Making Satellite Precipitation Data Work for the Developing World

ABEBE GEBREGIORGIS AND FAISAL HOSSAIN
Department of Civil and Environmental Engineering, University of Washington, Seattle, USA

Abstract—In an era of declining ground-based networks for measurement of precipitation, satellite precipitation data, that is now routinely available in increasing frequency and spatial coverage, represents an interesting paradox. Specifically, effective assessment frameworks and error metrics for satellite precipitation data must be developed for advancing the utility of satellite data for global applications. While there seems to be a concerted effort by the community to evaluate satellite precipitation data, there does not seem to be similar efforts to resolve the paradoxical issue of balancing the need for global uncertainty information and the stark lack of global GV datasets for doing so. In this article, we present one practical approach to estimating satellite precipitation uncertainty that is not dependent on the notion of ground validation (GV) data. By using input that is more readily available around the globe (i.e., satellite data and geophysical features of terrain, climate and seasons), the approach can potentially advance applications as it allows a coherent way to merge available satellite precipitation data products to a more superior state, particularly for hydrologic applications. We provide an assessment of how the approach works in various regions of the developing world as a way to encourage the community to further the development of such ideas and provide end-users with a practical decision-making tool.

1. INTRODUCTION

The traditional approach to measuring precipitation by placing a probe on the ground will likely never be adequate or affordable in most parts of the world. Fortunately, satellites today provide a continuous global bird's-eye view (above ground) at any given location. Emerging high resolution and multi-sensor satellite-based precipitation estimates, such as those anticipated from the Global Precipitation Measurement (GPM) [1], [2] satellites, now hold great promise, especially over parts of the world where surface observation networks are sparse, declining or non-existent. Among applications, most aspects of a hydrological study and its findings have a clear benefit in terms of societal value. Whether it is floods, droughts, climate change, ecosystem impacts, land use management or agriculture, the importance of knowing the hydrological mechanisms for better prediction, forecasting and decision making has always been obvious [3]. Thus, satellite precipitation data, which is a key input to hydrologic models, is a benefactor of many hydrologic applications over regions where it is already difficult to obtain data from conventional ground networks. These regions are typically the developing world faced with challenging financial resources. Hereafter, we shall interchangeably use the term 'rainfall' with 'precipitation' to signify the same.

However, the usefulness of such precipitation products for hydrological applications depends on their error characteristics and how intelligently we can harness the implications of uncertainty for surface hydrology [4]–[12]. The need to take advantage of uncertainty represents a unique paradox when it comes to making satellite precipitation data 'work' for the developing world. On one hand, the decline of the few existing global ground based measurement networks for precipitation means that ground validation data from in-situ measurements are mostly absent in most parts of the world for estimating the uncertainty. On the other hand, satellite precipitation data is most useful where there exists little to none conventional measurements. As a result, the conventional method of comparing satellite estimate against in-situ records to 'harness' the uncertainty is unrealistic and impractical [9], [12]. As a community tasked with the job of making satellite precipitation 'work' for applications in most parts of the world, there is now a need think outside the box [13]–[16].

2. THE KEY HURDLE TO MAKING SATELLITE PRECIPITATION DATA WORK

Obviously the existing high resolution satellite rainfall estimates have a significant role to play in filling this

Digital Object Identifier 10.1109/MGRS.2014.2317561
Date of publication: 24 June 2014

widening gap of data-shortage at operational timescales for hydrologic applications. Current pre-GPM satellite products provide quasi-global coverage and acceptable spatial (~25 km) and temporal (~3 hour) sampling. To 'beat' this estimation uncertainty, which persists in large amounts, we are now witnessing an explosion of various multi-sensor satellite precipitation products, each based on a combination of competing concepts, satellite observations and algorithms. There are at least ten such multi-sensor products on the 'market' (i.e., ScaMPR [17], 3B41RT [18], 3B42V6 [19], 3B42RT [19], CMORPH [20], [21], QMORPH [20], PERSIANN-CCS [22], PERSIANN-REFAME [23], NRL-Blended [24], GsMAP [25], [26]). Most of these products essentially use similar inputs from a consistent constellation of sensors.

The key difference among the products available in the 'market' lies in their algorithm to infer satellite precipitation from the measured electromagnetic properties. For example, 3B42RT is one of the products provided by the TRMM Multi-satellite Precipitation Analysis (TMPA) algorithm at spatial resolution of 0.25×0.25 degree and temporal sampling of 3 hours [18]. It is a combination of Passive Microwave (PMW) and PMW-calibrated Infrared (IR) data in manner that MW precipitation estimate is considered where it is available, and the IR estimate is used to fill the gap (in space and time) elsewhere. CMORPH is a high-resolution satellite rainfall product known as the Climate Prediction Center (CPC) using MORPHing technique [20]. This product is also available at a spatial resolution of 0.25° degree and temporal resolution of 3 hours. This product uses rainfall estimates from MW and the rainfall patterns are propagated in space and time over via motion vectors obtained in fact from IR data to bridge the MW sampling gaps [20]. PERSIANN (Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks) is based on extraction of cloud features from IR imagery of geostationary satellite to derive rainfall estimates at finer scale ($0.04^\circ \times 0.04^\circ$) and hourly temporal resolution using MW data as a guide for the artificial neural network [23]. Most satellite precipitation products essentially use the same suite of PMW and

**CALLOUT PLACEHOLDER
CALLOUT PLACEHOLDER
CALLOUT PLACEHOLDER
CALLOUT PLACEHOLDER
CALLOUT PLACEHOLDER
CALLOUT PLACEHOLDER
CALLOUT PLACEHOLDER
CALLOUT PLACEHOLDER**

IR sensors, such as Advanced microwave sounding unit (AMSU), TRMM Microwave Imager (TMI), Special Sensor Microwave/Imager (SSM/I), Advanced Microwave Scanning Radiometer for Earth Observing System (AMSR-E), Geostationary Operational Environmental Satellite (GOES) etc. Such a plethora of products without a proper user manual for the layman leads the novice user in the developing world to wonder, *'which one do I use?'* and *'why do we have so many out there?'*

The satellite precipitation product development community has rightfully progressed in the direction of embracing multiple sensor data and blending various algorithms to push the envelope of estimation uncertainty reduction. Although the exact details are not yet known due to the very recent launch of GPM precipitation radar (Feb. 24, 2014), the nature of the combined algorithm that we shall have available during the GPM era will likely involve the following components: 1) combination of both Infrared (IR) and Passive Microwave (PMW) sensor data calibrated to GPM radar observables [18]; 2) space-time downscaling [22]; 3) artificial neural networks for cloud patch detection [27]; and 4) data assimilation (filtering) approach to synergize the complementary sampling strengths of IR and PMW scans [21]. In this effort to 'combine' different algorithms and products, one question that has been left out, is, *'for the end-user, is it possible to reduce estimation uncertainty by leveraging the individual performance of each product and merging them accordingly?'*

CALLOUT PLACEHOLDER
CALLOUT PLACEHOLDER
CALLOUT PLACEHOLDER
CALLOUT PLACEHOLDER
CALLOUT PLACEHOLDER
CALLOUT PLACEHOLDER
CALLOUT PLACEHOLDER
CALLOUT PLACEHOLDER

We believe that the accuracy and appeal of satellite rainfall products can be further improved for the practical user interested in applications by optimal merging of the available products. The assumption based on which we make this claim is that *the inherent (diagnostic) uncertainty associated with each individual product is a function of geophysical features and is insightful for merging through a relative weighting scheme in the prognostic mode (i.e., forward in time)* [7]–[12]. Indeed, such a priori hydrologic predictability based merging is already proving effective [10], [11]. Recently, we investigated satellite rainfall uncertainty and its propagation through a hydrologic model by tracing the source of runoff and soil moisture errors as function of rainfall error (bias) components over the United States (US) [7], [8].

To explore the feasibility of such a merging concept (that linearly weighs the inverse of error variance) and the validity of the assumption, the Variable Infiltration Capacity (VIC) macroscale hydrologic model [28] was set up over the entire Mississippi River Basin (MRB) and Northwest Basins (NWB) (Fig. 1(a)) for three widely used, near-real time, and multi-sensor satellite rainfall products (3B42RT, CMORPH and PERSIANN). These products were assessed of their a priori ability to predict the surface hydrologic state and fluxes such as runoff, soil moisture and stream flow (Fig. 1(b) and (c)).

Based on the a priori hydrologic predictability, a merging scheme was developed for the products using the inverse of simulation error variance in runoff and soil moisture [7]–[12]. Our investigations have shown that a product merged according to a priori simulation error in either soil moisture or runoff was consistently more superior (during an independent validation/prognostic period) than the original products for predicting stream flow forward in time (Fig. 1(b) and (c)). Products "unified" in this way had similar rainfall patterns as the ground validation data (Fig. 1(d)) and performed far better in stream flow simulation than a merging scheme based purely on precipitation measurement uncertainty (i.e., no hydrological conditioning).

However, such a method of a priori hydrologic predictability-based merging for the practical user only works where a model can be set up with quality controlled in-situ hydrologic data. Therefore, this is not truly a global option for users around the world. The more pressing and global issue which we need to address now is '*how can such a merging scheme be implemented (validated/calibrated) in un-gauged basins around the globe where ground data to test the quality of satellite data is not available?*' It is obvious from Fig. 1 that each satellite product has a unique response to simulation of stream flow (which is key to applications). The performance of these products also seems complimentary as well as a complex function of the underlying surface physical features (such as terrain, vegetation, elevation, storm regime, and climate type). We can rephrase the previously stated practical question as a science question as follows, *"What can terrestrial features tell us about the property of satellite rainfall errors in different parts of the globe in order to make more practical use across the globe?"* For example, climate type can indicate the most frequent type of rainfall systems that will be remotely sensed, and topography information can indicate the likelihood of fog-rain-snow and orographic processes that are usually hard to estimate [29]–[31]. Since these geophysical features (topography, land use/land cover and climate) are easily available across the world, we should be able to estimate satellite precipitation uncertainty based on these readily (and freely) available features towards the weighted merging of satellite precipitation data for the user anywhere around the world.

3. A PRACTICAL APPROACH TO MAXIMIZING APPLICATION POTENTIAL

Our practical approach to making satellite precipitation data work for the developing world is based on the development of a globally-applicable regression error model approach to estimate rainfall uncertainties (error variance) in un-gauged basin from the readily available geophysical information. We selected globally four diverse regions around the world where topography, climate and landuse/landcover (LULC)

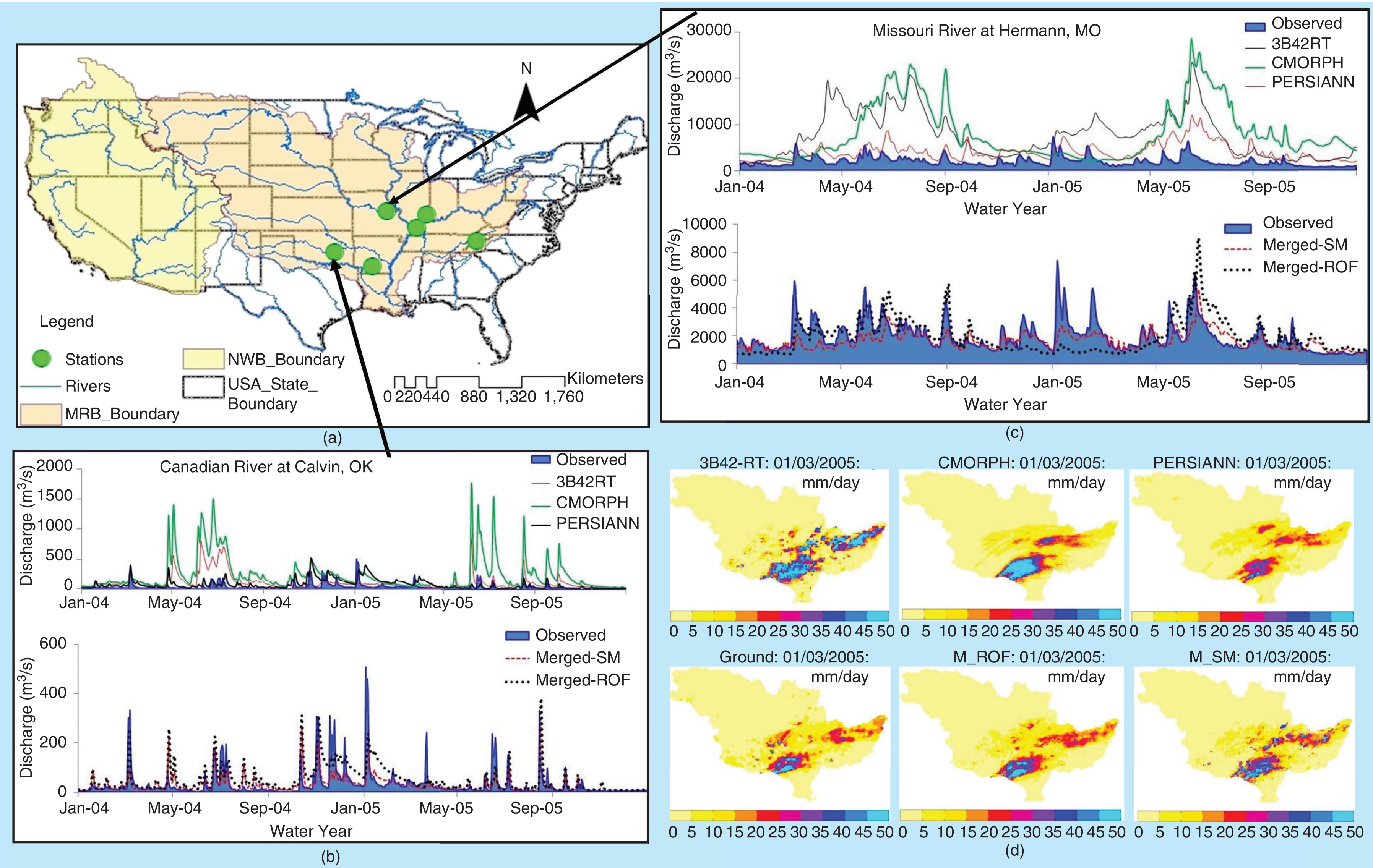


FIGURE 1. (a) Mississippi River Basin (MRB) and Northwest Basin (NWB) in USA including gauging stations where stream flow simulations were performed. (b) and (c) Simulated stream flow using three major satellite rainfall products (the top graphs on both panels) and the simulated stream flow using two merged products; runoff based and soil moisture based merged products (the bottom graphs on both panels). (d) Comparison of spatial rainfall pattern of original satellite rainfall products (top three) and the two merged products with ground truth data (bottom). *After Gebregiorgis and Hossain (2011).*

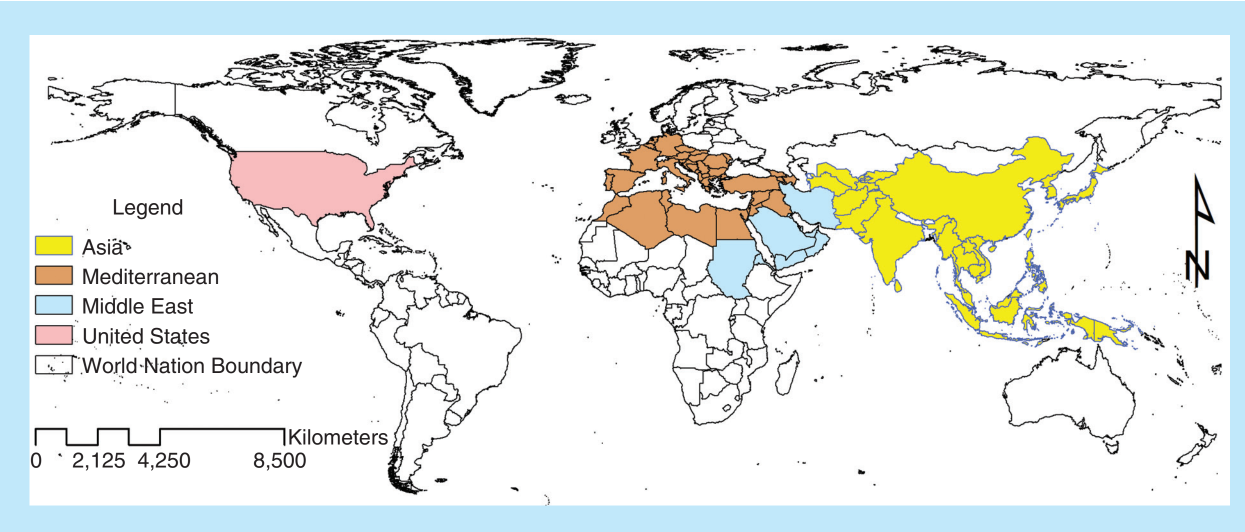


FIGURE 2. Globally selected study regions for developing and validating error variance regression model and satellite rainfall products merging scheme.

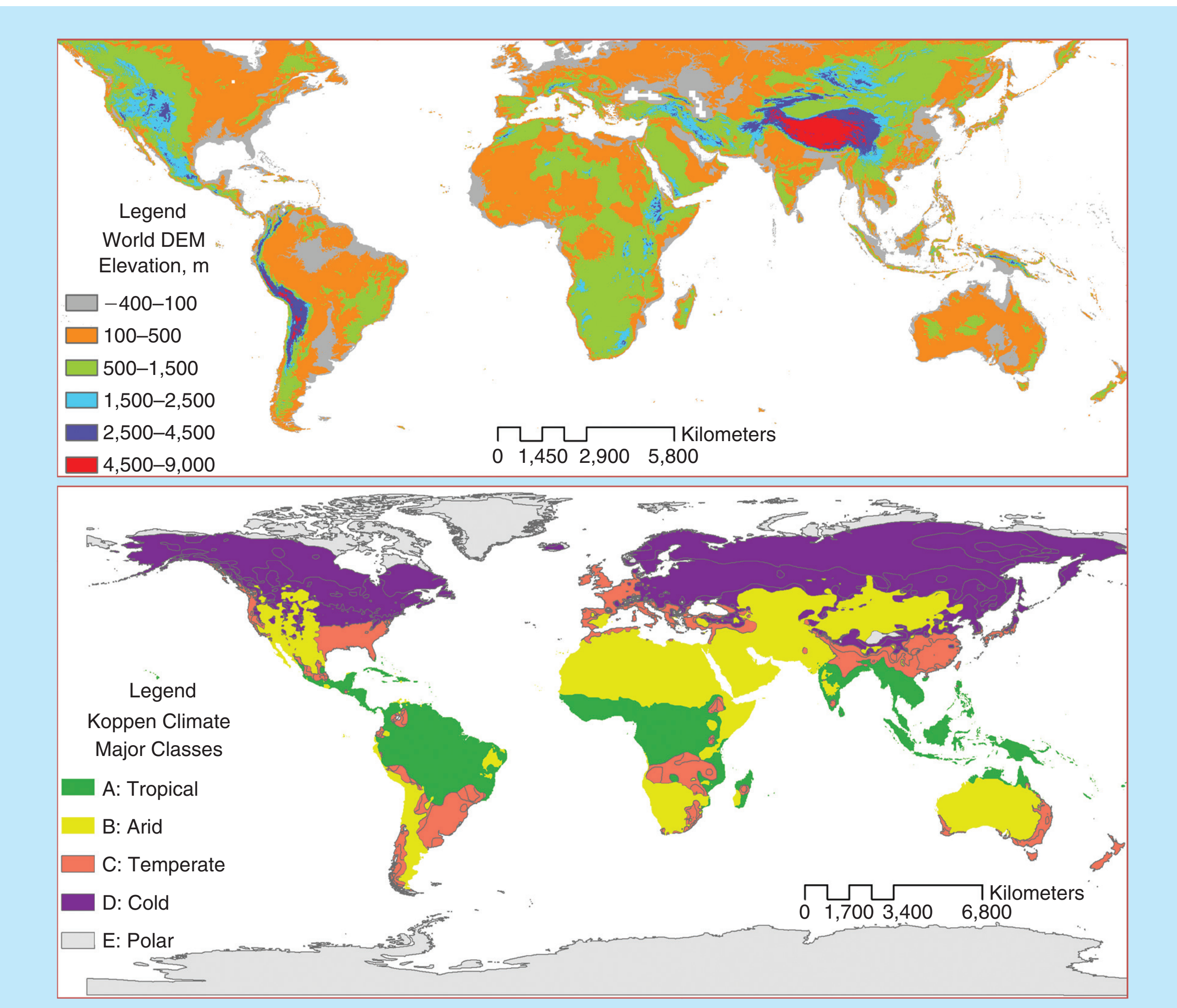


FIGURE 3. Topographic classes and Koppen climate types for global regions used in regression model for runoff error variance estimation.

varied. These regions comprised USA, Asia, Middle East, and Mediterranean regions (Fig. 2).

The contiguous United States (48 adjoining U.S. states, called CONUS) comprises a total area of 3,119,885 square miles (8,080,464 km^2), which is 1.58% of the total surface area of the Earth. This region comprises a diverse topography that ranges from 0–4500 m above sea level (a.s.l.). The highest elevation is the Rocky Mountains which are located in the west central part of CONUS. The major climates are arid (highland of west-central), temperate (south, east and west coast), and cold (northern part of the CONUS). Tropical and polar climates are not common in US due to the positioning of the states in terms of latitude (see Figure 2 for detail topography and climate features of the regions). The Monsoon Asia is the largest and most populous region which is located in the eastern and northern hemisphere. This region encompasses the most diverse region both in topography and climate type. All the topography and climate classes are found in this region. The world highest mountains (collectively called Himalayas) are located in this region including the Everest Mountain which is about 8500 m tall above sea level. All the six major climate types are also found in the region: tropical, arid, temperate, cold, and polar climate. The Mediterranean region encompasses the lands around the Mediterranean Sea. The topography of the region ranges from the lowest elevation region on land (The Dead Sea) -420 to 2600 m a.s.l. It includes arid, temperate, and cold types of climate. The Middle East is a region that roughly covers Western Asia region. The topography varies from -300–2700 m a.s.l and is dominantly characterized by arid climate type. To embrace the combination of all types of topographic and climate features, USA and Asia regions are selected to calibrate the error variance regression model; whereas, Mediterranean and Middle East regions are chosen to validate the performance of the model on independent area.

We also chose these regions based on the availability of reference (GV) data to calibrate and validate our method. Fig. 3 shows the variation in the readily available geophysical features of interest (topography and climate). The topography and climate are the two major governing factors considered to characterize satellite rainfall and runoff errors and implement the error variance regression model [8], [9], [12]. Three satellite rainfall products, namely 3B42RT, CMORPH, and PERSIANN-CCS, were used to develop the framework of error variance regression model over the selected study regions. These satellite rainfall products are widely used, available on near-real time, and are considered fairly high resolution products for satellite-based hydrologic application. Both 3B42RT and CMORPH data is available at 0.25 degree spatial and 3 hourly temporal resolution [19], [20]. The global PERSIANN-CCS data exists at 0.04 degree spatial and daily time scale. This data is then remapped to the consistent scale of 0.25 degree to allow inter-comparisons among and merge with the other products.

Fig. 4 summarizes our 'practical' approach for making satellite data work for the developing world through implementing runoff error variance model and then merging of the available products. The selected regions were delineated based on topography features (Fig. 3) to develop the regression model framework. Each region was classified according to the dominant Köppen climate type. Moreover, the satellite rainfall and runoff error variance (the independent and dependent variables, respectively) were segregated based on seasons to account for the periodic variation of meteorological and hydrological events. After the region classification and data segregation were completed, the model estimators (α and β; see next paragraph) were obtained using the least square method through minimization of the sum of runoff error variance square. At this point, we want to remind the reader that the runoff simulated from the ground rainfall data was considered as synthetic truth in the computation of error variance for the satellite products.

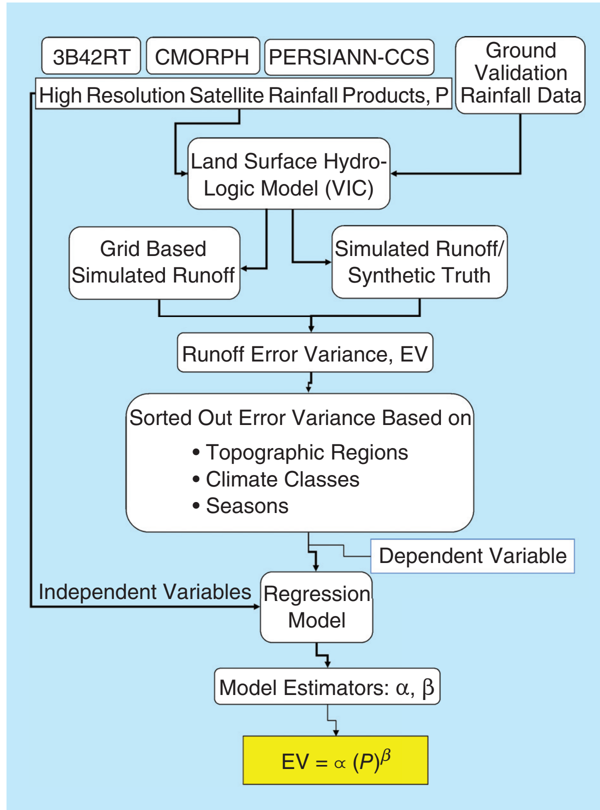


FIGURE 4. Flow chart that demonstrates the development of regression equation based on geophysical features (topographic, climate, and season) to estimate the runoff error variance for global regions.

CALLOUT PLACEHOLDER
CALLOUT PLACEHOLDER
CALLOUT PLACEHOLDER
CALLOUT PLACEHOLDER
CALLOUT PLACEHOLDER
CALLOUT PLACEHOLDER
CALLOUT PLACEHOLDER
CALLOUT PLACEHOLDER

The runoff error variance equation is generally expressed as power function as: $EV = \alpha(RR)^{\beta}$ where the parameters α and β serve as simple scaling factor and measure of rate of growth or decay, respectively. The error variance is expressed as a function of satellite rainfall rate (RR) explicitly and topography, climate, and season implicitly. The parameters, α and β, are calibrated and validated on the selected regions for each geophysical feature combination. This allows us to transfer the error information to ungauged regions for the purpose of merging.

After estimation of runoff error variance, the next most important task is the merging of the available satellite rainfall products (i.e., 3B42RT, CMORPH, and PERSIANN-CCS). These products have their own specific strengths and weaknesses in retrieval technique, accuracy, resolution, availability, coverage, and quality control. Our hypothesis is, by implementing a priori performance based merging of precipitation data obtained from different sources, we can improve the accuracy of precipitation estimates. The a priori performance analysis helps us to exploit the complementary strengths of the products involved in the merging. Herein, the term complementary means that each product can have strengths in rainfall estimation that is unique to its algorithm at the expense of other weaknesses such that, when merged, only the strengths are combined. For example, one product may have superior rain and no-rain discrimination property while suffering from high bias. On the other hand, another product may have poor rain discrimination skill for heavy rain systems but low bias when it estimates rain. Combining these two 'complementary' products should yield a product that has both good rainfall discrimination and low bias. The merging procedure linearly weighs the inverse of error variance as shown in the next equation.

$$\mathrm{RR}_{\mathrm{PBMP}}^{l,t} = \frac{\mathrm{EV}_{3\mathrm{B}42}^{l,s}}{\sum_{i=1}^{s} \mathrm{EV}_i^{l,s}} * \mathrm{RR}_{3\mathrm{B}42}^{l,t} + \frac{\mathrm{EV}_{\mathrm{CMO}}^{l,s}}{\sum_{i=1}^{s} \mathrm{EV}_i^{l,s}} * \mathrm{RR}_{\mathrm{CMO}}^{l,t} + \frac{\mathrm{EV}_{\mathrm{PER}}^{l,s}}{\sum_{i=1}^{s} \mathrm{EV}_i^{l,s}} * \mathrm{RR}_{\mathrm{PER}}^{l,t},$$

where RR: rainfall rate in mm/day; EV: runoff error variance $(\mathrm{mm/day})^2$; PBMP: performance based merged product; 3B42: 3B42RT rainfall product; CMO: CMORPH; PER: PERSIANN-CCS; l: latitude-longitude location, t: time at a day scale; s: seasons (1-winter, 2-spring; 3-summer, 4-fall).

4. ASSESSMENT OF THE APPROACH AT GLOBAL SCALES

The most widely used error metrics, e.g. [32]–[37], are employed to assess the performance of the merged satellite rainfall product. These include grid-box based error metrics such as Probability of Detection (POD), False Alarm Ratio (FAR), and Threat Score (TR) and Root Mean Square Error (RMSE). To assess the spatial accuracy of satellite rainfall estimates and characterize the performance of satellite rainfall data, grid-box dependent error metrics are more useful. They tell us how the spatial pattern of the rainfall event is captured across the region. On the other hand, the RMSE measures the average error magnitude by aggregating the errors between satellite rainfall estimates and reference data of various times into a single measure of predictive power. The RMSE implies how the temporal rainfall variation is accurately estimated.

4.1 SETTING UP OF A PROXY GROUND VALIDATION PRECIPITATION DATASETS

In order to obtain and evaluate the a prior predictability of satellite rainfall products, calibrate and validate the error variance model across the globe, and assess the accuracy of merged precipitation product, good quality of ground validation data are indispensable. As mentioned in section 3, one of the requirements in the selection of the study regions was the availability of good quality reference data. For USA, gridded ground observation rainfall [38] and NEXRAD-IV [39] data were used as validation data.

The gridded ground observation rainfall data is obtained from the University of Washington Surface Hydrology Group at the 0.125 degree daily scale. This data pertained to the contiguous United States (CONUS) and is derived from more than 7000 stations collected from the National Oceanic and Atmospheric Administration (NOAA) at an average density of one station per 700 km^2. The point data is gridded using synergraphic mapping system (SYMAP) interpolation algorithm [39]. NEXRAD-IV (Next-Generation Radar stage IV) data is operated by the National Weather Service (NWS) of NOAA. It is an estimate of doppler weather radars that have been adjusted based on gauge data from NOAA's highest accuracy precipitation stations. This data is available at 0.04 degree spatial and 1 hour temporal resolution.

Asian Precipitation—Highly-Resolved Observational Data Integration Towards Evaluation of Water Resources (APHRODITE's) project develops a daily gridded precipitation datasets from a dense observational network stations (up to 12,000 stations) for Asia (including Himalayas, south and southeast Asia) and Middle East regions [40]. For Mediterranean region, the gridded precipitation data is collected from European Climate Assessment & Dataset (ECAD). As a quality control (QC) measure, all the reference datasets are validated against other source of good quality precipitation datasets which include CPC-Unified gauged gridded data and 2A25 precipitation radar (PR) orbital data. The result of QC analysis shows that the validation datasets are consistent with 2A25 PR rainfall measurement [12].

4.2 HOW WELL DOES THE PRACTICAL APPROACH WORK?

We validated our approach independently by splitting our region with GV data into two regions: one for calibration (estimation of regression parameters) and the other for validating how well the regression equation worked when compared with error variance derived directly from GV data. Fig. 5 compares the spatial distribution of rainfall for the original and merged satellite precipitation products at global scale. The fundamental concept of the merging procedure

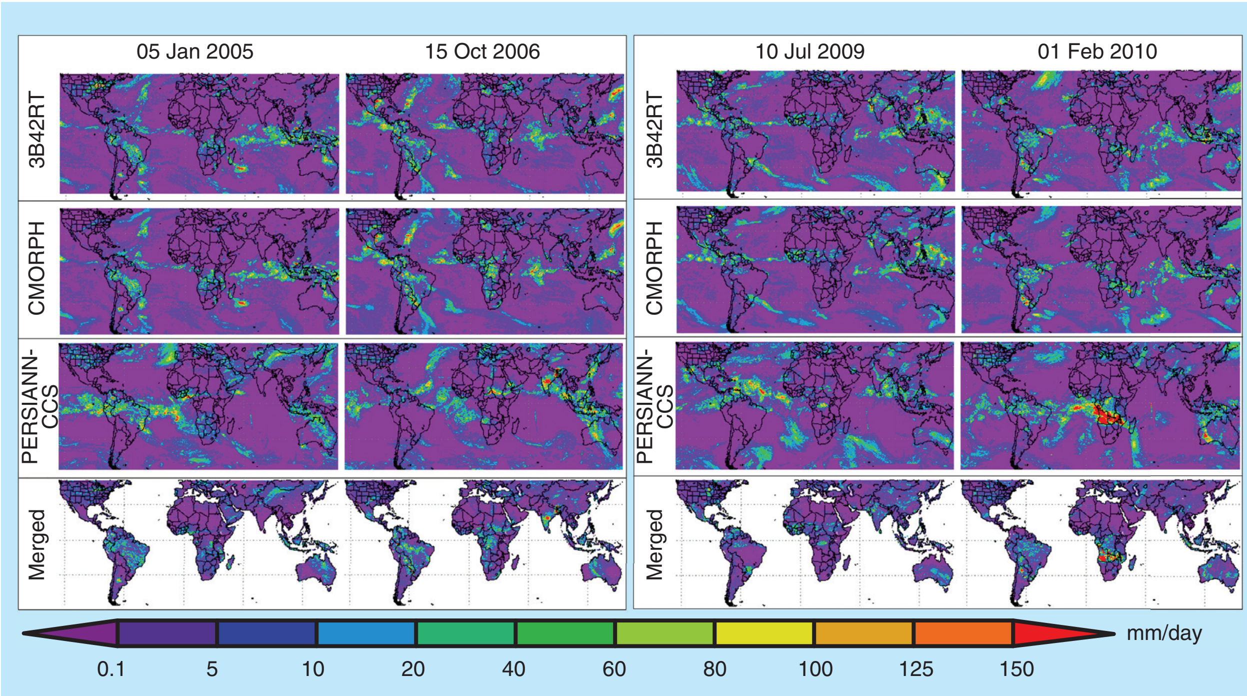


FIGURE 5. Comparison of Performance Based Merged Product (PBMP) and individual satellite rainfall products at 0.25 degree spatial and a day temporal resolution for randomly selected days.

is based on runoff error variance which is estimated from the regression model as discussed in section 3. The extent of the merged product is, therefore, limited to the land portion of the earth's surface. The merged product is now available at spatial resolution of 0.25 degree between 50° north and south latitude and temporal scale of a day for the period of 2003-2010. For the interested readers and due to size limitations, we have made publicly available only a subset of this merged dataset spanning May 2003 to July 2003 at http://iweb.tntech.edu/fhossain/papers/MergedPrecipDataSample.zip. However, the entire 8 years (2003-2010) merged data (8 GB in size) can be provided on request to any of the authors via ftp or media mail.

As seen in Fig. 5, the magnitude and spatial rainfall distribution pattern of the three satellite rainfall products are not consistently the same. Undeniably, the 3B42RT and CMORPH show a close similarity in all selected days. The PERSIANN-CCS has a different feature both in magnitude and spatial pattern than the other two products. Therefore, the question is how well does the merged product derived from the three satellite rainfall estimates capture the magnitude and spatial pattern of the ground truth data in selected test sites?

Fig. 6(a) shows the POD of the original and merged satellite rainfall products over the study regions. The POD signifies the percentage of rainfall events that are detected correctly. In all study regions and all seasons, the merged product exhibits high value of POD (almost greater than 0.6, except for summer season in Middle East region). This shows that in terms of the spatial accuracy, the merged product is the best estimates from the original products. High POD implies that the spatial distribution of the rainfall pattern is well spotted by the algorithm during the screening stage of the retrieval process. But it does not fully indicate the level of accuracy in estimation of the rainfall magnitude.

Fig. 6(b) demonstrates a false alarm categorical verification measure for rainfall forecast that is associated with no rain observed. The FAR represents the fraction of detected rainy grid cells that were found to be non-rainy. The merged product has the highest FAR next to PERSIANN-CCS product. As it is a combined signature of three satellite rainfall products, high FAR should be expected in the merged product. As seen from the result, most of the false signal within PERSIANN-CCS estimate is also inherent into the merged product. Like POD, FAR is also associated with the spatial accuracy but not with the accuracy of the estimated rainfall magnitude.

CALLOUT PLACEHOLDER CALLOUT PLACEHOLDER CALLOUT PLACEHOLDER CALLOUT PLACEHOLDER CALLOUT PLACEHOLDER CALLOUT PLACEHOLDER CALLOUT PLACEHOLDER CALLOUT PLACEHOLDER

The next verification measure of spatial accuracy is the Threat Score (TR), which represents the fraction of detected rain event that were detected correctly. TR is also called Critical Success Index (CSI) with an ideal value of one. The CSI is not affected by the number of non-event forecasts that verify a no-event forecast associated with no event observed. In case of large number of miss and false precipitation events, the CSI value is generally low. Fig 6(c)

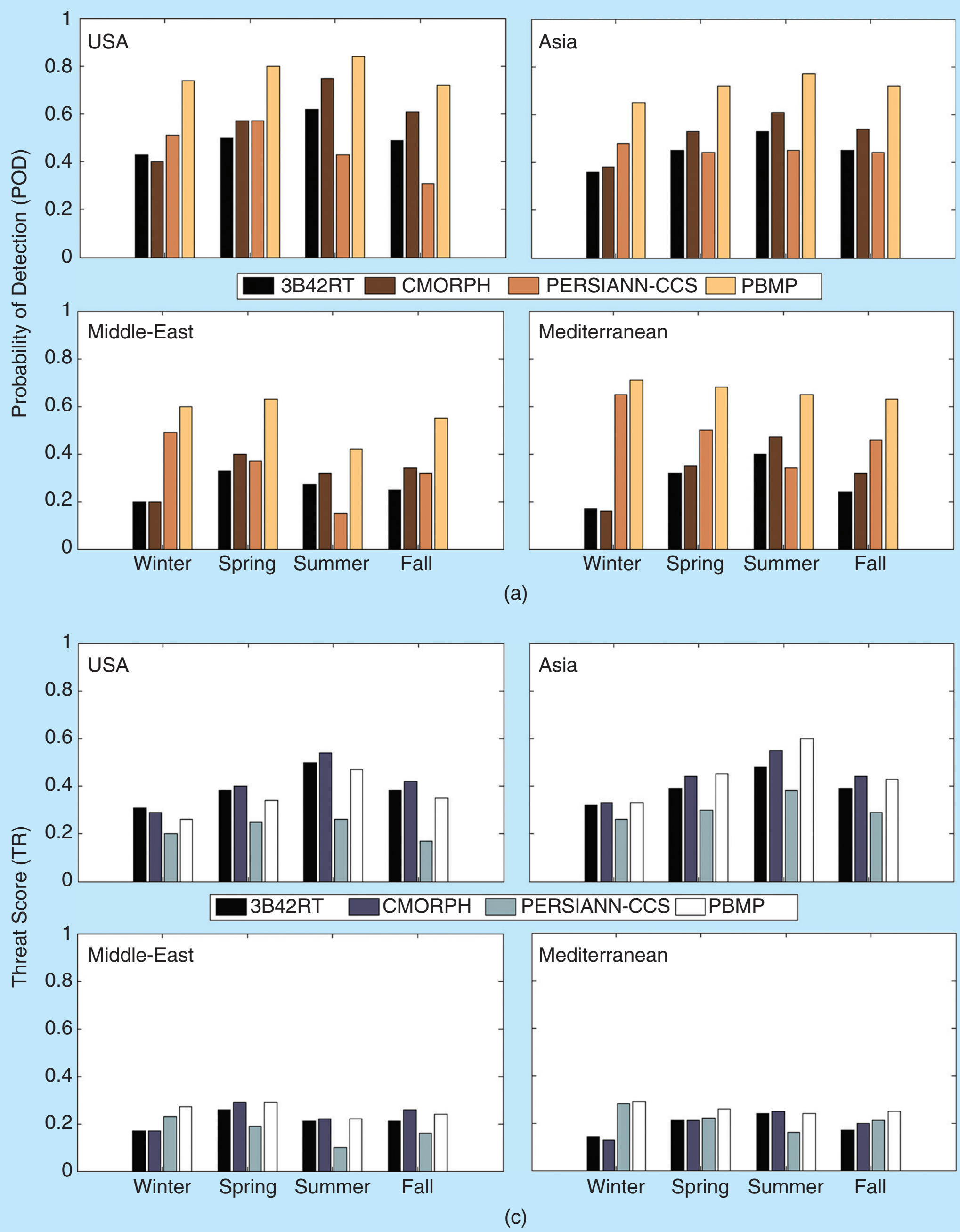
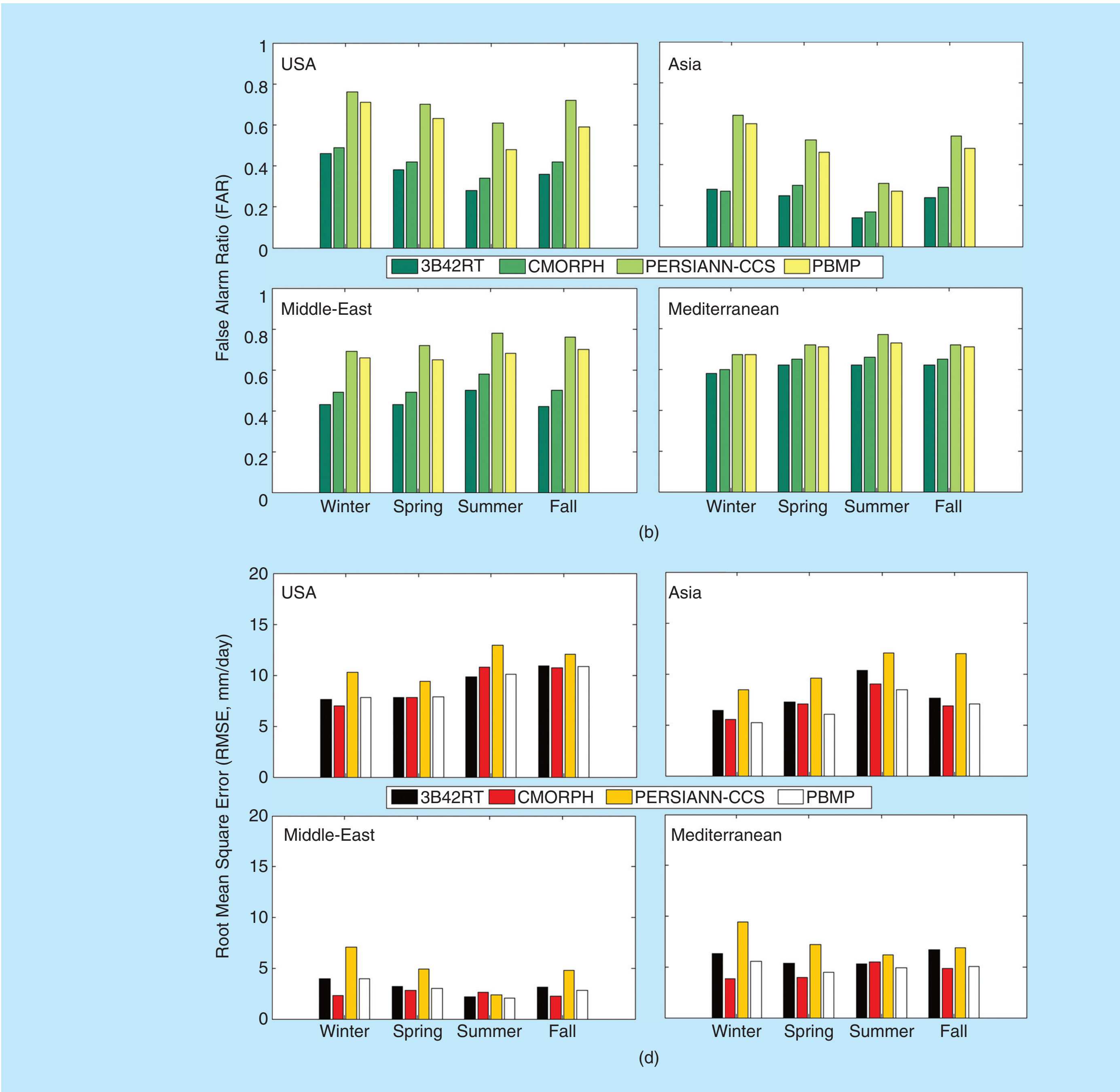


FIGURE 6. (a) Probability of Detection, POD for the merged and individual 584 satellite rainfall products at selected validation regions (Fig. 1). (Ideal POD = 1, worst value = 585 0); (b) False Alarm Ratio, FAR (Ideal FAR = 0, worst value = 1); (c) Threat 586 Score, TR (Ideal TR = 1, worst value = 0); (d) Root Mean Square Error, RMSE.

shows the TR of the original and merged satellite rainfall products over the four study regions. Based on TR measure, the merged product has good spatial accuracy in all regions except it demonstrates similar performance with 3B42RT and CMORPH products in a few cases.

In Fig. 6(d), the RMSE of the original and the merged satellite rainfall products. The categorical measures presented so far demonstrate the spatial accuracy of the rainfall data; however, RMSE quantifies the deviation of the estimated rainfall from the observed values. Therefore, the smaller the RMSE the satellite rainfall product has, the closer the fit is to the observed rainfall data. In most cases, the merged product has either the smallest RMSE from all original satellite rainfall products (e.g. Asia region in winter, spring, summer; Middle East in summer; Mediterranean in summer) or comparable RMSE with the original satellite rainfall product that has the smallest RMSE (e.g. USA in spring, summer, fall; Asia in fall, Middle East in spring; Mediterranean in fall). There are also



cases where some satellite rainfall products have lower RMSE than the merged product (e.g the CMORPH has the lowest RMSE for Middle East in winter and fall seasons; and Mediterranean in winter season). Even though the merged product does not have the lowest RMSE in those specific cases, overall it has tackled and reduced the high RMSE of the other satellite rainfall products involved in the merging process.

Finally, on Fig. 7, time series of the individual and merged satellite rainfall estimates has been demonstrated. To avoid visual cluttering for the reader, a 31 day moving average shown here. As seen on the Fig. 7, the merged product captures well the temporal variation of the observed rainfall values. In general, these performance measures discussed above have their own unique implication in the residual error analysis. The accuracy should be determined not only based on a single performance measure but also the combined inference of different measures. From hydrological application point of view, the implications of the

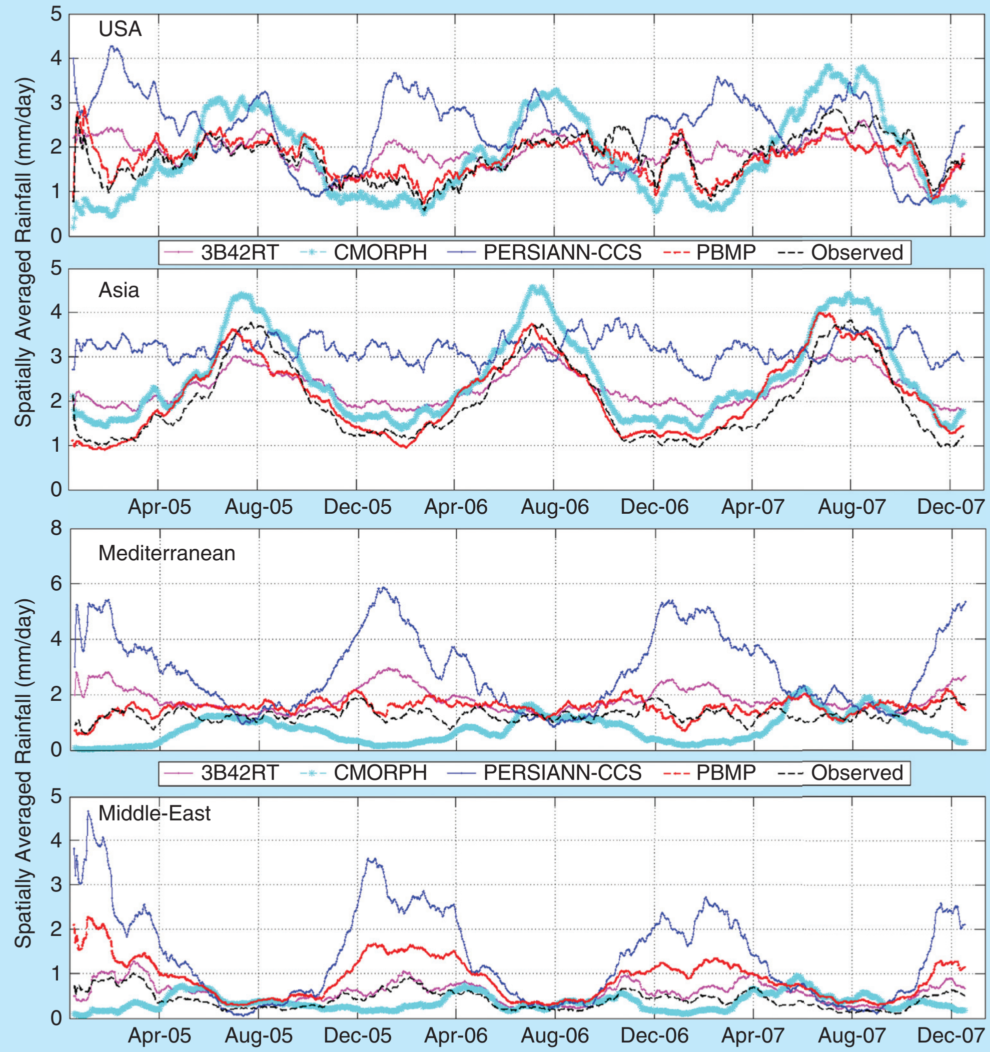


FIGURE 7. Spatially averaged time series of merged, individual satellite, and observed rainfall over the selected four regions for the period of 2005–2007. To avoid visual cluttering, a 31 day moving average is applied. (PBMP: performance based merged product).

performance measures have also different perception. For instance, from the perspective of reducing risk, a satellite rainfall product with high POD value is more appropriate in flood modeling. On the other hand, from the economic point of view, such as in design of hydraulic structure for low to medium return periods (10–25 years), satellite rainfall product with high FAR may not be appropriate as, it could overestimate the design flood. In summary, the merged product presented in this study has highest POD, high FAR, comparable TR with the individual satellite rainfall products and consistently lower RMSE. Therefore, the authors believe that the merged rainfall product will have better merit and contribution for hydrologic applications compared to the individual products, particularly in the developing world that is mostly ungauged.

Our approach is not without limitations. A key limitation of the error regression approach, although very practicable, is that a detailed physical (process-based) understanding of rainfall uncertainties is attainable only for regions that have ground truth (gauged) data. Another limitation is the bias of satellite precipitation data. If all input satellite data have similar bias, then there is no addition skill to be enhanced by the merging process. In such situations, various non-linear data fusion techniques might be more appropriate. Nevertheless, satellite rainfall products are more valuable for data sparse or remote regions of the world. So a key concern is addressing the nature of errors in poorly instrumented regions.

5. CONCLUSION

As satellite rainfall estimates become more important for hydrologic and atmospheric applications, users' knowledge on uncertainty associated with the satellite rainfall product is a necessary step to advance its application. Availability of uncertainty information associated with each satellite rainfall product can assist the data users as a 'HOW TO USE' guideline in the practical world. We developed a practical approach involving a simple non-linear regression model to estimate the error variance for satellite precipitation products and used it for merging (linearly weighted according to inverse of error variance). A user can apply this approach to estimate probable error variance and then use it as a proxy for data quality and decision making. We argue that topography, climate and seasons are considered readily available geophysical features for the end-user at any location. The use of topography, climate and season as major governing factors in the development of regression framework is logical to identify the uncertainty type associated with satellite rainfall estimates.

In summary, high resolution and multi-sensor satellite-based precipitation estimates, such as those analyzed in this study and those anticipated from the Global Precipitation Measurement (GPM; Hou et al., 2008) satellites, now hold great promise for hydrologic applications, especially over parts of the world where surface observation networks are sparse, declining or non-existent. However, the usefulness of such precipitation products for hydrological applications will depend on their error characteristics and how successful we are in intelligently harnessing the implications of uncertainty for surface hydrology. The decline of the few existing global ground based measurement networks for rain and stream flow and the absence of in-situ measurement in most parts of the world represent a 'paradoxical' situation for evaluating satellite rainfall estimation uncertainty. By developing simple models for estimation of error variance for satellite data that a user can use anywhere and anytime using only readily available geophysical features, our study represents a first comprehensive step at resolving the paradox for making satellite precipitation data work around the world during the GPM era. More importantly, we have demonstrated that the accuracy of satellite rainfall products can be improved by merging the existing satellite rainfall products based on their hydrologic predictability. This will contribute an important finding to the existing NASA investigation on the merging of algorithms and processing sequence for the Integrated Multi-satellitE Retrievals for GPM (IMERGE).

The mission statement provided on the GPM website (http://pmm.nasa.gov) states "The GPM mission will help advance our understanding of Earth's water and energy cycles, improve the forecasting of extreme events that cause natural disasters, and extend current capabilities of using satellite precipitation information to directly benefit society." If "*to directly benefit society*" is indeed a community priority, much more must be done so that the scientific advancements translate to tangible products or utilities for the world that societies can actually benefit from. GPM has the unique potential as a pathfinder mission to show how satellites can truly improve lives of millions of people through more cost-effective water management.

6. REFERENCES

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

[2] E. A. Smith, G. Asrar, Y. Furuhama, A. Ginati, A. Mugnai, K. Nakamura, R. F. Adler, M.-D. Chou, M. Desbois, J. F. Durning, J. K. Entin, F. Einaudi, R. R. Ferraro, R. Guzzi, P. R. Houser, P. H. Hwang, T. Iguchi, P. Joe, R. Kakar, J. A. Kaye, M. Kojima, C. Kummerow, K.-S. Kuo, D. P. Lettenmaier, V. Levizzani, N. Lu, A. V. Mehta, C. Morales, P. Morel, T. Nakazawa, S. P. Neeck, K. Okamoto, R. Oki, G. Raju, J. M. Shepherd, J. Simpson, B.-J. Sohn, E. F. Stocker, W.-K. Tao, J. Testud, G. J. Tripoli, E. F. Wood, S. Yang, and W. Zhang, "International global precipitation measurement (GPM) program and mission: An overview," in *Measuring Precipitation from Space: EURAINSAT and the Future*, V. Levizzani, P. Bauer, and F. J. Turk, Eds. The Netherlands: Springer, 2007, pp. 611–654.

[3] A. W. Wood and D. P. Lettenmaier, "A test bed for new seasonal hydrologic forecasting approaches in the western United States," *Bull. Amer. Meteorol. Soc.*, vol. 87, no. 12, pp. 1699–712, 2006.

[4] B. Nijssen and D. P. Lettenmaier, "Effect of precipitation sampling error on simulated hydrological fluxes and states: Anticipating the global precipitation measurement satellites," *J. Geophys. Res.*, vol. 109, no. D2, 2004.

[5] F. G. Su, H. Gao, G. J. Huffman, and D. P. Lettenmaier, "Potential utility of the real-time TMPA-RT precipitation estimates in streamflow prediction," *J. Hydrometeor.*, vol. 12, no. 3, pp. 444–455, 2011.

[6] F. G. Su, Y. Hong, and D. P. Lettenmaier, "Evaluation of TRMM multisatellite precipitation analysis (TMPA) and its utility in hydrologic prediction in La Plata basin," *J. Hydrometeor.*, vol. 9, no. 4, pp. 622–640, 2008.

[7] A. S. Gebregiorgis, Y. Tian, C. Peters-Lidard, and F. Hossain, "Tracing hydrologic model simulation error as a function of satellite rainfall estimation bias components and land use and land cover conditions," *Water Resour. Res.*, vol. 48, no. 11, pp. W11–509, 2012.

[8] A. S. Gebregiorgis and F. Hossain, "Understanding the dependency of satellite rainfall uncertainty on topography and climate for hydrologic model simulation," *IEEE Trans. Geosci. Remote Sensing*, vol. 51, no. 1, pp. 704–718, 2012.

[9] A. S. Gebregiorgis and F. Hossain, "Estimation of satellite rainfall error variance using readily available geophysical features," *IEEE Trans. Geosci. Remote Sensing*, vol. 52, no. 1, pp. 288–304, 2013.

[10] A. S. Gebregiorgis and F. Hossain, "Performance evaluation of merged satellite rainfall products based on spatial and seasonal signatures of hydrologic predictability," *Atmos. Res.*, vol. 132–133, pp. 223–238, Oct.–Nov. 2013.

[11] A. S. Gebregiorgis and F. Hossain, "How much can a priori hydrologic model predictability help in optimal merging of satellite precipitation products?" *J. Hydrometeor.*, vol. 12, no. 6, pp. 1287–1298, 2011.

[12] A. S. Gebregiorgis and F. Hossain, "How well can we estimate error variance of satellite precipitation data around the world?" *J. Geophys. Res.*, 2013.

[13] S. Biancamaria, F. Hossain, and D. Lettenmaier, "Forecasting transboundary flood with satellites," *Geophys. Res. Lett.*, vol. 38, p. L11401, 2011.

[14] F. Hossain, "Conclusion to the featured series on 'satellites and transboundary water: Emerging ideas," *J. Amer. Water Resour. Assoc.*, vol. 46, no. 4, pp. 663–664, 2010.

[15] F. Hossain, "Introduction to the featured series on 'satellites and transboundary water: Emerging ideas," *J. Amer. Water Resour. Assoc.*, Apr. 2009.

[16] C. Funk and J. P. Verdin, "Real-time decision support systems: The famine early warning system network," in *Satellite Rainfall Applications for Surface Hydrology*, M. Gebremichael and F. Hossain, Eds. The Netherlands: Springer, 2010, pp. 295–320.

[17] R. J. Kuligowski, "The self-calibrating multivariate precipitation retrieval (SCaMPR) for high resolution, low latency satellite-based rainfall estimates," in *Satellite Rainfall Applications for Surface Hydrology*, M. Gebremichael and F. Hossain, Eds. The Netherlands: Springer, 2010, pp. 39–48.

[18] G. J. Huffman, R. F. Adler, D. T. Bolvin, G. Gu, E. J. Nelkin, K. P. Bowman, Y. Hong, E. F. Stocker, and D. B. Wolff, "The TRMM multi-satellite precipitation analysis: Quasi-global, multi- year, combined-sensor precipitation estimates at fine scale," *J. Hydrometeor.*, vol. 8, no. 1, pp. 38–55, 2007.

[19] G. J. Huffman, R. F. Adler, D. T. Bolvin, and E. Nelkin, "The TRMM multi-satellite precipitation analysis (TMPA)," in *Satellite Rainfall Applications for Surface Hydrology*, M. Gebremichael and F. Hossain, Eds. The Netherlands: Springer, 2010, pp. 3–22.

[20] R. L. Joyce, J. E. Janowiak, P. A. Arkin, and P. Xie, "CMORPH: A method that produces global precipitation estimates from passive microwave and infra-red data at high spatial and temporal resolution," *J. Hydrometeor.*, vol. 5, no. 3, pp. 487–503, 2004.

[21] R. J. Joyce and P. Xie, "Kalman filter-based CMORPH," *J. Hydrometeor.*, vol. 12, no. 6, pp. 1547–1563, 2011.

[22] K.-L. Hsu, A. Behrangi, B. Iman, and S. Sorooshian, "Extreme precipitation estimation using satellite-based PERSIANN-CCS algorithm," in *Satellite Rainfall Applications for Surface Hydrology*, M. Gebremichael and F. Hossain, Eds. The Netherlands: Springer, 2010, pp. 49–67.

[23] A. Behrangi, B. Imam, K. L. Hsu, S. Sorooshian, T. J. Bellerby, and G. J. Huffman, "REFAME: Rain estimation using forward-adjusted advection of microwave estimates," *J. Hydrometeor.*, vol. 11, no. 6, pp. 1305–1321, 2010.

[24] F. J. Turk, G. V. Mostovoy, and V. Anantharaj, "The NRL-blended high resolution precipitation product and its application to land surface hydrology," in *Satellite Rainfall Applications for Surface Hydrology*, M. Gebremichael and F. Hossain, Eds. The Netherlands: Springer, 2010, pp. 85–104.

[25] T. Ushio, T. Kubota, S. Shige, K. Okamoto, K. Aonashi, T. Inoue, N. Takahashi, T. Iguchi, M. Kachi, R. Oki, T. Morimoto, and Z. Kawasaki, "A Kalman filter approach to the global satellite mapping of precipitation (GSMaP) from combined passive microwave and infrared radiometric data," *J. Meteorol. Soc. Japan*, vol. 87A, pp. 137–151, 2009.

[26] T. Ushio and M. Kachi, "Kalman filtering applications for Global Satellite Mapping of Precipitation (GSMaP)," in *Satellite Rainfall Applications for Surface Hydrology*, M. Gebremichael and F. Hossain, Eds. The Netherlands: Springer, 2010, pp. 105–123.

[27] Y. Hong, K. Hsu, X. Gao, and S. Sorooshian, "Precipitation estimation from remotely sensed imagery using artificial neural network-cloud classification system," *J. Appl. Meteorol.*, vol. 43, no. 12, pp. 1834–1853, 2004.

[28] X. Liang, *A Two-Layer Variable Infiltration Capacity Land Surface Representation for General Circulation Models* (Water Resources Series, TR140, 208). Seattle, WA: Univ. of Washington, 1994.

[29] T. Dinku, S. Chidzambwa, P. Ceccato, S. J. Connor, and C. F. Ropelewski, "Validation of high resolution satellite rainfall products over complex terrain in Africa," *Int. J. Remote Sens.*, vol. 29, no. 14, pp. 4097–4110, 2008.

[30] M. Bitew and M. Gebremichael, "Evaluation through independent measurements: Complex terrain and humid region in Ethiopia," in *Satellite Rainfall Applications for Surface Hydrology*, M. Gebremichael and F. Hossain, Eds. The Netherlands: Springer, 2010, pp. 105–123.

[31] M. S. Shrestha, K. Takara, T. Kubota, and S. R. Bajracharya, "Verification of GsMAP rainfall estimates over the central Himalayas," *Annu. J. Hydraulic Eng., Japan Soc. Civil Eng.*, vol. 55, 2011.

[32] E. E. Ebert and M. J. Manton, "Performance of satellite rainfall estimation algorithms during TOGA COARE," *J. Atmos. Sci.*, vol. 55, no. 9, pp. 1537–1557, 1998.

[33] R. F. Adler, C. Kidd, G. Petty, M. Morrissey, and H. M. Goodman, "Intercomparison of global precipitation products: The third precipitation intercomparison project (PIP-3)," *Bull. Amer. Meteorol. Soc.*, vol. 82, no. 7, pp. 1377–1396, 2001.

[34] M. Steiner, T. L. Bell, Y. Zhang, and E. F. Wood, "Comparison of two methods for estimating the sampling-related uncertainty of satellite rainfall averages based on a large radar dataset," *J. Clim.*, vol. 16, no. 22, pp. 3759–3778, 2003.

[35] M. Gebremichael and W. F. Krajewski, "Characterization of the temporal sampling error in space-time-averaged rainfall estimates from satellites," *J. Geophys. Res.*, vol. 109, no. D11, 2004.

[36] F. Hossain and G. J. Huffman, "Investigating error metrics for satellite rainfall data at hydrologically relevant scales," *J. Hydrometeor.*, vol. 9, no. 3, pp. 563–575, 2007.

[37] E. E. Ebert, J. E. Jonowiak, and C. Kidd, "Comparison of near real-time precipitation estimates from satellite observations and numerical models," *Bull. Amer. Meteorol. Soc.*, vol. 88, no. 1, pp. 47–64, 2007.

[38] E. P. Maurer, A. W. Wood, J. C. Adam, and D. P. Lettenmaier, "A long-term hydrologically based dataset of land surface fluxes and states for the conterminous United States," *J. Clim.*, vol. 15, no. 22, pp. 3237–3251, 2002.

[39] Y. Lin and K. Mitchell, "The NCEP stage II/IV hourly precipitation analyses: Development and applications," in *Proc. Preprints, 19th Conf. Hydrology, American Meteorological Society*, San Diego, CA, 2005.

[40] A. Yatagai, K. Kamiguchi, O. Arakawa, A. Hamada, N. Yasutomi, and A. Kitoh, "APHRODITE: Constructing a long-term daily gridded precipitation dataset for asia based on a dense network of rain gauges," *Bull. Amer. Meteorol. Soc.*, vol. 93, no. 9, pp. 1401–1415, 2012.

GRS