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Numerical Weather Model based Adjustment of Satellite Precipitation Products and Hydrologic Evaluations

Xinxuan Zhang

University of Connecticut - Storrs, xinxuan.zhang1022@gmail.com

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Numerical Weather Model based Adjustment of Satellite Precipitation Products and Hydrologic Evaluations

Xinxuan Zhang
University of Connecticut, 2018

The quantification of heavy precipitation events over mountainous regions has been a challenge for all types of satellite precipitation products. This research developed a numerical weather model-based adjustment technique to correct satellite precipitation estimates for HPEs. To successfully apply the technique, there are two prerequisites: i) the raw satellite data captures the relative spatial and temporal variabilities of precipitation (i.e. no significant surface contamination effects on satellite precipitation detection), and ii) the model provides relatively accurate precipitation outputs in terms of overall magnitude (not necessarily location). The technique was demonstrated over mountainous areas all over the world representing varying terrain complexity and climatic conditions. Results show that model-based adjustment outperforms, or at least is comparable to, the gauge-based adjustment for all high-resolution satellite products examined. In addition, the model-based adjustment requires no in situ observations and much less processing time. The results are promising for future satellite precipitation applications over mountainous areas lacking ground observations. Furthermore, the model-adjusted satellite products were used in a distributed hydrological model to evaluate the error propagation on flood simulations. Results showed that the basin outlet runoff derived from model-adjusted satellite precipitation was comparable to the one with gauge-adjusted satellite precipitation, and both of them outperformed the runoff derived from raw satellite.
Numerical Weather Model based Adjustment of
Satellite Precipitation Products and Hydrologic Evaluations

Xinxuan Zhang
B.S., Nanjing University of Information Science & Technology, 2007
M.S., University of Connecticut, 2012

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Numerical Weather Model based Adjustment of Satellite Precipitation Products and Hydrologic Evaluations

Presented by

Xinxuan Zhang, B.S., M.S.

Major Advisor___________________________________________
Dr. Emmanouil N. Anagnostou

Associate Advisor___________________________________________
Dr. Guiling Wang

Associate Advisor___________________________________________
Dr. Marina Astitha

Associate Advisor___________________________________________
Dr. Efthymios I. Nikolopoulos

Associate Advisor___________________________________________
Dr. Malaquias Peña

University of Connecticut

2018
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Chapter 1

1.1 Background and Motivation

Accurate measurement of precipitation is prerequisite for understanding the related hydrologic processes. The fact that precipitation is highly discontinuous in space and time is a crucial challenge for observation. Over topographically complex regions, it is especially challengeable because of the more sophisticated variability and uncertainty of precipitation introduced by orographic effects (Roe 2005; Houze 2012). Generally, observed gridded precipitation data sets can be generated by three approaches: gauge data interpolation, surface radar network and satellite-based observation.

The accuracy of gauge interpolation depends largely on the gauge density and the quality of measurement. Gauge locations can never be homogeneously distributed. It always tend to lie at low elevation and densely populated areas relative to the mountainous terrain because of the higher costs of gauge installation and maintenance over complex topography. Moreover, since the gauge networks all over the world are operated by different countries, the observations are less accessible due to different data-sharing policies. Hence, gauge-based gridded precipitation data sets are usually in coarse temporal and spatial resolutions. So far most of the global products are in monthly or daily time scale and at 0.25° to 2.5° spatial resolutions (Becker et al. 2013; Schamm et al. 2014; NOAA 2013; Haylock et al. 2008; Yatagai et al., 2009).

For meso-scale studies such as extreme rainfall events and related floods, precipitation products with higher spatial and sub-daily temporal resolution are required. Surface radar network provides fine resolution products, but the data quality is highly susceptible to terrain complexity due to severe beam shielding and strong ground clutter (Krajewski and Smith 2002; Germann et
al. 2006; Villarini and Krajewski 2010). In addition, considering the expensive operating and maintenance costs, the spatial coverage of radar network is very limited especially in mountainous or less populated regions.

Besides surface observations, techniques of satellite-based measurements have been developed rapidly over the past 30+ years (Kidd and Levizzani 2011). Although satellite remote sensing already plays an irreplaceable role in precipitation measurement because it is the only means of gathering data with uninterrupted, quasi-global coverage, the products still suffer from severe bias over complex topographies especially for heavy precipitation. There are four types of satellite-based precipitation retrievals: long-wave infrared (IR), visible spectrum (VIS), passive microwave (PMW), and active microwave retrievals. The satellite IR and VIS sensors measure the cloud-top brightness temperature or reflectivity that researchers use to derive precipitation rates by certain retrieval algorithms (Ebert and Manton, 1998). These estimates represent an indirect measurement of precipitation, and their accuracy is largely affected by different cloud types, rain systems, and hydroclimatic regimes. The PMW measurements observe the microwave energy emitted by rain droplets or scattered by precipitating ice particles. While the IR/VIS and PMW techniques can only capture horizontal precipitation patterns and intensities, PR can provide three-dimensional storm structure. Nowadays, mainstream high-resolution satellite precipitation products are usually generated by combining IR/VIS, PMW, and PR measurements, a conjunction that takes advantage of the different techniques. A variety of satellite-based precipitation products came to be available over past two decades, including but not limited to, the Tropical Rainfall Measuring Mission (TRMM) near-real-time Multisatellite Precipitation product (3B42RT, Huffman et al. 2007), the National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center (CPC) morphing technique (CMORPH; Joyce et al. 2004), the Precipitation
Estimation from Remotely Sensed Information Using Artificial Neural Networks (PERSIANN, Sorooshian et al. 2000), and the Global Satellite Mapping of Precipitation Microwave-IR Combined Product (GSMaP) datasets produced by the Earth Observation Research Center (EORC) of the Japan Aerospace Exploration Agency (JAXA; Kubota et al. 2007; Ushio et al. 2013), and product of Global Precipitation Measurement (GPM) Integrated Multi-satelliteE Retrievals for GPM (IMERG; Huffman et al. 2015). Many studies indicate that these satellite products tend to largely underestimate heavy precipitation over mountainous regions (Hirpa et al. 2010; Gao and Liu 2013; Stampoulis and Anagnostou 2013; Derin et al. 2016; Maggioni et al. 2016; Beck et al. 2017).

Apart from single source data sets, precipitation products with combined data sources are available as well. Traditionally, gauge observations are incorporated into the raw radar or satellite products for the purpose of better accuracy (Lin and Mitchell 2005; Sinclair and Pegram 2005; Goudenhoofdt and Delobbe 2009). In fact, most satellite products mentioned above have their gauge-adjusted counterparts (Huffman et al. 2007; Mega et al. 2014; Xie et al. 2011; Huffman et al. 2015; Xie et al. 2017). In general, gauge-adjusted satellite products need weeks to months to process before releasing and the accuracy largely depends on the spatio-temporal representativeness of gauge network. Over mountainous regions, where usually have sparsely distributed gauge network and temporally coarser gauge observations, there are great uncertainties on the performance of gauge-adjusted satellite precipitation products (Derin et al. 2016; Beck et al. 2017).

To address the aforementioned disadvantages of gauge-based adjustment, Zhang et al. (2013) developed a numerical model based technique for satellite precipitation adjustment. This technique is designed specifically for heavy precipitation events over topographically complex
regions, where the raw satellite products experience considerable underestimation (Scofield and Kuligowski 2003; Derin et al. 2016). Model-adjusted satellite product is supposed to overcome the negative bias without gauge data input. In addition, the model-adjusted product can be generated in near-real-time, which means the data processing time is much less than the corresponding gauge-adjusted product.

1.2 Objectives

The research aims at improving the uses of satellite precipitation products in flood modeling by demonstrating the consistency of the numerical weather model based satellite precipitation adjustment technique over different mountainous regions and the impact of error corrections in hydrologic model simulations of flood events. Specific objectives to be addressed include:

- Evaluate the accuracy of numerical weather model simulations in terms of overall precipitation magnitude in regions with different topographic complexity and climatic condition.
- Evaluate the accuracy of raw- and gauge-adjusted satellite precipitation products in regions with different topographic complexity and climatic condition.
- Examine the feasibility of model-based satellite adjustment technique on a variety of satellite products, and evaluate the improvements of model-adjusted satellite products against the raw and gauge-adjusted satellite products for each study region.
- Make flood simulations with a distributed hydrological model forced by different satellite products (raw, gauge-adjusted and model-adjusted), and evaluate the improvement of error propagations from the different forcing precipitation data to streamflow.
1.3 Thesis Structure

This thesis is composed of six chapters. Chapter 1 is the introduction. Chapter 2 investigated the application of model-based satellite adjustment for CMORPH and GSMaP products over three tropical mountainous regions. Chapter 3 extended this study to a mid-latitude mountainous region with six hurricane induced storms and evaluated the response of hydrological processes regarding to the model-adjusted satellite precipitation. Chapter 4 further extended the study by applying the model-based satellite adjustment on the state-of-art IMERG product with a real-time ensemble model forecasts data set, to evaluate a large number of flood-inducing storms over CONUS. Chapter 6 presents the conclusions and future study directions.
Chapter 2

Application of model-based satellite adjustment in tropical regions

This Chapter has been submitted to Journal of Hydrometeorology

2.1 Introduction

Satellite remote sensing plays an irreplaceable role in precipitation measurement because it is the only means of gathering data with uninterrupted, quasi-global coverage. Precipitation-related satellite observations are of four main types: long-wave infrared (IR), visible spectrum (VIS), passive microwave (PMW), and active microwave retrievals. The satellite IR and VIS sensors measure the cloud-top brightness temperature or reflectivity that researchers use to derive precipitation rates by certain retrieval algorithms (Ebert and Manton, 1998). These estimates represent an indirect measurement of precipitation, and their accuracy is largely affected by different cloud types, rain systems, and hydroclimatic regimes. The PMW measurements observe the microwave energy emitted by rain droplets or scattered by precipitating ice particles. While the IR/VIS and PMW techniques can only capture horizontal precipitation patterns and intensities, PR can provide three-dimensional storm structure.

Nowadays, mainstream high-resolution satellite precipitation products are usually generated by combining IR/VIS, PMW, and PR measurements, a conjunction that takes advantage of the different techniques. Examples of these products include the National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center morphing technique (CMORPH;
Joyce et al., 2004); the Global Satellite Mapping of Precipitation project (GSMaP; Kubota et al., 2007; Mega et al., 2014); the Precipitation Estimation from Remotely Sensed Information Using Artificial Neural Networks (PERSIANN; Sorooshian et al., 2000); and the Tropical Rainfall Measuring Mission (TRMM) Multisatellite Precipitation Analysis (TMPA; Huffman et al., 2007, 2010, 2015). In addition, the Global Precipitation Measurements (GPM) mission, which was launched in 2014, has provided a new-generation satellite product, the Integrated Multisatellite Retrievals for GPM (IMERG; Huffman et al., 2015).

Although the past two decades have brought considerable progress in satellite precipitation retrieval techniques and algorithms, producing reliable satellite products over mountainous areas remains a big challenge. Many studies have been devoted to satellite precipitation evaluation over complex terrain. In South America, Dinku et al. (2010) found severe overestimation by PERSIANN and significant underestimation by GSMaP over Colombia. In Africa, Hirpa et al. (2010) showed significant underestimation of precipitation by PERSIANN over the Ethiopian Plateau, and Milewski et al. (2015) reported underestimation of precipitation by the TMPA product over high-elevation areas of Morocco. In Europe, Stampoulis and Anagnostou (2012) found that CMORPH and TMPA underestimated rainfall over the Italian Alps region. In Asia, Chen et al. (2013) showed significant underestimation of the 2009 extreme Typhoon Morakot by the CMORPH, PERSIANN, and TMPA precipitation products, while Tong et al. (2014) found that TMPA underestimated precipitation over the Tibetan Plateau. Finally, a recent comprehensive error analysis of nine satellite precipitation products over nine mountainous regions showed that all tended to underestimate the high rain rates significantly (Derin et al., 2016).

Typically, correction methods for satellite precipitation systematic error (bias) rely on comparisons of near-real-time satellite precipitation products with ground observations over large
spatial and temporal scales (1–5 degree and monthly; Xie and Arkin, 1997; Mega et al., 2014). To be efficient, this bias estimation requires data from dense in situ gauge networks, which are rarely available over mountainous areas, especially in some tropical regions. Some studies have even shown that the use of in situ gauge observations in data-sparse regions associated with significant spatial precipitation gradients could lead to increased errors in the gauge-adjusted satellite precipitation estimates (Ghajarnia et al., 2015; Derin et al., 2016).

To overcome this barrier in complex terrain, Zhang et al. (2012) developed a bias-correction technique based solely on high-resolution numerical weather prediction (NWP) simulations. This technique is designed to reduce satellite precipitation underestimation, which is typically due to the low-level orographic enhancement processes in mountainous areas. The technique has been tested for CMORPH using a few case studies in the Alpine region of northern Italy, the Massif Central Mountains in France (Zhang et al., 2013), the southern Appalachian Mountains in North America (Zhang et al., 2016), and the Rocky Mountains in Colorado in the western United States (Nikolopoulos et al., 2015). Results based on these studies have shown that the NWP-based adjustments can reduce the CMORPH underestimation of high rain rates and moderate the magnitude-dependent bias. Authors have argued that although the NWP-based adjustment is independent of any ground observation, the improvements are comparable to or even better than those from the post-processed, gauge-adjusted CMORPH precipitation product.

These previous studies were focused on subtropical or temperate zone climates. However, approximately two-thirds of global precipitation occurs in tropical areas, which highlights a need to test the satellite precipitation adjustment technique in those regions. In this study, we provide a comprehensive evaluation of the NWP-based adjustment technique, applied to two high-resolution
satellite precipitation products and based on 81 heavy precipitation events occurring in three tropical mountainous regions.

Section 2.2 describes the study regions, rain gauge and satellite precipitation data, and numerical model set-ups. Section 2.3 introduces the methodologies of the NWP-based adjustment technique and error analyses. Results and discussions are presented in section 2.4, and the conclusions are summarized in section 2.5.

2.2 Study regions and datasets

2.2.1 Study regions

We looked at three tropical mountainous regions in this study, two in the Andes Mountains and one in Taiwan; all have dense gauge network datasets available. Although the gauge data time periods vary across the regions, the heavy precipitation events we selected all took place during their common period of 2004 to 2010. We describe the criteria of event selection in section 2.3.1, below.

The Andes Mountains are located in South America, running from north (~10°N) to south (~53°S) along the western coast of the continent. The Colombia domain is a portion of the Northern Andes (see the left panel of Figure 2.1: Map of terrain elevation and gauge locations of the different study regions.Figure 2.1), where the climate is typically wet and warm. The Colombian Andes can be divided from east to west into three mountain ranges. This study uses 113 rain gauges, most of them located in the eastern mountain range, for reference data.

We chose the Peru domain in the Central Andes as the second study region (Figure 2.1, middle panel). Ground observations are from 124 rain gauges distributed throughout the mountains.
In the Central Andes, the summer season (December to February) contributes over 60 percent of the annual precipitation (Garreaud and Aceituno, 2001).

The third study region is in southeastern Taiwan (Figure 2.1, right panel). Complex terrain and an average annual precipitation of more than 2,500 mm characterize the island of Taiwan. The eastern part consists mostly of rugged mountains and the western part of the Chianan Plains. Taiwan’s climate is influenced by the East Asian Monsoon. The monsoon is especially significant in the southeastern region, where approximately 90 percent of the annual precipitation occurs during the wet season (May to October; Yu et al., 2006). The ground observations for this study area came from 40 rain gauges in the Tsengwen River Basin, where the elevations vary from near sea level to 2,540 m.

2.2.2 Satellite precipitation products

We applied the NWP-based adjustment technique to two passive microwave-based high-resolution satellite precipitation products, CMORPH and GSMaP. Both apply gauge-based corrections to the near-real-time satellite precipitation estimates.

a. CMORPH

The NOAA/Climate Prediction Center morphing technique (CMORPH) is a satellite rainfall retrieval algorithm that uses motion vectors derived from half-hour-interval, geostationary satellite IR imagery to propagate rainfall estimates obtained from Earth-orbiting satellite-based passive microwave (PMW) sensors (Joyce et al., 2004). This study used the CMORPH V1.0 near-real-time and gauge-adjusted products with 0.073°/30-minute resolution. The gauge-adjusted product is corrected by two widely used long-term datasets, the CPC (Climate Prediction Center) unified
gauge analysis over land and the pentad GPCP (Global Precipitation Climatology Project) over the ocean. We acknowledge that CMORPH has a newer version named V0.x which employed more advanced algorithms. However, CMORPH V0.x does not provide gauge-adjusted data set, and it is not available for the time period of storms in this study.

b. GSMaP

The second satellite product examined in this study was the Global Satellite Mapping of Precipitation product (Kubota et al., 2007; Tian et al., 2010). The GSMaP—abbreviated in full as GSMaP_MVK (version 5)—employs a morphing algorithm similar to that used by CMORPH to derive the cloud motion vectors. Unlike CMORPH, however, the GSMaP applies a Kalman filter to update the rain rates derived from the IR brightness temperature (Ushio et al., 2009). The spatial and temporal resolutions of the GSMaP product are 0.1 degree and hourly, respectively. The gauge-adjusted GSMaP product is available at the same resolutions (Mega et al., 2014). We acknowledge that GSMaP has two newer versions, v6 and v7, in which the algorithm was updated regarding to orographic rainfall retrievals (Shige et al. 2013; Yamamoto and Shige 2015; Yamamoto et al. 2017). However, the GSMaP v6 and v7 are not available before 2014, meaning that the data does not cover the storms in this study.

2.2.3 Numerical Weather Simulations

To simulate storm events in the different study areas, we used the numerical Weather Research and Forecasting Model (WRF), version 3.7.1 (Skamarock et al., 2008). The periods of our WRF storm simulations ranged from one to five days, with a 12-hour spin-up prior to each. We initialized and constrained the simulations at the model boundaries by NCEP Global Forecast System (GFS)
analysis fields of 0.5 or 1 degree, depending on the availability of GFS data. The WRF model uses a two-way interactive mode and a three-domain spatial configuration (18–6–2 km). The 2 km inner domains entirely cover the essential target areas (as shown in figure 1) with an hourly output.

Before using the WRF simulations in the satellite error adjustment technique, we tested them using various parameterizations against in situ gauge observations to verify the model’s ability to reproduce quantitatively the structure of those heavy precipitation storms and their interactions with topography. The main items of the final parameterizations are summarized in Table 2.1.

2.3 Methodology

2.3.1 Selection of precipitation events

The storms used in this study varied from one- to multi-day events. We based our selection of the events on their severity, represented by daily precipitation derived from gauge observations. We set two thresholds for the area-average rainfall accumulation over each study region. The first, $R_{\text{intensity}}$, constrained the storm maximum rainfall intensity; the second, $R_{\text{length}}$, constrained the storm length. In other words, an n-day storm event had to satisfy two conditions: (1) $\max(R_i) \geq R_{\text{intensity}}$ and (2) $R_i \geq R_{\text{length}}$, where $R$ is the region-average gauge daily rainfall intensity and $i \in [1,n]$ represents the event days.

The threshold values were empirical and unique to each study region. The Colombia and Peru regions had moderate threshold values, while Taiwan had much higher thresholds because of the frequent typhoons in the region. Table 2.2 summarizes the threshold values and number of events for the three study regions.
2.3.2 NWP-based adjustment technique

Before applying the adjustment technique, we spatially averaged the WRF-simulated hourly precipitation data, available at 2 km resolution, to match the coarser spatial resolutions of satellite products (8 km for CMORPH and 10 km for GSMaP). We then applied the adjustment procedure separately for each rainfall event and each satellite product. Since the adjustment focused on land area only, we ignored all the precipitation values over ocean background surfaces.

First, we adjusted the near-real-time satellite hourly precipitation rates by a power-law function (Eq. 1) derived from WRF and satellite precipitation quantile values:

\[ Y = a \times X^b, \]  

(1)

where X and Y corresponded to the satellite and WRF hourly precipitation rate quantile values, respectively. We derived these quantiles according to different cumulative probability values (i.e., 0.05, 0.1, 0.15, .... , 0.95). Values of parameters \( a \) and \( b \) were determined based on the least squares method by fitting the X and Y datasets for each rainfall event.

Once the power-law parameter set was obtained from the quantile–quantile datasets, we applied Eq. 1 to the near-real-time satellite precipitation product to derive the NWP-adjusted precipitation product. This time, X represented each precipitation rate value of the near-real-time satellite dataset, and Y represented the NWP-adjusted satellite precipitation rate. We repeated the adjustment procedure for each rainfall event based on \( a \) and \( b \) values fitted to each separately.

2.3.3 Error metrics

The primary task of the error analysis was to evaluate the improvement coming from the WRF-based adjustment relative to the post-analysis gauge-adjusted satellite product and the near-real-
time (nonadjusted) counterpart. We compared the WRF-based adjusted and gauge-adjusted satellite products to find out which worked best in each study region.

As described in section 2.2.1, seven gridded precipitation datasets were available for each event. The data came from the WRF simulation, the near-real-time CMORPH, the gauge-adjusted CMORPH, the WRF-based adjusted CMORPH, the near-real-time GSMaP, the gauge-adjusted GSMaP, and the WRF-based adjusted GSMaP. We evaluated all the datasets against gauge observations based on daily and storm-length (≥1 day) accumulations.

We performed the daily scale comparison using two statistical error metrics: bias ratio score (BS) and Heidke skill score (HSS; Heidke, 1926):

\[
BS = \frac{A + B}{A + C} \quad (2)
\]

\[
HSS = \frac{2(A \times D - B \times C)}{(A + C)(C + D) + (A + B)(B + D)} \quad (3)
\]

where A, B, C, and D were the numbers of occurrences for any specific precipitation threshold:

A was counted when Estimator > Threshold and Gauge observation > Threshold;
B was counted when Estimator > Threshold and Gauge observation < Threshold;
C was counted when Estimator < Threshold and Gauge observation > Threshold;
D was counted when Estimator < Threshold and Gauge observation < Threshold.

The value of “Estimator” was extracted from the gridded precipitation datasets by a simple nearest-neighbor method, according to the gauge location.

We calculated the BS and HSS at three daily precipitation thresholds for each event. The threshold values differed for each study region. A BS of 1 is considered as an unbiased estimation, while above or below 1 represents overestimation or underestimation, respectively. The HSS is defined as the number of correct estimated occurrences minus the number of correct estimated occurrences by chance, then divided by the total number of estimated occurrences minus the
number of correct estimated occurrences by chance. The HSS expression can be found in Zhang et al. (2013). The HSS values range from \(-\infty\) to 1, where 1 indicates a perfect estimation and less than or equal to zero indicates a random estimation.

We compared storm-length accumulated precipitation using scatterplots of region-average precipitation and three quantitative statistics: correlation (R²), normalized root-mean-square error (NRMSE), and mean relative error (MRE). R² is simply the square of Pearson correlation coefficient. The equations of NRMSE and MRE are shown below:

$$NRMSE = \sqrt{\frac{\sum_{i=1}^{n}(E_i - G_i)^2}{\sum_{i=1}^{n} G_i}},$$

(4)

$$MRE = \frac{\sum_{i=1}^{n}(E_i - G_i)}{\sum_{i=1}^{n} G_i},$$

(5)

where \(n\) was the number of events in each study region, and \(E\) and \(G\) were the region-average accumulated precipitation for each event from the estimator and gauge, respectively. Both NRMSE and MRE are scale independent, which made cross-region comparison more convenient.

### 2.4 Results and discussion

Results are discussed below for each study region. The rain accumulation error metrics (BS and HSS) are rendered as boxplots, and the accumulated rainfall comparisons are shown in scatter plots, with bulk statistics summarized in Table 2.3.

#### 2.4.1 Colombia domain

Figure 2.2 (top) presents the BS at three daily rainfall accumulation thresholds (5, 10, and 15 mm/day) for the Colombia domain. Overall, the near-real-time CMORPH and GSMaP products had the largest underestimation of precipitation at all thresholds compared to their adjusted
versions. For CMORPH, both adjusted products gave less underestimation than the near-real-time product. The WRF-adjusted CMORPH product performed better than the gauge-adjusted version. The GSMaP near-real-time product gave less underestimation than CMORPH, and the GSMaP adjusted product overestimated precipitation. Median values of the two adjusted GSMaP boxplots were comparable at lower rainfall accumulation thresholds (5 and 10 mm/day), but the WRF-adjusted version had smaller value ranges, which made the WRF-adjusted product exhibit the least uncertainty. At the highest rainfall accumulation threshold, WRF-adjusted GSMaP showed slight underestimation, while gauge-adjusted GSMaP showed overestimation.

The Colombia BS boxplot also demonstrates that the uncertainty of satellite products increased with rainfall magnitude. The underestimations from both near-real-time products tended to be more significant in higher rainfall accumulations, and the corrections from WRF and gauge adjustments of higher rainfall thresholds were shown to be more effective than their corrections of low rainfall thresholds.

We computed the HSS metric for the same rainfall accumulation thresholds as the BS. The variation in the HSS boxplots (Figure 2.2, bottom) among the different satellite products was not as significant as for the BS boxplots. Overall, the WRF-based adjusted products had the highest HSS values in both CMORPH and GSMaP retrievals and for all rainfall thresholds. We noted that for CMORPH, the performance of the gauge-adjusted product was similar to that of the near-real-time product, while for GSMaP, the HSS decreased with the gauge adjustment. This demonstrated that the gauge adjustment could worsen the performance of the product by introducing random error (Ghajarnia et al., 2015; Derin et al., 2016).

Moreover, the WRF-simulated rainfall performed better than all the satellite products in terms of the BS. It did significantly worse in terms of the HSS, however. This is because high-
resolution WRF simulations can resolve the low-level orographic enhancement that results in more accurate rainfall magnitudes over a relatively large area, but the model has difficulty in locating the orographic rainfall in space and time, which can result in significant errors in hydrological applications (Baldwin et al., 2001; Ducrocq et al., 2002; Zhang et al., 2013).

To illustrate our investigation of the error pattern on a larger temporal scale, we display in Figure 2.3 the storm-total rainfall scatter plots of each event for the CMORPH and GSMaP products, respectively. The figure clearly shows the near-real-time CMORPH and GSMaP products had the most significant underestimation in each satellite product, confirming the finding in the BS boxplots. The two adjustment methods effectively moderated this underestimation. In fact, the WRF-based adjustment tended to overestimate a bit, while the gauge-adjusted product continued to underestimate. Table 2.3 reports the quantitative comparisons for each product. The correlation ($R^2$) of all satellite products was around 0.6, with the exception of the gauge-adjusted GSMaP (0.46). The NRMSE values of the three CMORPH datasets were very similar (0.49, 0.47, and 0.48). The MRE value showed large underestimation, however, for the gauge-adjusted CMORPH product ($-0.34$), while the WRF-based adjusted CMORPH had moderate overestimation (0.13). For the GFSMaP product, the WRF-based adjusted product showed a significant overestimation (MRE $= 0.31$) as well as a high NRMSE (0.6). Overall, the WRF-based adjustment performed best in CMORPH, while the gauge-adjustment performed best in GSMaP.

### 2.4.2 Peru domain

For the Peru domain, we again calculated the BS values (Figure 2.4, top) for three daily rain rate thresholds (1, 9, and 18 mm/day). As in the Colombia region, the near-real-time CMORPH and GSMaP products were shown to have severe underestimation, especially for the higher rain rates.
For CMORPH, we noted no significant difference between the near-real-time and gauge-adjusted products, which may have been because of the limited in situ gauge data. In contrast, the WRF-adjusted product revealed noticeable improvement. It brought the BS median value from 0.5 to 0.9 at the 9 mm/day threshold and from 0.2 to 0.85 at the 18 mm/day threshold. The performance of GSMaP was consistent with that of CMORPH. Gauge-adjusted GSMaP showed similar results to the near-real-time one, while the WRF-adjusted product had median values very close to 1. In both CMORPH and GSMaP retrievals, the BS value ranges of the WRF-adjusted products were a little wider than those of the near-real-time products, representing a slight increase in uncertainty.

Results of the Peru HSS metrics are illustrated in Figure 2.4 (bottom). WRF simulations showed the lowest score values, again due to inaccuracies in capturing the spatiotemporal distribution of precipitation. WRF-adjusted satellite products showed the highest values. At higher rain rate thresholds, the WRF-adjusted GSMaP product exhibited not only higher HSS values, but also narrower value ranges. Meanwhile, the value ranges of the different CMORPH products were comparable.

The event-total rainfall comparisons are captured in Figure 2.5. The WRF adjustment significantly improved the near-real-time satellite estimation, especially for the heavier rainfall (>20 mm) events, while the gauge-adjusted products were almost identical to the near-real-time ones for most events. In the quantitative comparison shown in Table 2.3, the WRF-adjusted satellite products outperformed all other products because of their higher correlation values and lower NRMSE and MRE values. The Peru domain provided a very convincing example of the value of using high-resolution numerical weather simulations to evaluate bias adjustment over data-sparse complex terrain regions.
2.4.3 Taiwan domain

The results from the Taiwan domain are captured in Figure 2.6 and Figure 2.7. Unlike the other two study domains, heavy precipitation in Taiwan is from typhoons. As a result, rainfall events in this region have very high rainfall amounts. In fact, the average accumulated rainfall of the 24 Taiwan events studied was 419 mm, while the corresponding rainfall values in Colombia and Peru were 28 and 21 mm, respectively. So we calculated the BS and HSS values in Taiwan at much higher rain rate thresholds: 20, 50, and 80 mm/day.

The Taiwan BS boxplots (Figure 2.6, top) show the same trend seen in the Colombia and Peru regions: the near-real-time satellite products underestimated rainfall, and the adjusted products significantly moderated this underestimation. Unlike in Colombia and Peru, however, the WRF simulation did not show a “close to 1.” It exhibited large underestimation, especially for the higher rain rates. After combining the WRF and satellite products, however, we found the WRF-adjusted satellite products performed the best (closest to 1), with the exception only of the GSMaP at the lowest rainfall threshold (20 mm/day).

The HSS results (Figure 2.6, bottom) for Taiwan revealed different trends than in Colombia and Peru for the CMORPH and GSMaP products. Overall, the HSS metric in Taiwan was lower, and the HSS value ranges were much wider than in the other two regions. Also overall, the WRF-adjusted product showed the best estimation for the CMORPH product, while the gauge-adjustment and WRF adjustment were comparable for the GSMaP product.

Storm-total rainfall plots (Figure 2.7) for Taiwan show similar patterns to those in the Peru plots. The improvements from gauge-based adjustment were limited, and the improvements from WRF-based adjustment were significant. The advantage of WRF-based adjustment is even more noticeable in Table 2.3. The WRF-adjusted CMORPH and WRF-adjusted GSMaP products were
better than all the other products, including the WRF simulation, for all presented statistics: correlation, NRMSE, and MRE.

2.5 Summary

This study evaluated a WRF-based satellite precipitation adjustment technique based on two high-resolution satellite products over three tropical mountainous regions and 81 heavy precipitation events. We compared the WRF-based adjusted satellite products to the original WRF simulations, near-real-time satellite products, and gauge-adjusted satellite products.

Both the CMORPH and GSMaP near-real-time precipitation products exhibited severe underestimation over the tropical mountainous regions. GSMaP exhibited less underestimation than CMORPH. The satellite underestimations tended to be more significant for higher rainfall accumulations. Overall, the gauge-adjusted satellite precipitation products moderated the underestimation of the corresponding near-real-time products. Some storm events revealed the gauge-adjusted counterparts could do worse, however, than the near-real-time satellite estimates over data-sparse mountainous regions.

The WRF-based adjustment technique can be used to derive better satellite precipitation estimates, with significant performance improvements on the error analyses. In fact, the WRF-adjusted satellite products exhibited improvements over their gauge-adjusted counterparts. The WRF-based adjustments for higher rain rates were more effective than for low rain rates, which is important because the high rain rates are more potentially disastrous. The WRF-based adjustment may, however, bring overestimations for locations that already have nearly correct satellite participation magnitude. It should also be noted that the WRF-based adjustment technique could not correct for the missing detections in satellite precipitation products. Overall, WRF-based
adjustment performed very well in Peru and Taiwan but exhibited considerable overestimation for a few events in Colombia.
Table 2.1: WRF v3.7.1 model parameterizations.

<table>
<thead>
<tr>
<th>WRF parameter</th>
<th>Scheme</th>
</tr>
</thead>
<tbody>
<tr>
<td>Microphysics</td>
<td>WRF Double-Moment 6-class scheme.</td>
</tr>
<tr>
<td>Longwave radiation</td>
<td>Rapid Radiative Transfer Model (RRTM) scheme.</td>
</tr>
<tr>
<td>Shortwave radiation</td>
<td>Goddard shortwave: Two-stream multi-band scheme with ozone from climatology and cloud effects.</td>
</tr>
<tr>
<td>Surface layer</td>
<td>MM5 similarity: based on Monin-Obukhov with Carslon-Boland viscous sub-layer and standard similarity functions from look-up tables.</td>
</tr>
<tr>
<td>Land surface</td>
<td>Unified Noah land surface model.</td>
</tr>
<tr>
<td>Planetary boundary</td>
<td>Yonsei University scheme.</td>
</tr>
<tr>
<td>Cumulus parameterization</td>
<td>Grell 3D: an improved version of the Grell–Devenyi scheme that may also be used on high resolution.</td>
</tr>
</tbody>
</table>
Table 2.2: Summary of event selection criteria and number of events.

<table>
<thead>
<tr>
<th>Study region</th>
<th>$R_{\text{intensity}}$ [mm/day]</th>
<th>$R_{\text{length}}$ [mm/day]</th>
<th>Number of events</th>
</tr>
</thead>
<tbody>
<tr>
<td>Colombia</td>
<td>13.5</td>
<td>10</td>
<td>28</td>
</tr>
<tr>
<td>Peru</td>
<td>12</td>
<td>10</td>
<td>29</td>
</tr>
<tr>
<td>Taiwan</td>
<td>100</td>
<td>50</td>
<td>24</td>
</tr>
</tbody>
</table>
Table 2.3: Statistics of event accumulated precipitation.

<table>
<thead>
<tr>
<th>Study Region</th>
<th>Statistics</th>
<th>WRF (upscaled to CMORPH grid)</th>
<th>CMORPH</th>
<th>Gauge-adj CMORPH</th>
<th>WRF-adj CMORPH</th>
<th>WRF (upscaled to GSMaP grid)</th>
<th>GSMaP</th>
<th>Gauge-adj GSMaP</th>
<th>WRF-adj GSMaP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Colombia</td>
<td>R²</td>
<td>0.74</td>
<td>0.60</td>
<td>0.58</td>
<td>0.56</td>
<td>0.72</td>
<td>0.63</td>
<td>0.46</td>
<td>0.62</td>
</tr>
<tr>
<td></td>
<td>NRMSE</td>
<td>0.30</td>
<td>0.49</td>
<td>0.47</td>
<td>0.48</td>
<td>0.32</td>
<td>0.38</td>
<td>0.39</td>
<td>0.60</td>
</tr>
<tr>
<td></td>
<td>MRE</td>
<td>0.10</td>
<td>-0.38</td>
<td>-0.34</td>
<td>0.13</td>
<td>0.12</td>
<td>-0.24</td>
<td>-0.07</td>
<td>0.31</td>
</tr>
<tr>
<td>Peru</td>
<td>R²</td>
<td>0.64</td>
<td>0.57</td>
<td>0.77</td>
<td>0.65</td>
<td>0.63</td>
<td>0.49</td>
<td>0.45</td>
<td>0.67</td>
</tr>
<tr>
<td></td>
<td>NRMSE</td>
<td>0.45</td>
<td>0.66</td>
<td>0.58</td>
<td>0.47</td>
<td>0.45</td>
<td>0.60</td>
<td>0.60</td>
<td>0.51</td>
</tr>
<tr>
<td></td>
<td>MRE</td>
<td>-0.15</td>
<td>-0.53</td>
<td>-0.50</td>
<td>-0.06</td>
<td>-0.15</td>
<td>-0.44</td>
<td>-0.42</td>
<td>0.05</td>
</tr>
<tr>
<td>Taiwan</td>
<td>R²</td>
<td>0.59</td>
<td>0.48</td>
<td>0.55</td>
<td>0.75</td>
<td>0.59</td>
<td>0.60</td>
<td>0.66</td>
<td>0.79</td>
</tr>
<tr>
<td></td>
<td>NRMSE</td>
<td>0.62</td>
<td>0.93</td>
<td>0.78</td>
<td>0.41</td>
<td>0.65</td>
<td>0.85</td>
<td>0.78</td>
<td>0.39</td>
</tr>
<tr>
<td></td>
<td>MRE</td>
<td>-0.39</td>
<td>-0.69</td>
<td>-0.54</td>
<td>-0.04</td>
<td>-0.43</td>
<td>-0.62</td>
<td>-0.55</td>
<td>-0.15</td>
</tr>
</tbody>
</table>
Figure 2.1: Map of terrain elevation and gauge locations of the different study regions.
Left: Colombia domain. Middle: Peru domain. Right: Taiwan domain.
Figure 2.2: Boxplots for Colombia region. Top: Bias Ratio Score. Bottom: Heidke Skill Score.
Figure 2.3: Scatter plots for Colombia region. Left: Event total precipitation of WRF and CMORPH products. Right: Event total precipitation of WRF and GSMaP products.
Figure 2.4: Boxplots for Peru region. Top: Bias Ratio Score. Bottom: Heidke Skill Score.
Figure 2.5: Scatter plots for Peru region. Left: Event total precipitation of WRF and CMORPH products. Right: Event total precipitation of WRF and GSMaP products.
Figure 2.6: Boxplots for Taiwan region. Top: Bias Ratio Score. Bottom: Heidke Skill Score.
Figure 2.7: Scatter plots for Taiwan region. Left: Event total precipitation of WRF and CMORPH products. Right: Event total precipitation of WRF and GSMaP products.
Chapter 3

Application of model-based satellite adjustment in in mid-latitude region with hurricanes-induced storms

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3.1 Introduction

The quantification of heavy precipitation events (HPE) over mountainous areas has been a challenge for all types of satellite products. Many past research studies have focused on the quantitative evaluation of satellite precipitation over different complex terrain regions including the Appalachian mountainous area (Prat et al., 2010), South American Andes (Dinku et al., 2010, Zulkafli et al., 2014), Alps and Massif Central mountain range (Stampoulis et al., 2013), western Black Sea region of Turkey (Derin and Yilmaz, 2014), Ethiopia highlands (Hirpa et al., 2010; Romilly et al., 2011), and the Tibetan Plateau (Gao et al., 2013). These studies have mainly focused on three quasi-global satellite products: National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center morphing (CMORPH); the Tropical Rainfall Measuring Mission (TRMM) Multi-satellite Precipitation Analysis (TMPA) and the Precipitation Estimation from Remotely Sensed
Information using Artificial Neural Networks (PERSIANN). Major findings from these complex terrain error analyses include: the estimates are fairly accurate in capturing the precipitation spatial variability, but the quantification of rainfall exhibits strong underestimation of high rain rates and overestimation of light precipitation; the satellite products tend to underestimate rainfall values over regions with higher elevation. This fact has been discussed over different regions, including Nepal (Barros et al., 2000; Lang and Barros 2002; Barros and Tao, 2008), Taiwan (Chen et al., 2013), Ethiopia (Dinku et al., 2008), and the Continental Europe (Stampoulis et al., 2012); the CMORPH and TMPA estimates exhibited less biases than PERSIANN in most of the study regions, indicative of the fact that passive microwave based products (used in CMORPH and TMPA) can better represent precipitation processes than the infrared-based precipitation retrievals (PERSIANN).

Even though satellite precipitation products are strongly underestimating HPEs in mountainous areas, given their unrivalled advantage of spatial coverage over these data poor regions of earth, and the advent in precipitation remote sensing from the Global Precipitation Measurement satellite (Hou et al., 2014), there is great interest in advancing uses in hydrological applications. This entails the understanding of errors and investigation of correction techniques at different spatial and temporal scales, e.g. daily to monthly for deriving water budgets, and sub-daily for modeling floods and flash floods. Gauge-adjusted satellite products are usually considered as a more reliable data source for hydrological applications than the corresponding unadjusted estimates (Janowiak et al., 1999; Pan et al., 2010; Mei et al., 2014). However, gauge-adjustment requires a relatively dense gauge network and high quality ground measurements (Wilk et al., 2006; Gourley et al., 2011).
In most mountainous areas, lack of surface stations, or the weak characterization of spatial precipitation variability, challenges the reliability of satellite adjustment procedures. Research has even shown that in some cases gauge adjustment estimated with sparse gauge distributions may worsen the accuracy of satellite rainfall estimates (Bitew et al., 2011; Bitew et al., 2012).

To address this issue, Zhang et al. (2013) has proposed a bias correction technique based solely on high-resolution numerical weather prediction (NWP) simulations of mountainous HPEs. The technique was demonstrated on the high-resolution (8 km/hourly) CMORPH precipitation product based on major flood-inducing HPEs over an Alpine region in North Italy. The authors showed improved error statistics resulting from the NWP-adjusted CMORPH relative to the original CMOPRH precipitation estimates by comparing with a high-resolution (1 km/hourly) gauge-adjusted radar-rainfall product. It was argued that such method can be extended over different data-poor mountainous regions to derive error corrections for high-resolution satellite products. In a recent study, Nikolopoulos et al. (2015) tested the above technique on three near-real-time remotely sensed precipitation data sets (two satellite data sets and a radar-only data set) that severely underestimated the 2013 Colorado flood event (Gochis et al., 2014). They confirmed significant reduction of the precipitation underestimation for all examined remotely sensed precipitation products.

This study is built upon previous results demonstrating the feasibility of the NWP-based satellite precipitation adjustment technique for a different type of HPEs (i.e. Atlantic tropical cyclone) and evaluating impacts on flood simulation. Specifically, the study is based on heavy precipitation-induced flooding events associated with six tropical cyclones
over the Southern Appalachian mountainous area. Like in the previous studies, we focused on CMORPH precipitation due to its high spatio-temporal resolution (hourly/ 8-km) and the stronger correlation it exhibits in terms of precipitation patterns relative to other high-resolution products (Zeweldi et al., 2009). Runoff simulations for twenty medium to large size basins within the study area were conducted with a regional distributed hydrologic model currently used at NOAA/NSSL for issuing flood floods within the continental United States (Gourley et al., 2015).

This paper is organized as following: Section 3.2 describes the study area and precipitation datasets. Section 3.3 presents the numerical weather prediction and hydrological model setups for the study area and storm events. The methodology is explained in section 3.4, and results based on the six hurricane cases are shown in section 3.5. Section 3.6 provides the conclusions and discussions.

3.2 Study area and data

3.2.1 Study area

The study area (Figure 3.1) is centered in the Southern Appalachians and spanning into the Piedmont and Coastal Plain regions of North Carolina. The region is located between 33-38 °N latitude and 78-86 °W longitude. It is characterized by complex mountainous terrain in the upper reaches with average annual precipitation ranging between 1200 and 1500 mm. Twenty medium to large size basins (shown on Table 3.1 and Figure 3.1) were used to evaluate the error propagation on flood simulations. The basin areas range between 5847 km² and 64395 km².
Six past hurricane landfall events were selected as case studies of this paper: hurricanes Bill, Gaston, Frances, Ivan, Cindy and Fay. Table 3.2 summarizes the period of each event and the associated rainfall characteristics (peak rainfall rate and rain accumulation) over the study region.

3.2.2 Precipitation data

There are four precipitation datasets involved in the study: i) high-resolution (8 km/30 minutes) CMORPH rainfall product (Joyce et al., 2004; data source ftp://ftp.cpc.ncep.noaa.gov/precip/CMORPH_V1.0/); ii) gauge-adjusted CMORPH rainfall product (Xie et al., 2011), (iii) 2 km/hourly rainfall from the Weather Research and Forecasting Model (WRF) simulations (Skamarock et al., 2008) with initial and boundary conditions derived from the 0.5 degree Global Forecast System (GFS) analysis. The WRF model setup is explained in Section 3.3.1; iv) 4 km/hourly gauge-corrected Stage IV WSR-88D precipitation data (data source http://data.eol.ucar.edu/codiac/dss/id=21.093, Fulton et al., 1998, Lin and Mitchell, 2005). Stage IV precipitation data are considered as the reference for evaluating the CMORPH and WRF rainfall estimations. In order to apply a common data comparison, all datasets were scaled and projected into the CMORPH (Stage IV) rainfall spatial (temporal) resolutions, i.e. 8 km and hourly.

3.2.3 Runoff data

Hourly runoff data were simulated by the Coupled Routing and Excess STorage (CREST) distributed hydrological model (Wang et al., 2011) using the above precipitation datasets. Information on CREST model setup is provided in section 3.3.2.
3.3 Model Setup

3.3.1 Numerical weather prediction model

The NWP rainfall simulations are provided by WRF modeling system version 3.4 (http://www2.mmm.ucar.edu/wrf/users/docs/user_guide_V3.4/ARWUsersGuideV3.pdf). The WRF simulations of hurricane events are completed in a two-way interactive mode with three-domain nesting (18-6-2 km resolution) and 27 vertical level configurations. WRF’s 2-km inner domain extends to 390 by 324 grids and fully covers the Southern Appalachians area (Figure 3.1). In order to cover the entire period of rainfall from the hurricanes, each WRF simulation lasted 72 hours – i.e., simulations started one day before the hurricane landfall day as a warm-up period and ended the day after. Model output files were recorded at hourly time intervals. The rainfall used in this study comes from the entire simulation because there is almost no rain during the warm-up period.

The selection of WRF parameterization schemes is shown in Table 3.3. The Thompson et al. (2006) bulk parameterization scheme was used to describe the microphysical processes. This scheme uses parameters determining auto-conversion rate calculated by presetting cloud water droplet concentration. The rainfall from WRF simulations with the current parameterization have been compared to Stage IV by Quantile-Quantile plots for the six hurricane events (Figure 3.2) and general event characteristics are summarized in Table 3.2. Result show that rainfall magnitudes simulated by WRF are consistent with the Stage IV values, which is the prerequisite of using these estimates to guide the adjustment procedure of CMORPH precipitation.
3.3.2 Hydrological model setup

An implementation of the CREST distributed hydrological model over the Continental US was employed for the flood simulations of this paper. The water balance component of CREST consists of a variable infiltration curve and a conceptual mechanism for surface and subsurface partitioning of excess rainfall. In this version of CREST, the subsurface portion of excess rainfall is routed with a linear reservoir model, while the surface portion is routed with the kinematic wave approximation of the Saint-Venant equations of 1-D open channel flow (Chow et al., 1988). CREST is a model that represents the spatiotemporal variation of water fluxes and storages on a regular grid. An important feature of this model is its versatility for working on different user-defined spatial and temporal scales, which enables multi-scale applications. CREST can be easily configured for various forcing data, which facilitated the analysis in this study.

CREST was implemented herein with the configuration employed in the Flooded Locations And Simulated Hydrographs (FLASH; http://nssl.noaa.gov/projects/flash/) project for its real-time flash flood monitoring system (http://flash.ou.edu). It is configured on a 1-km grid over the Conterminous United States (CONUS). Given the scale of the analysis in this study, the model is integrated using a time step of 1 hour. Model parameters were estimated through an a-priori approach using raster-based data from soil datasets, land cover, and digital elevation model derivatives (Vergara et al., 2015). The use of a-priori estimates can reduce uncertainty in model simulations (Koren et al. 2003), and enables an unbiased comparison of multiple QPE products (Vergara et al., 2014).
3.4 Methodology

3.4.1 Adjustment procedure

In this paper we follow the adjustment technique described in Zhang et al. (2013). Specifically, the original CMORPH rainfall rates were adjusted using a power-law function (Eq. 1) between CMORPH and WRF precipitation rainfall rates derived for each storm event.

\[ Y = a \times X^b \]  

where \( X \) and \( Y \) correspond to the original CMORPH and WRF hourly rain rates, respectively. The parameters of the power law relationship are determined using quantile values of the original CMORPH and WRF rainfall rates derived for different cumulative probability values (i.e. 0.05, 0.1, 0.15, ..., 0.95). The least squares method was used to fit the power law function to the CMORPH-WRF quantile-quantile data of each hurricane event. The power law function with optimal parameter values was then applied on the original CMORPH rain rates to produce the WRF-adjusted CMORPH rainfall rates.

3.4.2 Precipitation error evaluation method

The evaluation is conducted for two temporal scales (storm-length period and hourly), and two spatial scales, i.e. satellite product resolution over the entire study domain and for basin-average storm-total accumulation values.

We first verified the power law relationship derived based on WRF-CMORPH quantiles against the power law relationships derived using the reference Stage IV hourly rain rates.
Subsequently, we evaluated the hourly rain rates of four precipitation products over the study domain (i.e. WRF simulations, original CMORPH, WRF-adjusted CMORPH and gauge-adjusted CMORPH) against the reference rainfall data from Stage IV using (i) qualitative comparison of event-total rainfall accumulation maps and (ii) quantitative comparisons based on two statistical error metrics: bias ratio score (BS; Eq. 2) and Heidke skill score (HSS, Heidke 1926; Eq. 3).

\[ BS = \frac{A+B}{A+C} \quad (2) \]

\[ HSS = \frac{2(A \times D - B \times C)}{(A+C)(C+D)+(A+B)(B+D)} \quad (3) \]

where A, B, C and D are the following occurrences, determined based on five different rain rate thresholds (1, 2, 4, 8 and 12 mm/h):

A: estimator > threshold and Stage IV > threshold;
B: estimator > threshold and Stage IV < threshold;
C: estimator < threshold and Stage IV > threshold;
D: estimator < threshold and Stage IV < threshold.

BS of 1 is considered as an unbiased estimation, while above or below 1 represents overestimation or underestimation, respectively. HSS metric tests the occurrences of exceeding or failing to reach a certain rain rate threshold; its values range from -∞ to 1, where 1 indicates a perfect estimation and less than or equal to zero indicates a random estimation.

Note that although WRF-based adjustment technique is practical in terms of modifying the CMORPH precipitation magnitude it cannot improve the spatial rainfall patterns or rainfall areas. Therefore, the degree of improvement from this technique largely
depends on the quality of spatial rainfall patterns from the original satellite precipitation product.

### 3.4.3 Hydrological impact analysis

As mentioned above we have identified 20 basins within the study domain to evaluate the impact of the WRF-based CMORPH precipitation error adjustment in terms of basin hydrology and flood simulations (Figure 3.1). Specifically, we used the Stage IV reference rainfall, original CMORPH, WRF-adjusted CMORPH and gauge-adjusted CMORPH hourly rain rates to derive hourly basin-average precipitation. These precipitation datasets were then used as input in the CREST model to simulate basin outlet runoff. Evaluation at basin scale is based on scatter plots of basin-average precipitation accumulation, peak runoff simulations and accumulated runoff between the various products and reference (Stage IV). The events’ mean RMSE ratio of accumulated rainfall and runoff are also evaluated to compare the performance of WRF-adjusted relative to the gauge-adjusted CMORPH datasets.

Three statistical metrics, namely bias ratio (Bias), Pearson correlation (COR) and central normalized root-mean-square error (NRMSE; Eq. 4), determined for storm-total rainfall accumulation, peak runoff and accumulated runoff values, are used to demonstrate the error structure of basin scale precipitation and runoff. The NRMSE error metric definition is shown below:

\[
NRMSE = \sqrt{\frac{\frac{1}{n} \sum (Estimator - Stage IV)^2 - \frac{1}{n} \sum (Estimator - Stage IV))}{Mean \ of \ Stage \ IV}}
\]

The NRMSE represents the relative (to the reference mean rainfall) random error component variability.
3.5 Results

3.5.1 CMORPH precipitation adjustment

An overview of the accumulated precipitation maps (Figure 3.3) show similar spatial rainfall patterns between Stage IV, original CMORPH and WRF data for all hurricane events. However, significant magnitude differences (primarily underestimation) are exhibited for the original CMORPH rainfall relative to the reference Stage IV rainfall. By contrast, WRF simulated rainfall exhibits overestimation for most cases except hurricane Gaston (slightly underestimated) where the main rain band is not located at the mountain range but at the eastern side of Appalachians.

The quantile-quantile plots of Figure 3.4 for the quantile ranges of 0.05 to 0.95 show an approximate power-law relationship between WRF and CMORPH, which is in close agreement with the relationship derived between Stage IV and CMORPH. This agreement supports the argument that WRF simulations can be used as proxy to derive the power law adjustment relationship parameters for CMORPH when ground reference is lacking. Furthermore, it should be noted that for all hurricane events, the power-law lines are enclosed in a relatively narrow range in which the WRF-CMORPH relationships tend to have slightly steeper slopes than the Stage IV-CMORPH relationships, which is attributed to the WRF overestimation shown in Figure 3.2 and Figure 3.4. The differences between WRF and Stage IV are more significant for low rain rates (below 8 mm/h) than for higher rain rates.

As shown by the maps of Figure 3.3, the WRF-adjusted CMORPH precipitation exhibits better consistency with the reference (Stage IV) than the original CMORPH product. A
point to note is that WRF-adjusted and gauge-adjusted CMORPH estimates seem to perform similarly in terms of rainfall accumulations for the six hurricane cases examined in this study. However, the gauge-adjusted CMORPH uses gauges that were also used in the Stage IV radar rainfall adjustment, while the WRF-based adjustment is independent of any ground rainfall measurement.

Next we provide quantitative error analysis (Figure 3.5) based on the error metrics of equations (2) and (3). As shown, the BS of the original CMORPH decreases sharply from a slight overestimation in low rainfall threshold (<2 mm/h) to significant underestimation at high rainfall rate thresholds (>8 mm/h). On the other hand, the WRF simulations tend to bias positively rainfall with overestimation ranging from moderate in low thresholds (<4 mm/h) to high in thresholds exceeding 8 mm/h. The WRF-adjusted CMORPH exhibits a more consistent BS score (around 1) and less dependence on rainfall magnitude. The gauge-adjusted CMORPH also exhibits improvements relative to the original CMORPH BS statistic, but it still has a strong magnitude dependent bias. For example, BS values of gauge-adjusted CMORPH are around 0.5 for the 12 mm/h threshold, while the corresponding WRF-adjusted CMORPH BS values are around 1. Evidently, WRF-adjusted CMORPH is the best estimation among the four estimators for these events. In terms of the HSS error metric (Figure 3.6) we show that the original CMORPH and WRF data exhibit lower scores than the two adjusted CMORPH estimates, especially at thresholds exceeding 8 mm/h. This indicates that adjustment not only reduces the bias score, but also improves the random component of the error. Comparison of the WRF-adjusted to the gauge-adjusted CMORPH error statistics shows similar level for all threshold rainfall values.
In terms of the storm total precipitation accumulation at basin scale, the two adjusted CMORPH datasets also perform much better than the original CMORPH. Figure 3.7 shows the scatter plot of storm-total rainfall for the six hurricane events over the 20 basins in our study area. The original CMORPH tends to underestimate the basin-average rainfall accumulation in all cases. Arguably, the WRF-adjusted CMORPH effectively moderates this underestimation. Qualitatively, the scatter shown in Figure 3.7 for the gauge-adjusted CMORPH data is better than the WRF-adjusted CMORPH, but as stated earlier gauge-adjustment in CMORPH is based on the same gauges used in Stage IV, while WRF-adjusted CMORPH is independent of ground reference data.

Table 3.4 shows quantitative error statistics for the basin-average rainfall accumulations. Results indicate that WRF-adjusted CMORPH rainfall values exhibit improved bias ratios and normalized RMSE values relative to the original CMORPH data. In terms of correlation, it is shown that the WRF-based adjustment tends to slightly reduce the score in rainfall. Consistent to the scatter plot of Figure 3.7, the gauge-adjusted CMORPH exhibits better error scores than the WRF-adjusted CMORPH. This aspect is also apparent in the plot of event rainfall-accumulation NRMSE ratios (Figure 3.10a). Specifically, the NRMSE ratios of gauge-adjusted CMORPH to original CMORPH are lower than the NRMSE ratios of WRF-adjusted CMORPH to original CMORPH for all events except hurricane Bill. It is also worth to note that the gauge-adjusted CMORPH data provide much lower NRMSE values than the original CMORPH for all events, while the WRF-based adjustment does not reduce the CMORPH estimates NRMSE as consistently as the gauge-adjustment.
In summary, the WRF-based adjustment is effective in reducing the systematic and magnitude-dependent error, but it is not as efficient in improving the random error component as exhibited by the central NRMSE and correlation statistics. Three events out of the six used in this study exhibited similar NRMSE values as the original CMORPH rainfall (Figure 3.10a); in two events though we showed significant reduction while in one event WRF-based adjustment worsened the NRMSE. This probably stems from inaccuracies in WRF simulations of high rainfall rates.

3.5.2 Hydrological impacts

Results on hydrological impacts are summarized in Figure 3.8 and Figure 3.9. Overall, this analysis shows that the WRF-based adjustment improves the accuracy of CMORPH rainfall driven hydrological simulations. Specifically, we note close agreement between the WRF-adjusted CMORPH-rainfall driven CREST simulations and the reference runoff simulations driven by Stage IV data. An example of runoff simulations for basin B6 based on the various precipitation-forcing datasets is shown in Figure 3.8. We note significant reduction of the underestimation of original CMORPH driven runoff simulations due to the two adjustment procedures (gauge-based and WRF-based). However, the time series runoff results do not demonstrate any clear preference between the two datasets. Consistent with the time series plots, the scatter plots of basin outlet runoff (Figure 3.9) show that the original CMORPH derived runoff exhibits strong underestimation. On the other hand, both WRF-adjusted and gauge-adjusted CMORPH derived runoff have values closer to those derived from Stage IV-driven simulations. As in the basin-scale rainfall
error analysis (Figure 3.7), the WRF-adjusted CMORPH reflects slightly higher biases than the gauge-adjusted CMORPH.

Table 3.4 summarizes bulk statistics for the runoff simulations. As shown in the results of Table 3.4, the WRF-adjusted CMORPH runoff performs better than the original CMORPH in terms of all error scores. The bias ratios of WRF-adjusted CMORPH runoff are close to 1 for both peak runoff and accumulated runoff values. WRF-adjusted CMORPH runoff also has higher correlation and less NRMSE values than the original CMORPH. Comparing results to the rainfall error statistics, the hydrological simulations moderate the differences of WRF-adjusted CMORPH to the gauge-adjusted CMORPH data. Figure 3.10b shows a comparison between WRF-adjusted and gauge-adjusted CMORPH datasets. Both datasets reduce the runoff NRMSE values of the original CMORPH; gauge adjustment provides a marginally better correction than the WRF-based correction. However, the point of pursuing this study is that the gauge adjustment is not a scenario always feasible, particularly when considering mountainous areas with limited in situ observations. Therefore the close similarity using WRF-adjusted CMORPH is a promising approach to improving the hydrologic use of satellite rainfall in global data poor mountainous areas.

### 3.6 Summary and Discussion

The study assessed the performance of NWP-based CMORPH adjustment at high spatio-temporal resolution based on WRF simulations of six hurricane landfall events in Southern Appalachians region. The error analysis was based on two aspects: (i) the evaluation of adjusted CMORPH precipitation error properties across the study domain and at basin scale;
and (ii) the hydrologic evaluation of the adjusted products in terms of rainfall and flood simulations derived from a distributed hydrological model. The major findings can be summarized as follows.

Original CMORPH data are likely to provide similar rainfall patterns as the reference radar rainfall (Stage IV) dataset, but with a strong magnitude-dependent systematic error. WRF simulations on the other hand overestimated rainfall magnitude, especially the higher rain rates. The WRF-adjusted CMORPH rainfall based on the Zhang et al. (2013) technique was shown to provide a significantly improved estimate. The technique could effectively moderate the magnitude-dependent systematic error; it particularly reduced the strong underestimation of high rain rates apparent in the original CMORPH estimates. Furthermore, WRF-adjusted CMORPH rain rates exhibited improved correlation scores relative to the original CMORPH as demonstrated by the HSS error metric.

Based on the entire study domain error analysis, the WRF-based adjustment on CMORPH performed similarly to the post-processing gauge adjustment. However, the gauge-adjusted CMORPH product is not available in real-time and its accuracy is prone to the density and availability of surface observations. On the other hand WRF-adjusted CMORPH rainfall can be applied for any mountainous region on earth based on NWP analysis or forecasts once the CMORPH product is available (usually 12 to 18 hours after the observation time). Note that the current WRF-adjustment method will have limited success when the satellite product i) has rain detection errors (both false detection and missing rainfall areas), and ii) varying error characteristics according to geographic and
storm development stages. These aspects will require extensions of the technique that is subject of future research.

The basin outlet runoff derived from WRF-adjusted CMORPH rainfall exhibited improved statistics relative to the ones derived from original CMORPH rainfall fields. In general, the gauge-adjusted CMORPH product performed better in terms of the hydrological analysis (i.e. basin average rainfall and flood simulations). Although the flash flood prediction based on WRF-adjusted CMORPH data does not show consistently superior performance relative to the gauge-adjusted product, this adjustment method presents an innovation with potential to advance real-time flash flood forecasting by satellite precipitation, especially in regions that are ungauged where the community is likely to get most societal benefit.
Table 3.1: Case study basins information

<table>
<thead>
<tr>
<th>Basin ID</th>
<th>Basin Area [km²]</th>
<th>Basin Outlet Location</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Latitude</td>
</tr>
<tr>
<td>B1</td>
<td>64395</td>
<td>34.50</td>
</tr>
<tr>
<td>B2</td>
<td>39769</td>
<td>33.17</td>
</tr>
<tr>
<td>B3</td>
<td>36667</td>
<td>33.48</td>
</tr>
<tr>
<td>B4</td>
<td>28941</td>
<td>36.30</td>
</tr>
<tr>
<td>B5</td>
<td>26060</td>
<td>32.43</td>
</tr>
<tr>
<td>B6</td>
<td>23584</td>
<td>35.94</td>
</tr>
<tr>
<td>B7</td>
<td>22861</td>
<td>34.19</td>
</tr>
<tr>
<td>B8</td>
<td>20899</td>
<td>33.30</td>
</tr>
<tr>
<td>B9</td>
<td>18167</td>
<td>37.39</td>
</tr>
<tr>
<td>B10</td>
<td>18039</td>
<td>38.67</td>
</tr>
<tr>
<td>B11</td>
<td>11715</td>
<td>37.64</td>
</tr>
<tr>
<td>B12</td>
<td>11217</td>
<td>38.40</td>
</tr>
<tr>
<td>B13</td>
<td>10199</td>
<td>35.30</td>
</tr>
<tr>
<td>B14</td>
<td>10030</td>
<td>32.73</td>
</tr>
<tr>
<td>B15</td>
<td>9581</td>
<td>39.08</td>
</tr>
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<td>B16</td>
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<td>B17</td>
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<td>B18</td>
<td>7306</td>
<td>37.99</td>
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<td>B19</td>
<td>7093</td>
<td>35.59</td>
</tr>
<tr>
<td>B20</td>
<td>5847</td>
<td>32.88</td>
</tr>
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</table>
Table 3.2: Hurricane landfall precipitation events used in the study.

<table>
<thead>
<tr>
<th>Hurricane</th>
<th>Event Period</th>
<th>Accumulated Rainfall [mm] (domain maximum)</th>
<th>Peak Rainfall [mm/h] (domain maximum)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Stage IV</td>
<td>WRF</td>
</tr>
<tr>
<td>Bill</td>
<td>2003-07-01 to 2003-07-03</td>
<td>198</td>
<td>274</td>
</tr>
<tr>
<td>Gaston</td>
<td>2004-08-29 to 2004-08-31</td>
<td>322</td>
<td>260</td>
</tr>
<tr>
<td>Frances</td>
<td>2004-09-07 to 2004-09-09</td>
<td>359</td>
<td>413</td>
</tr>
<tr>
<td>Ivan</td>
<td>2004-09-16 to 2004-09-18</td>
<td>292</td>
<td>357</td>
</tr>
<tr>
<td>Cindy</td>
<td>2005-07-06 to 2005-07-09</td>
<td>148</td>
<td>257</td>
</tr>
<tr>
<td>Fay</td>
<td>2008-08-26 to 2008-08-28</td>
<td>299</td>
<td>799</td>
</tr>
</tbody>
</table>
Table 3.3: WRF model set up.

<table>
<thead>
<tr>
<th>WRF parameter</th>
<th>Scheme</th>
</tr>
</thead>
<tbody>
<tr>
<td>Microphysics</td>
<td>New Thompson et al. (2008) scheme: a new scheme with ice, snow, and graupel processes suitable for high-resolution simulations</td>
</tr>
<tr>
<td>Longwave radiation</td>
<td>Rapid Radiative Transfer Model scheme</td>
</tr>
<tr>
<td>Shortwave radiation</td>
<td>Two-stream multi-band scheme with ozone from climatology and cloud effects</td>
</tr>
<tr>
<td>Surface Layer</td>
<td>MM5 similarity: Based on Monin-Obukhov with Carston-Boland viscous sub-layer and standard similarity functions from look-up tables</td>
</tr>
<tr>
<td>Land Surface</td>
<td>Unified Noah Land Surface Model</td>
</tr>
<tr>
<td>Planetary Boundary layer</td>
<td>Yonsei University scheme: Non-local-K scheme with explicit entrainment layer and parabolic K profile in unstable mixed layer</td>
</tr>
<tr>
<td>Cumulus Parameterization</td>
<td>Grell 3D: an improved version of the GD scheme that may also be used on high resolution</td>
</tr>
</tbody>
</table>
Table 3.4: Basin scale statistics of the different CMORPH estimates vs. Stage IV (statistics are based on 6 events over the 20 basins).

<table>
<thead>
<tr>
<th></th>
<th>Original CMORPH</th>
<th>WRF-adj CMORPH</th>
<th>Gauge-adj CMORPH</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Accumulated basin-average rainfall</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bias Ratio</td>
<td>0.72</td>
<td>0.89</td>
<td>0.91</td>
</tr>
<tr>
<td>Correlation</td>
<td>0.80</td>
<td>0.78</td>
<td>0.91</td>
</tr>
<tr>
<td>NRMSE</td>
<td>0.51</td>
<td>0.46</td>
<td>0.30</td>
</tr>
<tr>
<td><strong>Peak Runoff</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bias Ratio</td>
<td>0.67</td>
<td>1.05</td>
<td>0.88</td>
</tr>
<tr>
<td>Correlation</td>
<td>0.94</td>
<td>0.95</td>
<td>0.94</td>
</tr>
<tr>
<td>NRMSE</td>
<td>0.81</td>
<td>0.66</td>
<td>0.66</td>
</tr>
<tr>
<td><strong>Accumulated Runoff</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bias Ratio</td>
<td>0.71</td>
<td>1.00</td>
<td>0.90</td>
</tr>
<tr>
<td>Correlation</td>
<td>0.97</td>
<td>0.97</td>
<td>0.97</td>
</tr>
<tr>
<td>NRMSE</td>
<td>0.63</td>
<td>0.48</td>
<td>0.46</td>
</tr>
</tbody>
</table>
Figure 3.1: Study area with 20 basins. Elevation data source: Aster Global DEM. The map is also WRF inner domain: 2km resolution (390x324 grids).
Figure 3.2: Quantile-Quantile plot of WRF vs. Stage IV hourly rain rates for the six hurricane events.
Figure 3.4: Quantile-Quantile plots of original CMORPH vs. Stage IV (left panel) and CMORPH vs. WRF (right panel) hourly rain rates for the six hurricane events.
Figure 3.5: Bias Score (BS) of original CMORPH and WRF (left panel) and WRF-adjusted and gauge-adjusted CMORPH (right panel) vs. rain rate threshold. (The two sets of symbols are offset for clarity)
Figure 3.6: As in Figure 3.5, but for the HSS metric. (The two sets of symbols are offset for clarity)
Figure 3.7: Scatter plots of Stage IV vs. estimated (original CMORPH, WRF-adjusted and gauge-adjusted CMORPH) basin-average accumulated rainfall.
Figure 3.8: Basin B6 runoff time series from CREST simulations.
Figure 3.9: Scatter plots of Stage IV vs. estimated rainfall-driven simulated basin outlet peak runoff (upper) and basin outlet accumulated runoff (bottom).
Figure 3.10: The NRMSE ratios of accumulated rainfall (a) and accumulated runoff (b) for each event.
Chapter 4

Application of model-based adjustment of IMERG Precipitation for flood-inducing complex terrain storms

This Chapter has been submitted to Atmospheric Research

4.1 Introduction

Accurate measurement of precipitation is prerequisite for understanding the related hydrologic processes. The fact that precipitation is highly discontinuous in space and time is a crucial challenge for observation. Over topographically complex regions, it is especially challengeable because of the more sophisticated variability and uncertainty of precipitation introduced by orographic effects (Roe 2005; Houze 2012). Generally, observed gridded precipitation data sets can be generated by three approaches: gauge data interpolation, surface radar network and satellite-based observation.

The accuracy of gauge interpolation depends largely on the gauge density and the quality of measurement. Gauge locations can never be homogeneously distributed. It always tend to lie at low elevation and densely populated areas relative to the mountainous terrain because of the higher costs of gauge installation and maintenance over complex topography. Moreover, since the gauge networks all over the world are operated by different countries, the observations are less accessible due to different data-sharing policies. Hence, gauge-based gridded precipitation data sets are usually in coarse temporal and spatial resolutions. So far most of the global products are in monthly
or daily time scale and at 0.25° to 2.5° spatial resolutions (Becker et al. 2013; Schamm et al. 2014; NOAA 2013; Haylock et al. 2008; Yatagai et al., 2009).

For meso-scale studies such as extreme rainfall events and related floods, precipitation products with higher spatial and sub-daily temporal resolution are required. Surface radar network provides fine resolution products, but the data quality is highly susceptible to terrain complexity due to severe beam shielding and strong ground clutter (Krajewski and Smith 2002; Germann et al. 2006; Villarini and Krajewski 2010). In addition, considering the expensive operating and maintenance costs, the spatial coverage of radar network is very limited especially in mountainous or less populated regions.

Besides surface observations, techniques of satellite-based measurements have been developed rapidly over the past 30+ years (Kidd and Levizzani 2011). As a result, a variety of satellite-based precipitation products came to be available with quasi-global coverage, including but not limited to, the Tropical Rainfall Measuring Mission (TRMM) near-real-time Multisatellite Precipitation product (3B42RT, Huffman et al. 2007), the National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center (CPC) morphing technique (CMORPH; Joyce et al. 2004), the Precipitation Estimation from Remotely Sensed Information Using Artificial Neural Networks (PERSIANN, Sorooshian et al. 2000), and the Global Satellite Mapping of Precipitation Microwave-IR Combined Product (GSMaP) datasets produced by the Earth Observation Research Center (EORC) of the Japan Aerospace Exploration Agency (JAXA; Kubota et al. 2007; Ushio et al. 2013), and product of Global Precipitation Measurement (GPM) Integrated Multi-satellitE Retrievals for GPM (IMERG; Huffman et al. 2015). Many studies indicate that these satellite products tend to largely underestimate heavy precipitation over

Apart from single source data sets, products with combined data sources are available as well. Traditionally, gauge observations are incorporated into the raw radar or satellite products for the purpose of better accuracy (Lin and Mitchell 2005; Sinclair and Pegram 2005; Goudenhoofdt and Delobbe 2009). In fact, most satellite products mentioned above have their gauge-adjusted counterparts (Huffman et al. 2007; Mega et al. 2014; Xie et al. 2011; Huffman et al. 2015; Xie et al. 2017). In general, gauge-adjusted satellite products need weeks to months to process before releasing and the accuracy largely depends on the spatio-temporal representativeness of gauge network. Over mountainous regions, where usually have sparsely distributed gauge network and temporally coarser gauge observations, there are great uncertainties on the performance of gauge-adjusted satellite precipitation products (Derin et al. 2016; Beck et al. 2017).

To address the aforementioned disadvantages of gauge-based adjustment, Zhang et al. (2013) developed a numerical model based technique for satellite precipitation adjustment. This technique is designed specifically for heavy precipitation events over topographically complex regions, where the raw satellite products experience considerable underestimation (Scofield and Kuligowski 2003; Derin et al. 2016). Model-adjusted satellite product is supposed to overcome the negative bias without gauge data input. In addition, the model-adjusted product can be generated in near-real-time, which means the data processing time is much less than the corresponding gauge-adjusted product. Previous studies (Zhang et al. 2013, Nikolopoulos et al. 2015; Zhang et al. 2016, and Zhang and Anagnostou submitted) have successfully applied this technique on the raw CMORPH and GSMaP products with model analysis simulations for severe
storms over mountain ranges all over the world such as Alps, Andes, Appalachians, Rockies and mountains in Taiwan.

The objective of this paper was to examine the feasibility of model-based satellite adjustment technique on the latest near-real-time IMERG product with a NWP-based ensemble precipitation forecast data set produced by NCAR (Schwartz et al. 2015). The study focused on a large number of flood-inducing storms occurred in major mountain ranges over contiguous United States (CONUS), and is unique in that for a first time combines precipitation forecasts with near-real-time satellite precipitation products. The paper is organized into four sections. Section 4.2 provides the information of study regions and precipitation data sets. Section 4.3 explains the methodology of model-based satellite adjustment and data evaluation. Section 4.4 presents the results. Section 4.5 presents the conclusions and thoughts of future study.

4.2 Study Regions and Data Sets

4.2.1 Study regions

The selection criteria for study regions took into account both terrain complexity and annual precipitation amount. We picked seven regions from major mountain ranges in the contiguous United States (CONUS): the Appalachians, the Rocky Mountains, the Olympic Mountains, the Pacific Coast Ranges, the Cascade Range, and the Sierra Nevada. Each region was composed of multiple counties with complex terrain and relatively high annual precipitation. Four of the regions (Figure 4.1, regions a, b, c, and d) were along the Pacific coastline, where the climate is influenced heavily by the ocean and characterized by wet winters and dry summers. The other three (Figure 4.1, regions e, f, and g) were inland regions with continental climates. Region elevation maps
shown in Figure 4.2 are based on USGS Shuttle Radar Topography Mission (SRTM) data set (https://lta.cr.usgs.gov/SRTM).

The Western Washington region (Figure 4.2a) covers the Olympic Mountains and the windward side of the North Cascade Range. The terrain is complex, with elevation ranging from 500 to 1,500 m a.s.l. and several volcanoes reaching significantly higher altitudes than the rest of the mountains. This region is characterized by an oceanic climate with mild temperatures in all seasons. It has relatively dry summers, and most precipitation occurs in winter, spring, and fall. The annual average precipitation varies roughly from 1,500 to 3,300 mm in the higher altitude areas. On the western slopes of the Olympic Mountains, annual precipitation can exceed 4,000 mm, which makes this region the rainiest in CONUS.

The Western Oregon region (Figure 4.2b) is composed of the Pacific Coast Ranges, the windward side of the Central Cascade Range, the Northern Klamath Mountains, and Willamette Valley. The elevation of most mountainous areas ranges approximately from 500 to 1,500 m a.s.l. Like Western Washington, Western Oregon has an oceanic climate, with very wet winters and dry summers. The overall annual average precipitation in Western Oregon’s complex topography ranges between 1,200 and 3,000 mm, which is slightly lower than in Western Washington.

The study region of Northern and Central California (Figure 4.2c) covers the Southern Klamath Mountains, the Coast Ranges, the windward side of the Southern Cascade Range and the Sierra Nevada, and the Great Valley. This region is characterized by extremely steep topographic gradients, from the valleys to the mountains. The elevation in mountainous areas ranges approximately from 400 to 2,300 m a.s.l. A small portion of the Sierra Nevada can exceed 3,000 m a.s.l. Most of the precipitation occurs in the mountainous areas. The northwestern part of this
region has annual average precipitation between 1,300 and 3,000 mm, while other mountains in the region have less, ranging from 800 to 2,300 mm.

The Southern California study region (Figure 4.2d) is smaller than the others. It includes the Peninsular Ranges and part of the Transverse Ranges. The elevation in most mountainous areas ranges from 200 to 2,000 m a.s.l. Like the above three coastal regions, this region is under maritime influence, but the climate is much drier and hotter. Annual average precipitation ranges approximately from 200 to 700 mm.

The study region of Northern Idaho and Western Montana (Figure 4.2e) is an inland area covering part of the Middle Rocky Mountains. Elevation gradually increases from north to south and ranges roughly from 1,000 to 2,500 m a.s.l. The highest point, at Borah Peak, is over 3,800 m a.s.l. This region is dominated by a continental and subarctic climate with annual precipitation ranging from 500 to 1,400 mm.

The Central Colorado region (Figure 4.2f) is located in the Southern Rocky Mountains. It is between the Continental Divide and the western boundary of the Colorado Plains and includes Colorado’s most populated area (Front Range). The topography of most of this region is very complex, with elevation ranging between 1,500 and 3,000 m a.s.l., while the highest point is above 4,300 m a.s.l. Similar to the Idaho and Montana domain, Central Colorado has a continental or subarctic climate, but it has less precipitation. Annual average precipitation ranges between 350 and 800 mm.

The third inland region is located in the Southern Appalachians (Figure 4.2g). Specifically, it covers all of the Blue Ridge Mountains and part of the Ridge-and-Valley Appalachians, which are two physiographic provinces of the larger Appalachian range. Elevation of the mountainous areas ranges approximately from 500 to 1,700 m a.s.l. Although it has a humid subtropical and
temperate oceanic climate, we still count it as an inland region in this research because it includes no coastal area. Annual average precipitation ranges from 1,000 to 2,500 mm, with no significant seasonal differences.

4.2.2 Precipitation datasets

a. Satellite-retrieved products

The Integrated Multi-satellitE Retrievals for GPM (IMERG) precipitation product is available at 0.1°/30-minute resolution with quasi-global coverage (60°N–60°S). The IMERG algorithm merges all available satellite microwave precipitation estimates, the microwave-calibrated infrared (IR) satellite estimates, gauge analyses, and other precipitation estimators from the TRMM and GPM eras (Huffman et al. 2015). With the GPM core satellite in service, IMERG is considered a more comprehensive precipitation product than those of the TRMM era. In consideration of the observation data latencies, IMERG is run multiple times to provide quick estimates at first (herein called raw IMERG), followed by better estimates generated with more available data, and finalized with gauge data to create a research-level product (herein called gauge-adjusted IMERG).

This study used the IMERG version 5B final stage product. The product file contains two variables for precipitation estimates: precipitation with gauge-adjustment and without (raw) gauge adjustment. Since the research goal was to conduct IMERG correction solely by numerical model, a numerical weather prediction–based adjustment was applied to the raw IMERG estimates. To compare the two adjustment methods—NWP-based and gauge-based—we also included the gauge-adjusted IMERG estimates in the error analyses discussed in this paper.
b. Numerical Weather Prediction

We extracted the precipitation forecasts from NCAR’s Experimental Real-Time Ensemble Prediction System (Schwartz et al. 2015). This is a 10-member ensemble prediction system that produces 48-hour forecasts daily, with 3-km spatial resolution over CONUS. The ensemble data have been available since April 2015. All ensemble members share the same physics and dynamics model options, which makes them all equally likely to represent the “truth.”

In a study by Schwartz et al. (2015), the NCAR ensemble generally conducted reasonable amplitudes of precipitation from the viewpoint of multi-month accumulation (April 7 to July 5, 2015), while the analyses of hourly precipitation rates revealed over-prediction for higher rates (≥ 5.0 mm/hour) and under-prediction for lower rates. These results indicated the NCAR ensemble precipitation was potentially suitable for conducting model-based correction on the IMERG underestimation of the heavy precipitation events in the case study areas.

c. NCEP Stage IV product

For the reference precipitation data, we used the NCEP Stage IV precipitation dataset (Lin and Mitchell 2005), which is a multi-sensor (radar & gauge) product available over CONUS at 4-km spatial resolution. The final product is mosaicked by observations from twelve National Weather Service (NWS) River Forecast Centers (RFCs). Stage IV data are available in hourly, 6-hourly, and 24-hourly temporal resolutions. The 6-hourly and 24-hourly products cover the entire CONUS, while the hourly product is not available in western coastal states, where four of the coastal case study domains are located. This study therefore used the 6-hourly product for data evaluation.
4.3 Methodology

4.3.1 Event selection

The precipitation events we selected took place between May 2015 and December 2016 (a 20-month period). Since the research focused solely on flood-inducing storms, we first collected flood reports from the NOAA Storm Events Database (https://www.ncdc.noaa.gov/stormevents/) for that period for each study region. We then identified precipitation events associated with these flood reports. We eliminated coastal flood reports from the study because, precipitation aside, coastal flooding usually depends greatly on storm surge. We found a total of 523 flood and flash flood reports for the seven study regions and study period, associated with 81 heavy precipitation events.

4.3.2 IMERG adjustment

Before applying the adjustment, we aggregated the model forecast precipitation from its original (3-km) grid to the IMERG grid. We performed the remapping procedure by assigning model grid centers to the IMERG grid box. The average value of these model grid cells represented the remapped model value in the IMERG grid. We temporally aggregated the model and IMERG values at 6-hourly precipitation rates for consistency with the Stage IV temporal resolution.

We performed the adjustment by matching the IMERG precipitation quantile values with the model quantile values using a power-law relationship. Specifically, we computed precipitation quantile values from all non-zero, 6-hourly precipitation rates of each data set. To simplify the calculation, we used only 5%, 10%, 15%, …, 95% quantile values in the data fitting equation shown below,

\[ Y = a \times X^b, \]

(1)
where $X$ and $Y$ represented the precipitation quantile values of IMERG and model, respectively. We estimated the parameters $a$ and $b$ values by the least squares method. The adjustment was done in event scale, meaning $a$ and $b$ values varied for each precipitation event. After data fitting, we applied $a$ and $b$ values back to all IMERG precipitation rates by Eq. 1 again to produce model-adjusted IMERG data. Note that model precipitation is a 10-member ensemble data set. Each member was used in the adjustment separately. Eventually, a new product was generated: model-adjusted IMERG ensemble precipitation.

### 4.3.3 Data evaluation

We evaluated precipitation estimates for each event at 0.1° horizontal resolution, meaning we remapped Stage IV reference precipitation onto the IMERG grid by the same procedure we used for model remapping. We compared four estimators (model ensemble, raw IMERG, gauge-adjusted IMERG, and model-adjusted IMERG ensemble precipitation) against the Stage IV reference precipitation at 6-hourly/0.1° resolution. Since the mean values of the model ensemble and the second largest values of the model-adjusted IMERG ensemble performed best than other members in each ensemble group, the study results shown below will be for these two members only.

We quantitatively analyzed the 6-hourly precipitation rates using three error metrics: the Bias Ratio Score (BS), Heidke Skill Score (HSS; Heidke 1926), and Critical Success Index (CSI). These error metrics are derived from the 2-dimensional contingency table representing the following four occurrence conditions:

- $A$ is counted when Estimator > threshold and Stage IV > threshold (hits);
- $B$ is counted when Estimator > threshold and Stage IV < threshold (false alarms);
C is counted when Estimator < threshold and Stage IV > threshold (misses);

D is counted when Estimator < threshold and Stage IV < threshold (correct rejections).

Each score is calculated at three thresholds. Threshold values varied for each region, depending on local precipitation intensity. The equation for Bias Score is shown below:

$$BS = \frac{A+B}{A+C}$$  \hspace{2cm} (2)

BS aims to show an estimator’s bias for an entire study domain and a whole event, meaning BS is affected by the overall estimation, but not the exact location and timing of rainfall. It has a perfect value of 1, with below or above 1 representing under- or overestimation, respectively.

The following equations are used to estimate the Heidke Skill Score:

$$PC = \frac{A+D}{A+B+C+D}$$  \hspace{2cm} (3a)

$$F = \frac{(A+B)(A+C)+(B+D)(C+D)}{(A+B+C+D)^2}$$  \hspace{2cm} (3b)

$$HSS = \frac{PC-F}{1-F} = \frac{2(AD-BC)}{(A+C)(C+D)+(A+B)(B+D)}$$  \hspace{2cm} (3c)

PC is the percentage of correct estimates, and F is the fraction of correct estimations expected by chance. Finally, HSS is defined as the percentage of correct estimates that has been adjusted by the number expected to be correct by chance. HSS values range from $-\infty$ to 1, with 1 indicating a perfect set of estimation, and negative values indicating the given estimation has fewer hits (H) than a random estimation.

Finally, the Critical Success Index score is presented below:

$$CSI = \frac{A}{A+B+C}$$  \hspace{2cm} (4)

CSI measures the fraction of precipitation rates that were correctly estimated. It examines the accuracy of the estimator without considering the correct rejections (D). CSI is sensitive to hits
and penalized for misses and false alarms, so it is a function of probability of detection (POD) and false alarm ratio (FAR). The range of CSI values is from 0 to 1, with 1 as the perfect value.

To examine the performance of model-based IMERG adjustment in different topographic and climatic conditions, we classified the study regions into two groups: Pacific coastal regions and inland regions. Then we analyzed the domain average event total precipitation estimation performance by Pearson correlation coefficient (CORR) and normalized root-mean-square-error (NRMSE),

\[ NRMSE = \sqrt{\frac{\frac{1}{n} \sum_{i=1}^{n} (E_i - \bar{E})^2 - (\bar{S} - \bar{S})^2}{\frac{1}{n} \sum_{i=1}^{n} S_i}} \]  

where \( n \) is number of events in each group, and \( E \) and \( S \) are precipitation of estimator and Stage IV, respectively. NRMSE measures the random component of error after removing the bias. CORR reveals the similarity of each estimator to Stage IV data.

4.4 Results and Discussion

4.4.1 Comparisons of precipitation rates

The seven study regions are discussed separately in this section. Figure 4.3 shows the error statistics of the 6-hourly precipitation rate in the Western Washington region. The BS, HSS, and CSI scores of all ten precipitation events occurring in this region are shown in boxplots, with three different rain rate thresholds for all estimators. Gray bars represent the NCAR model, light blue represent raw IMERG, dark blue represent gauge-adjusted IMERG, and yellow represent model-adjusted IMERG.

As the BS plot shows (Figure 4.3, left panel), the IMERG product tended to underestimate precipitation, while the model data tended toward slight overestimation. The gauge-based
adjustment not only did not improve IMERG performance; it caused a considerable underestimation. In contrast, the model-adjusted IMERG product showed considerable improvement, with BS values around 1 for all precipitation thresholds.

HSS values (Figure 4.3, middle panel) showed that model forecasts exhibited highest score than the IMERG estimates for all thresholds, and the raw IMERG score was relatively low. The performances of the gauge-adjusted and model-adjusted IMERG products were similar to that of the raw IMERG. This result indicated that neither IMERG adjustment could reduce the random component of the error.

The CSI values (Figure 4.3, right panel) showed a clear decreasing trend for all estimators, with rain thresholds going from low to high. Although the CSI values of the raw and gauge-adjusted IMERG products were relatively low, the model-adjusted product produced higher values, indicating the model-based adjustment effectively increased the percentage of correct estimates. Overall, the model-adjusted IMERG performed the best out of all three IMERG-related products, although the NCAR model forecast provided an even better estimation.

Figure 4.4 shows the results of the analysis of 16 heavy precipitation events in the Western Oregon region. The raw IMERG exhibited underestimation in terms of BS values. While the model-based adjustment significantly moderated the negative biases, the gauge-based adjustment had no apparent impact on the product. In fact, the gauge-adjusted IMERG showed no improvement for any error matrix (BS, HSS, or CSI). Meanwhile, the model forecast was consistently superior to the three IMERG products at lower precipitation thresholds (2 and 4 mm/6h) for all error matrices, while at the high threshold (8 mm/6h) the performance of the model-adjusted IMERG was comparable to that of the model forecast.
Results for the North and Central California region (Figure 4.5) were based on 17 heavy precipitation events. BS values of the raw IMERG product continued to exhibit severe underestimation. Unlike in the Washington and Oregon regions, the gauge-based adjustment in this region did improve the precipitation estimates. Meanwhile, the model-based adjustment performed even better, especially at the 8 mm/6h threshold, where the median BS value was very close to 1. The advantage of model-based adjustment could be found in the HSS and CSI plots, as well. Overall, the model-adjusted IMERG had not only higher HSS and CSI median values but also narrower score value ranges than the other two IMERG products. Still, although the model-adjusted IMERG proved superior to the other IMERG products, the model forecast showed the overall best performance for all error matrices in this region.

Southern California (Figure 4.6) is the last coastal study region discussed here. Given the relatively dry climatic conditions of this area, only seven flood-inducing precipitation events were identified. Similar to the above three coastal regions, the raw IMERG product was shown to be the worst estimator, with apparent underestimations, and the model forecast performed the best for all error matrices. Nevertheless, unique to this region was the slightly better performance of the gauge-based adjustment relative to that of the model-based adjustment for BS, HSS, and CSI, even though both adjustments appeared to be more accurate than the raw IMERG. Moreover, comparison of BS plots across all four coastal regions showed Southern California with the greatest raw IMERG underestimation, and the two adjustment methods were unable to improve IMERG to a reasonable level.

Moving to inland areas, five flood-inducing precipitation events were included in the error matrices for the Northern Idaho and Western Montana region (Figure 4.7), which is a portion of the Rocky Mountains with generally high altitude. The raw IMERG product exhibited
underestimation, and the model forecast had BS values mostly around 1. At 1 and 2 mm/6h thresholds, the gauge-based adjustment shrunk the BS range, but the median BS values remained the same indicating no improvement, while the model-adjusted IMERG product exhibited significant improvement. At the 4 mm/6h threshold, the model-adjusted IMERG performed better than the model itself. HSS and CSI plots showed similar error characteristics in the comparison among the four estimators. Basically, the two adjusted IMERG products performed comparably to the model forecast at high thresholds and were less accurate at lower thresholds.

The second study region in the Rocky Mountains, Central Colorado, had nine precipitation events included in the analysis (Figure 4.8). As in all the above regions, the raw IMERG showed severe underestimation for all rain rate thresholds. Gauge-based adjustment had very limited impact on the IMERG product; thus, the error scores showed no significant improvement. Comparison of the BS, HSS, and CSI matrices indicated the model-adjusted IMERG product was superior to any of the other estimators, including the model forecast. In fact, the model forecast in this region had a general trend of overestimation and relatively low performance in terms of HSS and CSI values.

Seventeen precipitation events were analyzed in the region of the Southern Appalachians (Figure 4.9), with results similar to those for the Colorado region—that is, the raw IMERG tended to underestimate for all rain rate thresholds, and the model-adjusted product performed best overall. The accuracy of the model forecast was comparable to that of the model-adjusted IMERG in the BS matrix, but the HSS and CSI values were much less. A possible explanation for the disagreement between the HSS/CSI and BS plots is that the model successfully predicted the domain average rainfall intensity but with wrong spatial patterns.
Overall, for all study regions, the worst performance of rain rate estimation was exhibited by the raw IMERG product. Both the gauge- and model-based adjustments reflected effectiveness on IMERG correction. With the exception of Southern California, the model-adjusted IMERG product provided more notable improvements than the corresponding gauge-adjusted counterpart for all the regions. The best-performing product varied under different topographic and climatic conditions. In coastal regions, the model forecast was superior to the model-adjusted IMERG product, especially for lower rain rates, while the performance of the model-adjusted IMERG product was better than, or comparable to, that of the model forecast over inland regions.

4.4.2 Comparisons of event total precipitation

To illustrate the spatial rainfall distribution of each data set, we show in Figure 4.10 event total precipitation maps for three events. First, the typical characteristics of each product in coastal regions are shown by a 42-hour event that occurred in Northern and Central California, beginning on October 15, 2016, at 18:00 UTC (Figure 4.10, top panel). Taking Stage IV map as reference, the model forecast captured all major rain bands in this area with reasonable magnitude, which supports the finding above that the model had the best performance in rain rate error matrices over coastal regions. Although the raw IMERG product had severe underestimation, it accurately captured the northwestern corner rain band. Meanwhile, the rain band in Sierra Nevada was estimated in the wrong shape. The model-based adjustment was effective in dealing with the underestimation of precipitation over the northwestern corner, but it could not improve the estimation for Sierra Nevada because the adjustment is sensitive only to magnitude correction. The gauge-adjusted IMERG product did not show enough improvement, either.
The second event occurred in central Colorado on May 7, 2015, at 18:00 UTC and lasted for three days (Figure 4.10, middle panel). The model prediction was fairly accurate with regard to the overall rainfall magnitude, but the most intense precipitation was erroneously located to the upper right corner of the domain, while Stage IV showed intense rain over the lower right part. In contrast, although the raw IMERG product largely underestimated the rainfall magnitude, it captured the correct location of the intense rain. After the model-based adjustment, the IMERG product achieved the best estimation of the four estimators.

The model precipitation location issue arose in the Southern Appalachians, as well (Figure 4.10, bottom panel). This was a two-day event starting on September 29, 2016, at 00:00 UTC. As with the Colorado event, the model predicted rainfall intensity well from the domain average perspective, but with a wrong spatial distribution of precipitation. The raw IMERG product showed severe underestimation again but with correct spatial distribution of precipitation. The model-adjusted IMERG product had the best performance, taking advantage of rainfall intensity from the model and spatial distribution from the raw IMERG.

Statistics for the domain-average-event-total precipitation validated the findings from the rain maps (Table 4.1). We classified the mountainous heavy precipitation events into two groups: coastal region (50 events) and inland region (31 events). Then we calculated the CORR and NRMSE to reference Stage IV data. The raw IMERG product exhibited the lowest CORR and the highest NRMSE for both the coastal and inland regions. The two IMERG adjustment methods effectively improved the pure satellite product. Comparison between the two methods showed model-based adjustment being always superior to the gauge-based adjustment, with the exception of coastal region CORR, for which their performance was the same. Taking model forecast data into account, the model performed better than the model-adjusted IMERG.
product for coastal region events. For inland region events, however, the model-adjusted IMERG was more accurate than the model itself.

4.5 Summary

The primary objectives of this study were, first, to examine the feasibility of an ensemble model-based IMERG adjustment technique and, second, to compare the performances of the model-adjusted IMERG, a gauge-adjusted IMERG, and the model itself. Major conclusions are summarized below.

The raw IMERG product consistently underestimated heavy precipitation in all study regions over CONUS, in coastal and inland areas alike, while the rainfall magnitudes exhibited in the NCAR real-time model forecast were fairly accurate. From the perspective of spatial distribution, the raw IMERG product was more likely to have difficulty capturing the rain band structure over coastal regions but generally showed correct spatial distribution over inland regions. On the other hand, the model tended to erroneously locate intense precipitation over inland regions.

In general, the model-based adjustment could successfully increase the IMERG precipitation magnitude without changing its spatial pattern and, ultimately, provided a more accurate product. While the IMERG product could benefit from gauge-based adjustment as well, the improvement from model-based adjustment was consistently more significant, except in the Southern California region. Comparison between the model forecast and the model-adjusted IMERG product showed the former performed even better than the latter for coastal region events. For inland events, however, the model-adjusted IMERG was more accurate than the model itself.

As described in the IMERG technical document (Huffman et al. 2015), the gauge-adjusted IMERG product usually has a 2.5-month latency before it is available to public. On the other hand,
the model-adjusted IMERG precipitation can be produced concurrently with the raw IMERG, as it requires no gauge observations and is based on NWP forecasts. Moreover, given that the model-adjusted IMERG product performs consistently better than its gauge-adjusted counterpart, it is safe to conclude model-based adjustment is a feasible technique to improve IMERG data quality for mountainous heavy precipitation events.
Table 4.1: Statistics of domain average event total precipitation

<table>
<thead>
<tr>
<th></th>
<th>Coastal regions (50 events)</th>
<th>Inland regions (31 events)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CORR</td>
<td>NRMSE</td>
</tr>
<tr>
<td>Model</td>
<td>0.981</td>
<td>0.19</td>
</tr>
<tr>
<td>IMERG</td>
<td>0.916</td>
<td>0.444</td>
</tr>
<tr>
<td>Gauge-adjusted IMERG</td>
<td>0.961</td>
<td>0.277</td>
</tr>
<tr>
<td>Model-adjusted IMERG</td>
<td>0.961</td>
<td>0.255</td>
</tr>
</tbody>
</table>
Figure 4.1: Location of seven study regions over CONUS.
Figure 4.2: Map of terrain elevation for seven study regions [meters]. DEM data source: https://dds.cr.usgs.gov/srtm/version2_1/SRTM3/North_America/
Figure 4.3: Error statistics of precipitation rate in Western Washington region. Left: BS, Middle: HSS, Right: CSI
Figure 4.4: As in Figure 4.3, but for Western Oregon region.
Figure 4.5: As in Figure 4.3, but for Northern and central California region.
Figure 4.6: As in Figure 4.3, but for Southern California region.
Figure 4.7: As in Figure 4.3, but for Northern Idaho and Western Montana region.
Figure 4.8: As in Figure 4.3, but for Central Colorado region.
Figure 4.9: As in Figure 4.3, but for Southern Appalachians regions.
Figure 4.10: Event total precipitation maps for selected storms. Top panel: event in northern and central California (start at 2016-03-12_12:00 UTC, 48h length). Middle panel: event in central Colorado (start at 2015-05-07_18:00 UTC, 84h length). Bottom panel: event in southern Appalachians (start at 2016-09-29_00:00 UTC, 48h length).
Chapter 5

Conclusions and Future Research

This chapter summarizes the main results and conclusions of this dissertation, and suggests future researches.

5.1 Concluding Remarks

This research developed a model-based adjustment technique to correct satellite estimates for heavy precipitation in complex terrain. To successfully apply the technique, there are two prerequisites: i) the raw satellite data captures the relative spatial and temporal variabilities of precipitation (i.e. no significant surface contamination effects on satellite precipitation detection), and ii) the model provides relatively accurate precipitation outputs in terms of overall magnitude (not necessarily location).

The technique was first introduced by Zhang et al. (2013) and demonstrated based on five heavy precipitation events over the Italian Alps and French Massif Central. The raw CMORPH product was shown to largely underestimate high rain rates, while model simulations, represented by Weather Research and Forecasting Model (WRF), provided reasonable overall rainfall magnitudes. Results based on the five storms demonstrated the technique’s efficiently to reduce the severe CMORPH precipitation underestimation of high rain rates, thus providing an improved satellite precipitation product.

After the successful first attempt in middle-latitude regions, a more comprehensive study examined the technique in three tropical mountainous regions (Colombian Andes, Peruvian Andes
and Taiwan) by 81 storm cases (chapter 2). The raw and gauge-adjusted CMORPH and GSMaP products were involved. As in our previous study, raw CMORPH and GSMaP exhibited severe underestimation in all regions and the bias was more significant on higher rain rates. Improvements from gauge-based adjustment were limited, possibly due to the sparse gauge networks available in those mountainous areas. Meanwhile, model (WRF)-adjusted products outperformed both the gauge-based adjustments and WRF model itself. The adjustments for higher rain rates are more effective than low rain rates.

Aside from the above mid-latitude and sub-tropical case studies, there are three additional studies focusing on CONUS mountain ranges. One of them evaluated the technique on six extreme events induced by hurricane landfalls in Southern Appalachians (chapter 3, Zhang et al. 2016). Again, raw CMORPH underestimated all events. Improvements were comparable between WRF model-based and gauge-based adjusted products. In order to evaluate the impact of satellite adjustment on flood simulations, a hydrological model was ran for 20 basins in the study region where we showed significant improvements on the runoff outputs simulated by adjusted CMORPH products.

Nikolopoulos et al. (2015) focused on a single extreme rainfall event that occurred in September 2013, Colorado. Model forecasts produced by Regional Atmospheric Modeling System and Integrated Community Limited Area Modeling System (RAMS-ICLAMS) were utilized to adjust raw CMORPH, TRMM 3B42RT and weather radar (Multi-Radar Multi-Sensor (MRMS)) estimates. The adjustments were applied by two different procedures i) mean field bias and 2) the herein adjustment technique. Both procedures provided improvements to raw satellite and radar products, with the latter one performing better in terms of random error and correlation.
All the above studies focused on products during TRMM era. In GPM era, the new IMERG product is expected to be extensively used in many applications. In addition, an important gap in past studies was the use of NWP analysis (with the exception of single case study in Nikolopoulos et al. 2015) vs. forecasts that is needed for application with near-real-time IMERG products. The study in chapter 4 used the NCAR real-time ensemble forecasts for this purpose and demonstrated improvements based on 81 flood-inducing storms occurred in seven complex terrain areas over CONUS. We are encouraged by the results that the model-based adjustment technique can provide improvements to the state-of-the-art IMERG product, especially by the fact that model-adjusted product outperformed the gauge-adjusted one, which is consistent to findings of previous studies applied in CMORPH and GSMaP across global mountainous areas.

Combining all the studies so far, the technique of model-based satellite precipitation adjustment has been examined over mountainous areas all over the world with different terrain complexity and climatic conditions. Results show that the model-adjusted products outperform, or at least are comparable to, the gauge-adjusted for all high-resolution satellite products examined. In addition, the model-based adjustment requires no gauge network and much less processing time. The results are promising for future satellite precipitation applications over mountainous areas lacking ground observations. Furthermore, the model-adjusted satellite products were used in a distributed hydrological model to evaluate the error propagation on flood simulations (chapter 3). Results show the basin outlet runoff derived from model-adjusted satellite precipitation was comparable to the one derived from gauge-adjusted satellite precipitation, and both of them outperformed the runoff derived from raw satellite.
5.1 Future Research

Given that most of the heavy precipitation events in this research triggered river floods or flash floods over mountainous regions, a future study can focus on the hydrological processes of related flood events. The study in chapter 3 did an experimental test to run flood simulations with model-adjusted satellite precipitation and exhibited improvements on runoff outputs. This hydrological study can be extended to other regions.

Moreover, all previous studies used site specific power-law parameter values for each rainfall event, which means the numerical model simulations were performed for each event before applying the model-based adjustment technique. This approach is not efficient enough to correct satellite precipitation products for mountainous areas globally. Considering that i) orographic effects on precipitation systems vary across different storm types such as deep convection, fronts and tropical cyclones (Houze et al. 2012) and ii) the topographic and climatic conditions are different in each area, we can evaluate grouping the power-law parameter values for different regions and storm types based on a large number of historical events. In that case, the model-based adjustment technique would be applied on future events by specifying parameter values according to storm type and location. This will provide a real-time satellite adjustment without the need to run high-resolution weather forecasts.
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