Evaluation of bias-adjusted satellite precipitation estimations for extreme flood events in Langat river basin, Malaysia

Eugene Zhen Xiang Soo, Wan Zurina Wan Jaafar, Sai Hin Lai, Faridah Othman, Ahmed Elshafie, Tanvir Islam, Prashant Srivastava and Hazlina Salehan Othman Hadi

ABSTRACT

Even though satellite precipitation products have received an increasing amount of attention in hydrology and meteorology, their estimations are prone to bias. This study investigates the three approaches of bias correction, i.e., linear scaling (LS), local intensity scaling (LOCI) and power transformation (PT), on the three advanced satellite precipitation products (SPPs), i.e., CMORPH, TRMM and PERSIANN over the Langat river basin, Malaysia by focusing on five selected extreme floods due to northeast monsoon season. Results found the LS scheme was able to match the mean precipitation of every SPP but does not correct standard deviation (SD) or coefficient of variation (CV) of the estimations regardless of extreme floods selected. For LOCI scheme, only TRMM and CMORPH estimations in certain floods have showed some improvement in their results. This might be due to the rainfall threshold set in correcting process. PT scheme was found to be the best method as it improved most of the statistical performances as well as the rainfall distribution of the floods. Sensitivity of the parameters used in the bias correction is also investigated. PT scheme is found to be least sensitive in correcting the daily SPPs compared to the other two schemes. However, careful consideration should be given for correcting the CMORPH and PERSIANN estimations.

Key words | bias correction, extreme floods, Malaysia, satellite precipitation

INTRODUCTION

Flood disasters account for significant losses around the world, both tangible and intangible (Scofield & Kuligowski 2003; Khan et al. 2011; Seyyedi et al. 2014). Malaysia, being hot and humid all year round, with an average rainfall around 2,500 mm annually, is susceptible to extreme flooding events, especially on the east coast of Peninsular Malaysia. Generally, the rainfall distribution pattern over Malaysia is strongly influenced by regional wind flows (Nicholson et al. 2005). Two distinct wet seasons run from November to February, during which the northeast monsoon (NEM) produces heavy rainfall in the east region, and from May until mid-September, when the southwest monsoon (SWM) affects some areas in the west and southwest regions. The northwest, west and southwest regions experience two
wet seasons per year, from mid-March until May and from October until November; both are in the inter-monsoon period. These two subsequent inter-monsoon periods take place during the shifting of the primary NEM and SWM seasons and vice versa. Due to the change of wind direction and effect of local topography, substantial rainfall occurs.

Most of the major historical flood events have been related to NEM, which carries an abundance of rainfall to the east coast of Peninsular Malaysia, especially within the months of November until January. However, flooding events have been increasing in terms of frequency and impact in recent years. For example, the 2014 flood in Malaysia has been described as the worst flood in decades. The damage caused by this flood has badly affected the people, causing them great devastation, especially when it comes to the loss of homes and other infrastructure. This extreme flood event hit certain countries such as Indonesia, Malaysia, Thailand and Philippines where heavy rains fell due to the southeast monsoon blowing across the South China Sea, making the sea warmer than usual. In Malaysia, extreme floods that occurred on 15 December 2014–3 January 2015 have been considered as the worst flood events in decades. During this event, more than half of Peninsular Malaysia, including those regions at the west side, were affected and most of the rivers reached dangerous levels. More than 200,000 people were affected and 21 people were killed due to this natural disaster (Akasah & Doraisamy 2015). Hai et al. (2017) found that the strong wind surges from the South China Sea due to very intense cold-air outbreaks of the Siberian High (also known as Siberian Anticyclone) (Gong & Ho 2002) developed under ENSO (El Niño–Southern Oscillation) neutral conditions. In addition, the mesoscale convective systems that developed across the northeastern Indian Ocean (near northern Sumatra) in response to the propagation of a 500-hPa short-wave trough across the Indian subcontinent towards China were the combined factors for these unusual extreme rainfall and flooding events in Peninsular Malaysia.

In order to identify the trends in the statistics of historical stream flow, reliable climatic information is critical for climate analyses and for verification of climate model simulations (Easterling et al. 1999; Moazami et al. 2013). Rainfall data or precipitation is an important input required for water resource management, hydrologic and ecologic modelling, recharge assessment and irrigation scheduling (Su et al. 2008; Mair & Fares 2010; Behragi et al. 2011; Jiang et al. 2012). However, it is difficult to determine the amount of rain that falls across the world as the temporal and spatial distribution of rainfall is not even (Gu et al. 2010).

Rain gauges are the most common tools to provide a direct measurement of precipitation reaching the ground, but they cannot be representative of extensive areas and may contain significant bias arising from coarse spatial resolution, location, wind and mechanical errors (Strangeways 2004). Precipitation can also be estimated using weather radar due to its continuous spatial coverage (Habib et al. 2012). However, weather radar has difficulties with hardware calibration (Yilmaz et al. 2005). If the distance between the target area and the radar increases, the precipitation can be undetected, or the rate can be underestimated (Scofield & Kuligowski 2003; Gu et al. 2010; Diederich et al. 2015). Moreover, the accuracy of the reflectivity values can be influenced by fixed targets such as ground clutter, beam block or anomalous propagation (de Coning 2013; Diederich et al. 2015).

Satellite precipitation products (SPPs) have been emerging as one of the most important precipitation data sources in hydrology, climatology and meteorology studies for the last few decades. These products have been successfully applied in studying the precipitation patterns at global scale as well as regional scale. These remotely sensed data have several advantages over the traditional measurements, including higher spatial resolution and uninterrupted coverage and hence are beneficial over ungauged catchments, especially mountainous and oceanic regions (Collischonn et al. 2008; Tian et al. 2009; Behrangi et al. 2011; de Coning 2013; Moazami et al. 2013; Gado et al. 2017). Various new global high resolution SPPs are operationally available, including the National Oceanic and Atmospheric Administration Climate Prediction Center morphing technique product (CMORPH) (Joyce et al. 2004), the Tropical Rainfall Measuring Mission (TRMM) Multisatellite Precipitation Analysis products (TMPA) (Huffman et al. 2007), the Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN) (Hsu et al. 1997; Sorooshian et al. 2000), the Global Satellite Mapping of Precipitation (GSMaP) (Kubota et al. 2007), and so on. These satellite precipitation products have provided quasi-global high-temporal (<3 hours) and spatial (<0.25°) resolution precipitation maps.
Although SPPs have been widely used in various meteorological models, these satellite estimations are still imperfect and prone to systematic and random errors associated with observations, sampling and retrieval algorithms. (Dinku et al. 2009; Villarini et al. 2009; Pereira Filho et al. 2010; Piani et al. 2010; Teutschbein & Seibert 2013; Jiang et al. 2018; Vu et al. 2018; Wang et al. 2018; Soo et al. 2019).

The models could augment or suppress rainfall biases to the streamflow based on the response mode of the model (Segond et al. 2007; Habib et al. 2014; Fang et al. 2015). In Asia, the performance of the SPPs varies from country to country. For instance, CMORPH showed poorer performances compared to TRMM 3B42 Version 6 over Indonesia (Vernimmen et al. 2012) and Philippines (Jamandre & Narisma 2015). In contrast, Shen et al. (2010) showed that CMORPH performed better for spatial and temporal patterns of precipitation over China compared to TRMM. These findings are also supported by Shige et al. (2013) who reported that the accuracy of the satellite estimations varies for different regions or countries as well as topographic profiles. For Malaysia, Tan et al. (2015) compares daily, monthly, seasonal and annual rainfall amount at 342 rain gauges over Malaysia using five SPPs (3B42RT, 3B42V7, GPCP (Global Precipitation Climatology Project) 1DD, PERSIANN and CMORPH) and a ground-based precipitation product (APHRODITE – Asian Precipitation Highly Resolved Observational Data Integration Towards Evaluation). In their study, they assessed the accuracy and spatial variations of each SPP by region and found that the SPPs performed better in the NEM than in the SWM. Also, the SPPs’ performance was the best in the region receiving higher annual precipitation such as eastern and southern Peninsular Malaysia and northern East Malaysia. By contrast, poor SPP performance occurred over western Peninsular Malaysia which is characterized by low rainfall amounts since it is sheltered by the Titiwangsa Range and Sumatra. They also concluded that the TRMM products outperformed the PERSIANN product for this country particularly in estimating precipitation during the 2006–2007 flood event. The outputs were later supported by Soo et al. (2019), who reported that TRMM showed better performance at Kelantan river basin compared to the CMORPH and PERSIANN, as well as the other two basins located in the west (Langat river basin) and south (Johor river basin) parts of Malaysia.

Several bias correction (BC) schemes have been developed to downscale the meteorological variables from any datasets or models, ranging from the simple scaling approach to sophisticated distribution mapping (Haerter et al. 2011; Teutschbein & Seibert 2012). However, studies about performing BC or downscaling approach of SPPs in Malaysia are arguably limited. Therefore, it is critical to improve the satellite estimations, especially on the extreme events for Malaysia.

In the present study, the performance of SPPs on five extreme flood events due to NEM specifically during the month of December to January are of the main concern of this study. These two months were chosen due to the history of peak flood events that happened annually. As for the river basin, Langat river basin was chosen as flooding is common in this area when it coincides with localized rainfall. Although climatology adjustments or calibrations have been adopted on the algorithm of these selected SPPs, the rainfall estimations are still imperfect and their performance varies from region to region, as well as season to season. Thus, three BC schemes, which are linear scaling (LS), local intensity scaling (LOCI) and power transformation (PT) methods, were employed in this study to assess the capability of three advanced SPPs (i.e., CMORPH, TRMM 3B42 Version 7(V7) and PERSIANN) in improving SPPs’ accuracy based on Malaysia’s weather system after performing bias correction. Suitability of the bias correction methods on specific SPPs could vary regionally due to spatial and temporal heterogeneity of rainfall that might affect the performance of SPPs in capturing rainfall. It is noticeable that several bias correction methods are available, but this study aimed at evaluating these three widely used schemes in order to investigate characteristics of corrected SPPs’ data during extreme events.

**REVIEW ON BIAS CORRECTION**

Bias correction is a model output statistics approach that seeks to use information from biased model outputs (Chen et al. 2013a). The correction usually identifies possible differences between the observed and simulated climate variables, which provide the basis for correcting both control and scenario model runs with a transformation.
algorithm. However, BC of precipitation is more challenging compared to other climate variables such as temperature due to the fact of spatial/temporal heterogeneity and zero inflation.

In recent years, numerous studies to improve SPPs’ estimations by BC have been done, varying with location, season, topography, climatology and so on (Boushaki et al. 2009; Tesfagiorgis et al. 2011; Habib et al. 2014; Fang et al. 2015; Ahera et al. 2016; Guminidoga et al. 2016; Pan et al. 2016; Valdés-Pineda et al. 2016; Worqlul et al. 2018; Saber & Yilmaz 2018). Table 1 shows an overview of some BC methods used to correct precipitation data.

Table 1 | Overview of some bias correction schemes

| Method                          | Advantage                                                                 | Disadvantage                                                                                                                                                                                                 | Reference                                      |
|--------------------------------|---------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------|
| Linear scaling (LS)            | Mean-based. A mean monthly correction factor is applied to the RCM-simulated daily precipitation in a month. It is the simplest BC method | The daily precipitation sequence is the same as that of the RCM-simulated data (usually too many wet days compared to the observation). It does not account for the changes in the frequency distribution of precipitation. No adjustment is made to the temporal structure of daily precipitation occurrence | Lenderink et al. (2007), Teutschbein & Seibert (2013) |
| Local intensity scaling (LOCI) | Mean-based. The wet-day frequency is corrected. A mean monthly correction factor is applied to the RCM-simulated daily precipitation in a month | It does not account for the different changes in the frequency distribution of precipitation. No adjustment is made to the temporal structure of daily precipitation occurrence | Schmidli et al. (2006) |
| Power transformation (PT)      | Mean-based. A precipitation threshold can be introduced a priori to avoid too many drizzle days (i.e., very low but non-zero precipitation). Corrects mean and standard deviation (variance) events are adjusted non-linearly. Variability of corrected data is more consistent with original data | Adjustment of wet-day frequencies and intensities only to some extent | Leander & Buishand (2007) |
| Quantile mapping based on an empirical distribution (QME) | Distribution-based. Corrects the RCM-simulated precipitation based on point-wise daily constructed empirical cumulative distribution functions (ecdfs). The frequency of precipitation occurrence is corrected at the same time | No adjustment is made to the temporal structure of daily precipitation occurrence | Jakob Themeßl et al. (2011) |
| Quantile mapping based on a gamma distribution (QMG) | Distribution-based. Corrects the RCM-simulated precipitation based on a gamma distribution. The frequency of precipitation occurrence is corrected using the LOCI method | The performance depends on whether the observed and RCM-simulated precipitation follows the gamma distribution (or not). No adjustment is made to the temporal structure of daily precipitation occurrence | Piani et al. (2010), Teutschbein & Seibert (2012) |

The LS scheme corrects the average precipitation value based on the differences between the rain gauge data and satellite data. However, this method does not correct the standard deviation or variance and all events are adjusted with the same correction factor (Lenderink et al. 2007; Boushaki et al. 2009; Vila et al. 2009; Tesfagiorgis et al. 2011; Teutschbein & Seibert 2013; Ajaaj et al. 2016). The LOCI scheme combines a precipitation threshold with LS (Schmidli et al. 2006; Teutschbein & Seibert 2013; Ajaaj et al. 2016). This method separately corrects wet-day frequency and wet-day intensity, applied pointwise and individually for each day of the year, and the estimated
precipitation is corrected using a scaling factor. However, the output of this method is limited because, as with LS, the standard deviation and variance are not corrected and all events are adjusted using the same correction factor. The PT method is a nonlinear correction in an exponential form that combines the correction of the coefficient of variation (CV) with LS. This scheme corrects the mean and variance of the temporal series of estimated precipitation (Leander & Buishand 2007; Teutschbein & Seibert 2012, 2013). The coefficient of variation of both daily and multiple-day precipitation amounts depends on the wet-day frequency, but this correction does not adjust the frequency of wet days (Leander & Buishand 2007).

Quantile mapping (QM) (Leander & Buishand 2007; Piani et al. 2010; Teutschbein & Seibert 2013; Ajaj et al. 2016) also known as distribution mapping adjusts the cumulative distribution of estimated data to the cumulative distribution of rain gauge data using a transfer function. This correction can capture the evolution of the mean and the variability of precipitation while matching all statistical moments. Under this correction method, it can be referring to an empirical distribution or a gamma distribution. Hay et al. (2002) applied a gamma transform to correct regional climate model (RegCM2) precipitation data and Leander & Buishand (2007) applied a power transformation, which corrects for the CV and mean of the precipitation values. Hay et al. (2002) found that the corrected precipitation data did not contain the day-to-day variability which was present in the observed dataset. Piani et al. (2010) validated a statistical BC method based on QM method (with gamma distribution) and the performance was good for seasonal means, heavy rainfall events and seasonal drought index but not for the daily rainfall events. Lafon et al. (2015) compared the performance of LS, PT, gamma-based QM and empirical distribution-based QM methods and found that mean and standard deviation (SD) of daily rainfall can be effectively corrected while the correction of skewness and kurtosis of daily rainfall are sensitive to the choice of BC method and calibration period. Although, gamma-based quantile mapping method provides better results where the variability in rainfall is captured by gamma distribution, the study employed monthly gamma parameters to correct the daily rainfall data. The performance of distribution derived, parametric and nonparametric transformations was compared by Gudmundsson et al. (2012), who identified that nonparametric transformations possess good proficiency in the reduction of biases in rainfall simulated by regional climate models (RCMs). While assessing hydrological response to climate change, Teutschbein & Seibert (2012) reported that all BC methods improved RCM outputs (rainfall and temperature) and distribution mapping method was found to be superior for hydrological simulation but the corrections employed monthly factors.

Although the correction of climate variables can considerably improve the hydrologic simulations under current climate conditions (Teutschbein & Seibert 2012; Chen et al. 2013b), there is a major drawback whereby most methods follow the assumption of stationarity of model errors, which means that the correction algorithm and its parameterization for current climate conditions are assumed to also be valid for a time series of changed future climate conditions. Whether or not this condition is actually fulfilled for our future climate cannot be evaluated directly. This motivated us to address this issue and to test how well different correction schemes perform for conditions different from those used for calibration.

### SCOPE OF STUDY

**Description of study area and selected flood events**

In this study, Langat river basin is chosen mainly based on its history of great flood (Saudi et al. 2017). As shown by Figure 1, this basin is located in the western part of Peninsular Malaysia (latitudes 1°30 ‘–2°10’N and longitudes 103°20’–104°10’E) and covers the state of Selangor and Negeri Sembilan and also a portion of Federal Territory of Putrajaya, Kuala Lumpur and Klang, and Petaling Jaya district. This basin has a total catchment area of about 2,350 km². The larger part of the basin totalling 1,900 km² occupies the south and south-eastern parts of the state of Selangor. There are three major tributaries, i.e., Langat River (the main river), Semenyih River and Labu River. The Langat River has a total length of about 180 km, draining from the main range (Banjaran Titiwangsa) at the northeast of Hulu Langat district in a south–southwest direction.
direction into the Straits of Malacca. Both Langat River and Semenyih River originate from the hilly and forested areas on the western slope of Banjaran Titiwangsa, northeast of Hulu Langat. This water catchment is important as it provides raw water supply and other amenities to approximately 1.2 million people within the basin. Important conurbations served include towns such as Cheras, Kajang, Bangi, Government Centre of Putrajaya and others. There are two reservoirs (Semenyih and Hulu Langat) and eight water treatment plants (four of which operate 24 hours/day), which provide clean water to users after undergoing treatment. Figure 2 shows the monthly temporal precipitation and streamflow observations in Langat river basin from January 2012 until June 2017. Based on Figure 2, the overall rainfall pattern corresponded to the streamflow pattern. According to the WMO (2008), rainfall exceeding 10 mm/day is considered as heavy rain. From the graph, extreme streamflow (exceeding an average of 80 m³/s) occurred during heavy rainfall at the end of the years 2012, 2014 and 2015. Heavy rainfall also occurred at the end of years 2013 and 2016 too, but the peak streamflow does not fall at the same time. In this study, we selected

![Figure 1](image1.png)  
(a) Location of study area. (b) Distribution of gauge stations and digital elevation model (DEM) of the Langat river basin.

![Figure 2](image2.png)  
Monthly mean precipitation and streamflow series in Langat river basin.
these five extreme flood events due to NEM specifically during the months of December and January.

Table 2 shows the details and general statistics of the five selected flood events. The inter-correlation of the rain gauge observations between these events is tabulated in Table 3. It can be noticed that the rainfall patterns of the selected events were slightly different to each other even though they are for the same monsoon (NEM) and months. Figure 3 exhibits the frequency distribution of daily precipitation in different intensities to each flood event for Langat river basin. It is noticed that Events 2 and 4 are drier compared to the other events whereby more than 50% of the events are no-rain (0 mm/day). As for light rainfall (0–1 and 1–5 mm/day), this type of rainfall occurred for less than 20% of every period, whereas heavy rainfall (20–30 and >30 mm/day) occurred for about 3–8% of the event period.

### Data acquisition

This study attempts to evaluate the satellite estimations (before and after BC) with reference to the ground observations during five extreme flood events due to NEM specifically during the months of December and January. For ground observations, daily rainfall data collected at 28 operating rain gauge stations in Langat river basin were analysed. All data were collected from the Department of Drainage and Irrigation (DID), Malaysia. Table 4 represents examples of selected stations in the Langat river basin with detailed information including station name, district, river, latitude and longitude. The distribution of rain gauge networks of the selected study area is shown in Figure 1. More stations are located at latitudes 3°00′–3°15′N and longitudes 101°45′–102°00′E, but fewer active stations were found at the south-eastern portion of the basin.

The three satellite-derived rainfall products selected for the purpose of this study are TRMM 3B42 V7, CMORPH and PERSIANN. The selected resolution for each satellite product is summarized in Table 5.

The TMPA (TRMM Multisatellite Precipitation Analysis) was produced by the National Aeronautics and Space Administration (NASA). This product is a combined microwave-infrared precipitation product (Huffman et al. 2007), providing precipitation for the spatial coverage of 50°N–50°S at the latitude–longitude resolution. The latest version of this product, 3B42V7, can be freely downloaded from Goddard Earth Sciences Data and Information Services Center (http://mirador.gsfc.nasa.gov). In this study, the daily aggregated TRMM 3B42V7 observations at a spatial resolution of 0.25° were analysed.

The CMORPH product (Joyce et al. 2004) is a pure satellite precipitation product using only satellite infrared information about the spatial and temporal evolution of rain clouds and not the rainfall estimates themselves. This

### Table 2
Details and general statistics of rainfall for every selected flood event

| Event | Event 1 | Event 2 | Event 3 | Event 4 | Event 5 |
|-------|--------|--------|--------|--------|--------|
| Initial date | 1 December 2012 | 1 December 2013 | 1 December 2014 | 1 December 2015 | 1 December 2016 |
| End date | 31 January 2013 | 31 January 2014 | 31 January 2015 | 31 January 2016 | 31 January 2017 |
| Mean (mm/day) | 11.81 | 8.16 | 9.78 | 10.99 | 9.25 |
| SD (mm/day) | 13.25 | 11.30 | 13.26 | 21.34 | 15.87 |
| CV | 1.90 | 2.48 | 1.96 | 3.39 | 1.92 |
| Skewness | 2.96 | 4.64 | 3.04 | 11.64 | 3.85 |
| Kurtosis | 10.83 | 28.68 | 11.52 | 202.18 | 24.87 |

### Table 3
Inter-correlation of rain gauge observations between selected flood events in Langat river basin

| Flood event | 1 | 2 | 3 | 4 | 5 |
|-------------|---|---|---|---|---|
| 1 | 0.061 | –0.108 | 0.047 | –0.026 |
| 2 | 0.061 | 0.092 | 0.015 | 0.010 |
| 3 | –0.108 | 0.092 | –0.158 | –0.187 |
| 4 | 0.047 | 0.015 | –0.158 | 0.151 |
| 5 | –0.026 | 0.010 | –0.187 | 0.151 |
### List of rain gauge stations used in this study

| Station ID | Name of station | District        | River              | Latitude       | Longitude     |
|------------|-----------------|-----------------|--------------------|----------------|--------------|
| 2615133    | Tadika Kemas Kg. Tg. Sepat | Kuala Langat    | Sg. Tnig. Sepat    | 02° 40' 53"   | 101° 33' 48" |
| 2714001    | P/A Kg. Tali Air Morib | Kuala Langat    | Sg. Tali Air       | 02° 44' 39"   | 101° 27' 02" |
| 2717114    | Ldg. Bute       | Sepang          | Sg. Sepang         | 02° 45' 15"   | 101° 44' 55" |
| 2814119    | P/A Kelanang    | Kuala Langat    | Sg. Langat         | 02° 48' 44"   | 101° 25' 06" |
| 2815001    | Pejabat IPS Sg. Manggis | Kuala Langat    | Sg. Langat         | 02° 49' 35"   | 101° 32' 30" |
| 2815116    | P/A Pekan Banting | Kuala Langat    | Sg. Langat         | 02° 48' 38"   | 101° 30' 30" |
| 2815117    | P/A Sg. Sedu    | Kuala Langat    | Sg. Langat         | 02° 51' 21"   | 101° 30' 53" |
| 2817003    | Kg Jenderam Hilir | Kuala Langat    | Sg. Langat         | 02° 51' 41"   | 101° 44' 07" |
| 2818110    | Sek. Men. Bandar Tasik Kesuma | Kuala Langat    | Sg. Langat         | 02° 53' 55"   | 101° 52' 13" |
| 2914122    | P/A Bt. 9 Sijangkang | Kuala Langat    | Sg. Langat         | 02° 57' 23"   | 101° 26' 03" |
| 2914123    | P/A Bt 7 Sijangkang | Kuala Langat    | Sg. Langat         | 02° 57' 23"   | 101° 26' 03" |
| 2915116    | Ldg. Bkt. Cheeding | Kuala Langat    | Sg. Langat         | 02° 54' 40"   | 101° 34' 35" |
| 2916001    | Puncak Niaga Putrajaya | Kuala Langat    | Sg. Langat         | 02° 54' 40"   | 101° 41' 50" |
| 2917001    | RTM Kajang      | Kuala Langat    | Sg. Langat         | 02° 59' 46"   | 101° 47' 8.9" |
| 2917002    | Kolam Takungan Sg. Merab | Kuala Langat    | Sg. Merab          | 02° 56' 43"   | 101° 44' 60" |
| 3017105    | Sg. Raya Bt.9 Hulu Langat | Hulu Langat    | Sg. Langat         | 03° 04' 04"   | 101° 46' 19" |
| 3017106    | Sg. Serai Bt.12 Hulu Langat | Hulu Langat    | Sg. Langat         | 03° 05' 58"   | 101° 47' 51" |
| 3017108    | Sungai Balak Hulu Langat | Hulu Langat    | Sg. Balak          | 03° 00' 59"   | 101° 45' 49" |
| 3018101    | Empangan Semenyih | Hulu Langat    | Sg. Semenyih       | 03° 04' 43"   | 101° 52' 50" |
| 3018107    | Ldg. Dominion   | Hulu Langat    | Sg. Semenyih       | 03° 00' 13"   | 101° 52' 55" |
| 3118069    | Pemasokan Ampang | Wilayah Persekutuan | -             | 03° 09' 30"   | 101° 48' 05" |
| 3118102    | Sek.Keb.Kg.Sg. Lui | Hulu Langat    | Sg. Lui            | 03° 10' 25"   | 101° 52' 20" |
| 3118103    | Sg. Gabai di Kg. Lui | Hulu Langat    | Sg. Lui            | 03° 09' 27"   | 101° 53' 47" |
| 3118105    | Batu 14, Hulu Langat (Balai Polis) | Hulu Langat    | Sg. Langat         | 03° 06' 41"   | 101° 48' 59" |
| 3119001    | Sawah Sg. Lui    | Hulu Langat    | Sg. Lui            | 03° 10' 20"   | 101° 54' 20" |
| 3119002    | Lalong Sg. Lui   | Hulu Langat    | Sg. Lui            | 03° 08' 10"   | 101° 54' 20" |
| 3119104    | Bt.30, Jalan Genting Peres | Hulu Langat    | Sg. Semenyih      | 03° 08' 25"   | 101° 55' 47" |
| 3218101    | TNB Pansun       | Hulu Langat    | Sg. Langat         | 03° 12' 35"   | 101° 52' 35" |

**Figure 3** | Frequency distribution of daily precipitation of selected flood event in Langat river basin.

**Table 4** | List of rain gauge stations used in this study.
product provides precipitation for the spatial coverage of 60°N–60°S. In the latest CMORPH Version 1.0, bias correction was conducted by adjusting the satellite estimates against a daily rain gauge analysis and this can be accessed (ftp://ftp.cpc.ncep.noaa.gov/precip/global_CMORPH). Three spatial and temporal resolutions can be selected: 8 km–30 min, 0.25°–3 hourly and 0.25°–daily. In this study, the 0.25°–daily bias-corrected Version 1.0 CMORPH data were used.

The PERSIANN product estimates the rainfall rate from satellite observations by combining the infrared and passive microwave data using the artificial neural network function (Hsu et al. 1997; Sorooshian et al. 2000). This product can provide precipitation data for the spatial coverage of 60°N–60°S. In this study, the bias-corrected PERSIANN data, which maintain the total monthly precipitation estimation with GPCP (Global Precipitation Climatology Project), at the spatial resolution of 0.25° and daily temporal resolution were downloaded from the following website http://www.ngdc.noaa.gov/.

### METHODOLOGY

The satellite rainfall estimate was compared to gauged rainfall observation based on the selected events as stated in Table 2. The bias in every satellite estimate was assessed and corrected using the three schemes, i.e., LS, LOCI and PT methods. After being corrected, the improved satellite estimations were compared and analysed again with reference to the gauged rainfall observation. Extended analysis on the parameters of the methods applied was done. Figure 4 shows the overall procedure of this study.

### Bias correction methods

SPP estimates exhibit large systematic and random errors which may cause large uncertainties in hydrologic modelling. Moreover, the models could augment or suppress rainfall biases to the streamflow based on the response mode of the model (Segond et al. 2007; Habib et al. 2014; Fang et al. 2015). Several bias correction schemes have

### Table 5 Information about satellite precipitation products (SPPs)

| Satellite products | Spatial resolution | Temporal resolution | Spatial coverage | Data source |
|--------------------|--------------------|---------------------|-----------------|-------------|
| CMORPH             | 0.25 deg           | Daily               | 60°N–60°S       | ftp://ftp.cpc.ncep.noaa.gov/precip/global_CMORPH |
| TRMM 3B42V7        | 0.25 deg           | Daily               | 50°N–50°S       | http://mirador.gsfc.nasa.gov |
| PERSIANN           | 0.25 deg           | Daily               | 60°N–60°S       | http://www.ngdc.noaa.gov/ |

![Figure 4](image) Flow chart of the methodology.
been developed to downscale the meteorological variables from any datasets or models, ranging from the simple scaling approach to sophisticated distribution mapping (Teutschbein & Seibert 2012). However, these schemes have not been investigated in Malaysia. Thus, it is necessary to apply the BC schemes to improve the reliability of the estimation of SPPs in Malaysia. In the present study, all SPPs were bias-corrected utilizing three BC schemes, i.e., LS (Lenderink et al. 2007), LOCI (Schmidli et al. 2006) and PT (Leander & Buishand 2007) methods. In this study, quantile mapping which is known as the best effective correction scheme, was not selected as this scheme is often used to reduce biases in statistical downscaling of future climate change projections (Jeon et al. 2016) and ignores the correlation between raw ensemble forecasts and observations, thus there is still considerable uncertainty in representation of extreme precipitation (Huang et al. 2014; Zhao et al. 2017). A more detailed description of the selected methods is presented below.

**Linear scaling (LS)**

The LS method aims to perfectly match the monthly mean of corrected estimations with that of observed ones (Lenderink et al. 2007). This method operates with monthly correction values based on the differences between observed and estimated data. The daily satellite precipitation amounts, $P$ are transformed into $P^*$ by multiplying with the monthly scaling factor, $s$, as shown in Equation (1):

$$ P^* = s \times P $$ \hspace{1cm} (1)

The scaling factor is the ratio of the true mean to the mean of biased estimates (Anagnostou et al. 1998). In this case, this study assumed the rain gauge measurement as the true observation and the satellite estimations (TRMM 3B42 V7, CMORPH and PERSIANN) are the biased estimation, as shown by Equation (2):

$$ s = \frac{G}{S_i} $$ \hspace{1cm} (2)

where $S$ and $G$ represents satellite/gridded and gauge precipitation, respectively, $i$ is the date of the events, $S$ is the monthly average value of $S_i$ and $G$ is the monthly average value of $G_i$.

Unlike other studies (Schmidli et al. 2006; Teutschbein & Seibert 2013; Ajaj et al. 2016), this study focused on the calculation of the monthly scaling factors. These scaling factors were applied separately for every selected extreme event as the rainfall pattern was not consistent even though they are of the same monsoon (NEM) and same months, as shown in Table 3.

**Local intensity scaling (LOCI)**

The LOCI method (Schmidli et al. 2006) corrects the wet-day frequencies and intensities and can effectively improve the raw data which have too many drizzle days (days with little precipitation). It normally involves two steps: first, a wet-day threshold for the $m$th month $P_{\text{thres},m}$ is determined from the raw precipitation series to ensure that the threshold exceedance matches the wet-day frequency of the observation; second, a scaling factor $c = (\mu(P_{\text{obs},m,d}|P_{\text{obs},m,d} > 0))/\mu(P_{\text{raw},m,d}|P_{\text{raw},m,d} > 0))$ is calculated and used to ensure that the mean of the corrected precipitation is equal to that of the observed precipitation:

$$ P_{\text{LOCI},m,d} = \begin{cases} 0, & P_{S,m,d} < P_{\text{thres},m} \\ P_{S,m,d} \times c, & \text{otherwise} \end{cases} $$ \hspace{1cm} (3)

Similar to the LS scheme, the scaling factor was calculated and applied separately for every selected event.

**Power transformation (PT)**

Shabaloava et al. (2003) and Leander & Buishand (2007) advocated the PT method because it uses an exponential form to further adjust the standard deviation of precipitation series, $P$, as shown in Equation (4):

$$ P^* = a \cdot P^b $$ \hspace{1cm} (4)

To implement this method, there are two scaling factors to be calculated, $a$ and $b$. The $b$ factor is calculated iteratively so that the coefficient of variation (CV) of the satellite daily precipitation time series matches that of the gauged precipitation time series. Next, the $a$ factor is
calculated, such that the mean of the transformed precipitation values matches that of the gauged precipitation. Finally, these two scaling factors are applied to each uncorrected daily satellite observation corresponding to that month to generate the corrected daily time series.

RESULTS

Evaluation of raw satellite estimates

Before performing the BC schemes, the accuracy of the three selected satellite products (TRMM, CMORPH and PERSIANN) at Langat river basin were first examined for all events. Table 6 shows the summarized result of the raw satellite estimations for Langat river basin. TRMM is capable of estimating rainfall reasonably well with CC ranging from 0.52 to 0.77 and so does the CMORPH although poor correlation was shown for Event 2. As for PERSIANN, the estimation was slightly poor compared to TRMM and CMORPH for the first three events but somehow a slight improvement is noticeable in Events 4 and 5. Based on the bias, it is found that the raw TRMM and PERSIANN estimations almost overestimate the actual precipitation of every event of the same months (December and January) for about 6–60% whereas CMORPH underestimates the actual precipitation by 27–51%. Similar results were reported by Tan et al. (2015) and Derin & Yilmaz (2014), where CMORPH showed significant precipitation was underestimated over Peninsular Malaysia and the western part of Turkey, respectively, compared to other SPPs. According to Thiemig et al. (2012), the significant over- and underestimation of the SPPs might be due to poor ability in estimating heavy rain (>10 mm/day). Overall, the results found that PERSIANN performed poorly compared to the other two satellites for the selected basin. However, there are some studies that indicated PERSIANN can estimate well the rainfall compared in other regions (Kizza et al. 2012; Ghajarnia et al. 2015). Based on the NRMSE and MAE, it is noted that CMORPH has the lowest value among those three SPP estimations which implies the CMORPH rainfall estimation is more reliable.

Performance evaluation of bias-corrected SPPs

Rainfall pattern and distribution

Figure 5 shows the direct comparison of the daily and accumulated rainfall data of every raw and bias-corrected dataset over every study period at Langat river basin to give a first impression of the data characterization. It is found that LS-corrected rainfall estimates predict the overall gauged rainfall reasonably well but as for LOCI, this method was less effective for the PERSIANN estimations as it exacerbates the overall rainfall over the basin by 40–85% overestimation. Nevertheless, this method seemed suitable in certain events for TRMM and CMORPH estimations. This might be due to the rainfall threshold that we set (1 mm) to ensure that the threshold exceedance matches the wet-day frequency of the observation. In our opinion, sensitivity analysis based on the rainfall threshold is recommended as every region has different geographical conditions and the rainfall will never be equally distributed. Thus, the rainfall threshold might vary from region to

Table 6 | Statistical results of raw satellite estimations for the overall Langat river basin

| Satellite estimations | Event | 1 | 2 | 3 | 4 | 5 |
|-----------------------|-------|---|---|---|---|---|
|                       |       | T | C | P | T | C | P | T | C | P | T | C | P | T | C | P | T | C | P |
| Correlation           |       | 0.54 | 0.63 | 0.30 | 0.52 | 0.49 | 0.50 | 0.77 | 0.63 | 0.37 | 0.66 | 0.80 | 0.56 | 0.61 | 0.68 | 0.54 |
| Relative bias (%)     |       | 14.9 | −37.9 | 6.4 | 54.5 | 1.9 | 61.8 | 17.6 | −37.6 | 43.9 | 6.1 | −51.2 | −15.1 | −3.1 | −26.9 | 28.7 |
| NRMSE                 |       | 1.4 | 0.8 | 1.1 | 2.5 | 1.9 | 2.4 | 1.3 | 1.0 | 1.8 | 1.4 | 1.1 | 1.2 | 1.2 | 1.0 | 1.2 |
| MAE (mm/day)          |       | 5.4 | 4.0 | 5.6 | 5.1 | 4.0 | 5.8 | 5.0 | 4.3 | 7.9 | 5.4 | 3.8 | 4.5 | 5.6 | 4.9 | 6.6 |

For satellite estimations, T – TRMM, C – CMORPH and P – PERSIANN.
Figure 5 | Time series of daily rainfall data (mm/day) and daily accumulated rainfall data (mm) of gauge observations, raw and bias-corrected satellite estimations for selected flood events in Langat river basin.
Figure 6 | Quantile-quantile plots of raw and corrected satellite estimations versus gauged observations for every flood event in Langat river basin.
region. For PT-corrected rainfall estimates, it is noted that this scheme is much better compared to LOCI. As shown by the result, the difference in total rainfall compared to the accumulated gauge observations was less than 20%, except for PERSIANN estimations corrected by the PT scheme in Event 4 whereby the corrected estimation overestimated the total rainfall over the basin by 31%.

Next, the distribution of the data was evaluated based on the quantile-quantile plots (QQ plots) as shown by Figure 6, and accompanied by Table 7. The QQ plot provides useful comparison of the response of rainfall distribution across various bias-corrected rainfall values. In every QQ plot (Figure 6), a 45º reference line is also plotted. If the two sets come from a population with the same distribution, the points should fall approximately along this reference line. The greater the departure from this reference line, the greater the evidence for the conclusion that the two datasets have come from populations with different distributions. Based on Table 7, all the BC methods exhibit a significant improvement for TRMM and CMORPH estimations whereas a satisfactory level (0.70–0.80) for some selected events was achieved by PERSIANN estimations corrected by LS and LOCI. The PT scheme was found to be the best scheme for correcting the distribution of satellite estimations as it adjusted the rainfall data points closer to the reference line with high NSE values (>0.85) in all events.

### Statistical performance

In the scope of the study section, we described the methods of the BC employed to fit the mean, SD and CV for the precipitation data. Figure 7 shows several scatter plots for the fitting statistics of all events, which implies the observed statistics are plotted versus those of the uncorrected and corrected satellite data. The detailed statistical performances are shown in Table 8. Based on the scatter plots (Figure 7) and statistical performances (Table 8), it is observed that the LS scheme matches the mean precipitation of every satellite estimation, but it does not correct the biases in SD and CV. When applying a higher degree of BC scheme, such as LOCI and PT schemes, a significant improvement in the SD and CV were noted as the data points in the scatter plots are almost matched to the gauged observations. PT exhibits greater improvement compared to LOCI. These results are considered as good, as the method of BC schemes applied for this study was only intended to correct the aforementioned statistical parameters.

### Variation and sensitivity of parameters

Based on the statistical analysis, the determined parameters or bias factors (s for LS scheme, c for LOCI scheme as well as a and b for PT scheme) greatly affected the corrected daily precipitation value of the extreme flood. However, statistical analysis does not provide a true answer for the study as hydrological events are subjected to great variability and uncertainties. Thus, it is important to evaluate the sensitivity of these parameters based on the selected events of this study. Moreover, it is also important to assess whether these parameters can be applied in a similar event of different time period (Terink et al. 2010). Figure 8 shows the boxplots for every parameter applied throughout the five selected events, with the small circles representing the

| Table 7 | Nash-Sutcliffe efficiency |
|---------|---------------------------|
| Nash-Sutcliffe Efficiency (NSE) | Raw | LS | LOCI | PT |
| **TRMM** | | | | |
| Event 1 | 0.96 | 0.92 | 0.96 | 0.99 |
| Event 2 | 0.78 | 0.95 | 0.94 | 0.98 |
| Event 3 | 0.94 | 0.99 | 0.96 | 0.99 |
| Event 4 | 0.62 | 0.91 | 0.81 | 0.97 |
| Event 5 | 0.93 | 0.99 | 0.97 | 0.99 |
| **CMORPH** | | | | |
| Event 1 | 0.65 | 0.91 | 0.97 | 0.99 |
| Event 2 | 0.97 | 0.98 | 0.98 | 0.99 |
| Event 3 | 0.77 | 0.99 | 0.98 | 0.99 |
| Event 4 | 0.33 | 0.89 | 0.87 | 0.95 |
| Event 5 | 0.81 | 0.96 | 0.97 | 0.98 |
| **PERSIANN** | | | | |
| Event 1 | 0.74 | 0.78 | 0.84 | 0.97 |
| Event 2 | 0.84 | 0.91 | 0.77 | 0.99 |
| Event 3 | 0.86 | 0.81 | 0.88 | 0.94 |
| Event 4 | 0.35 | 0.72 | 0.76 | 0.88 |
| Event 5 | 0.80 | 0.77 | 0.82 | 0.95 |
Mean

Standard Deviation (SD)

Coefficient of Variation (CV)

* Raw  LS  LOCI  PT  Reference line

Figure 7 | Scatter plots of statistics of the rain gauge (RG) precipitation versus raw and corrected SPP estimations.
outliers. For the LS scheme, the parameter \( s \) was determined. It is found that most of the rainfall points (for both the months of December and January) of TRMM and PERSIANN were multiplied with the parameter \( s \) around 1.00 which indicates that most of the data points are almost accurate and there is no significant correction. For CMORPH, most of the parameter \( s \) were more than 1.00, which means the actual precipitation was underestimated and thus correction should be applied on the CMORPH data from a dry to a wet condition for every extreme flood event. For the LOCI scheme, the parameter \( c \) was almost in the same range as parameter \( s \) in the LS scheme for TRMM and CMORPH estimations. However, the multiplier is slightly larger for PERSIANN estimation. For the PT scheme, there are two parameters, \( a \) and \( b \), used to correct the mean and the standard deviation or variance of the data-sets, respectively. It is noted that the parameter \( a \) applied on all three estimations varies over every event except for PERSIANN estimation in January. The parameter \( a \) applied on PERSIANN estimation in January is smaller than 1.00, which means that PERSIANN overestimated the actual rainfall that happened in January over the five flood events.

To address the uncertainty concerning the determined parameters of every scheme, bootstrapping \((\text{Tian et al.} 2014)\) was performed for every parameter of the selected BC scheme. Based on the parameters obtained, 1,000 random samples were generated and the sampling distribution was visualized using histograms to observe the skewness of the samples. This bootstrapping procedure was repeated for every parameter and every satellite estimation. Figure 9 shows one of the histograms for resampled parameter \( s \) (bias factor of LS scheme) for January’s TRMM estimations. The mean of the original and resampled parameters as well as the 95% confidence intervals are shown in Table 9. These results can be a reference for correcting the near-real-time data for further use.

Based on the results, it is noted that the uncertainty range of every parameter applied for the month of December is larger compared to that for the month of January. Thus, careful consideration should be given when improving the satellite rainfall estimations. By comparing the BC scheme, the difference between the original and the resampled mean for parameter \( a \) and \( b \) of the PT scheme is much smaller compared to \( s \) for the LS scheme and \( c \).
for the LOCI scheme. However, there is still a large uncertainty range for this scheme to be applied in CMORPH (parameter $b$ in January) and PERSIANN estimations (parameter $a$ in January and $b$ in December).

**CONCLUSION AND RECOMMENDATIONS**

Satellite precipitation has provided an alternative for precipitation measurement due to its large-scale approach. However, these satellite data have their own accuracy or dependability issues. This study presents an application of three BC schemes (LS, LOCI and PT) to improve the accuracy of three satellite estimations (TRMM 3B42 V7, CMORPH and PERSIANN) at the Langat river basin during the five selected extreme flood events due to NEM specifically in the months of December and January. Studies of BC on satellite estimations in Malaysia is arguably limited and therefore accuracy of this global coverage rainfall data should be assessed according to Malaysia’s topography, location and weather system. The selection of BC methods for this study is considered universal as these methods have been applied in most of the studies. However, due to rapid evolution of the SPP estimations, as well as
changing of climate, it is crucial to implement these BC on the latest version of SPPs for the extreme events in the Malaysia region.

In this paper, we investigated the capability of BC schemes in improving the satellite estimations. During the process of BC, we noticed that the parameters or bias factors (s for LS scheme, c for LOCI scheme as well as a and b for PT scheme) vary for every flood event even though these floods happened in the same season monsoon. Thus, we also evaluated the sensitivity of these parameters to the extreme floods selected and whether these parameters can be applied in a similar event of a different time period.

Based on the findings, all BC schemes are able to improve the satellite estimations. LS-corrected rainfall estimates predict the overall gauged rainfall of the catchment very well. Nevertheless, this method matches well the mean precipitation of every satellite estimation and does not correct the SD and CV of the estimations. For LOCI, in the present study, we set 1 mm as the rainfall threshold

Figure 9 | Sample histogram of bootstrap values for 1,000 random samples.

Table 9 | The mean, resampled mean and 95% confidence interval (95% CI) for every parameter applied on the SPP

| Method | Parameter | Parameter | Mean | Resampled mean | 95% CI | Mean | Resampled mean | 95% CI |
|--------|-----------|-----------|------|----------------|--------|------|----------------|--------|
| LS     | s         | T         | 0.86 | 5.13           | [0.38, 5.77] | 0.94 | 2.43           | [0.11, 1.04] |
|        |           | C         | 1.43 | 12.62          | [0.02, 8.45] | 2.15 | 6.97           | [0.53, 1.60] |
|        |           | P         | 0.89 | 8.65           | [0.60, 8.98] | 0.88 | 3.11           | [0.46, 2.20] |
| LOCI   | c         | T         | 0.81 | 3.88           | [0.27, 4.40] | 0.78 | 1.87           | [0.36, 1.08] |
|        |           | C         | 1.65 | 11.62          | [0.26, 6.62] | 2.00 | 7.29           | [0.47, 2.26] |
|        |           | P         | 1.34 | 10.14          | [0.41, 6.81] | 1.57 | 5.25           | [0.71, 2.11] |
| PT     | a         | T         | 1.48 | 1.82           | [0.95, 2.98] | 1.97 | 1.9            | [0.65, 3.07] |
|        |           | C         | 1.18 | 1.66           | [0.74, 3.04] | 1.15 | 1.68           | [0.43, 2.77] |
|        |           | P         | 6.62 | 3.5            | [1.55, 5.29] | 0.19 | 1.36           | [0.49, 2.26] |
|        | b         | T         | 1.18 | 0.22           | [−0.49, 0.81] | 0.86 | 0.51           | [−1.26, 0.26] |
|        |           | C         | 1.19 | 0.12           | [−0.49, 0.65] | 1.10 | −0.09          | [−0.75, 0.56] |
|        |           | P         | 1.02 | −2.56          | [−4.17, −0.20] | 1.81 | 0.07           | [−0.54, 0.74] |
to ensure that the threshold exceedance matches the wet-day frequency of the observation. We found that this scheme is suitable in correcting the TRMM and CMORPH estimations in certain flood events, but is not suitable for PERSIANN estimations as it overestimated the overall rainfall of the catchment by 40–85%. Sensitivity analysis on the setting of the daily rainfall threshold should be carried out. The PT scheme offers the best results in this study as it corrects up to the second statistical moment of the frequency distribution, such as SD and CV, and corrected well the rainfall distribution of satellite estimations.

In a nutshell, different BC schemes can have different effects on the distribution of precipitation, and can thus particularly impact the extreme values of an event (Hagemann et al. 2011; Willkofer et al. 2018). According to Teutschbein & Seibert (2012), the underlying principle and thus the most crucial assumption, is that the bias correction factors retrieved by any such methods must necessarily be considered valid for the future, assuming a temporal stationarity and thus introducing another, yet often neglected source of uncertainty. This may help the hydrologists to understand the efficiency and application of bias correction on satellite estimation data in rainfall–runoff modelling to predict the river discharge in this catchment, which may be useful to our water resources management.

ACKNOWLEDGEMENTS

The authors wish to acknowledge the University of Malaya, Kuala Lumpur, Malaysia for financial support (FP039-2014B and PG194-2015B). The authors also would like to acknowledge the Department of Irrigation and Drainage Malaysia for providing the daily precipitation data as well as the developers of all SPPs for providing the downloadable data.

REFERENCES

Abera, W., Brocca, L. & Rigon, R. 2016 Comparative evaluation of different satellite rainfall estimation products and bias correction in the Upper Blue Nile (UBN) basin. *Atmospheric Research* 178–179 (Supplement C), 471–483. doi:10.1016/j.atmosres.2016.04.017.

Ajaaj, A. A., Mishra, A. K. & Khan, A. A. 2016 Comparison of BIAS correction techniques for GPCC rainfall data in semi-arid climate. *Stochastic Environmental Research and Risk Assessment* 30 (6), 1659–1675. doi:10.1007/s00477-015-1155-9.

Akash, Z. A. & Doraisamy, S. V. 2015 2014 Malaysia flood: impacts and factors contributing towards the restoration of damages. *Journal of Scientific Research and Development* 2 (14), 53–59.

Anagnostou, E. N., Krajewski, W. F., Seo, D.-J. & Johnson, E. R. 1998 Mean-field rainfall bias studies for WSR-88D. *Journal of Hydrologic Engineering* 3 (3), 149–159. doi:10.1061/(ASCE)1084-0699(1998)3:3(149).

Behrang, A., Khakbaz, B., Jaw, T. C., AghaKouchak, A., Hsu, K. & Sorooshian, S. 2011 Hydrologic evaluation of satellite precipitation products over a mid-size basin. *Journal of Hydrology* 397 (5–4), 225–237. doi:10.1016/j.jhydrol.2010.11.043.

Boushaki, F. I., Hsu, K.-L., Sorooshian, S., Park, G.-H., Mahani, S. & Shi, W. 2009 Bias adjustment of satellite precipitation estimation using ground-based measurement: a case study evaluation over the southwestern United States. *Journal of Hydrometeorology* 10 (5), 1231–1242. doi:10.1175/2009jhm1099.1.

Chen, J., Brissette, F. P., Chaumont, D. & Braun, M. 2013a Finding appropriate bias correction methods in downscaling precipitation for hydrologic impact studies over North America. *Water Resources Research* 49 (7), 4187–4205. doi:10.1002/wrcr.20331.

Chen, J., Brissette, F. P., Chaumont, D. & Braun, M. 2013b Performance and uncertainty evaluation of empirical downscaling methods in quantifying the climate change impacts on hydrology over two North American river basins. *Journal of Hydrology* 479 (Supplement C), 200–214. doi:10.1016/j.jhydrol.2012.11.062.

Collischonn, B., Collischonn, W. & Tucci, C. E. M. 2008 Daily hydrological modeling in the Amazon basin using TRMM rainfall estimates. *Journal of Hydrology* 360 (1–4), 207–216. doi:10.1016/j.jhydrol.2008.07.032.

de Coning, E. 2015 Optimizing satellite-based precipitation estimation for nowcasting of rainfall and flash flood events over the South African domain. *Remote Sensing* 5 (11), 5702–5724.

Derin, Y. & Yilmaz, K. K. 2014 Evaluation of multiple satellite-based precipitation products over complex topography. *Journal of Hydrometeorology* 15 (4), 1498–1516. doi:10.1175/jhm-d-13-0191.1.

Diederich, M., Ryzhkov, A., Simmer, C., Zhang, P. & Trömel, S. 2015 Use of specific attenuation for rainfall measurement at X-band radar wavelengths. Part II: rainfall estimates and comparison with rain gauges. *Journal of Hydrometeorology* 16 (2), 503–516. doi:10.1175/jhm-d-14-0067.1.

Dinku, T., Ruiz, F., Connor, S. J. & Ceccato, P. 2009 Validation and intercomparison of satellite rainfall estimates over

Downloaded from http://iwaponline.com/hr/article-pdf/51/1/105/758879/hrh0510105.pdf by guest
Khan, S. I., Hong, Y., Wang, J., Yilmaz, K. K., Gourley, J. J., Adler, R. F., Brakenridge, G. R., Policelli, F., Habib, S. & Irwin, D. 2011 Satellite remote sensing and hydrologic modeling for flood inundation mapping in Lake Victoria Basin: implications for hydrologic prediction in ungauged basins. IEEE Transactions on Geoscience and Remote Sensing 49 (1), 85–95.

Kizza, M., Westerberg, I., Rodhe, A. & Ntale, H. K. 2012 Estimating areal rainfall over Lake Victoria and its basin using ground-based and satellite data. Journal of Hydrology 464–465 (Supplement C), 401–411. doi:10.1016/j.jhydrol.2012.07.024.

Kubota, T., Shige, S., Hashizume, H., Aonashi, K., Takahashi, N., Seto, S., Hirose, M., Takayabu, Y. N., Ushio, T., Nakagawa, K., Iwanami, K., Kachi, M. & Okamoto, K. 2007 Global precipitation map using satellite-borne microwave radiometers by the GsMAP Project: Production and validation. IEEE Transactions on Geoscience and Remote Sensing 45 (7), 2259–2275. doi:10.1109/TGRS.2007.895337.

Lafon, T., Dadson, S., Buys, G. & Prudhomme, C. 2013 Bias correction of daily precipitation simulated by a regional climate model: a comparison of methods. International Journal of Climatology 33 (6), 1567–1581. doi:10.1002/joc.3518.

Leander, R. & Buishand, T. A. 2007 Resampling of regional climate model output for the simulation of extreme river flows. Journal of Hydrology 332 (3), 487–496. doi:10.1016/j.jhydrol.2006.08.006.

Lenderink, G., Buishand, A. & van Deursen, W. 2007 Estimates of future discharges of the river Rhine using two scenario methodologies: direct versus delta approach. Hydrology and Earth System Sciences 11 (3), 1145–1159. doi:10.5194/hess-11-1145-2007.

Mair, A. & Fares, A. 2010 Comparison of rainfall interpolation methods in a mountainous region of a tropical island. Journal of Hydrologic Engineering 16 (4), 371–383.

Moazami, S., Golian, S., Kavianpour, M. R. & Hong, Y. 2013 Comparison of PERSIANN and V7 TRMM Multi-satellite Precipitation Analysis (TMAPA) products with rain gauge data over Iran. International Journal of Remote Sensing 34 (22), 8156–8171. doi:10.1080/01431161.2013.835360.

Nicholson, S. E., Some, B., McCollum, J., Nelkin, E., Klotter, D., Berte, Y., Bae, M. B., Gaye, I., Kpabea, G., Ndiaye, O., Noukpozounkou, J. N., Tanu, M. M., Thiam, A., Toure, A. A. & Traore, A. K. 2005 Validation of TRMM and other rainfall estimates with a high-density gauge dataset for West Africa. Part II: validation of TRMM rainfall products. Journal of Applied Meteorology 42 (10), 1355–1368. doi:10.1175/1520-0450(2003)042<1355:votaor>2.0.co;2.

Pan, X., Yang, D., Li, Y., Barr, A., Helgason, W., Hayashi, M., Marsh, P., Pomeroy, J. & Janowicz, R. J. 2016 Bias corrections of precipitation measurements across experimental sites in different ecoclimatic regions of western Canada. The Cryosphere 10 (5), 2347–2360. doi:10.5194/tc-10-2347-2016.

Pereira Filho, A. J., Carbone, R. E., Janowiak, J. E., Arkin, P., Joyce, R., Hallak, R. & Ramos, C. G. M. 2010 Satellite rainfall estimates over South America – possible applicability to the water management of large watersheds. JAWRA Journal of the American Water Resources Association 46 (2), 344–360. doi:10.1111/j.1752-1688.2009.00406.x.

Piani, C., Weedon, G. P., Best, M., Gomes, S. M., Viterbo, P., Hagemann, S. & Haerter, J. O. 2010 Statistical bias correction of global simulated daily precipitation and temperature for the application of hydrological models. Journal of Hydrology 395 (3), 199–215. doi:10.1016/j.jhydrol.2010.01.024.

Saber, M. & Yilmaz, K. K. 2005 Evaluation and bias correction of satellite-based rainfall estimates for modelling flash floods over the Mediterranean region: application to Karpuz River Basin, Turkey. Water 10 (5), 657.

Saidi, A., Kamarudin, M., Ridzuan, I., Ishak, R., Azid, A. & Rizman, Z. 2017 Flood risk index pattern assessment: case study in Langat river basin. Journal of Fundamental and Applied Sciences 9 (28), 12–27.

Schmidli, J., Frei, C. & Vidale, P. L. 2006 Downdscaling from GCM precipitation: a benchmark for dynamical and statistical downscaling methods. International Journal of Climatology 26 (5), 679–689. doi:10.1002/joc.1287.

Scofield, R. A. & Kuligowski, R. J. 2003 Status and outlook of operational satellite precipitation algorithms for extreme-precipitation events. Weather and Forecasting 18 (6), 1037–1051. doi:10.1175/1520-0434(2003)018<1037:ssaoos>2.0.co;2.

Segond, M.-L., Wheeler, H. S. & Onof, C. 2007 The significance of spatial rainfall representation for flood runoff estimation: a numerical evaluation based on the Lee catchment, UK. Journal of Hydrology 347 (1), 116–131. doi:10.1016/j.jhydrol.2007.09.040.

Seyyedi, H., Anagnostou, E. N., Beighley, E. & McCollum, J. 2014 Satellite-driven downsampling of global reanalysis precipitation products for hydrological applications. HESS 18 (12), 5077–5091. doi:10.5194/hess-18-5077-2014.

Shabalova, M. V., van Deursen, W. P. A. & Buishand, T. A. 2003 Assessing future discharge of the river Rhine using regional climate model integrations and a hydrological model. Climate Research 23 (3), 233–246.

Shen, Y., Xiong, A., Wang, Y. & Xie, P. 2010 Performance of high-resolution satellite precipitation products over China. Journal of Geophysical Research: Atmospheres 115 (D2) D02114, doi:10.1029/2009JD012097.

Shige, S., Kida, S., Ashiwake, H., Kubota, T. & Aonashi, K. 2003 Improvement of TMI rain retrievals in mountainous areas. Journal of Applied Meteorology and Climatology 52 (1), 242–254.

Soo, E. Z. X., Wan Jaafar, W. Z., Lai, S. H., Islam, T. & Srivastava, P. 2019 Evaluation of satellite precipitation products for extreme flood events: case study in Peninsular Malaysia. Journal of Water and Climate Change 10 (4), 871–892. doi:10.2166/wcc.2018.159.
Sorooshian, S., Hsu, K.-L., Gao, X., Gupta, H. V., Imam, B. & Braithwaite, D. 2000 Evaluation of PERSIANN system satellite-based estimates of tropical rainfall. Bulletin of the American Meteorological Society 81 (9), 2035–2046. doi:10.1175/1520-0477(2000)081<2035:epspse>2.3.co.2.

Strangeways, I. 2004 Improving precipitation measurement. International Journal of Climatology 24 (11), 1443–1460. doi:10.1002/joc.1075.

Su, F., Hong, Y. & Lettenmaier, D. P. 2008 Evaluation of TRMM Multisatellite Precipitation Analysis (TMPA) and its utility in hydrologic prediction in the La Plata Basin. Journal of Hydrometeorology 9 (4), 622–640. doi:10.1175/2007jh944.1.

Tan, M. L., Ibrahim, A. L., Duan, Z., Cracknell, A. P. & Chaplot, V. 2015 Evaluation of six high-resolution satellite and ground-based precipitation products over Malaysia. Remote Sensing 7 (2), 1504–1528.

Tesfagiorgis, K., Mahani, S. E., Krakauer, N. Y. & Khanbilvardi, R. 2011 Bias correction of satellite rainfall estimates using a radar-gauge product; a case study in Oklahoma (USA). Hydrology and Earth System Sciences 14 (4), 687–703.

Teutschbein, C. & Seibert, J. 2012 Bias correction of regional climate model simulations for hydrological climate-change impact studies: review and evaluation of different methods. Journal of Hydrology 456–457 (Supplement C), 12–29. doi:10.1016/j.jhydrol.2012.05.032.

Teutschbein, C. & Seibert, J. 2013 Is bias correction of regional climate model (RCM) simulations possible for non-stationary conditions? Hydrology and Earth System Sciences 17 (12), 5061–5077. doi:10.5194/hess-17-5061-2013.

Thiemig, V., Rojas, R., Zambrano-Bigiarini, M., Levizzani, V. & Roo, A. D. 2012 Validation of satellite-based precipitation products over sparsely gauged African River Basins. Journal of Hydrometeorology 13 (6), 1760–1783. doi:10.1175/jhm-d-12-032.1.

Tian, Y., Peters-Lidard, C. D., Eyjólfsson, G. J., Adler, R. F., Hsu, K.-L., Joseph Turk, F., Garcia, M. & Zeng, J. 2009 Component analysis of errors in satellite-based precipitation estimates. Journal of Geophysical Research: Atmospheres 114 (D24). doi:10.1029/2009JD011949.

Tian, W., Song, J., Li, Z. & de Wilde, P. 2014 Bootstrap techniques for sensitivity analysis and model selection in building thermal performance analysis. Applied Energy 135, 320–328. doi:10.1016/j.apenergy.2014.08.110.

Valdés-Pineda, R., Demaría, E. M. C., Valdés, J. B., Wi, S. & Serrat-Capdevilla, A. 2016 Bias correction of daily satellite-based rainfall estimates for hydrologic forecasting in the Upper Zambezi, Africa. Hydrology and Earth System Sciences Discussions 2016, 1–28. doi:10.5194/hess-2016-473.

Vernimmen, R., Hooijer, A., Aldrian, E. & Van Dijk, A. 2012 Evaluation and bias correction of satellite rainfall data for drought monitoring in Indonesia. Hydrology and Earth System Sciences 16 (1), 133–146.

Vila, D. A., Goncalves, L. G. G. d., Toll, D. L. & Rozante, J. R. 2009 Statistical evaluation of combined daily gauge observations and rainfall satellite estimates over Continental South America. Journal of Hydrometeorology 10 (2), 533–543. doi:10.1175/2008jh51048.1.

Villarini, G., Krajewski, W. F. & Smith, J. A. 2009 New paradigm for statistical validation of satellite precipitation estimates: application to a large sample of the TMPA 0.25° 3-hourly estimates over Oklahoma. Journal of Geophysical Research: Atmospheres 114 (D12). doi:10.1029/2008JD011475.

Vu, T. T., Li, L. & Jun, K. S. 2008 Evaluation of multi-satellite precipitation products for streamflow simulations: a case study for the Han River Basin in the Korean Peninsula, East Asia. Water 10 (5), 642.

Wang, Z., Chen, J., Lai, C., Zhong, R., Chen, X. & Yu, H. 2018 Hydrologic assessment of the TMPA 3b42-V7 product in a typical alpine and gorge region: the Lancang River basin, China. Hydrology Research 49 (6), 2002–2015. doi:10.2166/nh.2018.024.

Willkofer, F., Schmid, F.-J., Komischke, H., Korck, J., Braun, M. & Ludwig, R. 2008 The impact of bias correcting regional climate model results on hydrological indicators for Bavarian catchments. Journal of Hydrology: Regional Studies 19, 25–41. doi:10.1016/j.ejrh.2018.06.010.

World Meteorological Organization 2008 Chapter 14; Observation of present and past weather; state of the ground. Guide to Meteorological Instruments and Methods of Observation. WMO, Geneva, pp. I.14–7.

Worqlul, A. W., Ayana, E. K., Maathuis, B. H. P., MacAlister, C., Philpot, W. D., Osorio Leyton, J. M. & Steenhuis, T. S. 2018 Performance of bias corrected MPEG rainfall estimate for rainfall-runoff simulation in the upper Blue Nile Basin, Ethiopia. Journal of Hydrology 556, 1182–1191. doi:10.1016/j.jhydrol.2017.01.058.

Yilmaz, K. K., Hogue, T. S., Hsu, K.-L., Sorooshian, S., Gupta, H. V. & Wagener, T. 2005 Intercomparison of rain gauge, radar, and satellite-based precipitation estimates with emphasis on hydrologic forecasting. Journal of Hydrometeorology 6 (4), 497–517. doi:10.1175/jhm431.1.

Zhao, T., Bennett, J. C., Wang, Q. J., Schepen, A., Wood, A. W., Robertson, D. E. & Ramos, M.-H. 2017 How suitable is quantile mapping for postprocessing GCM precipitation forecasts? Journal of Climate 30 (9), 3185–3196. doi:10.1175/jcli-d-16-0652.1.

First received 25 May 2019; accepted in revised form 11 November 2019. Available online 18 December 2019