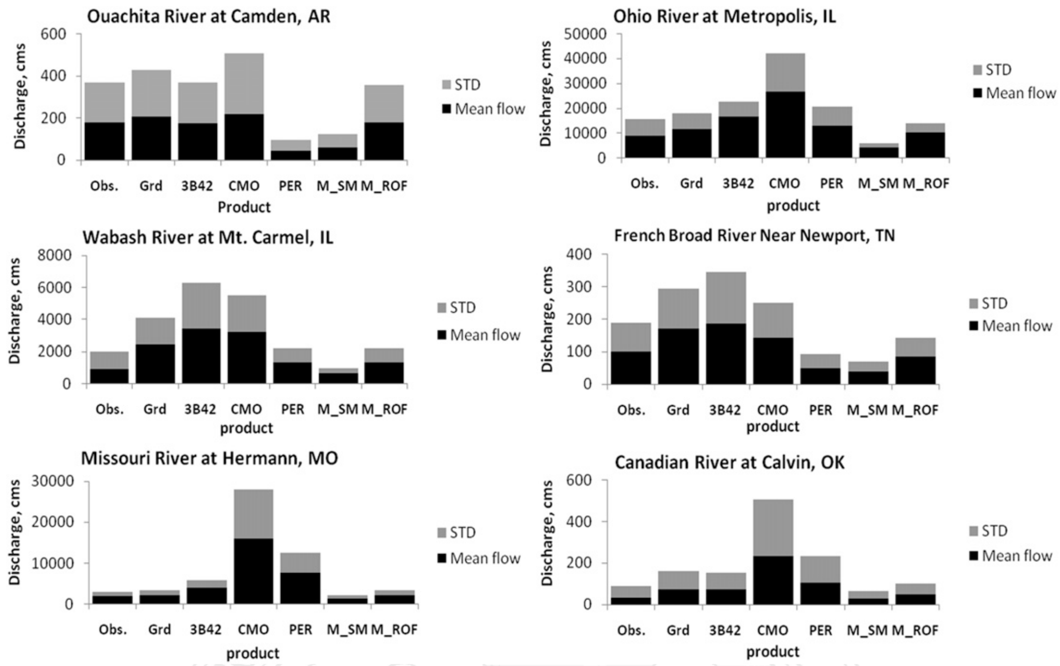

FIG. 6. Statistical comparison (mean and standard deviation) of observed and simulated streamflow from various rainfall products for the period of 2004–05. The area of each subbasin is shown in Table 1. The following are were shown (abbreviated accordingly): standard deviation, observed streamflow, gridded GV rainfall, 3B42-RT satellite product, CMORPH, PERSIANN-CCS, M_SM, and M_ROF.

annual rainfall of 600–800 mm (Fig. 2). CMORPH, on the other hand, has the minimum weight factor, between 0 and 0.1, extending into northern, central, and southern parts of Mississippi basin. As was shown earlier in Fig. 3, the CMORPH product overestimated the streamflow for most seasons and therefore has relatively small weights over most of the basin. PERSIANN-CCS has moderately high weights, particularly in the eastern part of the basin, which receives the maximum mean annual rainfall (above 1200 mm).

For the case of soil moisture–based merging, the bottom-left panel map indicates a good performance of 3B42-RT product in the western part of the basin. In this region, the weight factors ranges from 0.5 to 0.7, whereas, in the other part of the basin, the merging weight varies between 0.2 and 0.4. Unlike the runoff-based merging weights, all the three satellite rainfall products have fairly similar range of weight factors (between 0.2 and 0.4) over most part of the basin (Fig. 4, bottom). This is because the rainfall first accounts for the soil moisture storage in the hydrologic process for unsaturated soils. Thus, regardless of the magnitude of the rainfall rate, the soil moisture distribution remains the same and results in similar weight factors across the basin.

Figure 5 shows the performance of merged satellite rainfall product for simulation of streamflow at the three gauge stations. Accordingly, the soil moisture–based merged satellite rainfall product (M_SM) underestimated the streamflow in most cases. It appears that the merged satellite rainfall product obtained by leveraging only soil moisture error simulates only the low-flow regime well. Closer inspection indicated that the soil moisture–based merged product failed to capture the peak flows (Fig. 5). This revealed an inherent weakness of a merging concept that leverages only soil moisture predictability. For example, if all products yield saturation of soil, then the soil moisture error will be the same. Consequently, this will result in similar weight factors, despite different rainfall estimation errors of individual products.

When we observe the performance of merging based on runoff predictability, a different picture is revealed. The runoff-based merged product (M_ROF) captures the peak flows and reflects the seasonal flow pattern remarkably better than soil moisture–based merging or individual satellite products. In terms of both the correlation coefficient and scalar performance measures, this merged satellite rainfall product yields the highest performance in predicting streamflow during the validation period (Table 1 and Fig. 6). The mean and standard deviation of the runoff-based merged product is apparently very similar with the observed streamflow in six gauge stations. Runoff is basically unbounded flux so that it can be more dictated by the spatial and temporal

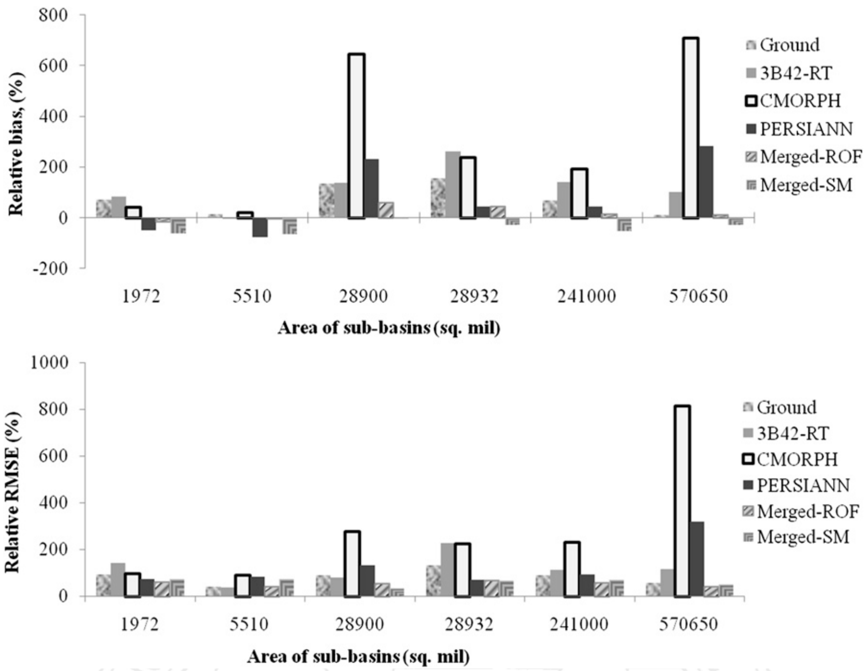

FIG. 7. The histogram of (top) relative bias and (bottom) RMSE of streamflow vs subbasin area (name of subbasin as per Table 1).

variability of the rainfall in the basin. Hence, the runoff-based merged rainfall product has produced a more accurate streamflow simulation. Unfortunately, the CMORPH shows a significant variation from the observed both in mean and standard deviation (Fig. 6). The nature of underestimation of streamflow for the soil moisture–based merged product is also reflected in Fig. 6 because the soil moisture is bounded by the maximum moisture storage capacity and thickness of soil layer. In all cases, the mean and standard deviation of streamflow

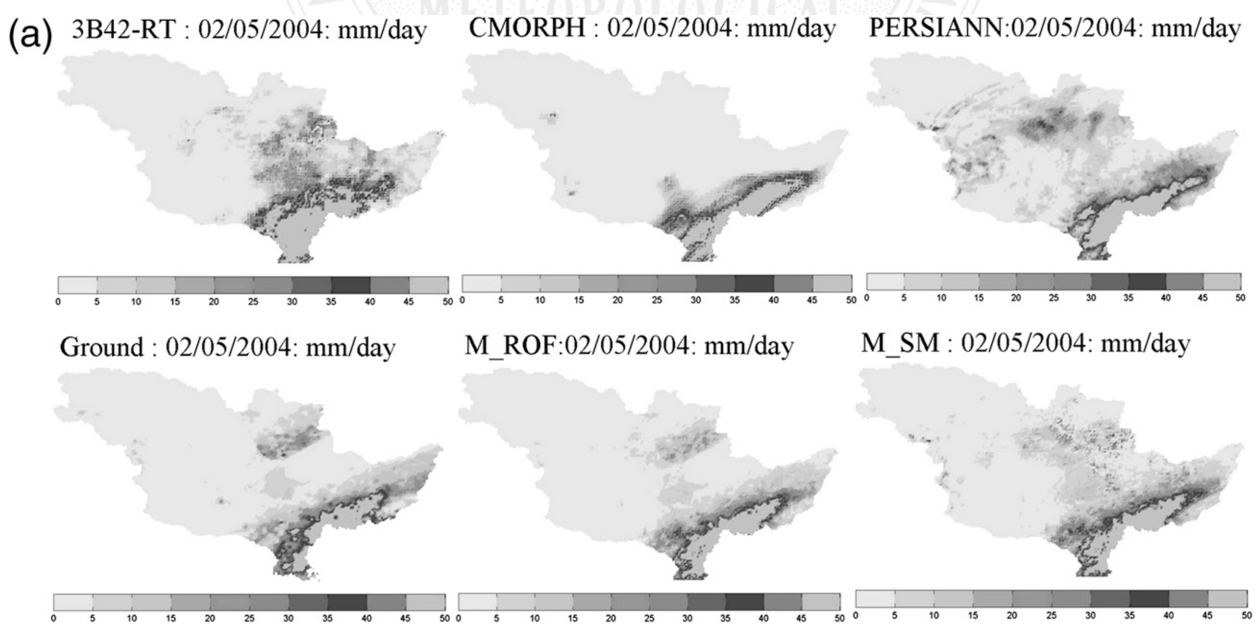

FIG. 8. Qualitative comparison of rainfall pattern and distribution among the three satellite rainfall products (3B42-RT, CMORPH, and PERSIANN-CCS), ground observation, M_SM, and M_ROF for randomly selected 3 days during validation period.

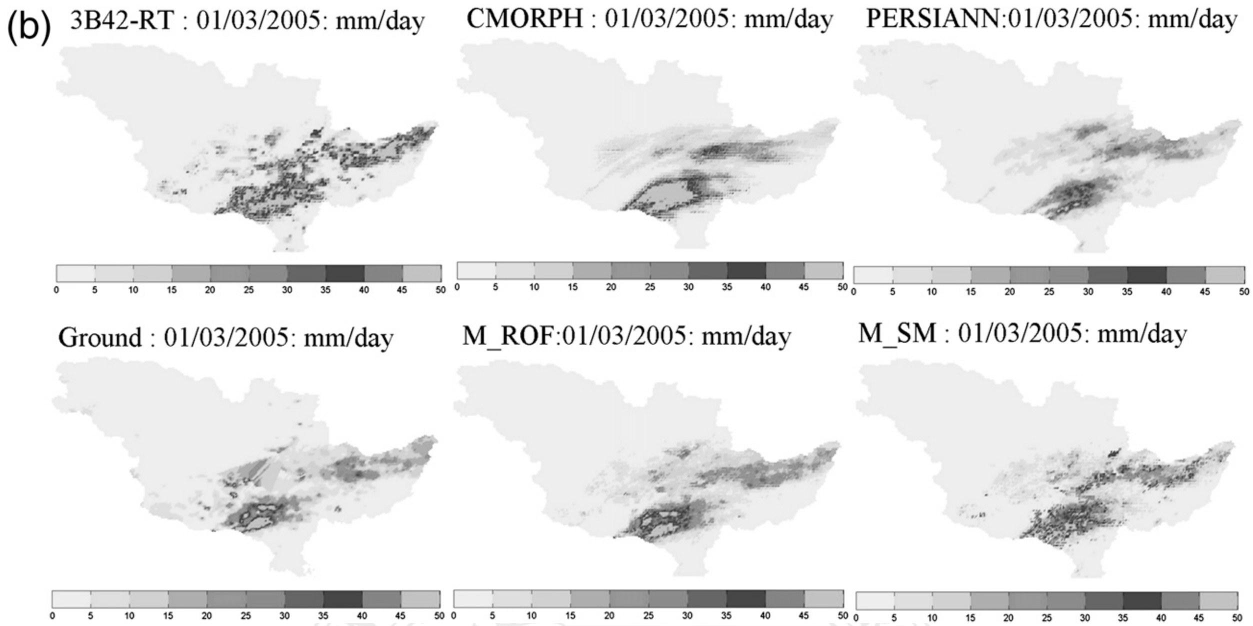

FIG. 8. (*Continued*)

simulated from the soil moisture merged product is less than the observed flow. In Fig. 7, the CMORPH product yielded high positive streamflow bias for the Missouri River basin at Herman and for the Canadian River at Calvin. These basins are mainly characterized by semiarid regions (Fig. 2). In semiarid area, because the actual average soil moisture content is below saturation, the actual runoff generated was considerably less (by the infiltration-excess mechanism). Hence, a positive streamflow simulation bias is not unexpected using rainfall products with high overestimation.

Qualitative rainfall pattern, distribution, and magnitude of merged satellite rainfall products are compared with individual satellite products and ground observation data for randomly selected dates from the validation period. As is shown in Fig. 8, the merged product's

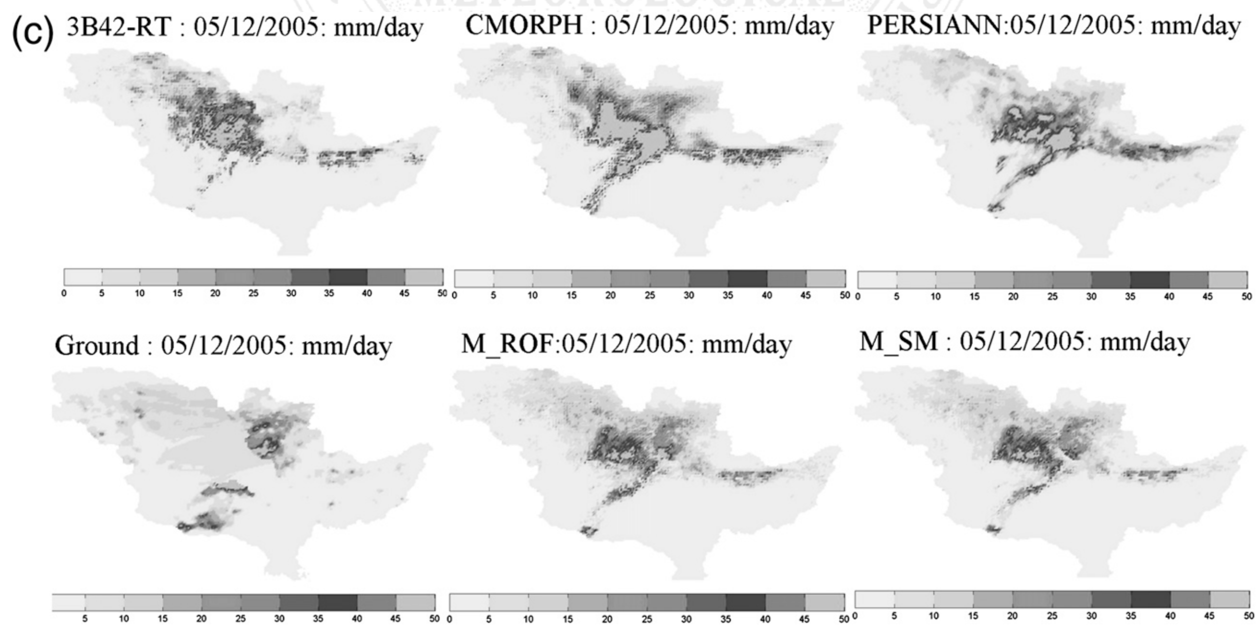

FIG. 8. (*Continued*)

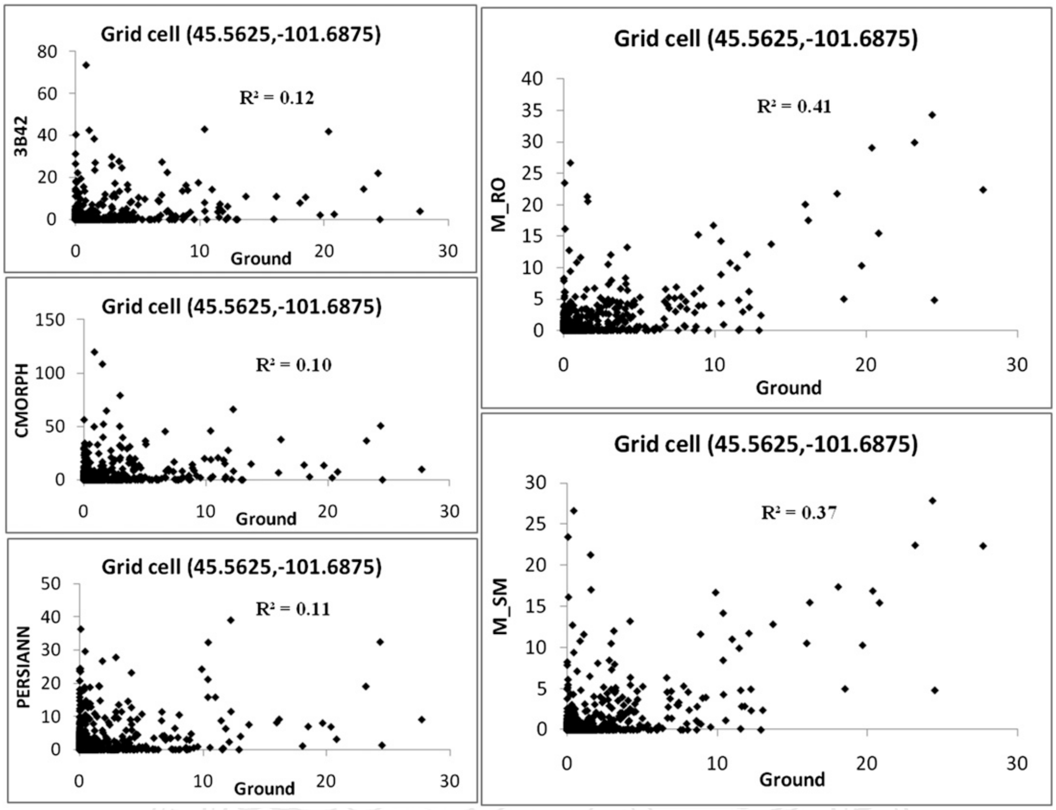

FIG. 9. Scatterplots of ground observation vs satellite rainfall data at a particular grid cell. It shows the improvement of correlation coefficients of the merged satellite products for the period of 2004–05.

performance is by far the closest to that of the GV data. Figure 9 also shows the scatterplot of satellite versus GV daily rainfall for a particular grid cell within the Mississippi basin during the study period. From the graph, the correlation is seen to improve for both runoff-based and soil moisture–based merged satellite rainfall products.

The performance of rainfall product in simulating the streamflow was also assessed using relative bias, root-mean-square error (RMSE), correlation coefficient, and Nash–Sutcliff efficiency as shown in Table 1. The relative bias for the merged satellite product was moderately acceptable in comparison with the other products. For the worst case, the runoff-based merged product shows 44% and 59% of positive relative bias for the Wabash and Canadian Rivers, respectively. This means that it overpredicted the mean streamflow by 44% and 59% at these two streamflow gauging stations. For the other stations, it performs considerably better. On the other hand, the soil moisture–based merged product underestimated the mean flow by 62% and 66% for the Ouachita and French Broader Rivers, respectively. The correlation and Nash–Sutcliff efficiency prove the better accuracy of the merged product than individual satellite products.

5. Discussion

As a preliminary analysis, leveraging a priori hydrologic predictability, like runoff and soil moisture, for merging satellite products seems to yield clear benefits for predicting streamflow in a macroscale hydrologic model. This is an important and promising finding for hydrologic modeling applications using satellite precipitation products. Because of the differences in performance among various satellite rainfall products, it makes more sense to optimize performance by merging them accordingly to their spatially (and temporally) varying individual predictability. Such a gridbox by gridbox merging concept should be advocated for hydrologic prediction.

Because the merging coefficients vary spatially, the merged rainfall product may not always be smooth like a real rainfall pattern. Thus, spatial smoothing techniques need to be devised to get the real representation of rainfall pattern. In our proposed merging methodology, the sum of the weight factor is also constrained to one for each grid cell. This can be a major limitation under specific circumstances. For example, if all the three satellite products overestimate or underestimate the rainfall value at the same time over the same grid box, then the merged satellite will also do likewise. Application of unconstrained optimization may thus be able to overcome this limitation of the "unbiased estimator" weight factor merging approach.

Finally, the result of this particular study also suggests that further exploration into the merging concept with respect to climate and landform features may have great significance in developing globally applicable rules for merging rainfall products for ungauged basins. Because in situ GV data are likely to be unavailable for most river basins around the world, using climate and landform features as a proxy for the relative weight for hydrologic predictability of an individual satellite product may have merit. The result shown in Fig. 4 also assures the possibility of transferring the merging weights from gauged to ungauged basins that have similar landform feature and climate characteristic. A similar approach reported by Tang and Hossain (2011) has revealed that certain error metrics for satellite rainfall bear similarities across different continental landmasses within the same Koppen climate class. Abdulla and Lettenmaier (1997) have reported work on the transfer of model parameters for large river basins (ungauged) for the VIC model. They found that simulations based on the regional regression transfer scheme performed significantly superior to parameter interpolations. Hence, it is plausible that streamflow predictability of satellite rainfall products may exhibit similar climate-centric behavior and transferability at ungauged river basins. Work is currently underway to explore some of the above open issues, and we hope to report our further explorations in the near future.

Acknowledgments. This work was supported by NASA New Investigator Program Grant NNX08AR32G. The first author was also supported partially by the Center for the Management, Utilization and Protection of Water Resources, Tennessee Technological University. The authors gratefully acknowledge the help received from Dr. Andrew Wood and various members of the University of Washington Land Surface Hydrology group in preparation of datasets and model runs for the VIC hydrologic model.

REFERENCES

Abdulla, F. A., and D. P. Lettenmaier, 1997: Development of regional parameter estimation equations for a macroscale hydrologic model. *J. Hydrol.,* **197,** 230–257.

Bowling, L. C., J. W. Pomeroy, and D. P. Lettenmaier, 2004: Parameterization of blowing snow sublimation in a macroscale hydrology model. *J. Hydrometeor.,* **5,** 745–762.

Crow, W. T., and J. D. Bolten, 2007: Estimating precipitation errors using spaceborne surface soil moisture retrievals. *Geophys. Res. Lett.,* **34,** L08403, doi:10.1029/2007GL029450.

Gebremichael, M., W. F. Krajewski, M. Morrissey, D. Langerud, G. J. Huffman, and R. Adler, 2003: Error uncertainty analysis of GPCP monthly rainfall products: A data-based simulation study. *J. Appl. Meteor.,* **42,** 1837–1848.

Hong, Y., K. Hsu, S. Sorooshian, and X. Gao, 2004: Precipitation estimation from remotely sensed imagery using an artificial neural network cloud classification system. *J. Appl. Meteor.,* **43,** 1834–1853.

——, ——, H. Moradkhani, and S. Sorooshian, 2006: Uncertainty quantification of satellite precipitation estimation and Monte Carlo assessment of the error propagation into hydrologic response. *Water Resour. Res.,* **42,** W08421, doi:10.1029/2005WR004398.

Hossain, F., and G. J. Huffman, 2008: Investigating error metrics for satellite rainfall at hydrologically relevant scales. *J. Hydrometeor.,* **9,** 563–575.

Hou, A., G. S. Jackson, C. Kummerow, and C. M. Shepherd, 2008: Global precipitation measurement. *Precipitation: Advances in Measurement, Estimation, and Prediction,* S. Michaelides, Ed., Springer, 1–39.

Hsu, K., A. Behrangi, B. Imam, and S. Sorooshian, 2010: Extreme precipitation estimation using satellite-based PERSIANN-CCS algorithm. *Satellite Rainfall Applications for Surface Hydrology,* M. Gebremichael and F. Hossain, Eds., Springer, 3–22.

Huffman, G. J., R. F. Adler, B. Rudolf, U. Schneider, and P. R. Keehn, 1995: Global precipitation estimates based on a technique for combining satellite-based estimates, rain gauge analysis, and NWP model precipitation information. *J. Climate,* **8,** 1284–1295.

——, and Coauthors, 1997: The Global Precipitation Climatology Project (GPCP) combined precipitation dataset. *Bull. Amer. Meteor. Soc.,* **78,** 5–20. AU7

——, R. F. Adler, M. M. Morrissey, D. T. Bolvin, S. Curtis, R. Joyce, B. McGavock, and J. Susskind, 2001: Global precipitation at one-degree daily resolution from multisatellite observations. *J. Hydrometeor.,* **2,** 36–50.

——, and Coauthors, 2007: The TRMM Multisatellite Precipitation Analysis: Quasi-global, multiyear, combined-sensor precipitation estimates at fine scales. *J. Hydrometeor.,* **8,** 38–55.

——, R. F. Adler, D. T. Bolvin, and E. J. Nelkin, 2010: The TRMM Multisatellite Precipitation Analysis (TMPA). *Satellite Rainfall Applications for Surface Hydrology,* M. Gebremichael and F. Hossain, Eds., Springer, 3–22.

Joyce, R., J. E. Janowiak, P. A. Arkin, and P. Xie, 2004: CMORPH: A method that produces global precipitation estimates from passive microwave and infrared data at high spatial and temporal resolution. *J. Hydrometeor.,* **5,** 487–503.

Kidd, C., D. R. Kniveton, M. C. Todd, and T. J. Bellerby, 2003: Satellite rainfall estimation using combined passive microwave and infrared algorithms. *J. Hydrometeor.,* **4,** 1088–1104.

Liang, X., 1994: A two-layer variable infiltration capacity land surface representation for general circulation models. Ph.D. thesis, University of Washington, Seattle, XX pp. AU8

——, and Z. Xie, 2001: A new surface runoff parameterization with subgrid-scale soil heterogeneity for land surface models. *Adv. Water Resour.,* **24** (9–10), 1173–1193.

——, D. P. Lettenmaier, E. F. Wood, and S. J. Burges, 1994: A simple hydrologically based model of land surface water and energy fluxes for GCMs. *J. Geophys. Res.,* **99** (D7), 14 415–14 428.

——, ——, and —— , 1996: One-dimensional statistical dynamic representation of subgrid spatial variability of precipitation in the two-layer variable infiltration capacity model. *J. Geophys. Res.,* **101** (D16), 21 403–21 422.

——, E. F. Wood, and D. P. Lettenmaier, 1999: Modeling ground heat flux in land surface parameterization schemes. *J. Geophys. Res.,* **104** (D8), 9581–9600.

Lohmann, D., E. Raschke, B. Nijssen, and D. P. Lettenmaier, 1998: Regional scale hydrology: I. Formulation of the VIC-2L model coupled to a routing model. *Hydrol. Sci. J.,* **43,** 131–141.

Nijssen, B., and D. P. Lettenmaier, 2004: Effect of precipitation sampling error on simulated hydrological fluxes and states: Anticipating the Global Precipitation Measurement satellites. *J. Geophys. Res.,* **109,** D02103, doi:10.1029/2003JD003497.

Tang, L., and F. Hossain, 2011: Investigating the similarity of satellite rainfall error metrics as a function of Koppen climate classification. *Atmos. Res.,* in press. AU9

Xie, P., and P. A. Arkin, 1996: Analysis of global monthly precipitation using gauge observations, satellite estimates, and numerical model predictions. *J. Climate,* **9,** 840–858.