Bias correction schemes for CMORPH satellite rainfall estimates in the Zambezi River Basin

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Abstract

Obtaining reliable records of rainfall from satellite rainfall estimates (SREs) is a challenge as SREs are an indirect rainfall estimate from visible, infrared (IR), and/or microwave (MW) based information of cloud properties. SREs also contain inherent biases which exaggerate or underestimate actual rainfall values hence the need to apply bias correction methods to improve accuracies. We evaluate the performance of five bias correction schemes for CMORPH satellite-based rainfall estimates. We use 54 raingauge stations in the Zambezi Basin for the period 1998–2013 for comparison and correction. Analysis shows that SREs better match to gauged estimates in the Upper Zambezi Basin than the Lower and Middle Zambezi basins but performance is not clearly related to elevation. Findings indicate that rainfall in the Upper Zambezi Basin is best estimated by an additive bias correction scheme (Distribution transformation). The linear based (Spatio-temporal) bias correction scheme successfully corrected the daily mean of CMORPH estimates for 70 % of the stations and also was most effective in reducing the rainfall bias. The nonlinear bias correction schemes (Power transform and the Quantile based empirical-statistical error correction method) proved most effective in reproducing the rainfall totals. Analyses through bias correction indicate that bias of CMORPH estimates has elevation and seasonality tendencies across the Zambezi river basin area of large scale.

Keywords: *Bias correction factor, Seasonality influences, Space-time variable, Elevation influences*

1. Introduction

A plethora of error (hereafter bias) correction schemes for satellite-derived rainfall estimates (SREs) have been published (e.g. Woody et al., 2014;Habib et al., 2014;Vernimmen et al., 2012;Gebregiorgis et al., 2012;Tesfagiorgis et al., 2011;Shrestha, 2011). Bias correction schemes are important because SREs are prone to systematic and random errors related to the fact that SREs are indirect rainfall estimates from visible, infrared (IR), and/or microwave (MW) based information of cloud properties (Pereira Filho et al., 2010). Bias is defined as the systematic error or difference between raingauge estimates and SREs, and can be positive or negative (Moazami et al., 2013;Qin et al., 2014). Bias can be expressed for rainfall depth, its occurrence and intensity. Bias often exhibit a topographical and latitudinal dependency as, for instance, shown for the National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center-MORPHing (CMORPH) bias in the Nile Basin (Bitew et al., 2011;Habib et al., 2012;Haile et al., 2013). For Southern Africa, Dinku et al (2008) and Thorne et al (2001) show that bias in rainfall occurrences and intensities can be related to location, topography, local climate and season. SRE’s tested are Tropical Applications of Meteorological Satellites (TAMSAT), Tropical Rainfall Measuring Mission (TRMM-3B42), Precipitation Estimation from Remotely Sensed Information using Artificial Neural Network (PERSIANN) and Climate Hazards Group InfraRed Precipitation with stations (CHIRPS). Studies in the Zambezi Basin, show evidence necessitating the correction of bias in SREs by comparing SREs against gauge observations. For example Cohen Liechti (2012) show that CMORPH rainfall have challenges in estimation of rainfall volumes at daily and monthly scales. Matos et al. (2013) and Thiemig et al. (2012) show that bias varies across geographical domains in the basin and may be as large as ±50 %. Negative bias indicates underestimation of rainfall whereas positive bias indicates overestimation (Moazami et al., 2013).

Bias correction schemes serve to correct for systematic errors of the SREs and aim to improve the reliability of SREs (Tesfagiorgis et al., 2011). Most bias correction schemes rely on assumptions that adjust for rainfall variability in space and time (Habib et al., 2014). As such, methodologies for bias correction were developed for multi-sensor (Breidenbach and Bradberry, 2001) and radar-gauge approaches (Vernimmen et al., 2012), and for climate models (Lafon et al., 2013) that provide rainfall estimates systematically in the time domain covering vast areas. Examples of correction schemes are mean bias (Seo et al., 1999), ratio bias (Anagnostou et al., 1999;Tesfagiorgis et al., 2011), distribution transformation (Bouwer, 2004), spatial bias (Bajracharya et al., 2014), histogram equalisation (Thiemig et al., 2013), regression analysis (Cheema and Bastiaanssen, 2010;Shrestha, 2011;Yin et al., 2008) and probability distribution function (QME) matching (Gudmundsson et al., 2012;Gutjahr and Heinemann, 2013).

Most bias correction schemes have background in climate models. Schemes aim to correct bias for satellite precipitation totals but do not address aspects of temporal variability of the precipitation (Botter et al., 2007). Bias correction techniques such as those based on regression techniques where rainfall totals are corrected relative to estimates from a reference rain gauge station, have reported distortion of frequency and intensity of rainfall (Botter et al., 2007). On one hand, some bias schemes are developed using multiplicative shifts procedures and tend to adjust only rainfall intensity to reproduce the long-term mean observed monthly rainfall, but these are reported not to correct any systematic error in rainfall frequency ~~rainfall~~ (Ines and Hansen, 2006). On the other hand, non-multiplicative bias correction procedures provide an option for using the daily corrected satellite rainfall in a manner that preserves any useful information about the timing of rainfall ~~frequency~~ within a season (Fang et al., 2015;Hempel et al., 2013). For many hydrologic applications correct representation of daily rainfall is important. Non-linear bias correction schemes are well known in literature for mitigating the underestimation of SREs in dry months without leading to an overestimation of rainfall during wet months (Vernimmen et al., 2012). Power function derived bias correction schemes correct for extreme values (depth, intensity, rate and occurrence) in CMORPH estimates (Vernimmen et al., 2012). Contrary, the Bayesian (likelihood) analysis techniques are found to over-adjust both light and strong rainfall intensities toward more intermediate intensities (Tian et al., 2010).

Besides that bias may change over time, some correction schemes (e.g. the γ -distribution correction method) do not account for spatial patterns in bias (Müller and Thompson, 2013). Studies by Habib et al. (2014) and Tefsagiorgis et al. (2011) evaluated different forms of the space bias correction schemes. They concluded that the space fixed (invariant) technique which is obtained by using gauge and or SREs bias values lumped over the entire domain is ineffective in reducing rainfall bias as compared to space variant technique. This approach of using the average bias for all stations (space fixed) to correct SREs has its roots in radar rainfall (Seo et al., 1999) and is unsuitable in large basins (> 10,000 km^2) where bias varies spatially and over time (see Habib et al., 2012).

Applications of bias correction schemes mostly are reported for northern America, Europe and Australia. For less developed areas such as in the Zambezi Basin (Southern Africa) that is selected for this study applications are very limited. This is despite the strategic importance of the basin in providing water to over 50 million people. An exception is the correction of the TRMM-3B42 product for agricultural purposes in the Upper Zambezi Basin (Beyer et al., 2014). Previous studies on use of SREs in the Zambezi river basin mainly focused on accuracy assessment of SREs with 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). Our selection of CMORPH satellite rainfall for this study is based on the fact that the product has successful applications in African basins such as in hydrological modelling (Habib et al., 2014) and flood predictions in West Africa (Thiemig et al., 2013).

The objective of this study is to assess suitability of bias correction of CMORPH satellite rainfall estimates in the Zambezi River Basin for the period 1998-2013 for which time series are available from 54 rain gauge stations. Specific objectives are 1) to perform quality control on gauge based estimates in the Zambezi Basin 2) to develop linear/non-linear and time-space variant/invariant bias correction schemes using gauge based estimates in the basin 3) to apply and compare bias correction schemes to CMORPH satellite rainfall and 4) To assess the influence of elevation and seasonality on CMORPH performance and bias correction in the basin.

This article is organised as follows: Section 2 gives a description of the study area and data availability. Methods used in this study are described in Section 3. Findings of the study are presented in Section 4. Section 5 concludes and discusses findings of the study.

2. Study area

The Zambezi River is the fourth-longest river (~2,574 km) in Africa ~~and~~ 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 partly constitutes boundaries of Angola, Namibia Botswana, Zambia, Zimbabwe and Mozambique (Fig. 1). Because of its vastness in size, the basin has ~~much~~ difference in elevation, topography and climatic seasonality. For that reason the basin ~~well suited~~ for this study and divided into three hydrological regions, i.e., the lower Zambezi comprising the Tete, Lake Malawi/Shire, and Zambezi Delta subbasins, the middle Zambezi made up of the Kariba, Mupata, Kafue, and Luangwa sub catchments, and the Upper Zambezi constituted by the Kabompo, Lungwebungo, Luanginga, Barotse, and Cuando/Chobe subbasins (Beilfuss, 2012).

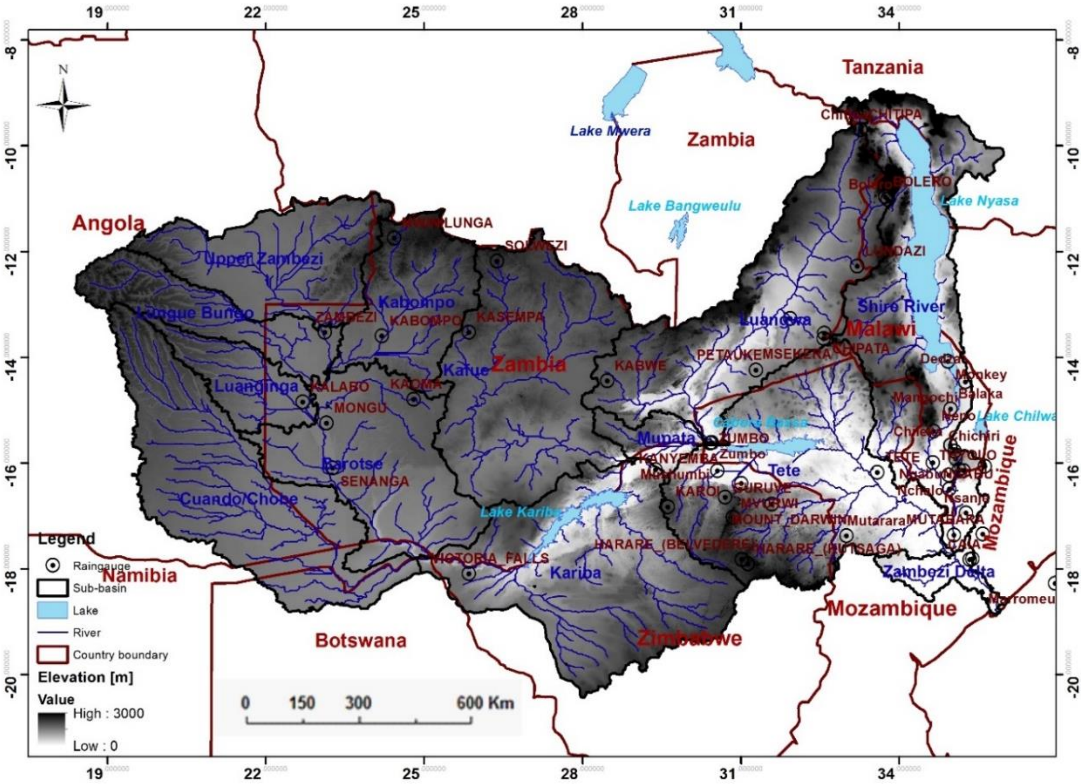

Figure 1: Zambezi River Basin with sub basins, major lakes, rivers, elevation and locations of the 54 rain gauging stations used in this study.

The elevation of the Zambezi basin ranges from 0.0 m (for some parts of Mozambique) to ~3000 m above sea level (for some parts of Zambia). 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) in the northern and north-eastern areas but low annual rainfall (<500 mm) in the southern and western parts (World Bank, 2010a). Due to the varied rainfall distribution, northern tributaries contribute much more water to the Zambezi River (e.g., the Upper Zambezi Basin contributes 60 % of total discharge) (Tumbare, 2000). The ~~River~~ and its tributaries are subject to cycles of 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.

3. Materials and Methodology

3.1. Data

3.1.1. Satellite derived rainfall

For this study time series (1998-2013) of CMORPH rainfall product at (8 km × 8 km, 30 minutes resolution are selected. Images were downloaded from the GeoNETCAST ISOD toolbox by means of ILWIS GIS software (http://52north.org/downloads/). CMORPH estimates are derived from a combination of infrared (IR) temperature fields from geostationary satellites and passive microwave (PMW) temperature fields from polar orbiting satellites at 30 minute temporal resolution (Joyce et al., 2004). For this study, data were aggregated to daily totals to match the observation interval from available gauge measurements.

3.1.2. Gauge based rainfall data

Time series of daily rainfall from 60 stations was obtained from meteorological departments Mozambique, Malawi, Zimbabwe and Zambia that cover the study area. After screening, 6 stations with suspicious rainfall values were removed from the analysis to remain with 54 stations. Although a number of the 54 stations are affected by data gaps, the available time series are of sufficiently long duration (Table 1) to serve objectives of this study. The locations of the stations cover a wide range of elevation values (3 m to 1600 m amsl.) allowing to assess the effect of elevation on the SREs.

Table 1: HERE

3.1.3. Gauge based analysis: elevation influences

To investigate elevation influence on CMOPRH performance, the hierarchical cluster ‘within-groups linkage’ method in SPSS software was used to classify the Zambezi Basin into 3 elevation zones (Table 2). This was based on elevation vs correlation coefficient of CMORPH and gauge based estimates. The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) based ~~30m~~ DEM obtained from http://gdem.ersdac.jspacesystems.or.jp/, was used to represent elevation across the Zambezi basin.

Table 2: HERE

Figure 2 shows Mean Annual Rainfall (MAR) isohyets by inverse distance interpolation of mean annual gauged measurements (1998-2013).

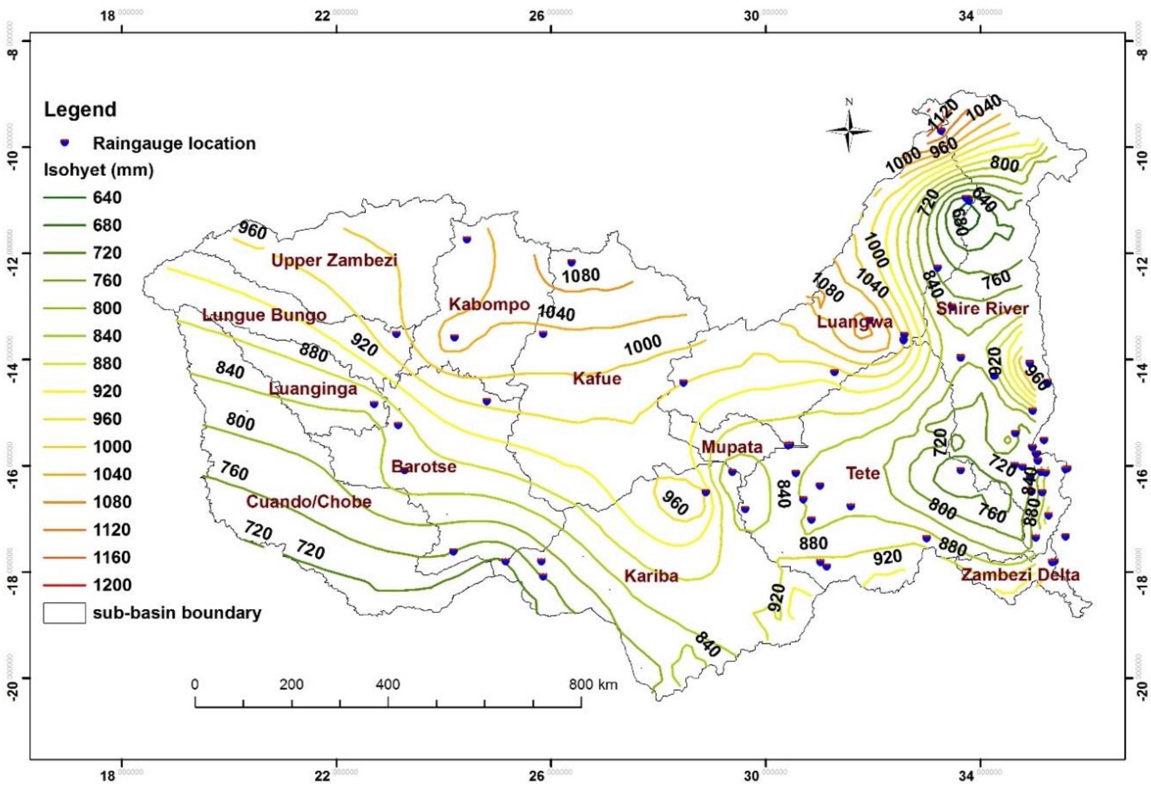

Figure 2: Mean Annual Rainfall (MAR) distribution for the Zambezi Basin (1998-2013).

The double mass-curve was used to check the consistency of rainfall of a single station with poor correlation coefficient (<0.4) against rainfall of nearby other stations (within 100 km radius) in the study area, following Searcy and Hardson (1960). Inconsistencies shown in the double mass-curve may be due to errors in the raingauge data collection. Any unreliable and inconsistent daily rainfall estimate for any year may be adjusted following:

$$P_a = \frac{b_a}{b_o} P_o \quad [1]$$

Where:

P_a	=	adjusted rainfall station X in any year
P_o	=	observed rainfall for station X in the same year
b_a	=	slope of graph to which records are adjusted
b_o	=	slope of graph at time P_o was observed

3.2. Bias correction schemes

In this study, the bias in CMORPH rainfall estimates was assessed and corrected using 5 schemes. Based on preliminary analysis ~~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 ten-day window with a minimum rainfall accumulation depth of 5 mm, otherwise no bias is estimated (i.e. a value of 1 is assigned). This means bias factors change value for each station for each 10 day period.

3.2.1. 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 (Lenderink et al., 2007;Teutschbein and Seibert, 2013). The bias is corrected for individual ~~raingauge~~ stations at daily time step implying that bias correction varies in space and over time, and is based on the use of the BF_{STB} factor estimated from equation [2]:

$$BF_{STB} = \frac{\sum_{t=d}^{t=d-l} S(i,t)}{\sum_{t=d}^{t=d-l} G(i,t)} \qquad \textbf{[2]}$$

The CMOPRH daily rainfall estimates are then multiplied by the BF_{STB} for the respective time windows resulting in corrected CMORPH estimates in a temporally and spatially coherent manner. 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.

Where:

G and *S*	=	daily gauge and CMORPH rainfall estimates, respectively
i	=	gauge location
t	=	julian day number
l	=	length of a time window for bias calculation
n	=	the total number of gauges within the entire domain of the study
T	=	full duration of the study period.

3.2.2. Elevation zone bias correction (EZB).

This bias scheme is proposed in this study and aims at correction of satellite rainfall by understanding elevation influences on the rainfall distribution. The method groups raingauge stations into 3 elevation zones (Table 2). The assumption is that stations in the same elevation zone have the same error characteristics and are assigned a spatial but temporally variant bias correction factor. The resulting bias correction factor is used to adjust satellite estimates by multiplying each daily station data by the daily bias factor, BF_{EZB}.

$$BF_{EZB} = \frac{\sum_{t=d}^{t=d-l} \sum_{i=1}^{i=n} S(i,t)}{\sum_{t=d}^{t=d-l} \sum_{i=1}^{i=n} G(i,t)} \qquad \textbf{[3]}$$

The merits of this bias correction scheme is that the daily time variability is preserved up to a constant multiplicative factor and at the same time accounting for spatial heterogeneity in topography (but fixed for each zone).

3.2.3. Power transform (PT)

This nonlinear bias correction scheme is aimed at achieving a closer fit between monthly CMORPH and raingauge data. The bias scheme has its origins in general circulation models (Lafon et al., 2013) but has been extended to satellite rainfall estimates for hydrological modelling and drought monitoring (Vernimmen et al., 2012). The bias corrected CMORPH rainfall (P^*) is obtained using:

$$P^* = aP^b \quad \textbf{[4]}$$

Where

P = raingauge monthly rainfall

a = prefactor such that the mean of the transformed precipitation values is equal to the gauge based mean.

b = factor calculated iteratively such that for each station the Coefficient of Variation (CV) of CMORPH matches the gauge based estimates

Optimized values of a and b are obtained through the generalized reduced gradient algorithm (Fylstra et al., 1998). The bias correction is estimated for monthly periods but is applied at daily time step. The advantage of this bias scheme is that rainfall variability of the daily time series is preserved by adjusting both the monthly mean and standard deviation of the CMORPH estimates. The bias scheme also adjusts extreme precipitation values in CMORPH estimates (Vernimmen et al., 2012).

3.2.4. 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 raingauge station estimates as well as CMORPH values at the respective stations. The CMORPH statistical distribution function is matched from the raingauge data distribution following steps described in equations [5-9]. Both the difference in mean value and the difference in variation are corrected. First the bias correction factor for the mean ($\mathrm{D}T_\mu$) is determined using equation [5]:

$$\mathrm{D}T_\mu = \frac{G_\mu}{S_\mu} \quad \textbf{[5]}$$

G_μ and S_μ are mean monthly gauge and CMORPH rainfall estimates for all stations, respectively.

Secondly, the correction factor for the variation ($\mathrm{D}T_\tau$) is determined by the quotient of the standard deviations, G_t and S_t, for gauge and CMORPH respectively.

$$\mathrm{D}T_\tau = \frac{G_\tau}{S_\tau} \quad \textbf{[6]}$$

Once the correction factors are established, they are applied to correct all raingauge stations data from CMORPH image following:

$$S_{\mathrm{DT}} = (S_{\mathrm{o}} - S_{\mathrm{u}})\, \mathrm{D}T_{\tau} + \mathrm{D}T_{\mu} * S_{\tau}) \quad \textbf{[7]}$$

Where:

$S_{\mathrm{DT}} =$ corrected CMORPH

$S_{\mathrm{o}} =$ uncorrected CMORPH

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).

3.2.5. 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 based on point-wise daily constructed empirical cumulative distribution functions (ecdfs). The frequency of precipitation occurrence is corrected at the same time (Themeßl et al., 2010).

The adjustment of precipitation using quantile mapping can be expressed in terms of the empirical CDF (ecdf) and its inverse ($ecdf^{-1}$):

$$P_{QME} = ecdf_{obs}^{-1}(ecdf_{raw}(P_{raw})) \quad \textbf{[8]}$$

Where:

$P_{QME} =$ bias corrected CMORPH

$P_{raw} =$ 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 landuse or climate change. Furthermore, it preserves the extreme precipitation values (Themeßl et al., 2012).

3.3. Performance evaluation of CMORPH rainfall types

A comparison of corrected and uncorrected CMORPH satellite rainfall estimates with rain gauge data was performed using statistics that measure systematic differences (i.e. bias and relative bias), accumulated error (e.g. root mean square error), measures of association (e.g. correlation coefficient) and random differences (e.g. standard deviation of differences and coefficient of variation) (Haile et al., 2013). Comparison is also made for the dry and wet seasons and for different rainfall intensities (light rains-heavy rains). The root mean square error (RMSE), was used to measure the average error following Jiang et al. (2012). Thus RMSE is used to test the accuracy of CMOPRH rainfall estimates against rain gauge based estimates. The correlation coefficient (CC) was used to assess the agreement between satellite-based rainfall and rain gauge observations. Equations [9-12] apply.

$$Bias \quad = \frac{\sum(P_{satellite} - P_{rain\ gauge})}{N} \qquad [9]$$

$$Rbias \; = \frac{\sum(P_{satellite} - P_{rain\ gauge})}{\sum P_{rain\ gauge}} \qquad [10]$$

$$RMSE \; = \sqrt{\frac{(P_{satellite} - P_{rain\ gauge})^2}{N}} \qquad [11]$$

$$CC \quad = \frac{\sum(P_{raingauge} - \bar{P}_{raingauge})(P_{satellite} - \bar{P}_{satellite})}{\sqrt{\sum(P_{raingauge} - \bar{P}_{raingauge})^2}\sqrt{\sum(P_{satellite} - \bar{P}_{satellite})^2}} \qquad [12]$$

where:

$P_{satellite}$ = rainfall estimates by satellite (mm/day)
$\bar{P}_{satellite}$ = mean values of the satellite rainfall estimates (mm/day)
$P_{rain\ gauge}$ = rainfall recorded by rain gauge (mm/day)
$\bar{P}_{raingauge}$ = mean values of the rain gauge observations (mm/day)
N = sample size (days).

Bias, Rbias and RMSE range from 0.00 (CMORPH measurements = gauge based measurements) to infinity (CMORPH measurements ≠ gauge based measurements) (Mashingia et al., 2014). Correlation Coefficient (CC) ranges from -1 to 1 with a perfect score of 1.

Visual comparison was also done using Taylor diagrams which provides a concise statistical summary of how well patterns match each other in terms of their CC, their root-mean-square difference (*RMSE*^{i}), and the ratio of their variances on a 2-D plot (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 root-mean-square difference, and the ratio of their variances are related by the following:

$$RMSE^{i2} = \delta_f^2 + \delta_r^2 - 2\delta_f\delta_r CC \qquad [13]$$

Where:

$\delta_f^2 + \delta_r^2$ = standard deviation between CMORPH and raingauge rainfall, respectively

4. Results and Discussion

4.1. Basic statistics for the CMORPH and gauge estimates

The mean rainfall, highest rainfall and sum of the gauged and CMORPH rainfall estimates for the period 1998-2013 vary widely (Table 3). Statistical scores (based on the mean, maximum and sum) indicate underestimation of the CMORPH rainfall for both the lowland and the highland stations, with more underestimation experienced in the highland stations. In as much CMORPH matches the standard deviation of gauge based estimates (+/- 2 mm/day) for 30 out of 54 stations, a summary for the lowland and highland stations shows lower standard deviation for CMORPH than the gauge based estimates. There are also instances where CMORPH shows agreement with the gauge estimates (e.g. CV of 3.12 for both CMORPH and gauge in the highland stations). The minimum recorded rainfall for both the CMORPH and gauge estimates is 0.0.

Table 3: HERE

Figure 3 also shows a comparison of the mean annual rainfall (MAR) for the gauge based estimates (through Universal Krigging interpolation technique) and CMORPH observations in the Zambezi Basin. The raingauge map shows higher estimated values in the northern parts of the basin compared to the CMORPH estimates. There are also patches of higher MAR values found in the Shire and Kariba Basin for the CMORPH estimates.

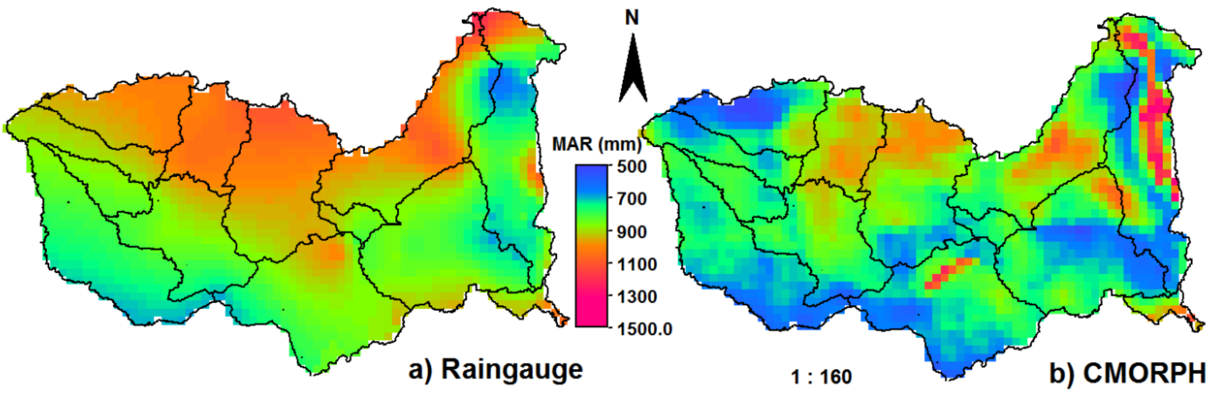

Figure 3: Mean annual rainfall (1998-2013) for the Rain gauge and CMORPH observations in the Zambezi Basin

4.2. Quality assessment using double-mass curves

Figure 4 reports four (4) selected double mass curves, with Figure 4d being the best in terms of the rainfall matching, followed by Figure 4b and Figure 4c. The worst in terms of match is Figure 4a. Pairs of stations with less pronounced differences in slope gradients are Neno vs Monkey, Bolero vs Chitipa and Mvurwi vs Karoi. However, there are stations that show clear break points and pronounced differences in slope gradients (staircase-like features) in double-mass curves. These are observed in the Nchalo vs Nsanje, Mvurwi vs Muzarabani and these could be caused by changes due to errors in the rain gauge data collection at Nchalo or Mvurwi stations. Results also confirm that stations with relatively greater distance from each other (e.g. Bolero to Lundazi ~ 180km) shows poor match and hence more pronounced differences in slope gradients than stations that have close proximity (e.g. Mvurwi to Guruve ~ 45 km). In addition stations that show close match exhibit similar elevation (e.g. Neno and Makoka have elevation difference ~ 96 m asl.) compared to stations that show poor match (e.g Mvurwi and Muzarabani ~1064 m asl.). In cases where break point are not clearly shown, we used nearby stations to adjust for the inconsistencies in these suspicious stations for years prior to the break. This analysis highlights the critical need for quality gauge based stations that can provide reliable validation datasets as a prerequisite for the assessment of satellite based rainfall estimates and bias correction.

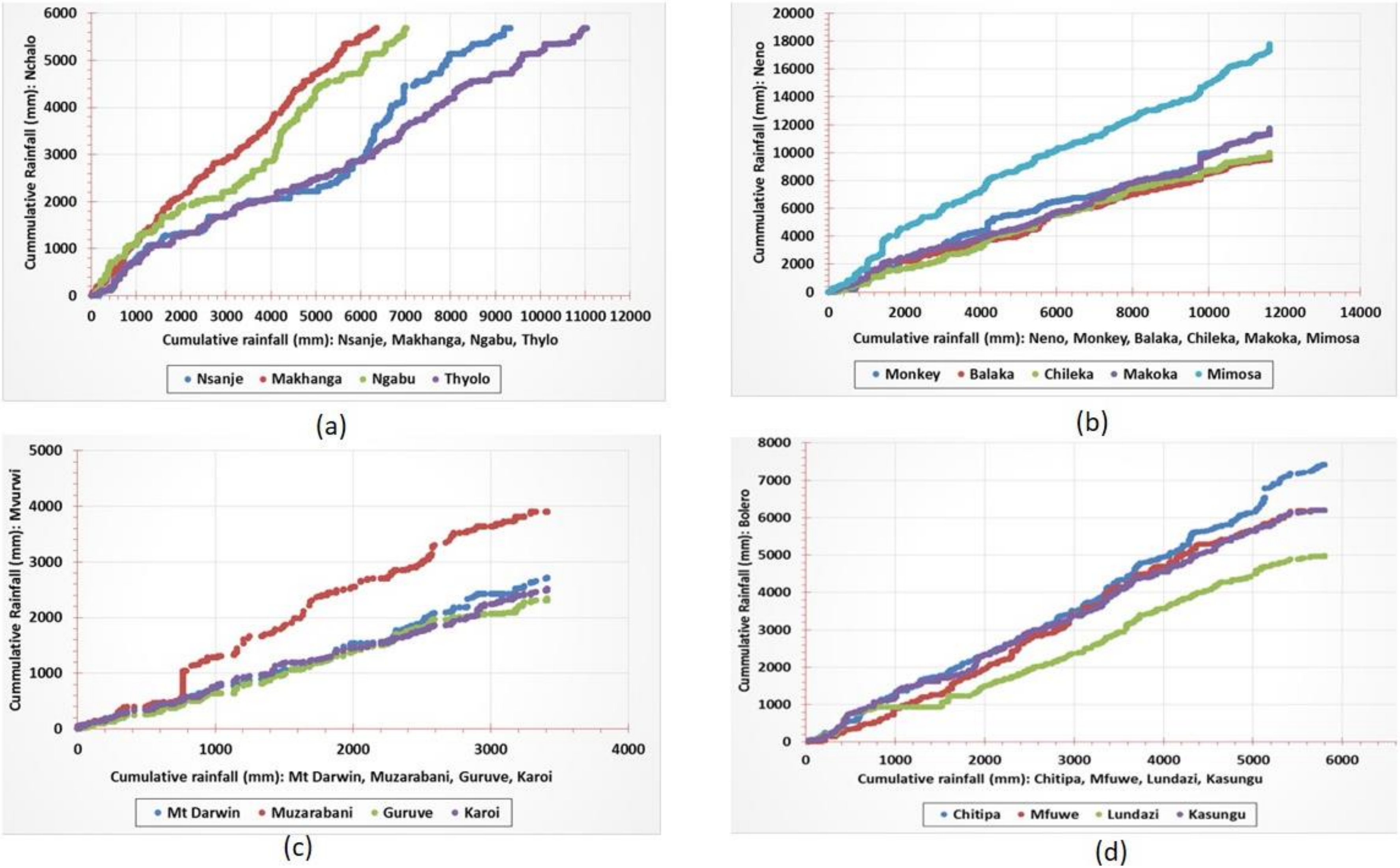

Figure 4: Double Mass Curves for accumulated amount of rainfall in selected suspicious raingauges. Top left panes: Nchalo vs Nsanje, Makhanga, Ngabu and Thyolo. Top right: Neno vs Monkey, Balaka, Chileka, Makoka and Mimosa. Bottom left: Mvurwi vs Mt Darwin, Muzarabani, Guruve and Karoi. Bottom right: Bolero vs Chitipa, Mfuwe, Lundazi and Kasungu

4.3.. Elevation influences: CMORPH and gauge rainfall

A Taylor Diagram with a comparison of the daily averaged time series (1998–2013) CMORPH and rain gauge observations for the 3 elevation zones is shown in Figure 5. The diagram was prepared with the adjusted rainfall stations (Petauke, Harare Kutsaga, Bolero, Mvurwi, Kanyemba, Neno and Nchalo) to show if the relation between CMORPH and gauge rainfall is elevation dependent. Nearly 90 % (47 out of 54) of the stations fall below the reference mean standard deviation (8.45 mm/day). It can be noted that 16 % (5 out of 31) of the stations in the highland area (>1600 m) have a standard deviation below 6 mm/day indicating low variability in their data. In addition 25 % (2 out of 8) of the stations in the lower elevation zone (<250 m) are above the reference 8.4 mm/day standard deviation and, as such, indicate high variability in the data. Kanyemba, Muzarabani and Mimosa stations in the intermediate elevation zone (250-950 m) lie on the dashed arc (line of standard deviation) and implies matching standard deviation with gauged based estimates. However, no station is close to the indicated reference point implying that the whole basin has low correlation and low RMSE.

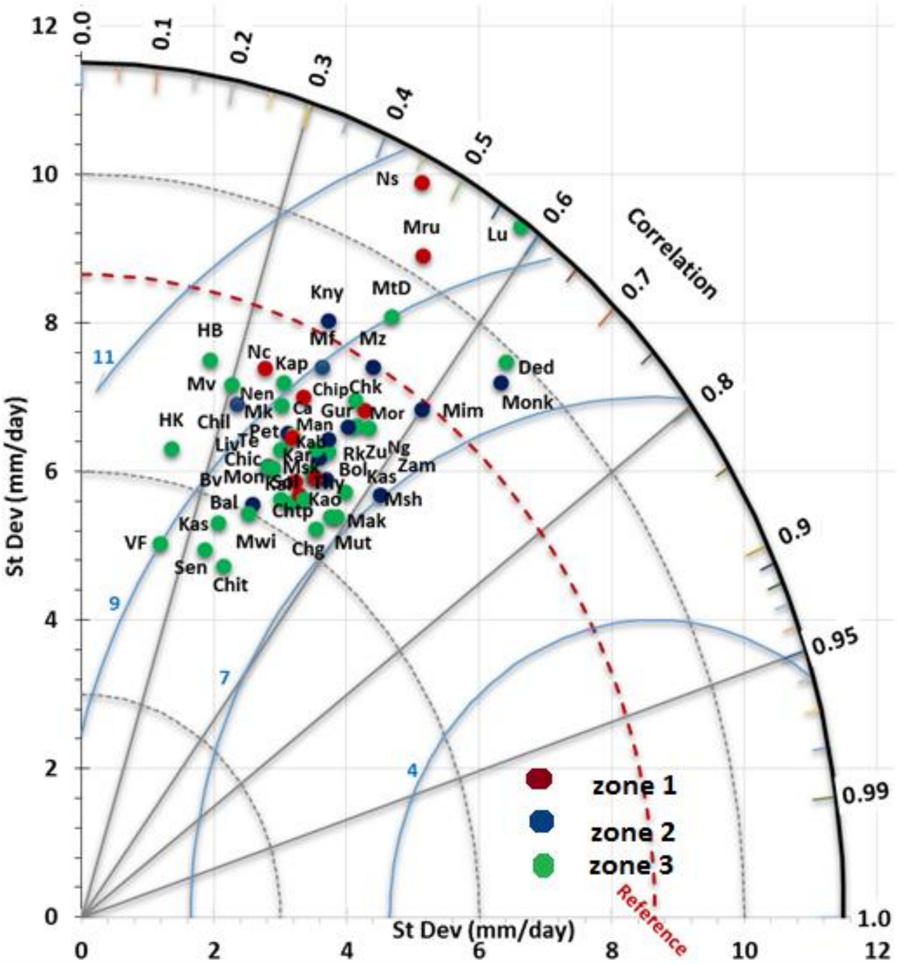

Figure 5. Normalised statistical comparison between time series of Raingauge (reference) vs CMORPH estimations, period 1998-2013, for the 54 raingauge stations. Refer to Table 1 for full names of the stations. The correlation coefficients for the radial line denote the relationship between CMORPH and gauge based observations. Standard deviations on the x and y axes show the amount of variance between the two time series. The distance of the symbol to the origin depicts the ratio of CMORPH standard deviation to Raingauge standard deviation. The angle between symbol and abscissa measures the correlation between CMORPH and Raingauge observations. The distance of the symbol from point (1, 0) is a relative measure of the CMORPH error (for details, see Taylor (2001).

All the stations have a RMSE above 7 mm/day with higher values (> 10 mm/day) found at Nsanje and Harare (Belvedere). Results are also consistent with findings in West Africa's Benin and Niger where the daily mean RMSE between CMORPH and gauge based measurements for a period ranging from 2003-2009, was found to be 9 mm/day and 13.8 mm/day, respectively (Gosset et al., 2013). Overall the CMORPH performance in terms of correlation coefficient, RMSE and standard deviation over the 3 elevation zones does not follow a specific pattern even though the high lying stations show a slightly better match to CMORPH estimates. We can conclude that aspects of elevation in the Zambezi Basin are not well shown in the relationship between CMORPH and gauge rainfall. This finding is also described in Vernimmen et al. (2012) in Indonesia who found no relationship between performance of TMPA 3B42RT precipitation against and elevation (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 topography. Contrary to these findings, Romilly and Gebremichael (2011) showed that the accuracy at a monthly scale of high resolution SREs: CMORPH, PERSIANN and TRMM TMPA 3B42RT is related to elevation for six river basins in Ethiopia. This difference could be due to the fact that the range of elevation in Ethiopia is from minus 196 m to 4 500 m asl. (Romilly and Gebremichael, 2011). In contrast, the Zambezi basin stations used in this study have elevation ranges from 3m to 1 575 m asl.

4.4. Performance of CMORPH rainfall vs Gauge estimates

The spatial distribution of values of bias, Rbias, RMSE and CC are presented at (sub) basin level (Figure 6-8) but also for individual stations (Table 4). Figure 6 shows the bias estimate of gauge and CMORPH daily rainfall for the Zambezi Basin. Large bias values are identified at Lower Zambezi stations such as Mimosa (1.57 mm/day), Thyolo (1.47 mm/day), Bvumbwe (1.24 mm/day) and Chichiri (0.95 mm/day). Negative bias at Middle Zambezi stations such as Mfuwe (-1.7 mm/day) and Chitedze (-0.9 mm/day) indicates rainfall underestimation. Generally CMORPH overestimates rainfall estimates at 9 stations (33 %) of the Lower Zambezi. Most of these Lower Zambezi stations are in south eastern part of the basin in Mozambique where the Zambezi Basin enters the Indian Ocean. CMORPH overestimates daily rainfall estimates at 7 out of 10 stations in the Upper Zambezi stations of which most are at high elevated areas. Most of these highland stations are in Zambezi's Kabompo Basin, the headwater catchment of the Zambezi to the West. Overall, data for stations in the Middle Zambezi Basin underestimates rainfall based on basin average bias (-0.12 mm/day).

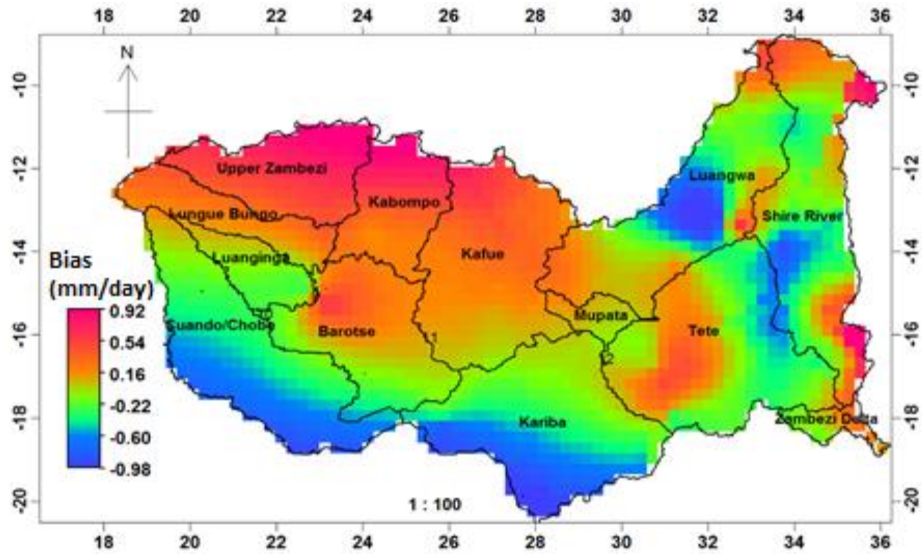

Figure 6: Bias estimate of gauge and CMORPH daily rainfall for the Zambezi Basin

Figure 7 shows that a number of stations such as Nchalo in the Lower Zambezi and Karoi in the Middle Zambezi have Rbias relatively close to zero, -2.24 mm/day and, 1.17 mm/day, respectively (see also Table 4). CMORPH accurately estimates rainfall at these stations. Stations such as Tyolo, Mimosa and Victoria Falls have very high Rbias (>40 mm/day) and indicates that the daily rainfall of this product does not correspond well with the observed rainfall. It is worth noting that there is overestimation at 70 % of the stations (19 out of27 stations) of the Lower Zambezi areas. There is overestimation at 35 % of the stations (6 out of 17 stations) in the Middle Zambezi stations. All the 10 stations in the Upper Zambezi are overestimating rainfall (>7mm/day). Note that the basin mean for the Middle Zambezi stations is as low as -0.59 compared to 14.32 for the Upper Zambezi and 11.24 for the Lower Zambezi.

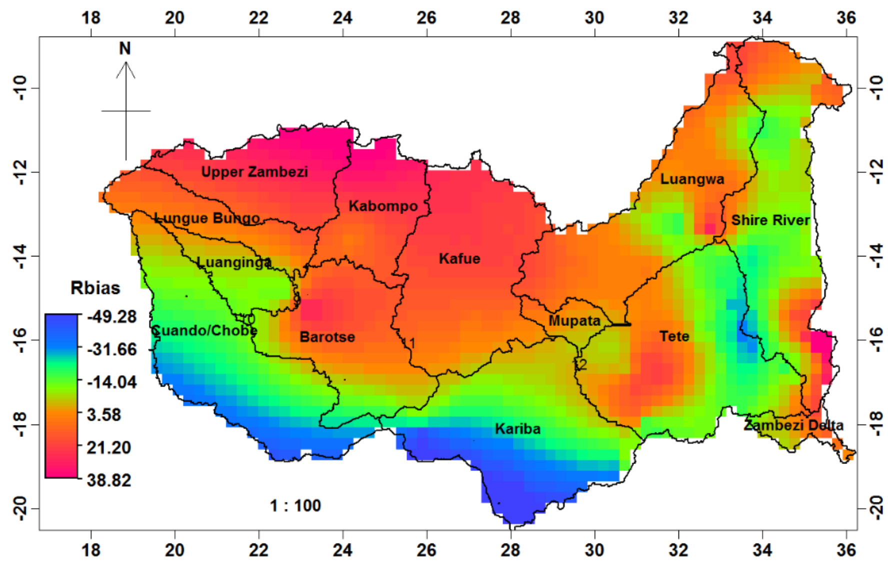

Figure 7: Rbias estimate of gauge and CMORPH daily rainfall for the Zambezi Basin

The lowest RMSE (Figure 8) is found in highland stations of the Upper Zambezi such as Senanga (4.99 mm/day) and this suggest that CMORPH rainfall matches the gauge based estimates. This is comparable to the lowest RMSE found in the Lower Zambezi's lowland stations such as Mfuwe (6.41 mm/day). Studies such by Moazami et al. (2013) in Iran demonstrated more accurate estimations of satellite rainfall in highland and mountainous areas than in lowland areas. Contrary to our findings, some studies report that satellite rainfall estimations have much smaller error in lowland areas than in mountainous regions (Gebregiorgis and Hossain, 2013;Stampoulis and Anagnostou, 2012).

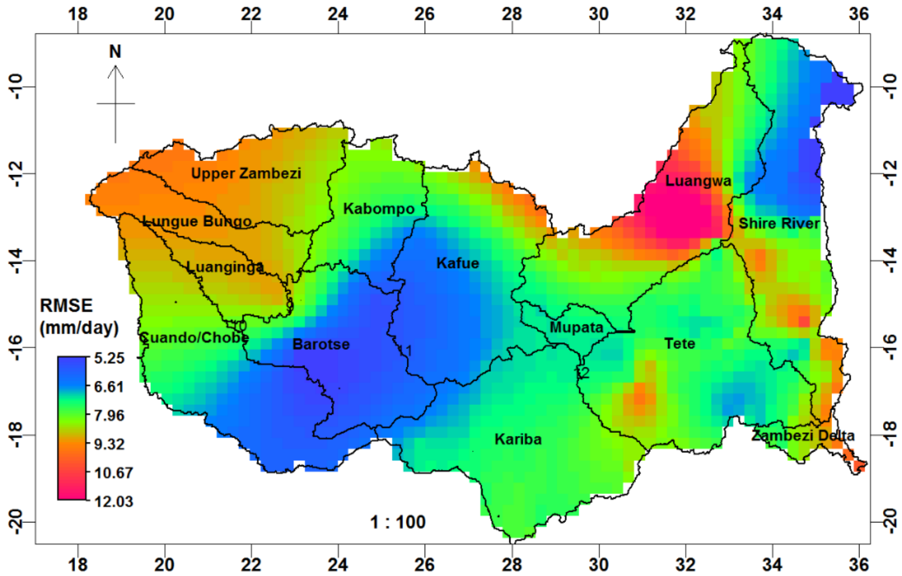

Figure 8: RMSE estimate of gauge and CMORPH daily rainfall for the Zambezi Basin

The generally poor performance by CMORPH shown by some of the performance indicators suggest that satellite estimates do not provide results similar to the gauge measurements. This could be a result of both the temporal and the spatial samples being different. In addition, the low spatial coverage (e.g. for Angola to the NW of Zambezi Basin) could have contributed to poor representation of the above skills over large areas.

4.5. Rainfall bias correction

The statistics for the gauge, uncorrected and bias corrected satellite rainfall types for each of the Zambezi basins are shown in Table 4. The Spatio-temporal bias (STB) and Distribution transformation (DT) bias correction schemes are effective in correcting for the mean values of the CMORPH estimations. The Power tranform (PT) in the Lower Zambezi, STB in the Middle Zambezi and DT in the Upper Zambezi have standard deviations closer to the gauge observations than all other bias correction schemes. The PT also has the closest maximum rainfall estimates to the gauge observations in the Lower and Middle Zambezi Basins as compared to greater overestimation by other bias correction schemes (e.g. STB: 216 mm/day vs Gauge: 107 mm/day). Our results are consistent with findings by Ahmed et al (2015) who showed that PT is the most reliable and suitable method for removing bias in GCM model derived monthly rainfall in an arid Baluchistan mountainous province of Pakistan. In the Lower and Upper Zambezi basins, the DT total volume of rainfall is closer to the gauge observations and suggests effectiveness of the bias correction scheme. In the Middle Zambezi Basin, the uncorrected CMORPH (R-CMORPH) actually peforms better than the bias correction schemes in reproducing the total rainfall volume. Underestimation of runoff volume is experienced for most bias correction schemes as shown by ratios of less than 1.0. Using the standard statistics, it can be observed that the DT bias correction scheme was effective in removing bias in the CMORPH rainfall particularly in the Upper Zambezi basin. However we observe that the bias schemes perfomance depends on the original aim they are designed for. For example the STB and PT are meant to adjust the mean and standard deviations of CMORPH rainfall estimates respectively. Statistics in Table 4 for the 3 Zambezi basins confirm these findings.

Table 4: HERE

Figure 9 shows generally high bias values of the six bias correction schemes for the Upper Zambezi Basin. The highest bias range (-0.38 to 0.46 mm/day) is found in the Middle Zambezi Basin. The negative bias prevalent for the DT bias correction scheme in all the three Zambezi basins suggests underestimation of rainfall while the rest tend to generally overestimate.

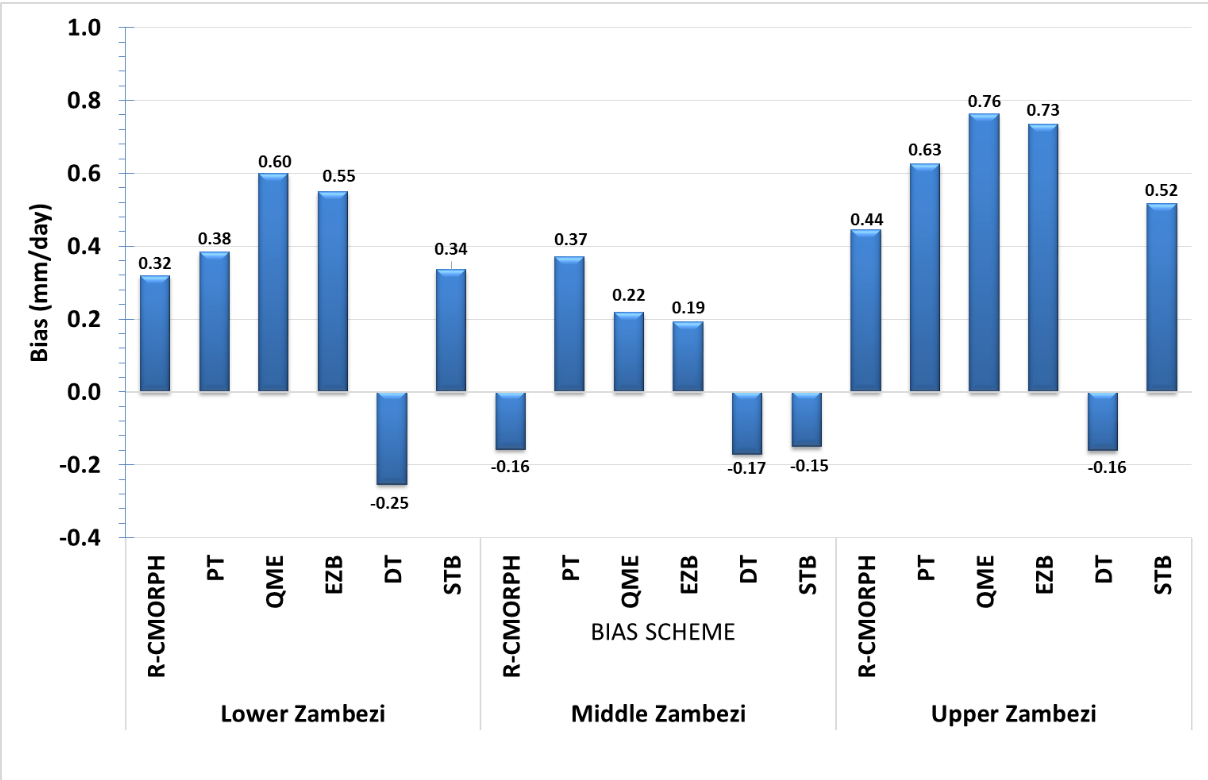

Figure 9: Bias values of gauge and CMORPH daily rainfall for the uncorrected CMORPH and the 5 bias correction schemes averaged for the Lower Zambezi, Middle Zambezi and Upper Zambezi.

The highest Rbias is consistently found for the EZB bias correction scheme. Significant underestimation of rainfall is by DT for the Lower and Middle Zambezi Basin (Figure 10). The most significant skill in reproducing gauge based estimates (-17.06) is captured in the Middle Zambezi Basin for all the bias correction schemes save for DT

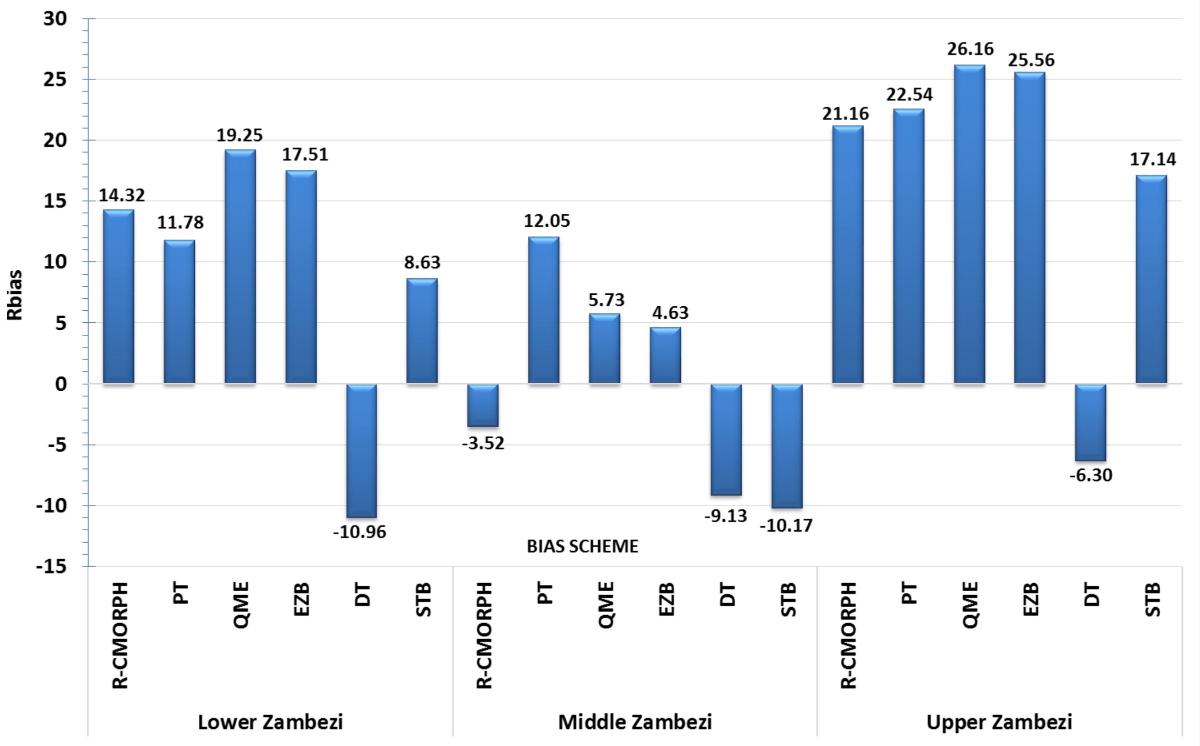

Figure 10: Rbias of gauge and CMORPH daily rainfall for the uncorrected CMORPH and the 5 bias correction schemes averaged for the Lower Zambezi, Middle Zambezi and Upper Zambezi.

Based on the RMSE, the best perfoming bias correction scheme for the Lower, Middle and Upper Zambezi basin is DT, EZB and PT respectively. The lower the RMSE score, the less difference there is between the bias corrected CMORPH and gauge based estimates (Figure 11). The most unsatisfactory perfoming bias correction scheme is PT for the lower Zambezi (10.10 mm/day). This RMSE is even poorer compared to the uncorrected CMORPH (8.63 mm/day) and shows the ineffectiveness of the bias correction scheme.

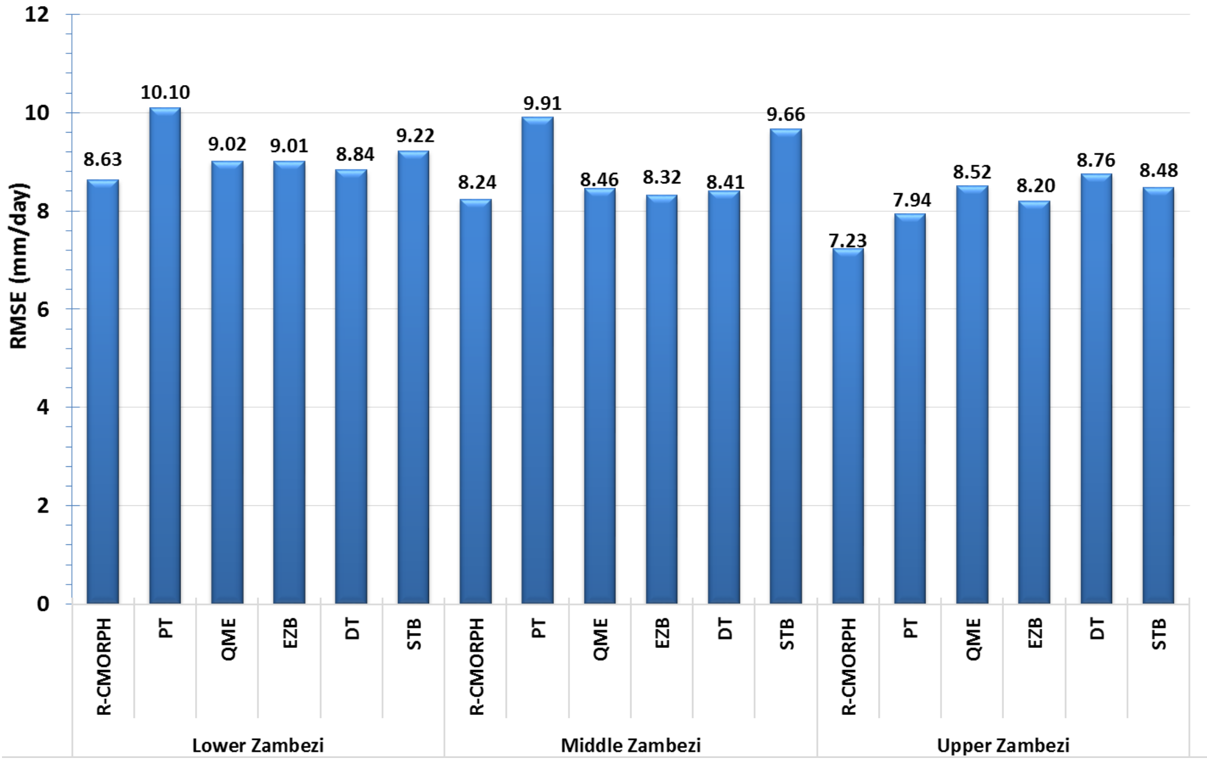

Figure 11: RMSE of CMORPH daily rainfall for the uncorrected CMORPH and the 5 bias correction schemes averaged for the Lower Zambezi, Middle Zambezi and Upper Zambezi.

Figure 12 shows the Taylor diagram statistical comparison between the time series of rain gauge (reference) observations vs CMORPH bias correction schemes averaged for the Lower Zambezi, Middle Zambezi and Upper Zambezi for the period 1998-2013. There is no data for any bias correction scheme that lies closer to the reference point on the X-axis suggesting the overal ineffectivenes of the bias correction schemes in removing errors. Only the PT for the Lower Zambezi basin lie on the dashed arc (line of standard deviation) and means they have the correct standard deviation which indicates that the pattern variations are of the right amplitude. There is no consistent pattern of variability in the bias correction schemes. However gauged against the reference raingauge mean standard deviation of 8.5 mm/day, most bias correction schemes exhibit high variability in CMORPH perfomance across all the Zambezi basins.

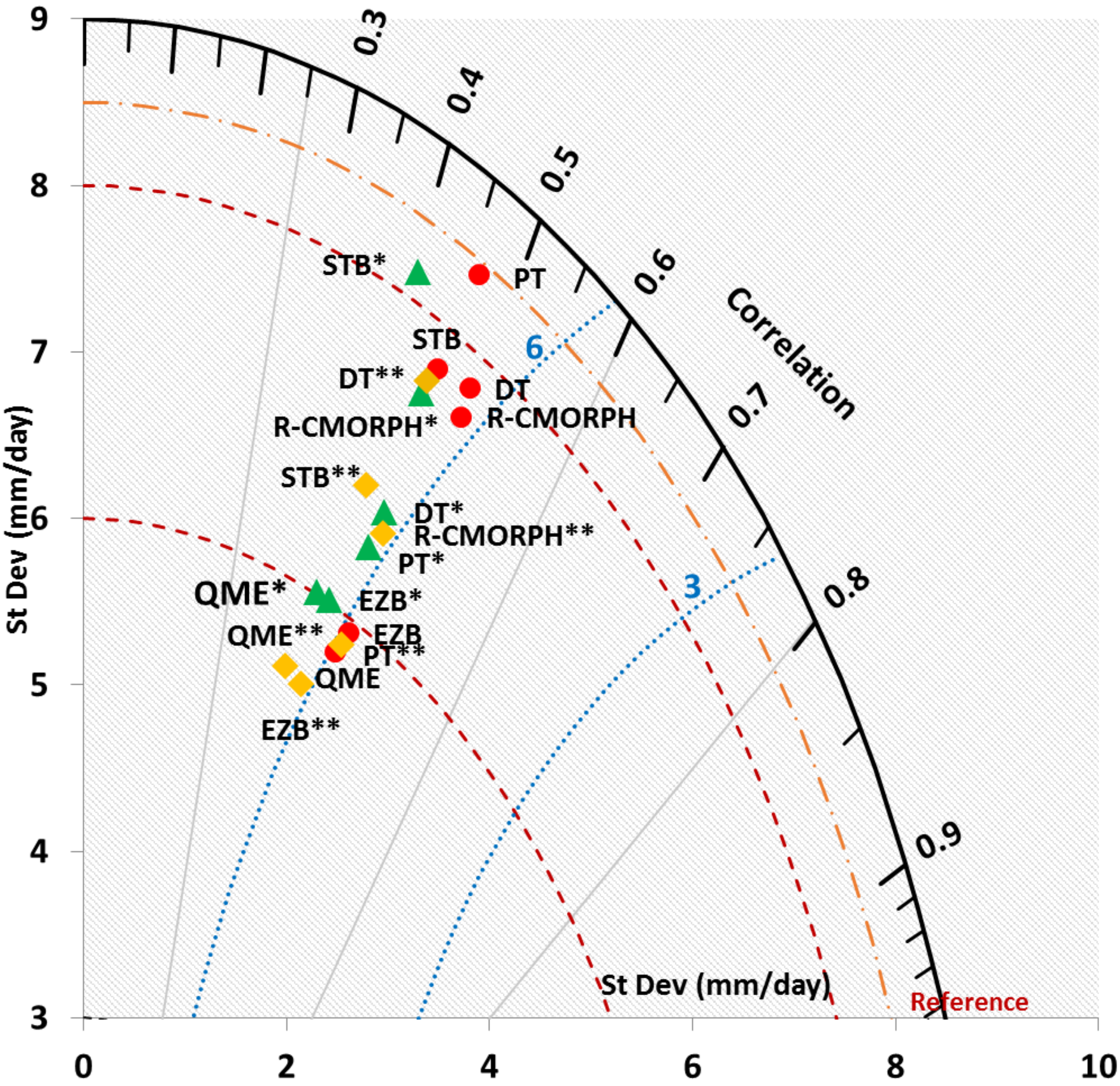

Figure 12: Taylor's diagram of statistical comparison between the time series of Raingauge (reference) observations vs CMORPH bias correction schemes averaged for the Lower Zambezi, Middle Zambezi and Upper Zambezi for the period 1998-2013. The distance of the symbol from point (1, 0) is a relative measure 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 the raingauge. Lower Zambezi=no asterisk, Middle Zambezi= *, Upper Zambezi = **. The blue contours indicate the RMSE values.

Most of the bias correction schemes lie in the range 6.0 to 9.0 mm/day (Figure 12). There is a consistent pattern betwen the bias correction schemes that have low correlation and high RMSE. Overal, the best performing bias correction schemes (DT and PT) have CC close to 0.5, standard deviation close to the reference (8.5 mm/day) and a RMSE less than 6mm/day. This is mainly for the Lower and Middle Zambezi basins showing a fair agreement with gauge based estimates and also an effectivenes of this bias correction scheme. The least perfoming bias correction scheme is QME and EZB with a low CC < 0.43 and standard deviation (< 6.0) that is lower than the reference suggesting poor skill of these bias correction schemes. Inherent to the methodology of most of the bias correction schemes (e.g. DT and QME) is that the spatial pattern of the SRE does not change and therefore the correlation for a specific station for daily precipitation does not necessarily improve.

The percentage of days belonging to the five rainfall intensities in the Zambezi basin for each bias correction scheme is shown in Table 5. The greater percentage of rainfall (>82 %) falls under the very light shower rains, 0-2.5 mm/day. A smaller percentage falls under the 2.5-5.0 mm/day which are the fairly light showers. A very low percentage belongs to the heavy showers of greater than 20 mm/day. Compared to the gauge based estimates, the STB, PT and DT generally resembles the gauge based estimates in terms of the five rainfall intensities in all the Zambezi basins and this presents the effectiveness of the three bias correction schemes. All the five rainfall types in the Lower and Middle Zambezi basins generally tend to overestimate the moderately heavy rainfall (10–20 mm/day) and underestimate moderate and heavy rainfall (>20 mm). Results are consistent with findings by Gao and Liu (2013) who also found consistent under and overestimation in the Tibetan Plateau by monthly high-resolution precipitation products including CMORPH for almost the same rainfall range (>10mm/day).

Table 5: HERE

4.6. Seasonality influences on CMORPH bias correction

Table 6 shows standard statistics for the gauge, uncorrected and bias corrected satellite rainfall for the dry and wet seasons. Compared to the gauge based and uncorrected CMORPH, the Distribution transformation (DT) and Spatio-temporal bias (STB) schemes are more effective in correcting errors in satellite rainfall than the Power transform (PT), Elevation Space bias (EZB) and Quantile based empirical-statistical error correction method (QME). The DT is more effective in reducing bias in the dry season than the wet season. For both the wet and dry season, the STB is most effective in reducing bias in the Upper Zambezi Basin. This result agrees with findings in Ines and Hansen (2006) for semi-arid eastern Kenya which showed that multiplicative bias correction schemes (in this case STB) were effective in correcting monthly and seasonal rainfall totals.

Table 6: HERE

4.7. Elevation influences on CMORPH bias correction

Using the elevation space (EZB) bias correction scheme, bias correction effectiveness at the Zambezi escarpment (highland) and valley (lowland) of the Middle Zambezi Basin (Figure 13) was assessed. We took a closer look at 6 stations, of which 3 (Mushumbi, Zumbo and Kanyemba) are on the Zambezi escarpment with elevation above 1 100 m and the other 3 (Mvurwi, Guruve, Karoi) in the valley have an elevation below 400 m. The stations have an mean distance between gauges of about 105 km.

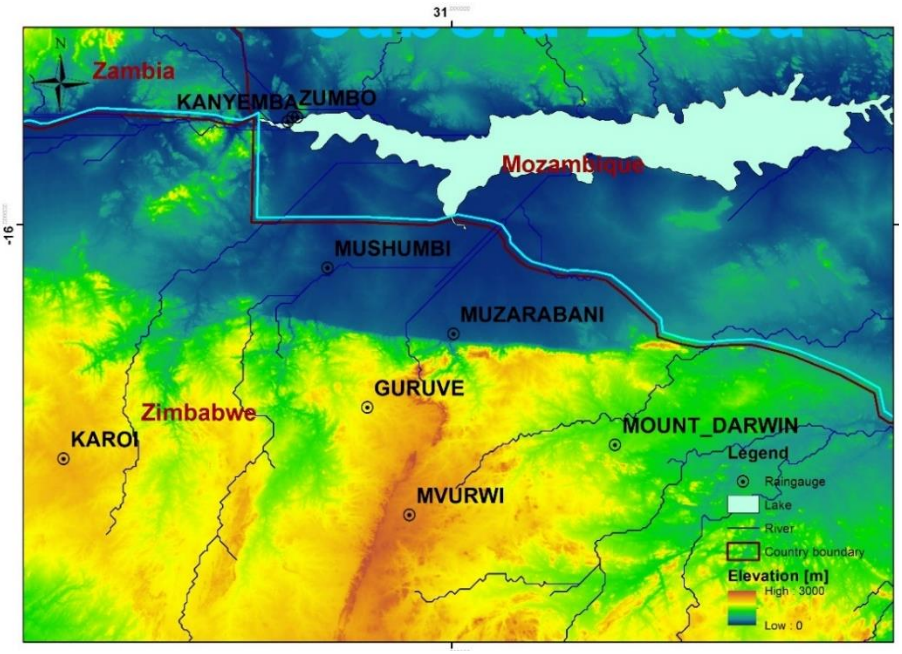

Figure 13: Location of stations and elevation of the Zambezi valley and escarpment

Table 7 reveals that for the uncorrected CMORPH, the rainfall data for stations in the valley has serious underestimation of rainfall than for the escarpment, save for Guruve station. Through EZB bias correction scheme, rainfall data for the stations on the Zambezi escarpment have effectively reduced the bias and Rbias in CMORPH rainfall than for stations on the escarpment. None of the valley stations' rainfall nor their escarpment counterparts were effective in reducing the RMSE. However, the CC slightly reduced for all the six stations after bias correction. The general conclusion is that rainfall data for stations in the Zambezi valley outperform that of sations on the escarpment in terms of uncorrected CMORPH perfomance and its bias correction.

Table 7. HERE

5. **Conclusions**

Rainfall in semi-arid river basins such as the Zambezi plays a central role in the livelihoods of human populations. The adoption of SREs offers a timely and cost efficiency opportunity to improve our understanding of the spatio-temporal variation of this water cycle component. The above is important for instance for climate monitoring, hydrologic prediction, model verification, or any other application that affect land or water rmanagement where rainfall data is required. Since SREs are prone to systematic and random errors by the fact that SREs are indirect rainfall estimates, this study aimed to to assess suitability of bias correction of CMORPH satellite rainfall estimates in the Zambezi River Basin for the period 1998-2013 for which time series are available from 54 rain gauge stations. From the study, the following can be concluded:

1. Quality control performed on the gauge based estimates in the Zambezi Basin helped to improve reliability of gauge based estimates. Uncorrected CMORPH rainfall estimates in the three Zambezi subbasins show inconsistences (in terms of rainfall volume, depth and intensity) when compared with gauge based estimates. Results also show that it is not always the case that the Lower, Middle or Upper Zambezi station estimations outperform one another. Analyses showed that the aspects of elevation in the Zambezi Basin are not well shown in the relationship between CMORPH and gauge rainfall. Findings from this study agree with previous work by Gao and Liu (2013) and Vernimmen et al. (2012) who found weak relationship between performance of SREs and elevation. The research yet contradict previous observations (e.g. Haile et al., 2009;Katiraie-Boroujerdy et al., 2013;Rientjes et al., 2013;Wu and Zhai, 2012) that found elevation dependant trends of CMORPH rainfall distribution. This shows that there is still room for further research in this area.

2. The additive bias correction scheme (Distribution transformation) has the best estimation of rainfall particularly in the Upper Zambezi Basin. However each bias correction factor has its desirable outcome depending on the performance indicators used. The linear based (Spatio-temporal) bias correction scheme successfully adjusted the daily mean of CMORPH estimates at 70 % of the stations and was also more effective in reducing the rainfall bias. The spatio-temporal bias correction scheme, using gauge and or SREs bias values that vary over time over the entire Zambezi basin is more effective in reducing rainfall bias than the EZB that does not consider spatial variation. The nonlinear bias correction schemes (Power transform and the Quantile based empirical-statistical error correction method) were more effective in reproducing the rainfall totals.

3. The study assessed the percentage of days belonging to the five rainfall intensities (0-2.5, 2.5-5, 5-10, 10-20 and >20 mm/day) in the Zambezi basin for each bias correction scheme. There is overestimation of the moderately heavy rainfall (10–20 mm/day) and underestimation of the moderate to heavy rainfall (>20 mm) by the five bias corrected rainfall types. Overall improved performance was experienced through the STB, PT and DT schemes.

4. Detailed analysis for stations in the Zambezi valley (< 400 m amsl) and escarpment (> 1 100 m amsl) indicate that bias correction of CMORPH rainfall is influenced by elevation. In addition, there is also seasonality tendencies are evident in the performance of bias correction schemes. The DT is more effective in reducing bias in the dry season than the wet season.

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Author Contributions

W.G. was responsible for the development of bias correction schemes in the Zambezi basin. T.R. was responsible for the research approach and conceptualization and quality control on the raingauges. A.T.H. was responsible for synthesising the methodology and made large contributions to the manuscript write-up. H.M. provided some of the raingauge data and related findings of this study to previous work in the Zambezi Basin. P.R. assisted in interpretation of bias correction results.

Conflict of Interests

The authors declare no conflict of interests.

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LIST OF TABLES

Table 1: Rain gauge stations in the Zambezi Basin showing station code, subbasin they belong to, years of data availability and elevation.

Station	Code	Subbasin	Zambezi classification	X Coord	Y Coord	Start date	End Date	% gaps (missing records)	Elevation (m)
Marromeu	Mru	Zambezi Delta	Lower Zambezi	36.95	-18.28	29/05/2007	31/12/2013	0.37	3
Caia	Ca	Zambezi Delta	Lower Zambezi	35.38	-17.82	29/05/2007	31/12/2013	0.13	28
Nsanje	Ns	Shire	Lower Zambezi	35.27	-16.95	01/01/1998	31/12/2013	3.49	39
Makhanga	Mk	Shire	Lower Zambezi	35.15	-16.52	01/01/1998	31/12/2013	9.43	48
Nchalo	Nc	Shire	Lower Zambezi	34.93	-16.23	01/01/1998	31/12/2013	0.60	64
Ngabu	Ng	Shire	Lower Zambezi	34.95	-16.50	01/01/1998	3112/2010	0.74	89
Chikwawa	Chk	Shire	Lower Zambezi	34.78	-16.03	01/01/1998	31/12/2010	0.93	107
Tete	Te	Tete	Lower Zambezi	33.58	-16.18	29/05/2007	31/12/2013	0.17	151
Chingodzi	Chg	Shire	Lower Zambezi	34.63	-16.00	29/05/2007	10/01/2013	11.8	280
Zumbo	Zu	Shire	Lower Zambezi	30.45	-15.62	29/05/2007	12/09/2012	0.16	345
Mushumbi	Msh	Kariba	Middle Zambezi	30.56	-16.15	11/06/2008	11/12/2013	7.47	369
Kanyemba	Kny	Tete	Middle Zambezi	30.42	-15.63	01/01/1998	30/03/2013	5.86	372
Morrumbala	Mor	Zambezi Delta	Lower Zambezi	35.58	-17.35	29/05/2007	10/01/2013	13.3	378
Muzarabani	Mz	Tete	Middle Zambezi	31.01	-16.39	01/01/1998	31/12/2013	1.14	430

Monkey	Mon	Shire	Lower Zambezi	34.92	-14.08	01/01/1998	30/11/2010	0.00	478
Mangochi	Man	Shire	Lower Zambezi	35.25	-14.47	01/01/1998	31/12/2010	0.02	481
Rukomechi	Rk	Kariba	Middle Zambezi	29.38	-16.13	01/01/1998	31/12/2013	6.40	530
Mutarara	Mut	Shire	Lower Zambezi	33.00	-17.38	29/05/2007	10/01/2013	11.7	548
Mfuwe	Mf	Luangwa	Middle Zambezi	31.93	-13.27	01/01/1998	31/12/2010	2.70	567
Mimosa	Mim	Shire	Lower Zambezi	35.62	-16.07	01/01/1998	31/12/2010	3.96	616
Balaka	Bal	Shire	Lower Zambezi	34.97	-14.98	01/01/1998	30/04/2010	0.78	618
Thyolo	Thy	Shire	Lower Zambezi	35.13	-16.13	01/01/1998	31/12/2010	0.11	624
Chileka	Chil	Shire	Lower Zambezi	34.97	-15.67	01/01/1998	31/12/2013	0.60	744
Neno	Nen	Shire	Lower Zambezi	34.65	-15.40	01/01/1998	01/01/2010	9.14	903
Mt Darwin	MtD	Tete	Middle Zambezi	31.58	-16.78	01/01/1998	02/03/2008	5.00	962
Chipata	Chip	Shire	Lower Zambezi	32.58	-13.55	01/01/1998	13/08/2003	1.11	995
Makoka	Mak	Shire	Lower Zambezi	35.18	-15.53	01/01/1998	31/12/2010	0.00	996
Livingstone	Liv	Kariba	Middle Zambezi	25.82	-17.82	01/01/1998	31/12/2013	0.00	996
Senanga	Sen	Barotse	Upper Zambezi	23.27	-16.10	01/01/1998	31/12/2013	8.90	1001
Petauke	Pet	Luangwa	Middle Zambezi	31.28	-14.25	01/02/1998	31/12/2013	0.40	1006
Msekera	Msk	Luangwa	Middle Zambezi	32.57	-13.65	01/03/1998	31/12/2015	19.7	1028
Kalabo	Kal	Lungue Bungo	Upper Zambezi	22.70	-14.85	01/01/1998	31/12/2011	5.20	1033
Mongu	Mong	Barotse	Upper Zambezi	23.15	-15.25	01/01/1998	31/12/2013	0.51	1052
Kasungu	Kas	Shire	Lower Zambezi	33.47	-13.02	01/01/2003	31/07/2013	0.00	1063
Victoria Falls	VF	Kariba	Middle Zambezi	25.85	-18.10	01/01/1998	31/12/2013	2.26	1065
Bolero	Bol	Luangwa	Middle Zambezi	33.78	-11.02	01/01/2003	31/05/2013	0.00	1070
Zambezi	Za	Lungue Bungo	Upper Zambezi	23.12	-13.53	01/01/1998	31/12/2013	1.60	1075
Kabompo	Kap	Kabombo	Upper Zambezi	24.20	-13.60	01/01/1998	30/04/2005	0.08	1086
Chichiri	Chic	Shire	Lower Zambezi	35.05	-15.78	01/01/1998	31/12/2010	0.00	1136
Chitedze	Chtd	Shire	Lower Zambezi	33.63	-13.97	01/01/2003	30/04/2013	0.00	1150
Lundazi	Lu	Luangwa	Middle Zambezi	33.20	-12.28	01/01/2003	30/04/2013	1.40	1151
Guruve	Gur	Tete	Middle Zambezi	30.70	-16.65	01/01/1998	30/03/2013	0.02	1159
Kaoma	Kao	Barotse	Upper Zambezi	24.80	-14.80	01/01/1998	31/11/2013	9.89	1162
Bvumbwe	Bv	Shire	Lower Zambezi	35.07	-15.92	01/01/1998	01/01/2011	0.00	1172
Kasempa	Kas	Kafue	Middle Zambezi	25.85	-13.53	01/01/1998	31/12/2013	9.10	1185
Kabwe	Kab	Luangwa	Middle Zambezi	28.47	-14.45	01/01/1998	13/10/2012	1.54	1209
Chitipa	Chit	Shire	Lower Zambezi	33.27	-9.70	01/01/2003	06/01/2013	0.05	1288
Mwinilunga	Mwi	Kabompo	Upper Zambezi	24.43	-11.75	01/01/1998	31/12/2013	4.81	1319
Karoi	Kar	Tete	Middle Zambezi	29.62	-16.83	01/01/1998	31/12/2004	15.08	1345
Solwezi	Sol	Kafue	Middle Zambezi	26.38	-12.18	01/01/1998	31/12/2013	0.02	1372
Harare (Belvedere)	HB	Tete	Middle Zambezi	31.02	-17.83	01/01/1998	31/03/2013	7.80	1472
Harare(Kutsaga)	HK	Tete	Middle Zambezi	31.13	-17.92	01/01/2004	30/09/2010	0.55	1488
Mvurwi	Mv	Tete	Middle Zambezi	30.85	-17.03	01/01/1998	11/12/2000	0.00	1494
Dedza	Ded	Shire	Lower Zambezi	34.25	-14.32	01/01/2003	31/10/2012	0.00	1575

Table 2: Elevation zones influenced by correlation between the satellite and gauge based estimates.

Elevation zone	**Station membership**
< 250 m (lowland)	Marromeu, Caia, Nsanje, Makhanga, Nchalo, Ngabu, Chikwawa, Tete (Chingodzi)
250- 950 m (medium)	Chingodzi, Zumbo, Mushumbi, Kanyemba, Muzarabani, Monkey, Mangochi, Rukomechi, Mutarara, Mfuwe, Mimosa, Balaka, Thyolo, Chileka, Neno
> 950 m (highland)	Mt Darwin, Chipata, Makoka, Livingstone, Senanga, Petauke, Msekekera, Kalabo, Mongu, Kasungu, Victoria Falls, Bolero, Zambezi, Kabompo, Chichiri, Chitedze, Lundazi, Guruve, Kaoma, Bvumbwe, Kasempa, Kabwe, Chitipa, Mwinilungu, Karoi, Solwezi, Harare (Belvedere), Harare (Kutsaga), Mvurwi, Dedza, Morrumbala

Table 3: Frequency based statistics for the CMORPH and gauge daily estimates for the lowland and highland stations in the Zambezi Basin

	Product type	Mean	St. dev	CV	max	sum	ratio
Lowland Stations	CMORPH	2.39	7.86	3.33	115.69	9796.81	
	Gauge	2.49	9.13	3.89	139.70	10486.42	0.93
Highland Stations	CMORPH	2.33	6.94	3.12	106.77	10099.85	
	Gauge	2.70	8.18	3.12	115.20	11578.93	0.87

Table 4: Frequency based statistics for the gauge, uncorrected and bias corrected satellite rainfall for each of the Zambezi basins. Bold figures shows improved performance of the bias correction scheme from the uncorrected CMORPH when compared against the gauge based estimates

Basin	B-scheme	Mean	Std dev	Max	Sum	Ratio
Lower Zambezi	Gauge	2.62	9.17	142.77	10792.58	
	R-CMORPH	2.39	7.58	156.50	9540.65	0.88
	PT	2.12	**8.42**	**139.33**	8883.26	0.82
	QME	2.21	8.07	129.46	9349.42	0.87
	EZB	1.46	5.92	112.77	8529.38	0.79
	DT	2.00	7.78	137.53	**11683.35**	1.08
	STB	**2.60**	7.73	165.63	9494.89	0.88
Middle Zambezi	Gauge	2.47	8.33	109.81	10112.74	
	R-CMORPH	2.51	7.74	112.39	**10373.64**	1.03
	PT	1.93	6.55	**109.76**	9186.37	0.91
	QME	1.86	6.78	114.87	8150.50	**0.99**

	EZB	1.55	6.02	110.61	9039.03	0.89
	DT	1.81	6.73	115.79	10555.56	1.05
	STB	**2.45**	**8.28**	214.74	10488.24	1.04
Upper Zambezi	Gauge	2.55	7.82	117.24	13008.24	
	R-CMORPH	2.12	6.44	103.25	10722.09	0.82
	PT	1.94	5.83	90.52	10284.19	0.79
	QME	1.98	6.22	94.32	8674.54	0.67
	EZB	1.67	5.56	96.43	9750.19	0.75
	DT	**2.49**	**7.72**	**112.81**	**14415.79**	**1.04**
	STB	2.08	6.88	175.84	10850.88	0.83

Table 5: Percentage of days that belong to the five rainfall intensities (0-2.5, 2.5-5, 5-10, 10-20 and >20 mm/day) for the Zambezi Basin. Bold figures shows best CMORPH performance when compared against the gauged and uncorrected CMORPH rainfall estimates.

	Rainfall intensity	Gauge	R_CMORPH	STB	PT	DT	EZB	QME
LZ	0.0-2.5	85.72	83.86	**85.41**	85.35	87.69	89.81	88.75
	2.5-5.0	2.87	4.71	4.30	4.20	3.08	**2.80**	3.09
	5.0 - 10	3.43	4.32	**3.93**	4.06	3.18	2.79	2.83
	10 - 20	3.53	3.78	3.38	3.48	2.88	2.39	2.45
	>20	4.45	3.32	2.98	2.91	3.17	2.20	2.88
MZ	0.0-2.5	84.91	83.67	87.38	86.38	88.55	90.24	**83.74**
	2.5-5.0	3.34	4.06	3.15	**3.48**	2.67	2.40	2.75
	5.0 - 10	3.90	4.31	3.42	**3.75**	3.02	2.41	2.79
	10 - 20	3.89	4.05	3.02	3.45	2.88	2.55	2.63
	>20	3.96	3.92	3.03	2.95	2.89	2.40	9.00
UZ	0.0-2.5	84.14	82.01	83.77	83.68	83.36	80.34	84.91
	2.5-5.0	3.62	5.30	5.01	5.08	4.35	5.50	**3.29**

5.0 - 10	4.24	5.62	5.01	5.11	**4.80**	5.76	3.27
10 - 20	4.09	4.35	3.76	3.87	**4.19**	5.07	2.77
>20	3.91	2.73	2.45	2.25	3.30	**3.32**	5.75

Table 6: Frequency based statistics for the gauge, uncorrected and bias corrected satellite rainfall for the dry and wet seasons.

		Dry season					Wet season				
Basin	Bfactor	Mean	Std dev	Max	Sum	Ratio	Mean	Std dev	Max	Sum	Ratio
LZ	Gauge	0.46	2.78	60.9	908.60		4.89	12.60	143.2	10039.9	
	R-CMORPH	0.39	2.42	55.4	836.47	0.92	4.29	9.91	110.5	8616.7	0.86
	PT	0.32	2.12	48.7	706.46	0.78	3.64	**10.46**	**121.5**	7563.1	0.75
	DT	0.22	**2.60**	**65.9**	654.12	0.72	3.64	9.94	109.0	10612.2	**1.06**
	QME	0.27	2.03	57.7	792.95	0.87	2.60	7.79	109.9	7564.8	0.75
	EZB	0.27	2.05	59.1	793.63	0.87	2.65	7.92	112.4	7729.0	0.77

	STB	0.37	2.39	56.3	866.58	0.95	3.93	10.19	117.3	8612.7	0.86
MZ	Gauge	0.33	4.69	187.9	762.88		4.99	18.31	238.1	10681.5	
	R-CMORPH	0.19	1.84	46.2	393.98	0.52	4.73	10.18	110.7	9969.2	0.93
	PT	0.13	1.41	38.1	319.72	0.42	3.27	7.85	**163.5**	7993.3	0.75
	DT	**0.31**	**2.52**	**61.6**	921.73	**1.21**	6.52	**13.47**	97.4	19032.2	1.78
	QME	0.13	1.52	45.8	370.56	0.49	2.97	8.10	108.3	8638.9	0.81
	EZB	0.13	1.51	45.6	369.73	0.48	3.00	8.11	108.3	8740.8	0.82
	STB	0.15	1.63	46.6	381.09	0.50	3.96	11.12	100.9	10187.7	**0.95**
UZ	Gauge	0.24	2.53	70.4	640.40		5.57	11.04	120.6	13240.4	
	R-CMORPH	0.22	1.98	61.1	577.44	0.90	4.56	8.75	101.4	10700.6	0.81
	PT	0.20	1.80	54.3	513.02	0.80	3.52	7.01	112.6	9130.1	0.69
	DT	0.08	**2.12**	**64.8**	233.24	0.36	3.48	7.83	105.0	10146.7	0.77
	QME	0.18	1.81	58.9	524.21	0.82	3.10	7.20	97.8	9022.3	0.68
	EZB	0.18	1.85	59.3	534.50	0.83	3.15	7.13	97.2	9199.9	0.69
	STB	**0.23**	2.11	63.1	601.79	**0.94**	3.97	**8.91**	**112.8**	10127.4	0.76

Table 7. Performance of uncorrected CMORPH (R-CMORPH), and the bias corrected CMORPH's Elevation zone bias (EZB) for three stations in the Middle Zambezi valley (Mushumbi, Kanyemba and Zumbo) and three on the escarpment (Guruve, Karoi and Mvurwi)

		Mushumbi	Kanyemba	Zumbo	Guruve	Karoi	Mvurwi
ELEVATION (m)		369	372	345	1159	1345	1494
Bias	R-CMORPH	-0.10	-0.33	-0.17	-0.05	0.03	0.53
	EZB	0.08	-0.07	0.001	0.27	0.35	0.8
Rbias	R-CMORPH	-5.38	-13.57	-8.35	-1.97	1.07	20.61
	EZB	0.21	4.22	10.22	13.63	25.98	4.22
RMSE	R-CMORPH	7.04	9.16	7.62	7.49	7.32	9.88
	EZB	7.44	9.56	8.06	7.43	7.44	9.99
CC	R-CMORPH	0.62	0.42	0.53	0.52	0.51	0.32
	EZB	0.55	0.36	0.50	0.49	0.47	0.28