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Discussions

Performance of bias correction schemes for CMORPH rainfall estimates in the Zambezi River Basin

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Abstract

Satellite rainfall estimates (SRE) are prone to bias because such estimates are indirectly derived from visible, infrared, and/or microwave based information of cloud properties. We tested the influence of elevation and distance from large scale water bodies on bias for Climate Prediction Center-MORPHing (CMORPH) rainfall estimates. Effectiveness of five linear/non-linear and time-space variant/invariant bias correction schemes is evaluated. Evaluation also covers for different magnitudes of daily rainfall and climatic seasonality. We used daily rain gauge time series (1998-2013) from 60 stations, and counterparts from CMORPH time series for the Zambezi Basin. Taylor diagrams show that station elevation and distance from water bodies do not influence the estimation error of uncorrected CMORPH rainfall. For correction, the Spatio-temporal bias (STB) and Elevation zone bias (EZ) schemes showed best results in removing CMORPH rainfall bias for the Lower, Middle and Upper Zambezi subbasins. STB improved the correlation coefficient by 53 % and reduced the root mean squared difference by 25 %. Assessment of mean estimates by using a Taylor Diagram with mean estimates of correlation coefficient, root mean square difference and standard deviation showed that the EZ, Power transform, Distribution transformation and STB correction schemes best removed errors related to rainfall depth. Corrected CMORPH rainfall revealed an overestimation of very light rainfall (< 2.5 mm/day) and underestimation of very heavy rainfall (>20.0 mm/day) for all five correction schemes. Bias is best reduced for rainfall magnitudes of 0.0-2.5 and 5.0-10.0 mm/day. Bias removal proved to be more effective in the wet season than in the dry season.

Keywords: *distance zone, elevation zone, satellite rainfall estimates, spatio-temporal bias, Taylor diagram*

1. Introduction

Correction schemes for rainfall estimates are developed for climate models (Maraun, 2016;Grillakis et al., 2017;Switanek et al., 2017), for radar approaches (Cecinati et al., 2017;Yoo et al., 2014) and for satellite based, multi-sensor, approaches (Najmaddin et al., 2017;Valdés-Pineda et al., 2016). In this study focus is on satellite rainfall estimates (SRES) so to improve reliability in water resource applications.

Studies in satellite based rainfall estimation show that estimates are prone to systematic and random errors (Gebregiorgis et al., 2012;Habib et al., 2014;Shrestha, 2011;Tesfagiorgis et al., 2011;Vernimmen et al., 2012;Woody et al., 2014). Errors result primarily from the indirect estimation of rainfall from visible (VIS), infrared (IR), and/or microwave (MW) based satellite remote sensing of cloud properties (Pereira Filho et al., 2010;Romano et al., 2017). Systematic errors in SREs commonly are referred to as bias, which is a measure that indicates the accumulated difference between rain gauge observations and SREs. Bias in SREs is expressed for rainfall depth and volume (Habib et al., 2012b), rain rate (Haile et al., 2013) and frequency at which rain rates occur (Khan et al., 2014). Bias may be negative or positive where negative bias indicates underestimation whereas positive bias indicates overestimation (Liu, 2015;Moazami et al., 2013).

Studies (Wehbe et al., 2017;Jiang et al., 2016;Liu et al., 2015;Haile et al., 2015) reveal that CMORPH satellite rainfall has variable accuracy accross different regions. As such correction schemes serve to correct for systematic errors and to improve aplicability of SREs. Correction schemes rely on assumptions that adjust errors in space and/or time (Habib et al., 2014). Some correction schemes consider correction only for spatial distributed patterns in bias, commonly known in literature as space variant/invariant. Approaches that correct for spatially averaged bias have roots in radar rainfall estimation (Seo et al., 1999) but are unsuitable for large scale basins (> 5,000 km^2) where rainfall may substantially vary in space (see Habib et al., 2014). Studies by Tefsagiorgis et al. (2011) in Oklahoma (USA) and Müller and Thompson (2013) in Nepal concluded that space variant correction schemes are more effective in reducing CMORPH and TRMM bias than space invariant correction schemes. In Bhatti et al. (2016), for the Upper Blue Nile basin in Ethiopia, it is shown that CMORPH bias correction is most effective when bias correction is for periods of 6 days.

Bias correction schemes based on regression techniques have reported distortion of frequency of rainfall rates (Ines and Hansen, 2006;Marcos et al., 2018). Multiplicative shift procedures tend to adjust SRE rainfall rates, but Ines and Hansen (2006) reported that they do not correct systematic errors in rainfall frequency of climate models. Non-multiplicative bias correction schemes preserve the timing of rainfall within a season (Fang et al., 2015;Hempel et al., 2013).

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Studies that have applied non-linear bias correction schemes such as Power function report correction of extreme values (depth, rate and frequency) thus mitigating the underestimation and overestimation of CMORPH rainfall (Vernimmen et al., 2012). The study by Tian (2010) in the United States noted that the Bayesian (likelihood) analysis techniques are found to over-adjust both light and heavy satellite rainfall toward moderate CMORPH rainfall.

Bias often exhibits a topographic and latitudinal dependency as, for instance, shown for the National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center-MORPHing (CMORPH) product in the Nile Basin (Bitew et al., 2011;Habib et al., 2012a;Haile et al., 2013). For Southern Africa, Thorne et al. (2001), Dinku et al. (2008) and Meyer et al. (2017) show that bias in rainfall rate and frequency can be related to location, topography, local climate and season. First studies in the Zambezi Basin (Southern Africa) on SREs show evidence that necessitates correction of SREs. For example Cohen Liechti (2012) show bias in CMORPH SREs for daily rainfall and for accumulated rainfall at monthly scale. Matos et al. (2013), Thiemig et al. (2012) and Toté et al. (2015) show that bias in rainfall depth at time steps ranging from daily to monthly varies across geographical domains in the Zambezi Basin and may be as large as ±50 %. Besides topographic effects, rainfall is affected by presence of large scale water bodies which influences surface or atmospheric properties (Haile et al., 2009;Rientjes et al., 2013). As such, SREs may be affected as well necessitating to correct for bias by presence of large scale water bodies.

For less developed areas such as in the Zambezi Basin that is selected for this study, applications of SREs are very limited. This is despite the strategic importance of the basin in providing water to over 50 million people. An exception is the study by Beyer et al. (2014) on correction of the TRMM-3B42 product for agricultural purposes in the Upper Zambezi Basin. First studies on use of SREs in the Zambezi River Basin mainly focused on accuracy assessment of the SREs using standard statistical indicators with little or no effort to perform bias correction despite the evidence of errors in these products. The use of uncorrected satellite rainfall is reported for hydrological modelling in the Nile Basin (Bitew and Gebremichael, 2011) and Zambezi Basin (Cohen Liechti et al., 2012), respectively, and for drought monitoring in Mozambique (Toté et al., 2015). The above studies highlight the demand for the use of corrected SREs for improved water resources management. Our selection of CMORPH satellite rainfall for this study is based on successful applications of bias corrected CMORPH estimates in African basins for hydrological modelling (Habib et al., 2014) and flood predictions in West Africa (Thiemig et al., 2013). In first publications on CMORPH, Joyce et al. (2004) describe CMORPH as a gridded precipitation product that estimates rainfall with information derived from IR data and MW data. CMORPH combines the retrieval accuracy of passive MW estimates with IR measurements which are available at high temporal resolution but with lower accuracy. The important distinction between CMORPH and other merging methods is that the IR data are not used for rainfall estimation but used only to propagate rainfall features that have been derived from microwave data. The flexible 'morphing' technique is applied to modify the shape and rate of rainfall patterns. CMORPH is operational since 2002 for which data is available at the CPC of the National Centers for Environmental Prediction (NCEP) (after http://www.ncep.noaa.gov/). Recent publications on CMORPH exist (Wehbe et al., 2017;Koutsouris et al., 2016;Jiang et al., 2016;Haile et al., 2015).

In this study we use CMORPH and rain gauge data for Upper, Middle, and Lower Zambezi basins to (1) test whether the performance of CMORPH rainfall estimates is affected by elevation and distance from large water bodies, (2) evaluate the effectiveness of linear/non-linear and time-space variant/invariant bias correction schemes and (3) assess the performance of bias correction schemes to represent different rainfall magnitudes for climate seasonality. The above improves reliability in water resource applications in the Zambezi basin such as in drought analysis, flood prediction, weather forecasting and rainfall runoff modeling.

2. Study area

The Zambezi River is the fourth-longest river (~2,574 km) in Africa with basin area of ~1,390,000 km^2 (~4 % of the African continent). The river drains into the Indian Ocean and has mean annual discharge of 4,134 m^3/s (World Bank, 2010b). The river has its source in Zambia and forms boundaries of Angola, Namibia Botswana, Zambia, Zimbabwe and Mozambique (Fig. 1). The basin has considerable differences in elevation, topography and climatic seasons and, as such, makes the basin well suited for this study. The basin is divided into three subbasins i.e., the Lower Zambezi comprising the Tete, Lake Malawi/Shire, and Zambezi Delta basins, the Middle Zambezi made up of the Kariba, Mupata, Kafue, and Luangwa basins, and the Upper Zambezi constituted by the Kabompo, Lungwebungo, Luanginga, Barotse, and Cuando/Chobe basins (Beilfuss, 2012).

The elevation of the Zambezi basin ranges from < 200 m (for some parts of Mozambique) to >1500 m above sea level (for some parts of Zambia). Large scale water bodies in and around the basin are Kariba, Cabora Bassa, Bangweulu, Chilwa and Nyasa. The Indian Ocean is to the east of Mozambique. Typical landcover types are woodland, grassland, water surfaces and cropland (Beilfuss et al., 2000). The basin is characterized by high annual rainfall (>1,400 mm/yr) in the northern and north-eastern areas but low annual rainfall (<500 mm/yr) in the southern and western parts (World Bank, 2010a). Due to this rainfall distribution, northern tributaries in the Upper Zambezi subbasin contribute 60 % of the mean annual discharge (Tumbare, 2000). The river and its tributaries are subject to seasonal floods and droughts that have devastating effects on the people and economies of the region, especially the poorest members of the population (Tumbare, 2005). It is not uncommon to experience both floods and droughts within the same hydrological year.

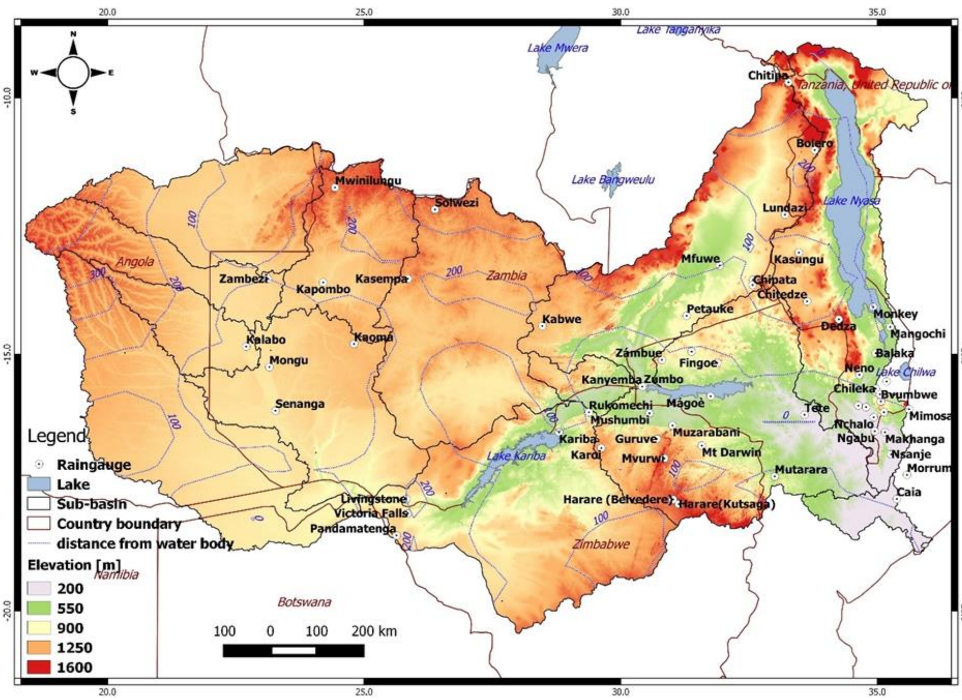

Figure 1: Zambezi River Basin with sub basins, major lakes, rivers, elevation and locations of the 60 rain gauging stations used in this study. The Euclidian distance (km) from large scale water bodies is also shown.

3. Materials and Methodology

3.1. Data

3.1.1. CMORPH rainfall

For this study time series (1998-2013) of CMORPH rainfall product at 8 km × 8 km, 30-minute resolution are selected. Images were downloaded from the GeoNETCAST ISOD toolbox by means of ILWIS GIS software (http://52north.org/downloads/). We aggregated half hourly data to daily totals to match the gauge based counter parts.

3.1.2. Rain gauge rainfall

Time series of daily rainfall from 66 stations was obtained from meteorological departments in Botswana, Malawi, Mozambique, Zambia and Zimbabwe that cover the study area. After screening, 6 stations with unreliable time series were removed. Although a number of the 60 remaining stations are affected by data gaps, the available time series are of sufficiently long duration to serve the objectives of this study. The location of the stations cover elevation values that range from 3 m to 1600 m asl. and distance to a large scale water bodies that range from < 10 km to > 500 km. This allows us to assess the effect of the above factors on SRE performance.

3.2. Topographic influences: Elevation and distance from lake water bodies

Studies such as in the Nile Basin (Habib et al., 2012a;Haile et al., 2009;Rientjes et al., 2013) reveal that elevation and distance from lake water bodies interact to produce unique circulation patterns that affect the performance of SREs. This study investigated topographic influences on rainfall distribution, frequency and rain rate by analysing effects of elevation and distance of the 60 rain gauges to large scale water bodies in the Zambezi Basin (See Table 1). As such the hierarchical cluster 'within-groups linkage' method in the Statistical Product and Service Solutions (SPSS) software was used to classify the Zambezi Basin into 3 elevation zones. These are zone 1: elevation of < 250 m (mean elevation ≈ 90 m), zone 2: elevation range of 250- 950 m (mean elevation ≈ 510 m) and zone 3: elevation > 950 m (mean elevation ≈ 1140 m). Based on rain gauge Euclidian distance to large scale water bodies 4 arbitrary distance zones are defined. These are zone 1: < 10 km (mean distance = 5 km), zone 2: 10 - 50 km (mean distance = 35 km), zone 3: 50 -100 km (mean distance = 80 km) and zone 4: > 100 km (mean distance = 275 km). The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) based DEM of 30 m resolution obtained from http://gdem.ersdac.jspacesystems.or.jp/, was used for representing elevation across the Zambezi Basin. The Euclidian distance of each rain gauge location to large scale water bodies was computed in a GIS environment through the distance calculation algorithm. Large scale water bodies are defined as perennial water bodies with surface area > 700 km^2.

3.3. Bias correction schemes

In this study, the bias in CMORPH rainfall estimates was assessed and corrected using five schemes. We note that findings on performance of bias correction schemes in literature do not allow generalization but only apply to the respective study domains. Based on the above studies we selected five approaches for evaluation for the Zambezi Basin. These are the Spatio-temporal bias (STB), Elevation zone bias (EZB), Power transform (PT), Distribution transformation (DT), and the Quantile mapping based on an empirical distribution (QME). The five schemes are chosen based on merits documented in literature and the aim of the present work to adjust for CMORPH rainfall variability in space and/or time. Following Habib et al. (2014) and Bhatti et al. (2016), and based on preliminary analysis in this study on rainfall distributions in the Zambezi Basin, the bias correction factor is calculated for a certain day only when a minimum of five rainy days were recorded within the preceding 7-day window with a minimum rainfall accumulation depth of 5 mm, otherwise no bias is estimated (i.e. a value of 1 applies as bias correction factor). This approach implies that bias factors change value for each station for each 7-day period.

In the approach, a time window of specified length moves forward in the time domain. Bhatti et al. (2016) in the Lake Tana basin (Ethiopia) carried out a sensitivity analysis on moving windows where bias factor change for each day, and on sequential windows were bias factor is constant for the window length. Tests for window lengths of 3, 5, 7, ..., 31 days indicated

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that a 7-day sequential time window is most appropriate for bias correction. Also in the present a 7-day moving time window is adopted by preliminary analysis with accumulated rainfall of minimum 5 mm that occurred over at least 5 rainy days during the 7-day window. Preliminary analysis of wet season rainfall on all gauges in the Zambezi Basin indicates that the criterion in Bhatti et al. (2016) are commonly met so the above thresholds are adopted for this study.

3.3.1. Spatio-temporal bias correction (STB)

This linear bias correction scheme has its origin in the correction of radar based precipitation estimates (Tesfagiorgis et al., 2011) and downscaled precipitation products from climate models. The CMOPRH daily rainfall estimates (S) are multiplied by the bias correction factor for the respective moving time windows for individual stations resulting in corrected CMORPH estimates (S_{STB}) in a temporally and spatially coherent manner (Equation [1]).

$$S_{STB} = S \frac{\sum_{t=d}^{t=d-l} S(i,t)}{\sum_{t=d}^{t=d-l} G(i,t)} \qquad \textbf{[1]}$$

Where:

G = daily gauge based rainfall observations
i = gauge location
d = selected day
t = julian day number
l = length of a time window for bias calculation

The advantages of the bias scheme are the simplicity and modest data requirements and that it adjusts the daily mean of CMORPH at each station.

3.3.2. Elevation zone bias correction (EZ).

This bias scheme is proposed in this study and aims at correction of satellite rainfall as affected by topographic and landsurface influences. The method groups rain gauge stations into 3 elevation zones (see section 3.2) based on station elevation. The grouping in this study is based on the hierarchical clustering technique as also guided by knowledge of the study area. The assumption is that a number of stations (n) in the same elevation zone have the same bias characteristics and are assigned a spatially invariant but temporally variant bias correction factor with a different bias factor for each 7-day window. The corrected CMORPH estimates (S_{EZ}) at daily base are obtained by multiplying the uncorrected the CMOPRH daily rainfall estimates (S) by the daily bias factor in each elevation zone.

$$S_{EZ} = S \frac{\sum_{t=d}^{t=d-l} \sum_{i=1}^{i=n} S(i,t)}{\sum_{t=d}^{t=d-l} \sum_{i=1}^{i=n} G(i,t)} \qquad \textbf{[2]}$$

The merits of this bias correction scheme is that the daily time variability is preserved but also effects of elevation is accounted for.

3.3.3. Power transform (PT)

In Lafon et al. (2013) it is described that the nonlinear *PT* bias correction scheme has its origin in general circulation models. Vernimmen et al. (2012)) revealed an application to correct satellite rainfall estimates for hydrological modelling and drought monitoring. The daily bias corrected CMORPH rainfall (S_{PT}) is obtained using:

$$S_{PT} = aG(i,t)^{b} \qquad \textbf{[3]}$$

Where

G = daily rain gauge rainfall

a = prefactor such that the mean of the transformed CMORPH values is equal to the mean of gauge observations

b = factor calculated such that for each station the coefficient of variation (CV) of CMORPH matches the gauge based observation

i = gauge location

t = julian day number

Optimized values for a and b are obtained through the generalized reduced gradient algorithm (Fylstra et al., 1998). Values for a and b vary within the 7-day time window since correction is at daily time base. The advantage of the PT scheme is that rainfall variability of the daily time series is preserved by adjusting both the mean and standard deviation of the CMORPH estimates. The bias scheme also adjusts extreme precipitation values in CMORPH estimates (Vernimmen et al., 2012).

3.3.4. Distribution transformation (DT)

This additive approach to bias correction has its origin in statistical downscaling of climate model data (Bouwer et al., 2004). In this study, the method determines the statistical distribution function at daily base of all rain gauge station observation as well as CMORPH values at the respective stations. The CMORPH statistical distribution function is matched from the rain gauge data distribution following the steps described in equations [4-8]. Both the difference in mean value and the difference in variation are corrected. First the bias correction factor for the mean DTu is determined following Equation [4]:

$$DTu = \frac{Gu}{Su} \qquad \textbf{[4]}$$

Gu and Su are mean values of 7-day gauge and CMORPH rainfall estimates for gauged counterparts.

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Secondly, the correction factor for the variation ($DT\tau$) is determined by the quotient of the 7-day standard deviations, $G\tau$ and $S\tau$, for gauge and CMORPH respectively.

$$DT\tau = \frac{G\tau}{S\tau} \quad \textbf{[5]}$$

Once the correction factors are established, varying within a 7-day time window, factors are applied to correct all daily CMORPH estimates (S) through equation [6] to obtain corrected CMORPH rainfall estimate (S_{DT}).

$$S\mathrm{DT} = (S(i,t) - Su)DT\tau \; + DTu * S\tau \quad \textbf{[6]}$$

To ensure non-negative values, the formula was modified to result in the retention of the uncorrected CMORPH daily values. The merit of this bias scheme is that it corrects for frequency-based indices such as standard deviation and percentile values (Fang et al., 2015).

3.3.5. Quantile mapping based on an empirical distribution (QME)

This is a quantile based empirical-statistical error correction method with its origin in empirical transformation and bias correction of regional climate model-simulated precipitation (Themeßl et al., 2012). The method corrects CMORPH precipitation (S) based on point-wise constructed empirical cumulative distribution functions (*ecdfs*) on a 7-day time window. Rainfall frequency is corrected at the same time (Themeßl et al., 2010).

The bias corrected rainfall (S_{QME}) using quantile mapping can be expressed in terms of the empirical cumulative distribution function (*ecdf*) and its inverse ($ecdf^{-1}$) that are developed on a 7-day time window but with new values for each day.

$$S_{QME} = \; ecdf_{obs}^{-1}(ecdf_{raw}(S(i,t))) \quad \textbf{[7]}$$

Where:

$ecdf_{obs}$ = empirical cumulative distribution function for the gauge based observation
$ecdf_{raw}$ = empirical cumulative distribution function for the uncorrected CMORPH

The advantage of this bias scheme is that it corrects bias in the mean, standard deviation (Fang et al., 2015) as well as errors in rainfall depth. The approach is important for long term water resources assessments under the influence of land use or climate change. Furthermore, it preserves the extreme precipitation values (Themeßl et al., 2012).

3.4. Evaluation according to rainfall magnitudes and seasons

Performance of SREs for different rainfall rate classes and for different seasons is distinct across the Zambezi river basin. As such five classes are defined that are 0.0-2.5, 2.5-5.0, 5.0-10.0, 10.0-20.0 and >20.0 mm/day to explore accuracy of CMORPH on different classification of magnitude of daily rainfall. Classes indicate very light (< 2.5 mm/day), light (2.5-5.0), moderate (5.0-10.0 mm/day), heavy (10.0-20.0 mm/day) and very heavy rainfall (> 20 mm/day) respectively.

Furthermore, CMORPH rainfall time series were divided into wet and dry seasonal periods to assess the influence of seasonality on performance of bias correction schemes. The wet season in Southern Africa spans from October-March whereas the dry season spans from April-September.

3.5. Performance evaluation of bias corrected rainfall

A comparison of corrected and uncorrected CMORPH satellite rainfall estimates with rain gauge data was performed using statistics that measure systematic differences (i.e. percentage bias), measures of association (e.g. correlation coefficient) and random differences (e.g. standard deviation of differences and coefficient of variation) (Haile et al., 2013). Bias is a measure of how the satellite rainfall estimate deviate from the raingauge estimate, and the result is normalised by the summation of the gauge values. The correlation coefficient (ranging between +1 and −1) represents the linear interdependence of gauge and CMORPH data.

Equations [8-9] apply.

$$bias\ (\%) = \frac{\sum(S-G)}{\sum G} * 100 \qquad \textbf{[8]}$$

$$R = \frac{\sum(G-\bar{G})(S-\bar{S})}{\sqrt{\sum(G-\bar{G})^2}\sqrt{\sum(S-\bar{S})^2}} \qquad \textbf{[9]}$$

Where:

S = rainfall estimates by a satellite (mm/day)
$\bar{S}$ = mean values of the satellite rainfall estimates (mm/day)
G = rainfall recorded by a rain gauge (mm/day)
$\bar{G}$ = mean values of rainfall recorded by a rain gauge (mm/day)

3.6. Assessment through Taylor diagram

Visual comparison of performance of SREs was done using Taylor diagrams which provide a statistical summary of how well patterns match each other in terms of the Pearson's product-moment correlation coefficient (R), root mean square difference (E), and the ratio of variances on a 2-D plot (Lo Conti et al., 2014;Taylor, 2001). The reason that each point in the two-dimensional space of the Taylor diagram can represent the above three different statistics simultaneously is that the centered pattern of root mean square difference (E^{i}), and the ratio of variances are related by the following:

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$$E^{i} = \sqrt{\sigma_f^2 + \sigma_r^2 - 2\sigma_f\sigma_r R} \qquad \textbf{[10]}$$

Where:

σ_f and σ_r = standard deviation of CMORPH and rain gauge rainfall, respectively.

Applications of Taylor diagrams have roots in climate change studies (Smiatek et al., 2016;Taylor, 2001) but also has frequent applications in environmental model evaluation studies (Cuvelier et al., 2007;Dennis et al., 2010;Srivastava et al., 2015). Bhatti et al., (2016) propose the use of Taylor Diagrams for assessing effectiveness of SREs bias correction schemes. The merits of the five bias correction schemes used in this study can be inferred from the Taylor diagram. The most effective bias correction schemes will have data that lie near a point marked ‘reference’ on the x-axis, relatively high correlation coefficient and low root mean square difference. Bias corrections schemes matching gauged based standard deviation have patterns that have the right amplitude.

4. Results and Discussion

4.1. Performance of uncorrected CMORPH rainfall

The spatially interpolated values of bias (%) covering the Zambezi Basin are shown in Figure 2. Areas in the central and western part of the basin have bias relatively close to zero suggesting good performance of the uncorrected CMORPH product. However large negative bias values are shown in the south-eastern part of the basin such as Shire River Basin, and in the Upper Zambezi‘s high elevated areas such as Kabompo and northern Barotse Basin. Significant underestimation is found in the Lower Zambezi’s downstream areas where the Zambezi River enters the Indian Ocean. Generally, CMORPH overestimates rainfall locally in Kariba, Luanginga, and Luangwa basins. As such CMORPH estimates do not consistently provide results that match gauge observations. We note that the rain gauge network with poor density could have attributed to the findings on bias by poor rainfall representation of spatially interpolated rainfall. Since CMORPH estimates have large error ($10 < \text{bias}\ (\%) < -10$), we first need to remove the bias before the product may be applied in hydrological and water resources applications. Figure 2 also show contours for rain gauge mean annual precipitation (MAP) in the Zambezi Basin with higher values in the northern parts of the basin (Kabompo and Luangwa) compared to the of lower localised estimates of MAP such as in Shire River and Kariba subbasins.

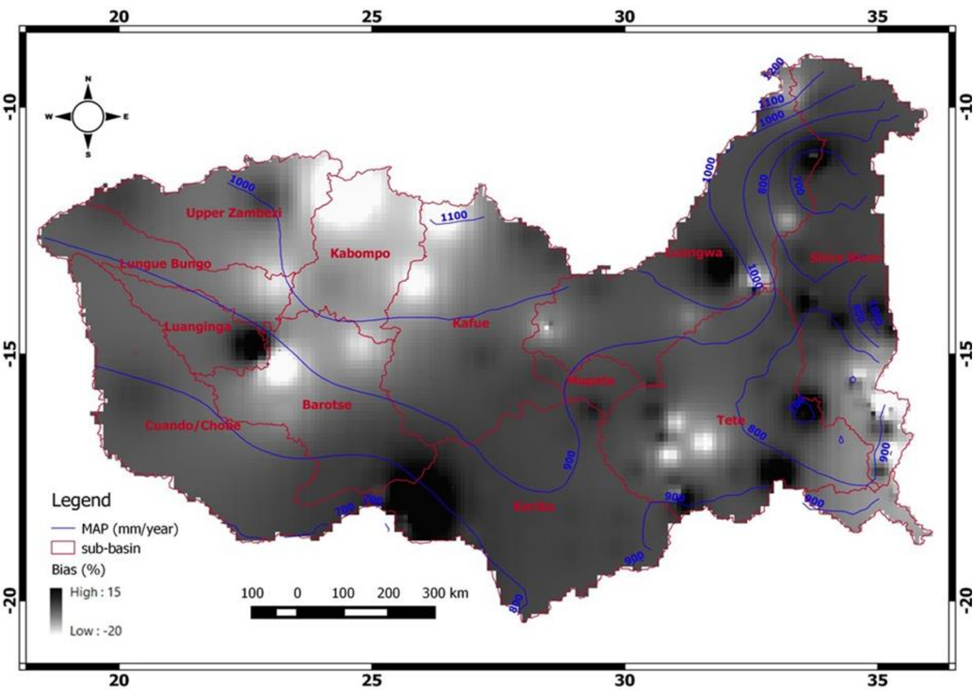

Figure 2: The spatial variation of bias (%) estimate for gauge vs CMORPH daily rainfall (1998-2013) for the Zambezi Basin. The CMORPH Mean Annual Precipitation (MAP) is also shown as blue contours.

4.2. Topographic influences for CMORPH and gauge rainfall

Figure 3 shows Taylor diagrams with a comparison of basin lumped estimates of daily uncorrected time series (1998–2013) of CMORPH and rain gauge observations for the 3 elevation zones (left panes) and 4 distance zones from large scale water bodies (right panes). The purpose of the diagrams is to show dependency of CMORPH and gauge rainfall on elevation or distance from large scale water bodies. Findings indicate that both elevation and distance from a large water body have no influence on the CMORPH error estimates because the standard deviations in the elevation zones and the distance zones from large scale water bodies (except for the < 10 km distance zone) are lower than the reference/rain gauge standard deviation which is indicated by the dashed brown arc (value of 8.45 mm/day). Figure 3 reveals that the standard deviations in the elevation zones and the distance zones (except for the < 10 km distance zone) are lower than the reference/rain gauge standard deviation which is indicated by the dashed brown arc (value of 8.45 mm/day). The stations in the high elevation zone (> 950 m) and long distance zone (> 100 km) reveal lower variability than stations at lower elevation and shorter distance zones. With respect to the reference line, CMORPH estimates lumped for respective elevation zones and distance to a large water body do not match standard deviation of raingauge based counterparts. Also, a low correlation coefficient (R) is shown with high root mean square difference (E) as compared to gauge based estimates (Figure 3). Overall, statistics (standard deviations, R and root mean square error) for uncorrected CMORPH show

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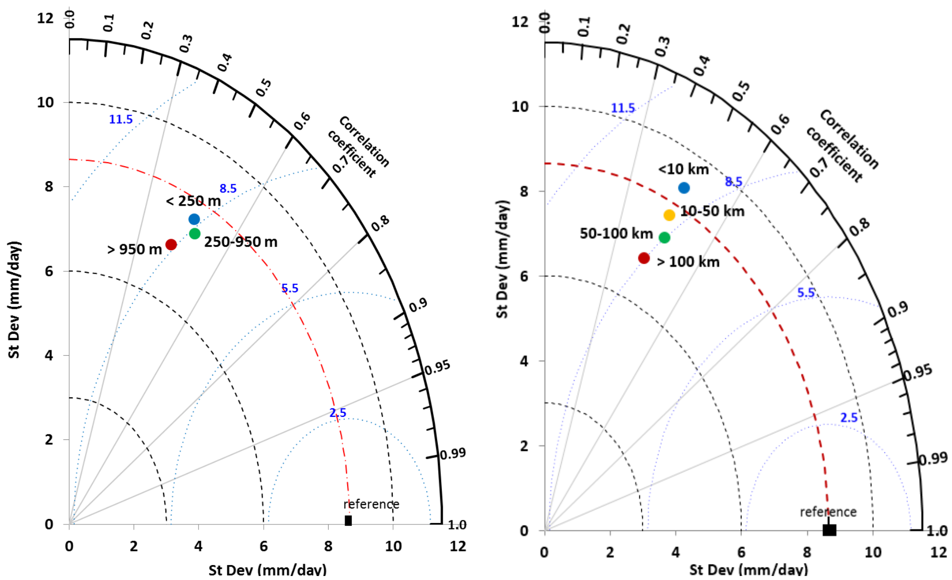
poor performance compared to the gauge based estimates but also do not vary for increasing or decreasing elevation and distance from large scale water bodies. This is despite that the intermediate elevation zone (250-950 m) and the intermediate distance zone (50-100 km) show a slightly better match to CMORPH estimates.



(a) Elevation zones (b) distance zones

Figure 3. Time series of rain gauge (reference) vs CMORPH estimations, period 1998-2013, for elevation zones (left panes) and distance zones (right panes) in the Zambezi Basin. The correlation coefficients for the radial line denote the relationship between CMORPH and gauge based observations. Standard deviations on both the x and y axes show the amount of variance between the two-time series. The standard deviation of the CMORPH pattern is proportional to the radial distance from the origin. The angle between symbol and abscissa measures the correlation between CMORPH and rain gauge observations. The root mean square difference (blue contours) between the CMORPH and rain gauge patterns is proportional to the distance to the point on the x-axis identified as "reference". For details, see Taylor (2001).

Results indicate that aspects of elevation and distance from large water bodies are not distinctively represented (no clear signature) in the relationship between CMORPH and gauge rainfall in the Zambezi Basin. For elevation, Vernimmen et al. (2012) had a similar conclusion in Indonesia (Jakarta, Bogor, Bandung, Java, Kalimantan and Sumatra regions) since a relationship for TRMM Multi-satellite Precipitation Analysis (TMPA) 3B42RT precipitation against elevation could not be identified (R^2 = 0.0001). The study by Gao and Liu (2013) showed that the bias in CMORPH rainfall over the Tibetan Plateau present weak dependence on elevation. Contrary to these findings, Romilly and Gebremichael (2011) showed that the accuracy of CMORPH at monthly time base is related to elevation for six river basins in Ethiopia. Whilst distance from large lake water bodies and elevation have been assessed separately for this study, Habib et al. (2012a) revealed that the two interact in the Nile Basin to produce unique circulation patterns to affect the performance of SRE.

4.3. Rainfall bias correction

4.3.1. Assessment of CMORPH bias correction effectiveness

The statistics for the gauge, uncorrected and bias corrected satellite rainfall for the Lower, Middle and Upper Zambezi subbasins are shown in Figure 4. Using the standard statistics (mean, maximum and ratio of gauge totals to CMORPH totals), the bias of CMORPH estimates has been moderately reduced by applying the five bias correction schemes. However the effectiveness of the schemes vary spatially with best performance in Lower and Upper Zambezi subbasin and relatively poor performance in the Middle Zambezi subbasin (see Figure 4).

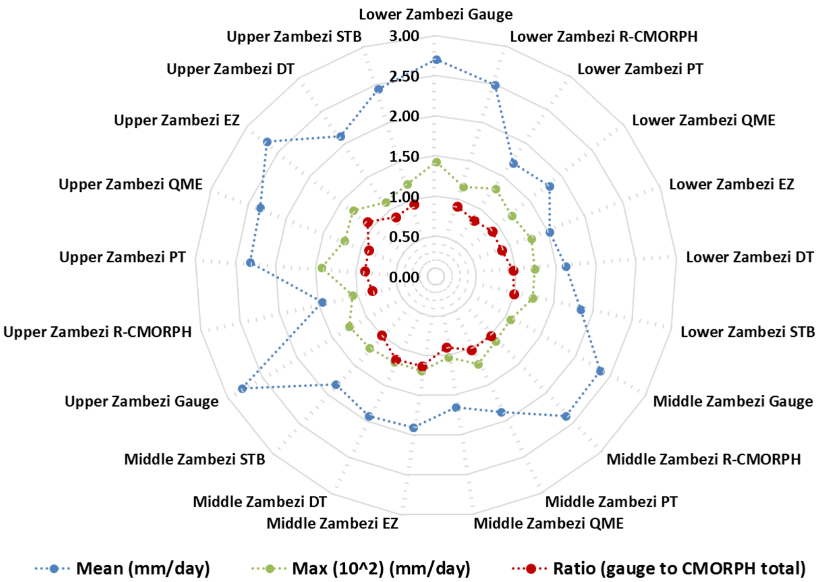


Figure 4: Frequency based statistics (mean, max, ratio of gauged sum vs CMORPH sum for 1998-2013) for the Zambezi Basin

Results indicate that STB bias correction scheme is consistently effective in removing CMORPH rainfall bias in the Zambezi Basin judging by all performance indicators. However, we observe that perfomance of the bias schemes depend on the objective they are originally designed for, such as, for instance, that STB and PT adjust for the mean of CMORPH rainfall estimates. Statistics in Figure 5 confirm these findings especially for the Upper Zambezi subbasin where the mean of corrected CMORPH estimates improved by > 60% from the mean of uncorrected estimates. In addition, PT in the Lower Zambezi, QME in both Middle and Upper Zambezi and STB in the Upper Zambezi were also effective (improvement by 16 %) in correcting for the highest values in the rainfall estimates. The STB performs better than other bias schemes in reproducing rainfall for the Lower and Upper Zambezi subbasin, where the ratio of gauge total to corrected CMORPH total is 1.0.

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Figure 5 shows the percentage bias in corrected and uncorrected CMORPH daily rainfall (1998-2013) averaged for the Lower, Middle and Upper Zambezi basins. The effectiveness of the bias correction by all schemes varies over the different parts of the basin but is higher in Lower and Upper than in Middle Zambezi.

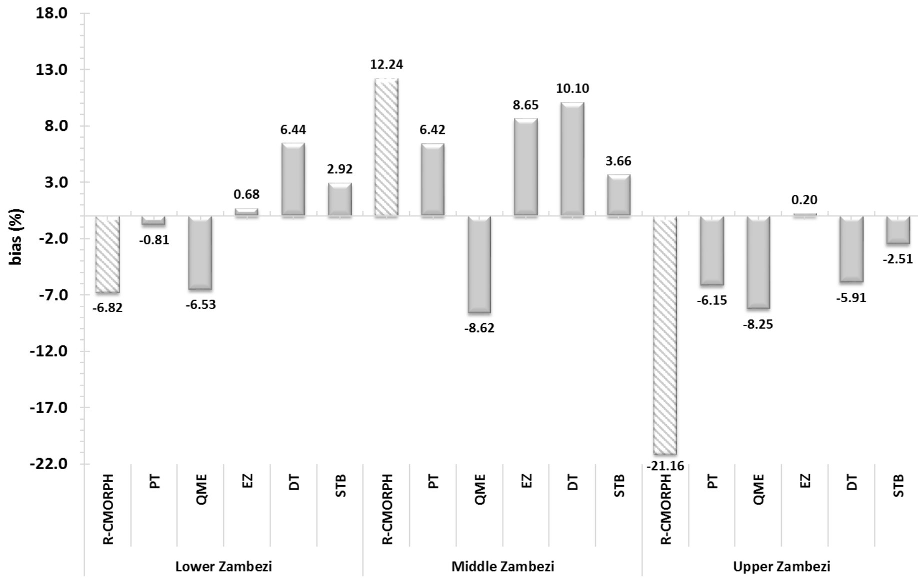

Figure 5: Percentage bias of corrected and uncorrected CMORPH daily rainfall averaged for the Lower Zambezi, Middle Zambezi and Upper Zambezi. Brown bars=uncorrected CMORPH and blue = bias corrected CMORPH.

With regard to reducing bias, best results are obtained by EZ in the Lower Zambezi (percentage bias of 0.7 % ~ absolute bias of 0.10 mm/day) and Upper Zambezi (0.22 % ~0.23 mm/day), PT in the Lower and Middle Zambezi (-0.84 % ~0.18 mm/day) and STB in all the basins (< 3.70 % ~0.24 mm/day). Gao and Liu (2013) asserts that EZ (a correction process based on elevation) is valuable in correcting systematic biases to provide a more accurate precipitation input for rainfall-runoff modelling. Significant underestimation for the uncorrected (-21.16 % ~0.44 mm/day) and for bias corrected CMORPH are shown for the Upper Zambezi subbasin. Note that bias correction effectiveness is similar in the Upper than Lower and Middle Zambezi subbasin.

Figure 6 shows the Taylor diagram for time series of rain gauge (reference) observations vs CMORPH bias correction schemes averaged for the Lower Zambezi (UZ), Middle Zambezi (MZ) and Upper Zambezi (UZ). The position of each bias correction scheme and uncorrected satellite rainfall (R-MORPH) on the plot quantifies how closely the rainfall by R-MORPH matches rain gauge observations as well as effectiveness of each of the bias schemes. Overall, all bias correction schemes show intermediate performance in terms of bias removal. Only the PT and STB for the Lower Zambezi subbasin lie on the line of standard deviation (brown dashed arc) and means the standard deviation of the data for the two bias correction schemes matches the gauge observations. This also indicates that rainfall variations after PT and STB bias correction for the Lower Zambezi resembles gauge based standard deviation. Note however that STB performs better than EZ because of superior correlation coefficient. Compared against the reference line of mean standard deviation (8.5 mm/day), the rainfall standard deviation for most bias correction schemes is below this line and as such exhibit low variability across the Zambezi Basin.

Figure 6 also shows that most of the bias correction schemes have standard deviation range of 6.0 to 8.0 mm/day. There is a consistent pattern between the bias correction schemes that have low R and high root mean square error difference indicating that these schemes are not effective in bias removal. Overall, the best performing bias correction schemes (STB and EZ) have R > 0.6, standard deviation relatively close to the reference point and a RMSE < 7 mm/day. The uncorrected CMORPH (R-MORPH) lies far away from the marked reference (gauge) point on the x-axis suggesting an intermediate overall effectiveness of the bias correction schemes such as STB, EZ, DT and PT in removing error as they are relatively closer to the marked reference point. A shorter distance of all bias correction schemes from the marked reference point would be preferable. However for much of the Zambezi Basin, the low spatial coverage of rain gauges imply low spatial dependency of the raingauges, before a comparison with SREs is done. For the above reason, studies (e.g. Tian et al., 2010;Lafon et al., 2013) noted that a too sparse gauge network such as the case in Upper and Middle Zambezi reduces the effectiveness of bias correction schemes. In the Gilgel Abbay Basin in Ethiopia, increases of R are reported from 0.35 to 0.58 for the STB between 2003-2010 and an improvement of daily root mean square error from 8 mm/day to 10.5 mm/day (Bhatti et al., 2016). The least performing bias correction scheme is QME, with a considered low R (< 0.49) and standard deviation (< 6.5 mm/day) that is lower than the reference, but with relatively large RSMD (> 8 mm/day). Inherent to the methodology of most of bias correction schemes (e.g. QME) is that the spatial pattern of the SRE does not change and therefore the R for a specific station for daily precipitation does not necessarily improve. The bias correction results by the Taylor Diagram in Figure 6 corroborates with findings shown in Figure 4 and Figure 5 for mean, max, ratio of rainfall totals and bias as performance indicators.

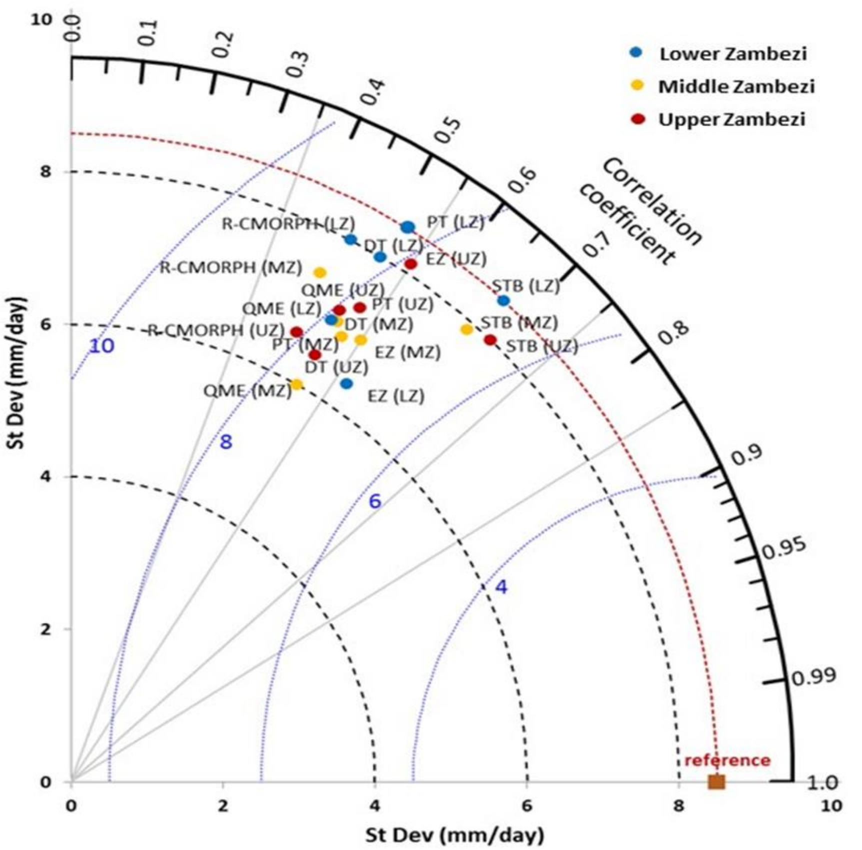

Figure 6: Taylor's diagram of statistical comparison between the time series of Rain gauge (reference) observations vs CMORPH bias correction schemes averaged for the Lower Zambezi (LZ), Middle Zambezi (MZ), and Upper Zambezi (UZ) for the period 1998-2013. The distance of the symbol from point (1, 0) is a relative measure of the bias correction scheme's error. The position of each symbol appearing on the plot quantifies how closely that bias correction scheme's precipitation pattern matches counterparts by rain gauge. The blue contours indicate the root mean square difference (mm/day).

4.3.2. Classification of CMORPH rainy days

The percentage magnitude of rainfall on rainy days in the Zambezi Basin for each bias correction scheme is shown in Figure 7. The largest magnitude of rainy days (80-90 %) is shown for very light rainfall (0.0-2.5 mm/day). A smaller percentage is shown for 2.5-5.0 mm/day which is the light rainfall class. Smallest percentage (< 5%) is shown for heavy rainfall (> 20.0 mm/day). The CMOPH rainfall corrected with STB, PT and DT matches the gauge based magnitude of rainy days in the Lower, Middle and Upper Zambezi suggesting good performance. All five bias correction schemes in the Zambezi Basin generally tend to overestimate low rainfall magnitudes (< 2.5 mm/day). There is a small difference for moderate rainy days classification of 10.0-20.0 mm/day. For QME in the Middle and Upper Zambezi, there is overestimation by >80 %. There is underestimation of rainfall for rainy days with greater than 20 mm/day. Results are consistent with findings by Gao and Liu (2013) in the Tibetan Plateau who also found consistent under and overestimation by CMORPH for rainy

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days >10.0 mm/day. The study by Zulkafli et al. (2014) in French Guiana and North Brazil noted that the low sampling frequency and consequently missed short-duration precipitation events between satellite measurements results in underestimation, particularly for heavy rainfall.

5.

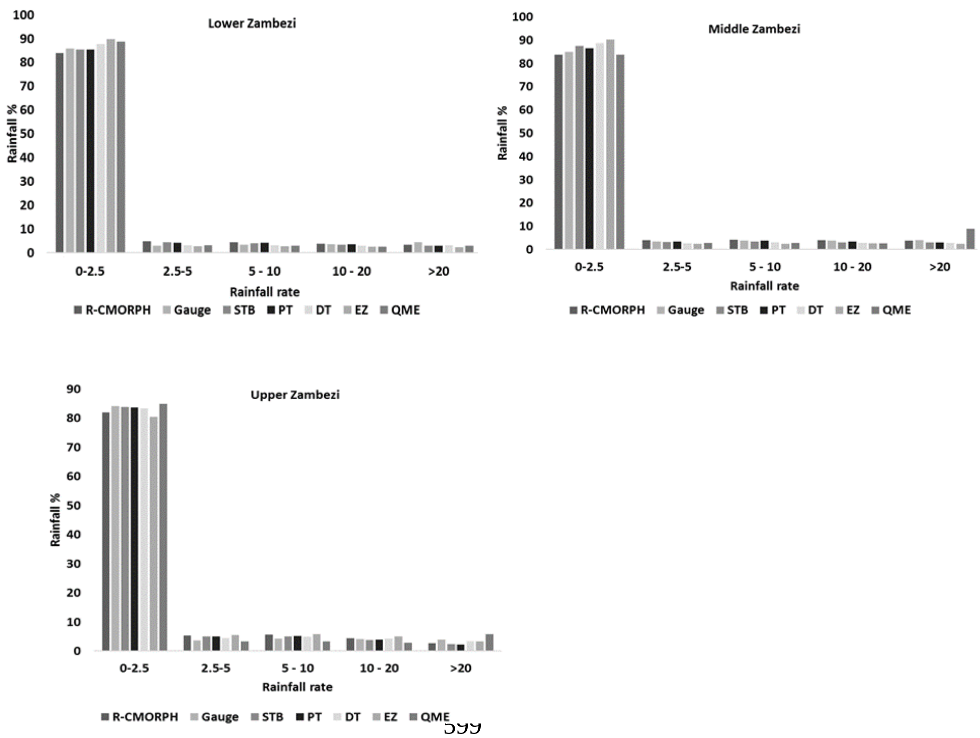

Figure 7: Percentage of days for rainfall rate classes

Figure 8 gives the bias correction performance for the different rainy days classes. Results of bias removal varies for the Lower, Middle and Upper Zambezi. Comparatively, the STB and EZ show effectiveness in bias removal with an average bias correction of 0.97 % and 3.6 % in the whole basin respectively. Results show more effectiveness in reducing the percentage bias for light rainfall and moderate rainfall (0-2.5 and 5.0-10.0 mmm/day) than the high to very high rainfall (10.0-20.0 mm/day and >20.0 mm/day) across the whole basin. The poor performance of correction for the heavy rainfall class is caused by, sometimes, large mismatch of high rain gauge values versus low CMORPH values. This leads to unrealistically high CMORPH values which remain poorly corrected by bias schemes.

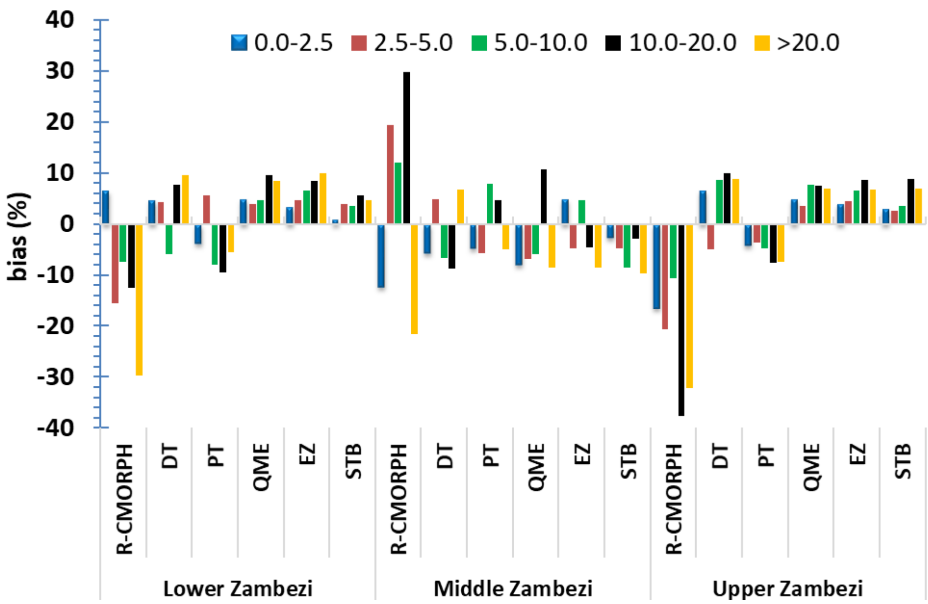

Figure 8: Bias correction (%) for respective rainfall rate classes

5.1.1. Seasonal influences on CMORPH bias correction

Table 1 shows bias correction scheme statistics for the dry and wet seasons. Seasonal rainfall here refers to the daily rainfall recorded in specic months belonging to the two defined seasons. Overall, STB, PT and EZ schemes are most effective in correcting errors in CMORPH estimates in the two seasons. The study by Ines and Hansen (2006) for semi-arid eastern Kenya showed that multiplicative bias correction schemes such as STB were effective in correcting the total of the daily rainfall grouped into seasons. Our results show that effectiveness in bias removal in the wet season is higher than in the dry season. Exception is rainfall totals for STB. This is contrary to Vernimmen et al. (2012) who showed that for the dry season, bias for PT decreased in Jakarta, Bogor, Bandung, East Java and Lampung regions after bias correction of monthly TMPA 3B42RT precipitation estimates over the period 2003–2008. Habib (2014) evaluated sensitivity of STB for the dry and wet season and concluded that the bias correction factor for CMOPRH shows lower sensitivity for the wet season as compared to the dry season. Our findings also reveal that bias factors for all the schemes are more variable in the dry season than in the wet season and lead to poor performance of the bias correction schemes in the dry season.

Table 1: Frequency based statistics for the gauge, uncorrected and bias corrected CMORPH estimates for the dry and wet seasons. R-Morph is the uncorrected R-CMOPRPH estimate. DT, PT, QME, EZ and STB are the bias corrected rainfall estimate. Bold values indicate best performance.

		Dry Season (April-Sept)			Wet Season (Oct-March)		
Basin	Rainfall Estimate	Bias (%)	Correlation	Estimated Ratio	Bias (%)	Correlation	Estimated Ratio
Lower Zambezi	R-CMORPH	-49.85	0.39	0.88	-24.1	0.46	0.88
	DT	5.75	0.53	0.82	-6.83	0.59	0.89
	PT	-9.61	0.53	0.87	**0.22**	0.58	1.02
	QME	8.29	0.52	0.79	-7.34	0.58	0.79
	EZ	8.67	0.54	1.03	-7.61	0.57	1.04
	STB	5.2	0.56	**1.02**	0.55	0.61	**0.99**
Middle Zambezi	R-CMORPH	-47.53	0.44	1.11	-18.23	0.39	1.03
	DT	-8.48	0.58	0.92	3.52	0.5	0.94
	PT	-1.63	0.55	1.03	-7.22	0.5	**1.01**
	QME	-4.33	0.55	0.91	6.07	0.51	0.95
	EZ	-4.48	0.56	1.09	7.4	0.59	1.13
	STB	-3.67	0.56	1.05	2.45	**0.62**	1.05
Upper Zambezi	R-CMORPH	-58.57	0.4	0.81	-32.13	0.37	0.83
	DT	8.03	0.54	0.75	-8.73	0.49	0.79
	PT	-6.93	0.52	0.82	-5.73	0.5	0.82
	QME	8.12	0.5	0.70	-7.18	0.49	0.7
	EZ	5.17	0.51	0.89	-6.96	**0.6**	**0.99**
	STB	**2.81**	**0.59**	0.87	-4.9	0.59	0.98

6. Conclusions

This study aimed to assess the performance of bias correction schemes for CMORPH rainfall estimates in the Zambezi River Basin. The four major conclusions of this study are:

1. The CMORPH rainfall estimates in the Zambezi Basin are not significantly affected by elevation. A similar finding was reported by Gao and Liu (2013) over the Tibetan Plateau and Vernimmen et al. (2012) who found a weak relationship between bias errors of SRE by influences of elevation. Our findings contradict findings in (e.g. Haile et al., 2009;Katiraie-Boroujerdy et al., 2013;Rientjes et al., 2013;Wu and Zhai, 2012) who found that bias of CMORPH rainfall estimates can be related to elevation ranges. Our study further shows that performance of CMORPH is not distinctly related to distance of a large water bodies in the Zambezi Basin. Such relation was evaluated for rain gauges located within specified distances of < 10 km, 10 -50 km, 50 -100 km and > 100 km. to a large water body. Overall findings on bias estimates show that bias of CMORPH estimates is too large to allow application of the uncorrected CMORPH product used in this study in hydrological and water resources applications in Zambezi Basin.

2. Removing bias (%) in CMORPH is by achieved by STB for Upper, Lower and Middle subbasins, and by EZ and PT for the Lower and Upper Zambezi. The STB bias correction scheme effectively adjusted the daily mean of CMORPH estimates by increasing the correlation coefficient by 53% and by reducing the root mean square difference by 25%. The EZ and DT were also effective in removing errors related to standard deviation and ratio of rainfall totals of gauge observations vs CMORPH estimates. Overall, the linear based correction scheme (STB) that considers space and time variation of SRE bias, is found more effective in reducing rainfall bias in the basin than the EZ which does not consider the spatial variability in rainfall. This indicates that the temporal aspect of SRE bias is more important than the spatial aspect of bias in the Zambezi Basin. In addition, the multiplicative bias correction schemes (STB and EZ) outperform schemes with power function correction (PT), quantile mapping (QME) and additive correction (DT). Findings in this study suggest that a single best bias correction scheme for the entire Zambezi basin cannot be selected.

3. We assessed whether bias correction varies for different magnitude of daily rainfall in the Zambezi Basin. There is overestimation of very light rainfall (< 2.5 mm/day) and underestimation of very heavy rainfall (>20 mm/day) by the bias correction schemes. Bias was more effectively reduced for very low to moderate rainfall (< 2.5 and 5.0-10.0 mmm/day) than for high to very high rainfall (10.0-20.0 mm/day and >20.0 mm/day). Overall, the STB and EZ more consistently removed bias in all the rainy days classification compared to the three other bias correction schemes.

4. Finally, CMORPH rainfall time series were divided into wet and dry seasonal periods to assess the influence of seasonality on performance of bias correction schemes. Overal, the bias correction schemes reveal that bias removal is more effective in the wet season than in the dry season.

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Author Contributions

Webster Gumindoga was responsible for the development of bias correction schemes in the Zambezi basin. Tom Rientjes was responsible for the research approach and conceptualization. Tom and Alemseged Haile were responsible for synthesising the methodology and made large contributions to the manuscript write-up. Hodson Makurira provided some of the rain gauge

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data and related findings of this study to previous work in the Zambezi Basin. Reggiani Paulo assisted in interpretation of bias correction results.

Conflict of Interests

The authors declare no conflict of interests.

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