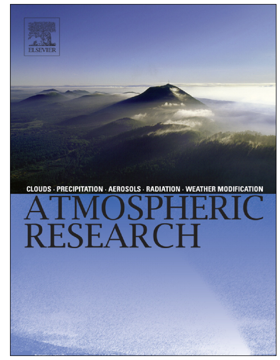

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Inter-comparison of remotely sensed precipitation datasets over Kenya during 1998-2016

Brian Ayugi[1, 2], Guirong Tan[1, 2*], Waheed Ullah[3], Richard Boiyo[4], Victor Ongoma[1, 5]

[1]Collaborative Innovation Center on Forecast and Evaluation of Meteorological Disasters/Key Laboratory of Meteorological Disaster, Ministry of Education, Nanjing University of Information Science and Technology, Nanjing 210044, China

[2]College of Atmospheric Sciences, Nanjing University of Information Science and Technology, Nanjing, Jiangsu 210044, China

[3]Collaborative Innovation Center on Forecast, Evaluation of Meteorological Disasters (CIC-FEMD), School of Geographical Sciences, Nanjing University of Information Science and Technology (NUIST), Nanjing 210044, China

[4]Department of Physical Sciences, Meru University of Science and Technology, P.O. Box 972-60200, Meru, Kenya

[5]School of Geography, Earth Science and Environment, The University of the South Pacific, Laucala Campus Private Bag, Suva, Fiji

[*]Email: 000600@nuist.edu.cn

Abstract

The paucity of reliable ground based datasets remains a major challenge over Kenya. In the advent of extreme wetness or drought events, reliable precipitation estimates for local characterization is a long overdue process. In the present study, four Satellite derived Precipitation Estimates (SPE): TMPA V7 3B42, PERSIANN-CDR, CHIRPS, and ARC2, are assessed over four homogeneous zones in Kenya with gauge based data during 1998 - 2016. Results show that variations of SPE products are based on complex geomorphology of different climatic zones. All SPE products depict bimodal annual precipitation pattern with west-east gradient representing heavier to lighter precipitation events. The Monthly analysis reveal good statistical agreement with reference datasets despite underestimation of precipitation in most regions. Seasonal precipitation events show that the PERSIANN-CDR perform better along low altitude humid climate and western zones around Lake Basin while ARC2 has uniform performance as gauge stations over highlands regions. Strong positive linear relationship on annual scale is evident in most SPE products with CHIRPS, ARC2, and TMPA exhibiting relatively high correlation (*r*) and minimum root mean square error (RMSE), except for PERSIANN-CDR. Overall, the findings of this study show the potentials of SPE products for applications over study domain. The TMPA V7 and PERSIANN-CDR could be useful in understanding individual floods events. Since the CHIRPS perform relatively well over ASAL regions, it could be utilized in monitoring droughts events.

Keywords: Satellites Precipitation products, Extreme events, Kenya

1. Introduction

Accurate precipitation measurements play a key role in reliable climate prediction and hydrological modelling (Michaelides et al., 2009, 2016; Tapiador et al., 2012, 2017; Ghajarnia et al., 2015). However, the main impediment to this is the dearth of reliable ground based data that can evidently reproduce spatial and temporal trends in precipitation over large domains. Moreover, availability and accessibility of long term in-situ data remains a hinderance factor in production of timely forecasts due to high cost involved in establishing and maintaining the station in most regions especially the developing countries (Camberlin and Okoola, 2003; Su et al., 2008).

Recent studies have focused on the role of satellite derived precipitation estimate (SPE) products as a way of quantifying precipitation and improvement of forecasts (Smith et al., 2006; Dinku et al., 2009; Tian et al., 2010; Kidd et al., 2012). In addition, applications of SPE products in understanding extreme weather occurrences and analysis such as flooding or drought events have been on an upward trend in many parts of the world (Toté et al., 2015; Gebrechorkos et al., 2017, 2018). This is due to their unique techniques in precipitation monitoring over large spatial and temporal scales. Their appraisals are primarily inferred on thermal infrared (IR) sensors on board geosynchronous satellites, and passive microwave (PMW) on board low earth cycling satellites. Some products are based on combination of a number of algorithms that can merge information from precipitation radar (PR), PMW and IR hence generating high resolution precipitation products (Sorooshian et al., 2000; Kidd et al., 2003; Joyce et al., 2004; Huffman et al., 2001, 2007). However, there is need to evaluate the performance of these SPEs based on their algorithm to establish their accuracy, quality and possible existing uncertainties in the merged products over different regions.

Past studies have reported unrealistic biases over most complex topographies (Nicholson et al., 2003; Ward et al., 2011; Dinku et al., 2011; Kimani et al., 2017). These biases are mostly observed in daily SPEs with significant decrease in longer timescales i.e. monthly and annual. Examples of such biases range from underestimation of SPEs in capturing short rainfall events, to decreased performance over high mountainous regions due to snow and ice surface that algorithms interpret as precipitation or over large water bodies (Tian et al., 2010; Dinku et al., 2010; Wang et al., 2014; Gebregiorgis and Hossain, 2015; Gehne et al., 2016).

Numerous studies have focused on comparison analyses of SPE products with respect to in situ or model data in a diverse topographies and temporal scales. Ebert et al. (2007) conducted a study over Australia in an effort to compare real time rainfall (RT) SPE products and numerical models. The study established a complimentary forecast by SPE products and numerical weather models with best performance reported during summer by SPE and winter by models. Kidd et al. (2012) focused over Europe reporting a satisfactory performance by SPE products in capturing seasonal cycles based on statistical metrics with poor estimates during winter. Overall, the study reported underestimation of precipitation over North West Europe during all seasons under study. Tian et al. (2010) carried out a study over United States based on daily data comparison reporting better probability of detection during summer than winter in all SPE products. Recently, Hussain et al. (2017) evaluated the performance of CMORPH, TMPA, and PERSIANN-CDR rainfall datasets over mountainous, plain and glacial regions of Pakistan and reported unsatisfactory performance over arid regions as compared to mountainous areas.

Despite progress in evaluating the performance of most SPE products at regional level, few studies have been conducted in most parts of sub-Saharan Africa (Adeyewa and Nakamura, 2003; Dembélé and Zwart, 2016; Cattaini et al., 2018). Examples of such regions is East Africa (EA), that has had limited studies investigating the performance and applications of SPE products. Studies conducted evaluated the performance of SPEs in selected climatic zones, i.e over Northern Tanzania (Dinku et al., 2011; Mashingia et al. 2014); Nzoia Basin along Lake Victoria (Li et al., 2009); Ethiopian highlands (Hirpa et al., 2010; Gebrechorkos et al., 2017) and western region of Uganda (Asadullah et al., 2008; Diem et al., 2014) based on different SPE products.

Studies by Agutu et al. (2017) assessed performance of CHIRPS in analyzing soil moisture deficits over arable lands in EA with the good performance reported by SPE product in monitoring agricultural droughts. However, the study did not extend to other climatic zones i.e. arid and semi-arid lands (ASALs) to assess the severity, duration and spatial extent of either meteorological, hydrological or agricultural droughts. The main economic activity in such region is pastoralism and hence the need to assess performance of SPEs in monitoring droughts and land use patterns. Kimani et al. (2017) evaluated the performance of monthly rainfall estimates including Climate Predication Centre (CPC) and Morphing technique (CMORPH), employing a locally developed gridded rainfall datasets. They revealed significant replications of rainfall patterns over EA region. However, the products investigated exhibited systematic errors, especially over localized orographic types.

The aforementioned studies reported a fair performance of SPEs over most zones studied albeit an underestimation during dry seasons and over high complex topography and coastal regions. However, a few studies have specifically evaluated the performance of SPE in diverse climate zones over Kenya. The study domain is the second most populated country in EA, with > 45 million populace (UN, 2007). A greater percentage of the mass population relies on rain fed agriculture as key source of sustenance and economic driver (Funk et al., 2008; Ongoma and Shilenje, 2016; Mumo et al., 2018).

The present study evaluates the performance of four SPE products over four distinct climatic zones in Kenya for a duration of 1998-2016. The SPEs evaluated are: African Rainfall Climatology version 2.0 (ARCV2) (Novella and Thiaw, 2010), Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) (Funk et al., 2015), Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks Climate Data Record (PERSIANN-CDR) (Sorooshian et al., 2000; Ashouri et al., 2015) and Tropical Rainfall Measuring Mission Multi-Satellite Precipitation Analysis (TMPAv7) (Huffman et al., 2007). Subsequent sections of the present study are as follows: Section 2 details the study domain, datasets and methods while Section 3 presents the main results. Section 4 elucidates summary, conclusion and recommendations based on the findings.

2. Study area, Data and Methods

2.1 Study area

Figure 1 shows the study domain; Kenya of azimuth 34° E - 42° E and latitude 5° S - 5° N. Vast coastline in the southern parts and mountainous features in the central parts characterize the study domain. Lake Victoria is located to the west of the country. The lake is the third largest in the world and borders; Uganda (45%), Tanzania (49%) and Kenya (6%) (Bowden, 2007). A number of studies including Indeje et al., (2001) and Ogwang et al., (2014) have documented that the lake regulates the local climate on the western part of the study domain creating a microclimate that is different from the rest of the country. The eastern and northeastern parts of the study domain are predominately ASALs.

The climate of the area is mostly diverse with mixture of equatorial (Af) and warm desert climate (BWh) (Kottek et al., 2006; Frinch et al., 2002; Otieno and Anyah, 2013). Moderate temperatures are experienced throughout the year with low temperatures recorded in the months of June to September (JJAS), whereas high temperatures characterize January to February (JF) (King'uyu et al., 2000; Christy et al., 2009; Boiyo et al., 2017; Ongoma and Chen, 2017; Ayugi et al., 2018b). Rainfall is mostly bimodal, experienced in March to May (MAM) locally referred to as 'long rains' and October to December (OND), referred to as 'short rains' (Yang et al., 2015; Ongoma and Chen, 2017; Ayugi et al., 2018a). The selected areas in Fig. 1 are based on rainfall homogeneity zones as previously classified by a number of authors including Cambelin and Planchon (1997); Indeje (2000); and Indeje and Semazzi (2000). There are six homogenous regions within the study domain i.e.; western (W), southwestern (SW), northwestern (NW), northeastern (NE), south (S), and southeastern (SE) (Indeje, 2000). However, the most dominant homogenous regions are the Lake Victoria region, the highlands, the coastal and desert regions. The present study focuses on these regions due to their different and distinct climatic features, population density, land use and availability of synoptic datasets.

2.2 Data

2.2.1 Gauge data

The study utilized daily rain gauge observations provided by the Kenya Meteorological Department (KMD) to validate the satellite derived precipitation estimate datasets. The distribution and density of in situ station varies, with dense distribution along western region while scarce characterizes ASAL region over study domain. Out of the existing stations with daily in situ datasets, four synoptic stations located in different climatic zone had complete daily datasets that covers the period of 19 years (1998 - 2016), and has relatively few data gaps. Quality check was conducted to the gauge data by screening for unrealistic values. Fig. 1 shows the red points indicating the locations of the in situ stations utilized in the present study.

2.2.2 Satellite derived Data

Four SPE were used for evaluation in this study. Table 1 presents an overview of each product employed in the present study. The SPEs uses a combination of passive microwave radiometers (PMW), and IR data from Low Earth Orbital (LEO) and geosynchronous satellites to forecast precipitation rates over diverse climatic zones. These data sets are denoted as TMPA V7 3B42, ARC2, PERSIANN-CDR, and CHIRPS.

The TRMM is produced by the National Aeronautics and Space Administration (NASA) and Japan Aerospace Exploration Agency (JAXA) on a joint mission to estimate precipitation over tropical regions. The TMPA 3hourly (3B42 version 7) product employed in this study is based on several instruments for monitoring precipitation rates. This includes: TRMM Microwave Imager (TMI), the Advanced Microwave Scanning Radiometer for the Earth Observing System (AMSR-E) on Aqua, the Visible and infrared Radiometer (VIRS) and the Precipitation Radar (PR). The TMPA products are adjusted using the GPCP precipitation gauge analysis from the Global Precipitation Climatology Centre (GPCC). The data has a resolution of 0.25° with ordinate covering (50° N – 50° S), available from 1998 to date. Detailed information regarding the datasets have been documented by Huffman et al. (2007).

The ARC2 (Novella and Thiaw, 2010) uses an algorithm that incorporates two main inputs with sources from 3 hourly geostationary Infrared (IR) data located over Africa and real time observations from Global Telecommunication Systems (GTS) recording 24-hour precipitations totals. The data has a high spatial resolution of (0.1°) grids, spanning from 1983 to date. This is an improved output product from the first version of ARC. The few studies conducted over some domains in Africa reported underestimations. Continuous evaluation of the SPEs products over study domain could improve accuracy reporting for the Famine Early Warning Systems Network (FEWS-NET) (Novella and Thiaw, 2013).

The PERSIANN-CDR (Ashouri et al., 2015) is daily product at 0.25° resolutions for right ascension band of 60° S – 60° N starting from the year 1983 to date. This dataset is produced from PERSIANN algorithms using GridSat-B1 infrared window (IRWIN) channel at a 3-hour samples and combines information from passive microwave and infrared to give it improved quality (Sorooshian et al., 2000). The datasets are ameliorated using Global Precipitation Climatology Project (GPCP) monthly product in bid to maintain the original resolutions (GPCP; Huffman et al., 2001). The choice of PERSIANN-CDR for evaluation is due to the fact that the study domain suffers from acute climate extremes of floods and therefore, understanding the performance of the data could help in improving climate studies.

The CHIRPS datasets, with spatial resolution of 0.05°, are developed from the combination of interpolation techniques and high resolution precipitation estimates based on infrared Cold Cloud Duration (CCD) observations. The data incorporates fine grids satellite imagery, in addition to daily, pentadal and monthly CCD-based precipitation products that spans from 1981-present. The outputs are further merged with station datasets to develop improved rainfall estimates products. More details of the SPE product can be found from Funk et al. (2015). See Table 1 for brief description of each SPE products. The study domain is prone to recurrent droughts and therefore evaluation of CHIRPS that is developed for specific trends analysis and monitoring of drought is paramount. The study uses daily datasets for the period 1998-2016 to have temporal agreement with other satellite datasets.

These SPEs have different spatial and temporal resolutions. In this study, the satellites data were accumulated to daily totals from 06Z to 06Z for comparison with daily gauge precipitation for the period 1998-2016.

2.3 Methodology

The study used in situ datasets in pair wise comparison with four SPE products of varying grid resolutions in estimating the amount of rainfall. Most of gauges were densely concentrated within western and southwestern zones with distinct geographical features and high population densities. This results into a major challenge in evaluating the rainfall datasets since some areas had sparse coverage and distribution of in situ stations. To overcome such drawbacks, the study considered one station as a representative for each different zone for the purposes of this analysis as previously used by Habib et al. (2009) and

Katiraie-Boroujerdy et al. (2017) over different domains. The comparison was conducted at monthly, seasonal and annual scales. Due to regional variability of rainfall over study domain, the study considered two main rainfall season of MAM and OND and dry seasons of JF and JJAS (Nicholson, 2000; Clark et al., 2003; Ayugi et al., 2016, 2018a; Ongoma and Chen, 2017).

The methods adopted include correlation coefficient (*r*), RMSE, bias, and standard deviation (SD) previously used in a number of studies (Mashingia et al., 2014; Boiyo et al., 2017; Ullah et al., 2018; Ongoma et al., 2018). More information regarding these descriptive statistics and their application can be found from previous studies (Wilks, 2006; Dinku et al., 2009; Chai and Draxler, 2014; Wang et al., 2015; Lekula et al., 2018). The study adopted varying thresholds of statistical metrics as an indicator of significant level as previous used by Condom et al. (2011) and Adeyewa and Nakumura (2003). The outputs of these metrics were displayed using scatter plots and Taylor diagrams (TD) (Taylor, 2001).

3. Results and Discussions

3.1 Climatology

Figure 2 shows mean precipitation patterns for the four seasons as derived from SPE products. In agreement with other studies, the western parts of the country receive more precipitation compared to other parts in all seasons. On average, all SPEs capture the seasonal climatology and exhibits clear bimodal patterns. However, the magnitude varies from one datasets to another. Insignificant difference in the spatial distribution of precipitation is observed during MAM and OND except for ARC2 that displays apparent less distribution of spatially extended west east patterns. The TMPA distribution indicates that significant rainfall is observed over northwestern parts of study area around Lake Turkana during JF and JJAS that are predominantly dry. This is remarkable performance since TMPA data is reported to underestimate precipitation during dry seasons. However, the findings are consistent with previous studies that reported the overestimation of TMPA in ASAL region and underestimation in complex topography areas (Huffman et al., 2007; Dinku et al., 2010). The JF precipitation is captured with more precision than JJAS precipitation events. Apparent regional difference observed in all SPEs agrees with past studies over different domains that reported a number of factors such as terrain, precipitation type, and climate affect precision of SPE products for each unique domain (Demaria et al., 2011; Seyyedi et al., 2014: Darand et al., 2017).

Figure 3 presents the annual precipitation cycle for the selected regions as described in Table 2. Results indicate that SPE products capture annual precipitation cycle for selected regions. However, the degree of variations varies with SPE products, regions and from one season to another. This agrees with previous studies that reported precision of SPE products for specific region to be dependent of diverse unique factors specific to the region (Demaria et al., 2011; Darand et al., 2017, and references therein).

In a region characterized by large water bodies and humid climate (Region 1), SPE products appear to overestimate precipitation with pronounced variation in PERSIANN-CDR. The overestimation in humid regions maybe attributed to low surface temperature and radiation absorption over the large water body of Lake Victoria, resulting in non-raining clouds being interpreted as rain. At the wet sub-humid region (2), most SPE products performed relatively well except ARC2 which underestimates precipitation throughout the cycle. Notably, during MAM, dry bias is observed over low altitude and highland regions. At the humid region (3), most SPEs show precipitation variation as ground based data except for CHIRPS that overestimate precipitation during wet and dry seasons. Over ASALs environment (Region 4), a relatively accurate performance is exhibited in most SPE products as in situ data except for CHIRPS that overestimates precipitation. The results reveal that most SPEs technique varies from one region to another with overestimation or underestimation of ground based precipitation.

3.2 Monthly analysis

Figure 4 provides results for monthly comparisons for selected regions. It is evident that most SPEs underestimate monthly precipitation over most regions apart from PERSIANN-CDR that is observed to overestimate precipitation events >50 mm/month, though it still has good relation with the station data in Kisumu (Fig. 4a). The CHIRPS has relatively close correspondence with station data except in Kisumu region. Overall, the TMPA exhibits good performance in all regions under study especially in Kisumu. The ARC2 shows a close relationship with the station data in four region.

The relative statistical metrics of various SPEs can be inferred from Table 3 and Taylor diagram in Fig. 5. The SPE products that correspond well with ground-based observations are nearest to points indicated as in situ data on the x-axis. The dashed arc indicates the standard deviation of SPEs. Over Kisumu region, it shows that TMPA and ARC2 generally agree with observations, each with higher values of slope, correlation coefficient, as 0.44/0.31, 0.83/0.69 and less RMSE 57.18/60.53 respectively. However, the TMPA has slightly higher correlation with in situ, whereas ARC2 shows minimal spatial variation. Out of unsatisfactory performing SPE products, the CHIRPS has low pattern correlation, while PERSIANN-CDR has high standard deviation resulting to relatively large centered RMSE in the precipitation field in both cases.

In Highland region, the TMPA show significant high correlation of 0.87 and lowest RMSE of 53.88 amidst the SPE products (see table 3), with minimal tendency distribution to that obtained from in situ. Although, the standard error of CHIRPS is closer to that of in situ data, this satellite product exhibit low correlation (r=0.68) and higher RMSE. Meanwhile the PERSIANN-CDR reveals the least correlation of (r=0.50) and larger RMSE coupled with poor standard deviation in comparison to in situ data. Regarding Mombasa region, most SPEs exhibited good correlation relative to the in situ except for CHIRPS with correlation of r=0.62. However, the ARC2 and TMPA demonstrates the greatest correlation of r=0.92 and 0.86 with least RMSE. The deviation of TMPA is nearer to in situ, followed by ARC2. The corresponding correlation of PERSIANN-CDR (r= 0.80) were also higher as compared to those found in Kisumu and Dagoretti regions but with lower standard deviations. Over the ASALs region, relatively large standard deviation is witnessed in most SPE products with PERSIANN-CDR showing the largest deviation compared to in situ value. CHIRPS however shows very close standard deviation with in situ data and insignificant correlation (r=0.60) as contrasted with other SPE products. The TMPA consistently exhibited good performance with correlation coefficient (0.87) and low RMSE.

Overall, the results for monthly scale comparison of SPE products underestimate precipitation events in most regions with only PERSIANN-CDR overestimating precipitation events in relatively humid regions. Statistical metrics reveals the regional variation with relatively good performance for most regions for TMPA, ARC2, CHIRPS, and PERSIANN-CDR, respectively. A study by Kimani et al., 2017 over East Africa, reported similar findings of underestimation of monthly rainfall estimates on diverse topography. The study noted the influence of mountainous areas, with warm orographic processes that drives most rainfall over the region. Consequently, the IR-based SPE products underestimated the rainfall over high altitude climate zones, with PERSIANN-CDR exhibiting consistent performance over such regions. The noteworthy performance by CHIRPS and TMPA-3B42 can be explained by the incorporation of rain gauge data and an algorithm relating MW to rain during the calibration.

3.4 Seasonal analysis

Analysis of SPEs performance during the four seasons is conducted to ascertain seasonal variations over different regions. Table 4 summarizes the statistical metrics during the local wet and dry seasons over the study domain. Fig. 6 illustrates seasonal comparison of precipitation variations over the Lake Region. The performance is chosen on basis of standard deviations of less than -1, the highest correlation and the least RMSE with respect to in situ data. Generally, TMPA exhibits low performance which is consistent with variations during the dry (Fig. 6a, c) and wet (Fig. 6b, d) seasons over lake region.

Although the cause of the observations is not investigated in this study, apparent low performance indicates the contrary dynamics of seasonal variations between in situ and other SPE products. The best SPE products for humid climate region during wet and dry seasons are as follows: PERSIANN-CDR, CHIRPS, and ARC2. The PERSIANN-CDR show strong positive correlation with in situ data indicating consistent seasonal variation among the SPEs products (table 4). The ARC2 exhibits a large standard deviation and unbiased root-mean-square difference (unRMSD>1.5), suggesting large magnitudes of variations and errors in comparison with in situ data. The overall best performing SPE products for humid climate region over study domain are as follows: PERSIANN-CDR, and CHIRPS, with corresponding higher correlation coefficient (0.98, 0.89), lowest RMSE (20.78, 28.03), and bias (14.27, 48.2) during local dry season.

Over high altitude regions (Fig. 7), seasonal climatology is further examined during wet and dry seasons. Overall, there is a general improvement of performance of SPE products during dry seasons (Fig. 7a, c) while poor performance characterized by low correlation of 0.27 for PERSIANN-CDR during wet seasons (Fig. 7b, table 4) and -0.57 during the local short rains (Fig. 7d, table 4). The TMPA and ARC2 consistently exhibit better performance in all seasons, each with higher values of correlation coefficient and low RMSE, as 0.82/0.84, 35.64/35.44 while CHIRPS show highest unRMSE during both the dry and wet seasons. As for this region, the best performing SPE products are as follows: ARC2, TMPA and CHIRPS.

Similar trends are observed in lower altitude with humid climate regions (Fig. 8) with ARC2 showing better performance during winter dry (Fig. 8a) and all other seasons (table 4). The low correlation patterns as previously observed over humid climate regions is observed to reoccur in TMPA, exhibiting negative correlation of -0.86/-0.42 during wet (Fig. 8b, d) and equally during local JF season (Fig. 8c) over highlands regions (table 4). Best performing SPE products are as follows: ARC2, PERSIANN-CDR and CHIRPS.

The ASALs (Fig. 9) depicts similar patterns as highlands regions with most SPE products performing better during dry seasons (Fig. 9a, c) and negative correlation witnessed during wet season (Fig. 9b, d). It is clear from the Taylor diagram and table 4 that the CHIRPS has high correlation coefficient ranging between r= 0.95 and 0.98 in all seasons which suggest that it has similar precipitation dynamics for seasonal variation with in situ precipitation events. The TMPA show weak positive correlation with in situ data during JF (Figs. 9a, c) and negative correlation during wet seasons (Fig. 9b, d and table 4) indicating different dynamics compared to that of station data. The ARC2 and PERSIANN-CDR exhibit large standard deviation rations >1.8 and unbiased root-mean-square difference (unRMSD>1.5) in all seasons, suggesting large magnitudes of variations and errors in comparison with in situ data. The best SPE products over ASALs regions are as follows: CHIRPS, ARC2, and PERSIANN-CDR. This agrees with recent studies that reported similar findings (Dahri et al., 2016; Katsanos et al., 2016; Peredes Trejo et al., 2017).

While the listed SPE products performs well with respect to RMSE, bias, and correlation (r) in reference to in situ data, some SPE products do not reproduce seasonal cycles of mean precipitation events. On that basis, the overall assessment of SPE products shows that most satellite technique vary in performance from one diverse region and season to another. The humid lake region has PERSIANN-CDR exhibiting consistent performance in all seasons while over highland region has ARC2 showing consistent performance in all seasons. The performance of SPEs over low altitude humid climate, located along coastal belt has ARC2 maintaining consistent performance while over ASALs region; CHIRPS show satisfactory performance in both dry and wet season. A study by Heidinger et al., (2012) reported low performance of TMPA over Lake Basin in the Andean Altiplano region, whereas Darand et al., (2017) showed that TMPA V7 overestimate heavy precipitation events. However, the performance of PERSIANN-CDR agrees with a related study by Katiraie-Boroujerdy et al., (2017). Parades-Trejo et al., (2017) concluded that the CHIRPS dataset could be a useful substitute for rain-gauge precipitation data over ASALs. This agrees with recent studies that reported similar findings (Dahri et al., 2016; Katsanos et al., 2016).

3.5 Annual analysis

Figure 10 shows annual comparison of SPE products and in situ precipitation for different regions representing unique climates and complex topography. The results show an overall variability of the performance of SPEs between regions with overestimation by all SPE products in humid climate region with linear relationship >1 (Fig. 10a). The ARC2, CHIRPS, and TMPA overestimate precipitation with smaller magnitude while PERSIANN-CDR overestimate larger precipitation event of >50 mm/year. From Fig. 10b, all SPE products underestimate precipitation over high altitude wet climate. The CHIRPS exhibits relatively better performance compared with other SPEs in this region. In low altitude humid climate (Fig. 10c), CHIRPS overestimate precipitation events while TMPA, ARC2, and PERSIANN-CDR underestimates. However, the TMPA and ARC2 appear to represent relatively closer linear relationship with ground based datasets. For ASALs region, (Fig. 10d), the CHIRPS overestimate observed precipitation events while the TMPA, ARC2, and PERSIANN-CDR continually underestimate in situ products.

The annual patterns for comparisons of climatological mean SPE products and ground based observations for stations are further evaluated and summarized by Taylor diagram (Fig. 11) and descriptive statistics in Table 5. Over Kisumu, TMPA show a significant linear correlation (*r*=0.93) amongst all SPE products, with RMSE of <50% and equally exhibits minimal tendency distribution to that considered from in situ data. The CHIRPS and ARC2 equally exhibit high correlation of *r*=0.91, 0.89, respectively, with relatively closer standard deviation to the in situ observation (table 5). Meanwhile, the PERSIANN-CDR show very high RMSE of 90.89 with low correlation relative to other SPE products. Over highland region (Fig. 11b), characterized by highland topography, CHIRPS show excellent performance with greatest value of *(r*=0.98) and least RMSE. The range of error of CHIRPS was nearest to the in situ as collated to that of TMPA and ARC2. In addition, ARC2 and TMPA show good correlation of (*r*=0.96, 0.95) with equally lowest RMSE. The PERSIANN-CDR exhibits the lowest correlation (*r*=0.69) showing poor performance with relatively high standard deviation and high RMSE compared to in situ observation (table 5).

Regarding Mombasa region (Fig. 11c), CHIRPS and ARC2 exhibits stronger correlation of *r*=0.98 in both cases, although the standard deviation of CHIRPS was higher than that of in situ data. The TMPA and PERSIANN-CDR show good correlation (*r*=0.94, 0.87) and moderately minimal RMSE with TMPA exhibiting the consistency preceding weak statistical results over the region. The study also analyzed the bias of SPE products and established that CHIRPS, ARC2, and TMPA exhibits low bias of -19.42%, 17.42% and 17.13% in comparison to that of PERSIANN-CDR, which has large bias of 24.17% over the region under study (table 5). The semi-arid region, Marsabit (Fig. 11d) entail all SPE products exhibiting high correlation with CHIRPS showing highest correlation of *r*=0.98 followed by TMPA and ARC2. Low RMSE in all SPE products and standard deviation are equally exhibited. However, CHIRPS show higher standard deviation than in situ datasets while PERSIANN-CDR is lowest amongst the SPE products.

The statistical metrics of SPE products show that CHIRPS, ARC2, and TMPA perform better at annual timescale in varying climate over the study domain with PERSIANN-CDR performing relatively poor in all different topographical features and climatic conditions. However, at ASALs climate, relatively good performance is exhibited in most SPE products agreeing with past studies that reported improved performance of most SPE products in such climates (Katiraie-Boroujerdy et al., 2013; Peredes-Trejo et al., 2017).

4. Conclusion and Recommendation

The performance of four high-resolution precipitation estimation products (TMPA V7 3B42, PERSIANN-CDR, ARC2, and CHIRPS.2) in estimating precipitation over four different homogenous regions in Kenya during 1998 to 2016 was studied. Various geo-statistical and illustrative techniques are used to assess varying dimension of the datasets from the reference data. The following conclusions can be inferred from the investigation:

- Monthly comparisons of SPE products show that SPEs underestimate monthly precipitation except for the Lake region along the western region where PERSIANN-CDR overestimate the precipitation events of > 50 mm/month. The statistical metrics for monthly precipitation revealed consistent satisfactory performance in TMPA, ARC2, CHIRPS, and least in PERSIANN-CDR.
- Seasonal precipitation events for SPE products show PERSIANN-CDR performs better along low altitude humid climate zones and western zones around Lake Basin. The ARC2 show consistent performance at gauge stations over highlands regions. The CHIRPS display excellent performance in ASAL regions with high correlation, low RMSE, and low standard deviation.
- Annual precipitation events can be well replicated with CHIRPS, ARC2, and TMPA exhibiting excellent performance over most regions. The PERSIANN-CDR shows poor performance in examining annual precipitation events.

In summary, The SPE products appears to perform best during the dry seasons on long term scale analysis which could be critical in drought monitoring especially over fragile arable lands which accounts for one third of total mass over the study domain. Underestimations is observed during the rainy seasons, notably, MAM and OND over most regions. The SPE products such as TMPA V7 and PERSIANN-CDR can be used in monthly analyses of precipitation while CHIRPS, ARC2 utilized for examination of long-term precipitation trends such as seasonal and scale annual. However, on drought analysis and light precipitation events, the CHIRPS and ARC2 are recommended. It is recommended that further improvement in the SPE products may be possible based on further evaluation of inter-annual performance during the wet season and monthly bias corrections.

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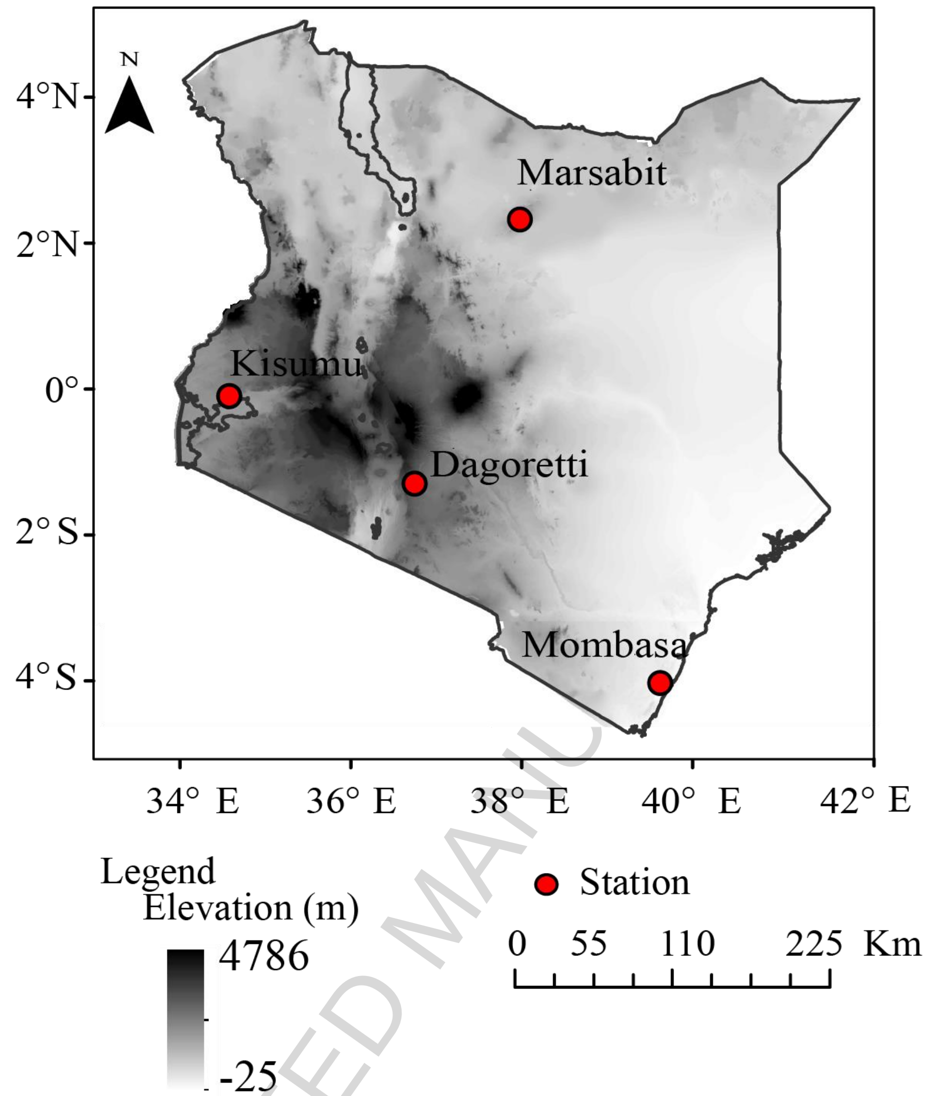

Fig. 1 The study area with topographical elevation (m) in dark color. The red points represents location of synoptic rain gauge stations in homogeneous zones of: Mombasa (39.62° E, 4° S); Dagoretti (36.75° E, 1.3° S); Kisumu (34.58°E, 0.1° S) and Marsabit (38° E, 2.32° N) based on Indeje (2000).

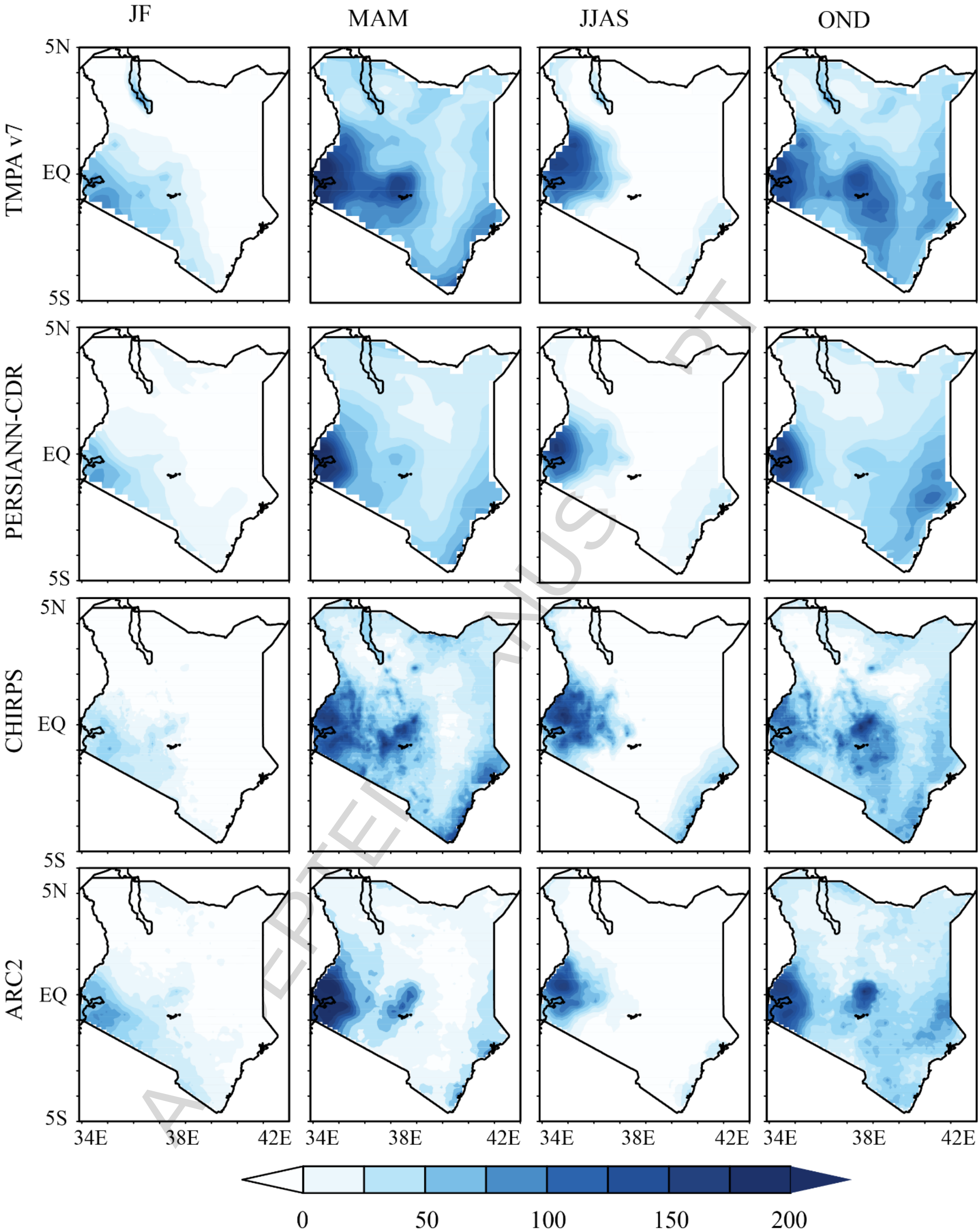

Fig 2. Climatology (1998-2016) of precipitation (mm) based on remotely sensed precipitation during different seasons over Kenya.

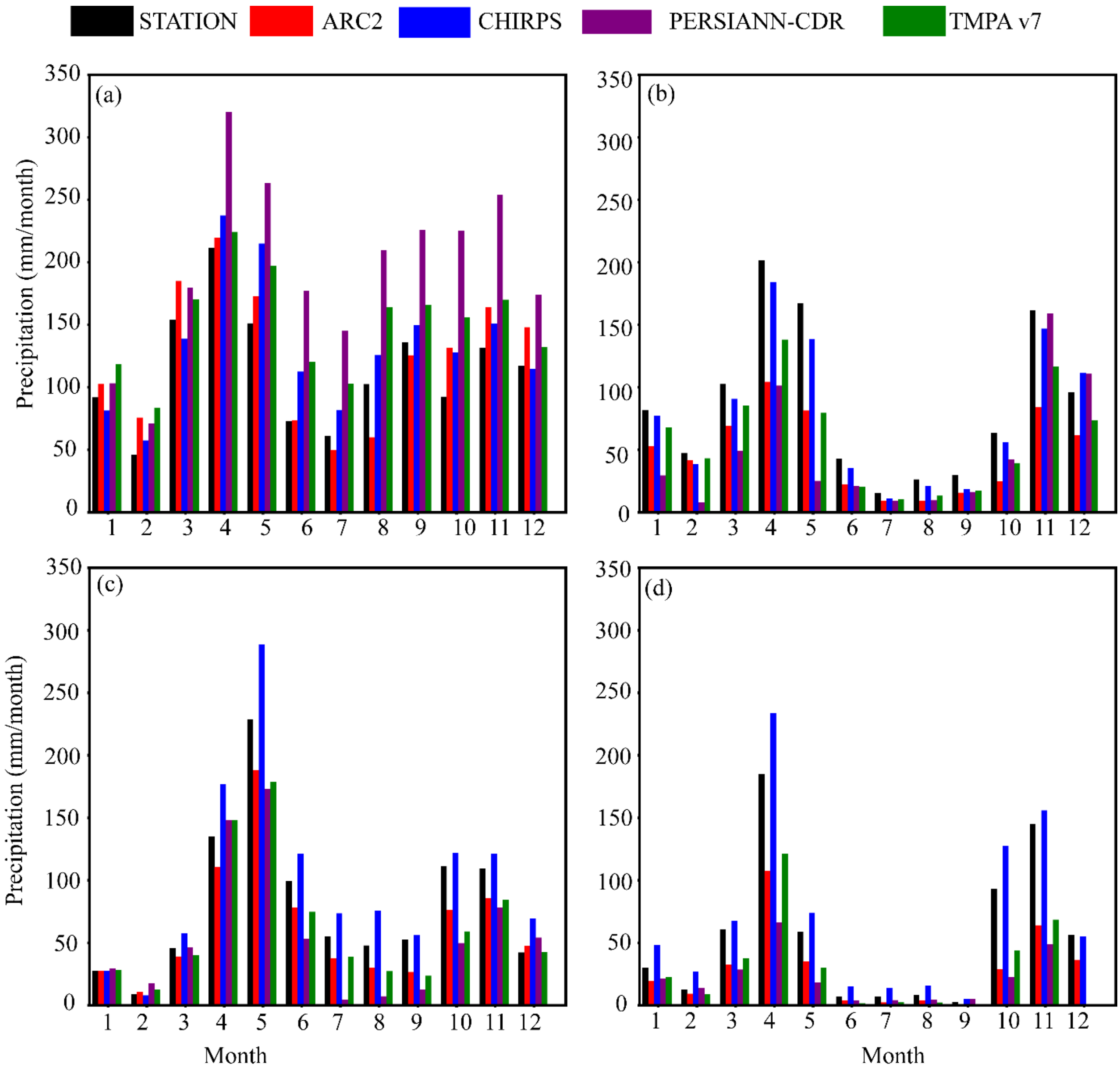

Fig. 3 The annual cycle of precipitation products during the study period over selected regions in Kenya. (a) Kisumu, (b) Dagoretti, (c) Mombasa, and (d) Marsabit. Details of these regions are provided in Table 2.

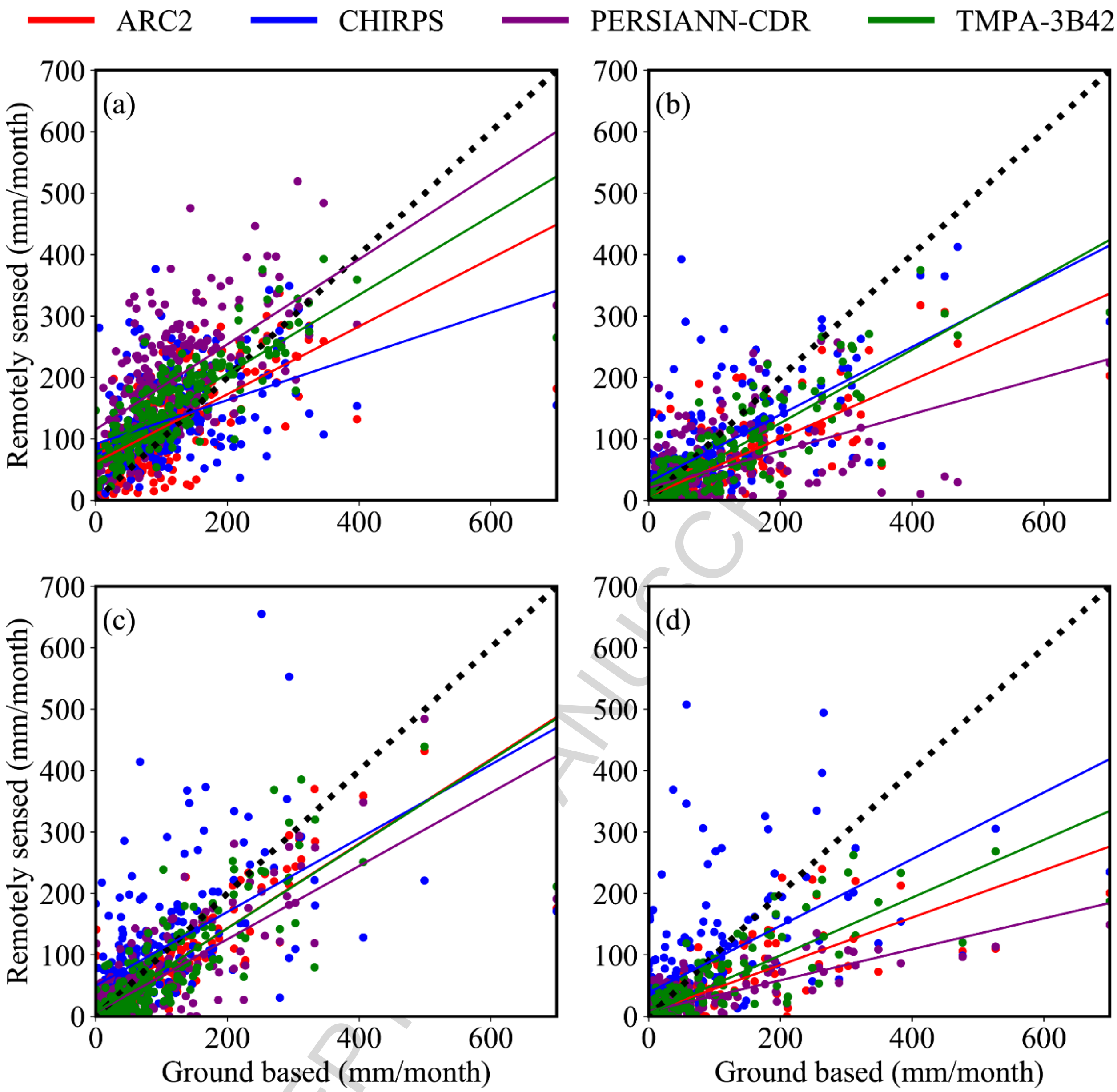

Fig. 4. Scatterplots of monthly precipitation of SPEs against ground based over (a) Kisumu, (b) Dagoretti, (c) Mombasa, and (d) Marsabit for period 1998-2016. The solid (red, blue, purple, green) and dash (black) lines in all panels represent linear regression and 1:1 lines, respectively.

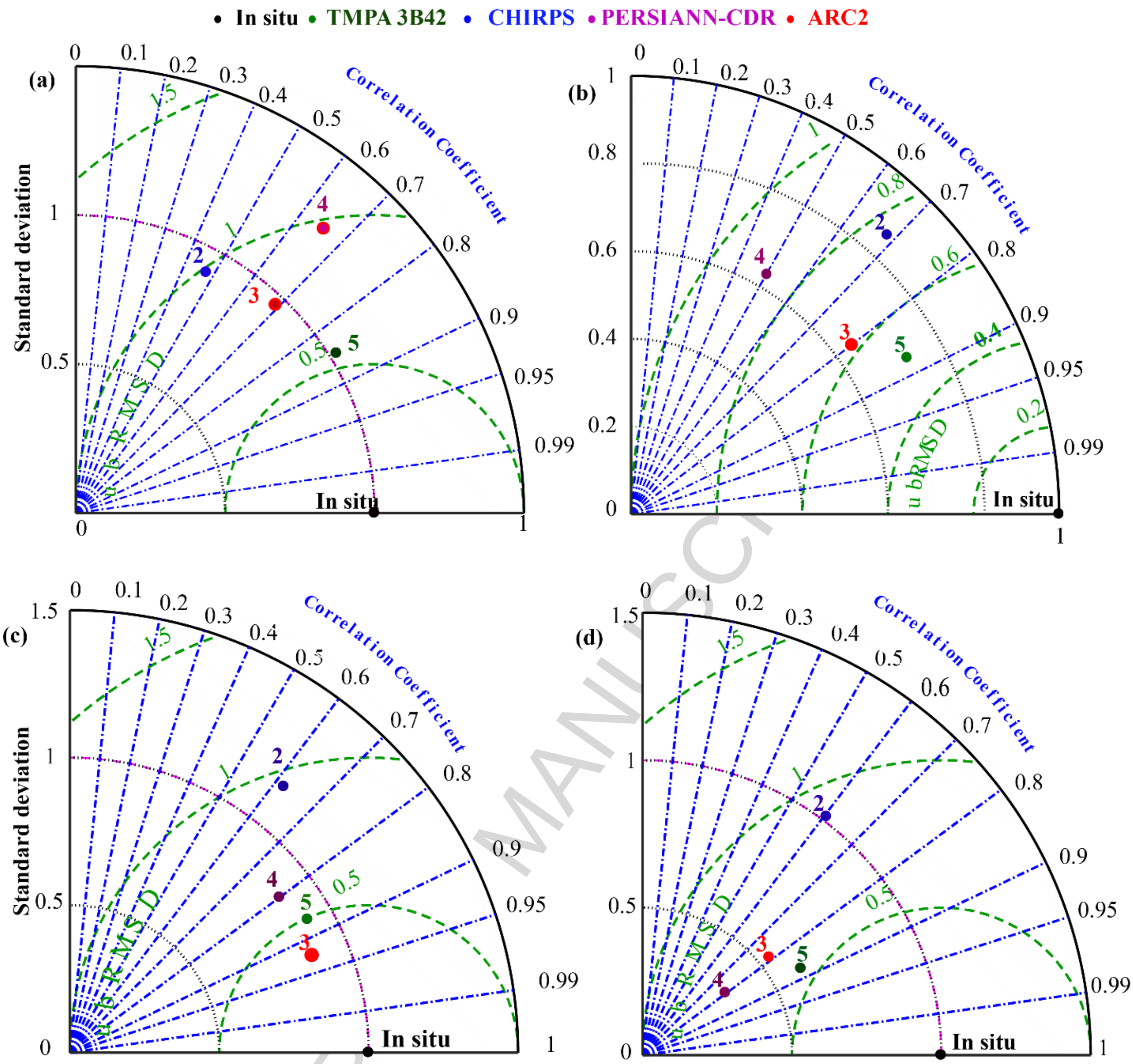

Fig. 5. Taylor diagram showing comparison of monthly statistical parameters obtained from the validation of ground based vs remotely sensed precipitation over four location in Kenya: (a) Kisumu, (b) Dagoretti, (c) Mombasa, and (d) Marsabit for period 1998-2016.

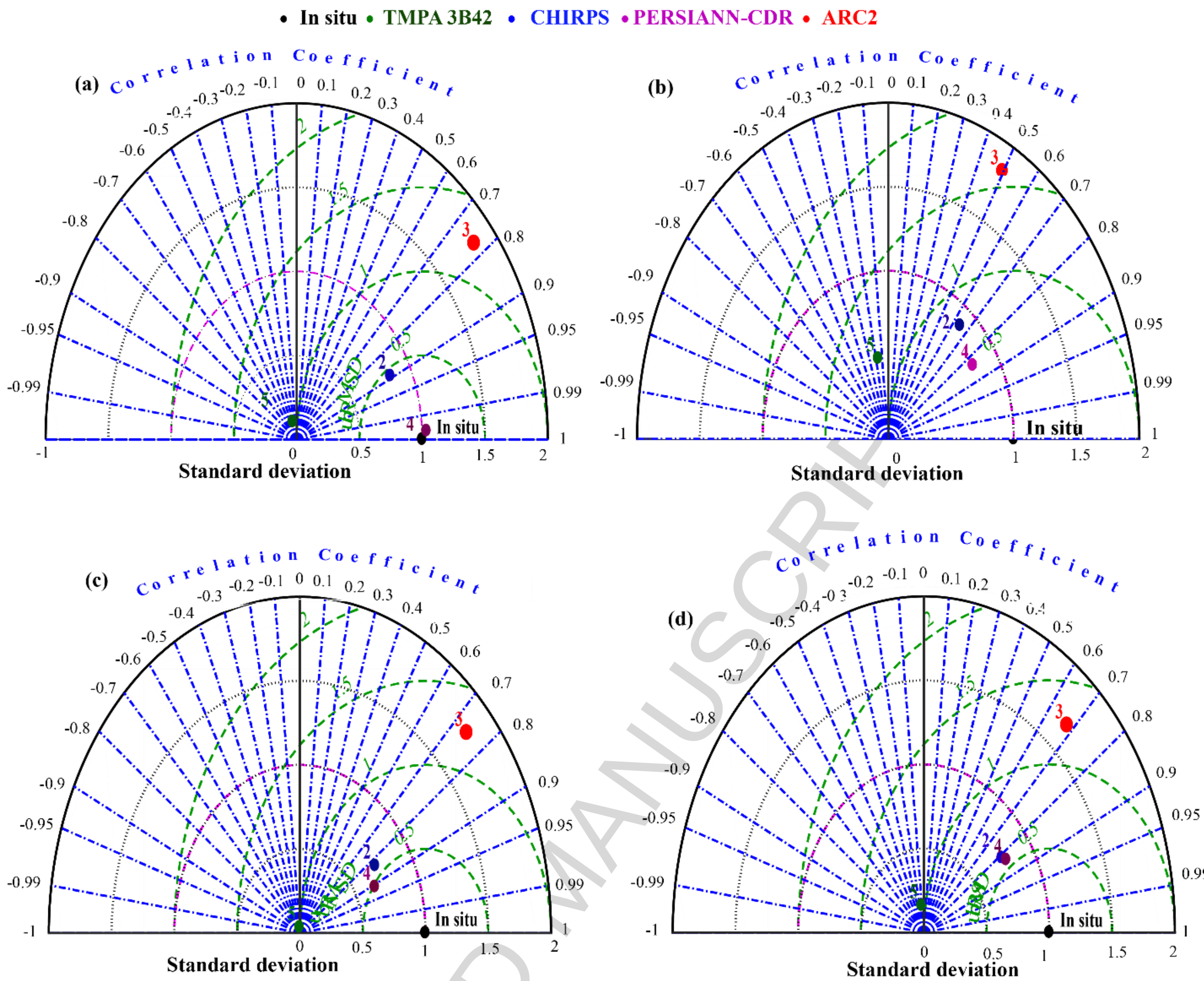

Fig. 6. Taylor diagram showing comparison of seasonal rainfall variation for lake region (a; JF, b; MAM, c; JJAS, and d; OND).

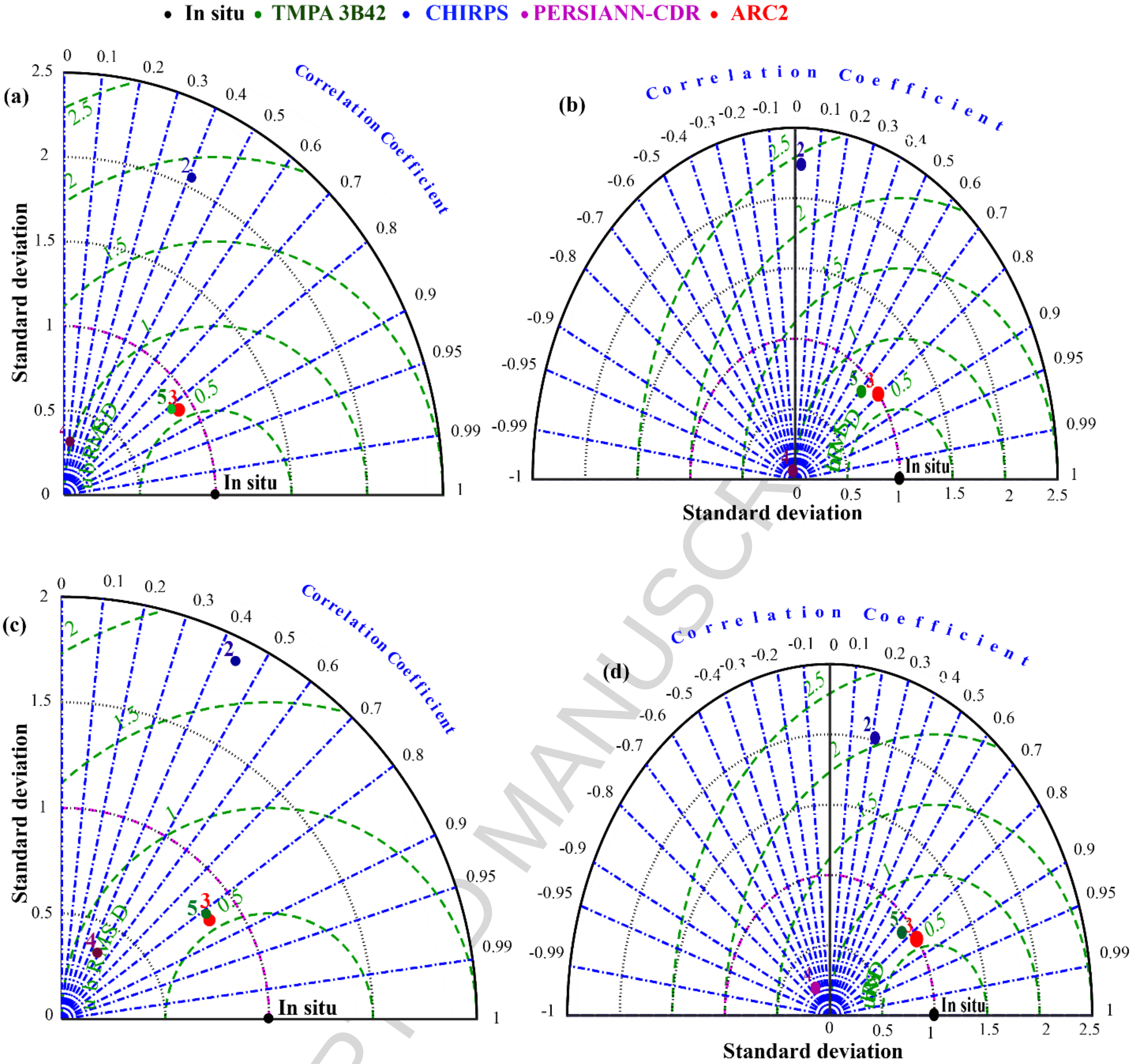

Fig. 7. Same as in Fig. 6, but for highlands region.

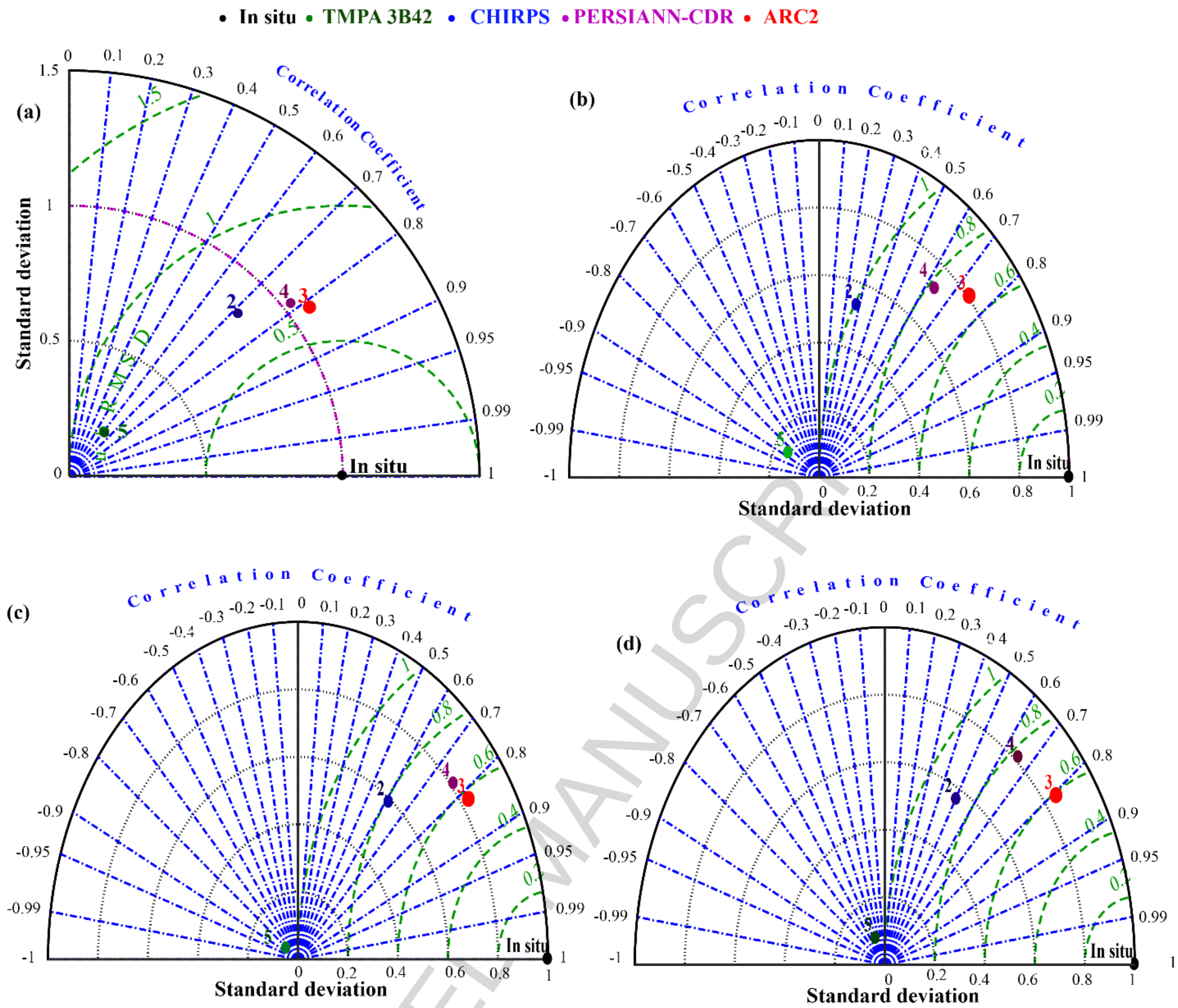

Fig. 8. Same as in Fig. 6, but for coastal region.

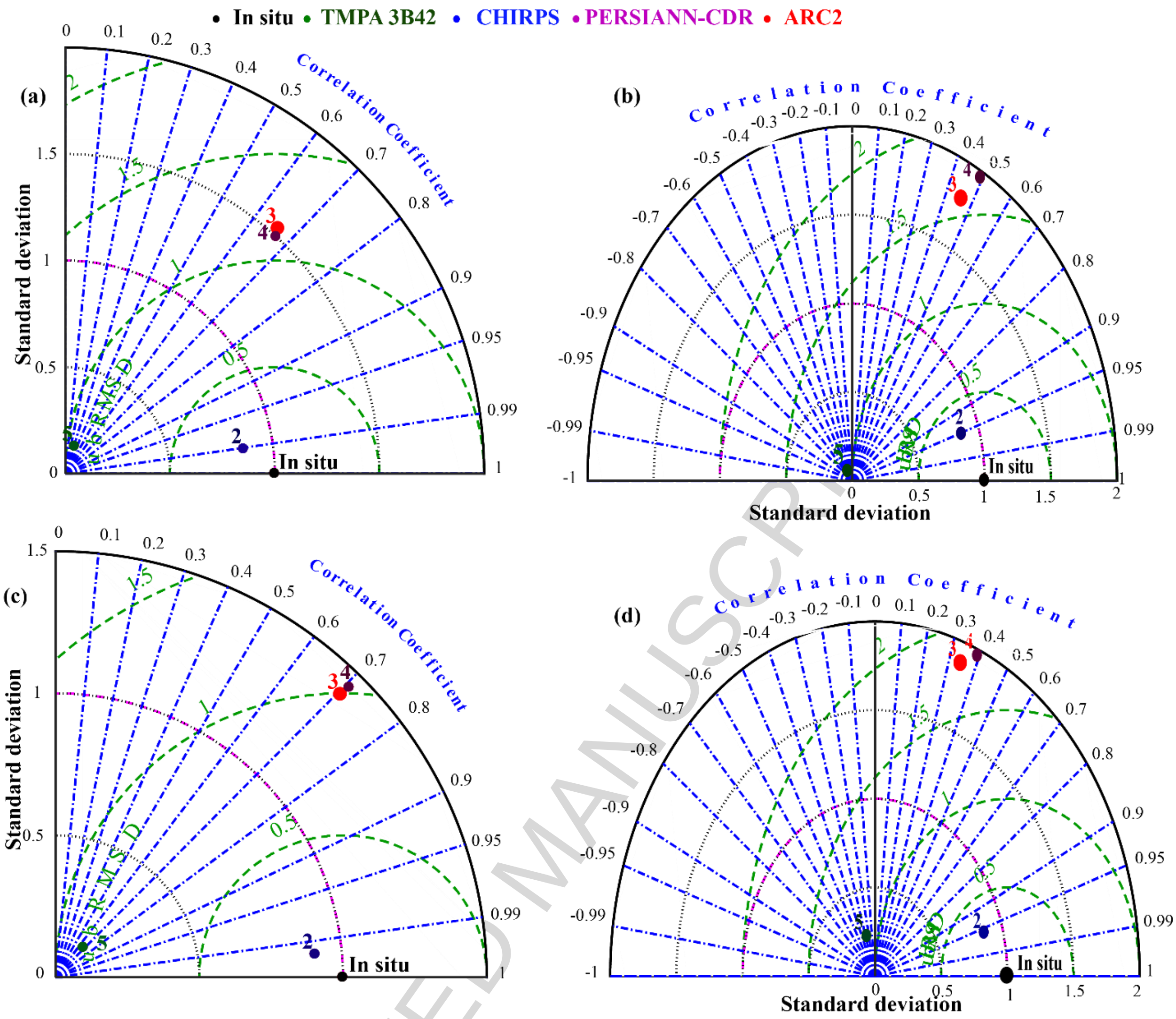

Fig. 9 Same as in Fig. 6, but for ASALs region.

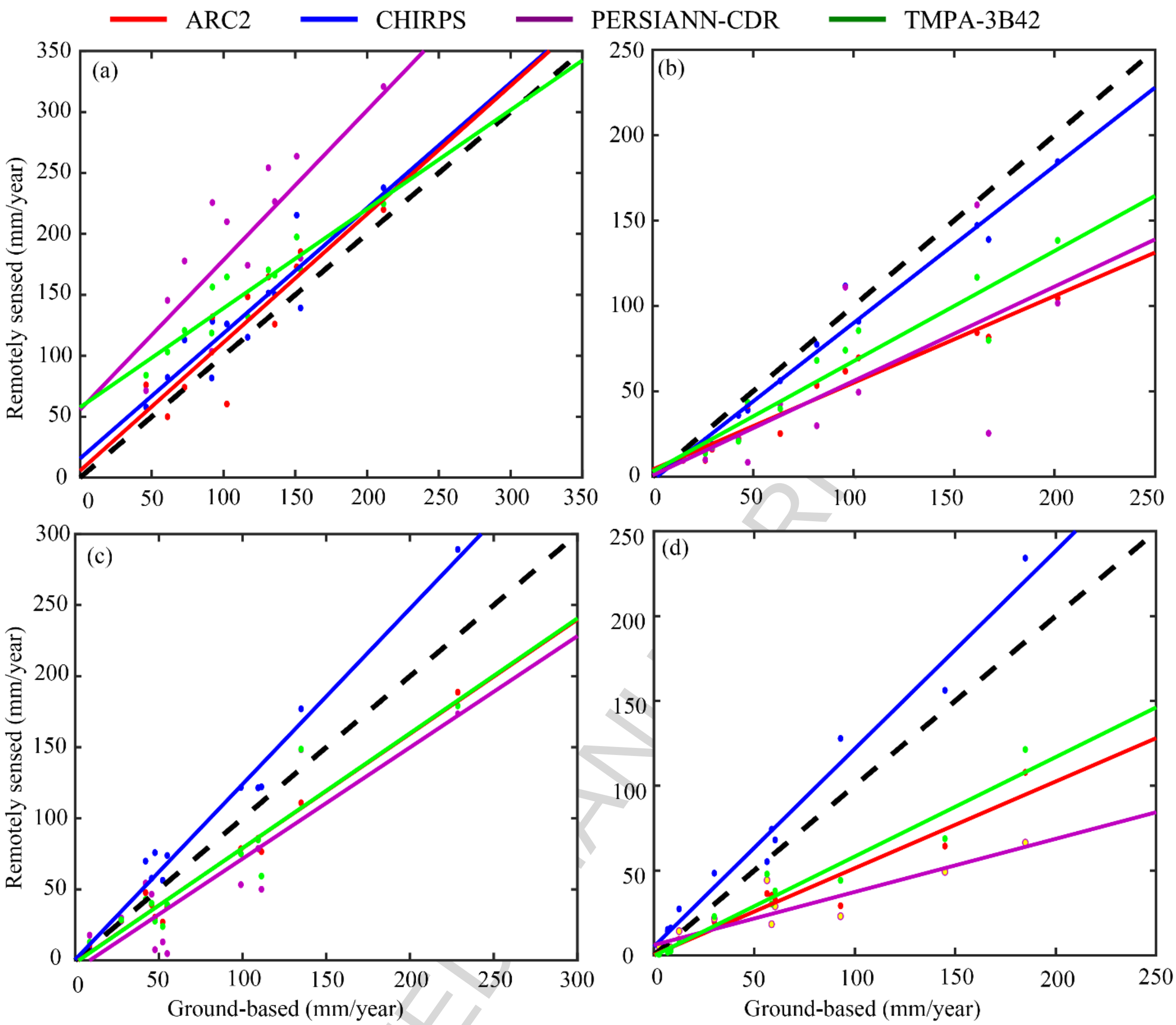

Fig. 10. Scatterplots showing comparison of annual statistical parameters obtained from the validation of ground based vs remotely sensed precipitation over four location in Kenya: (a) Kisumu, (b) Dagoretti, (c) Mombasa, and (d) Marsabit for period 1998-2016.

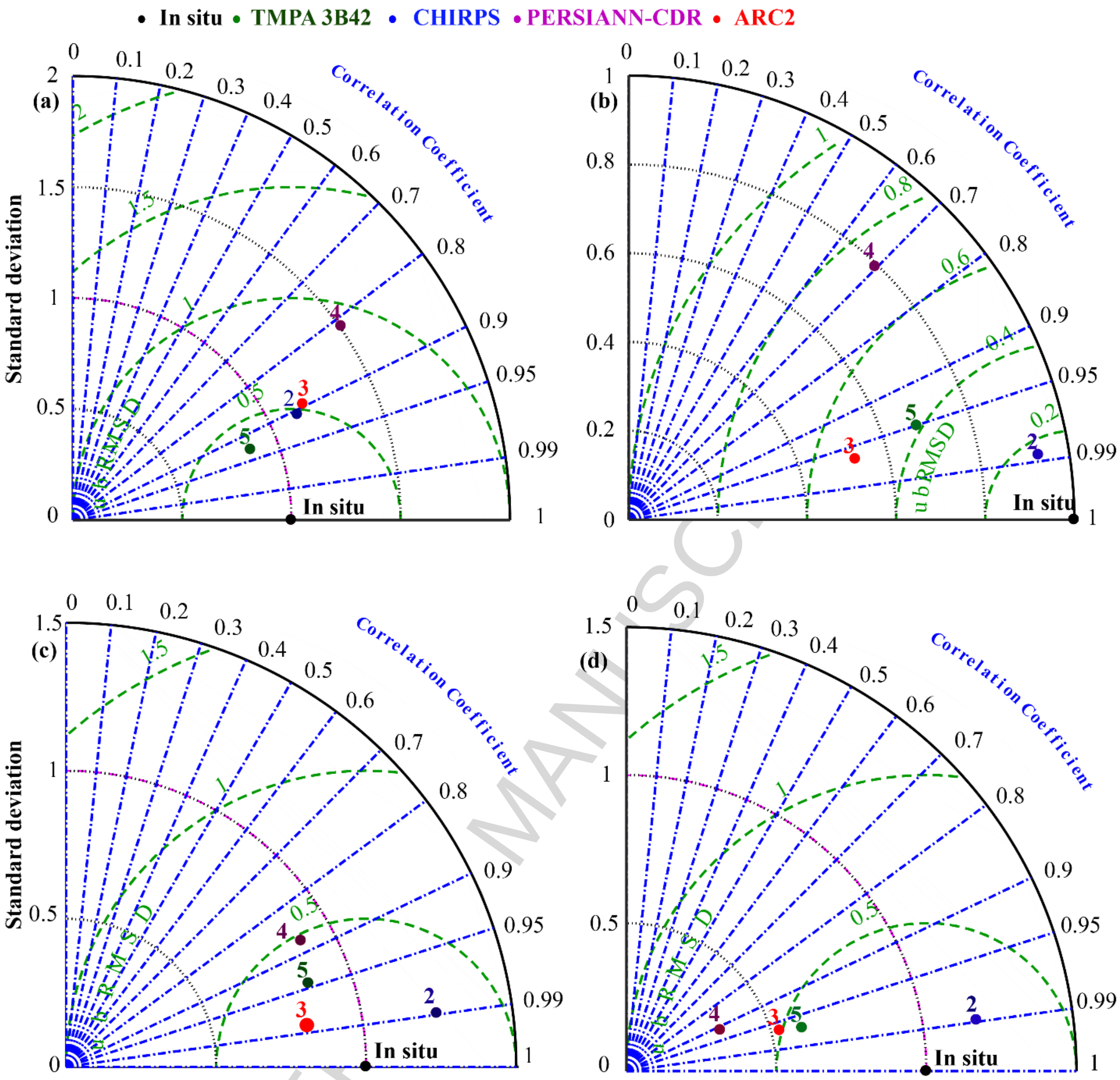

Fig. 11. Taylor diagram showing comparison of annual statistical parameters obtained from the validation of ground based vs remotely sensed precipitation over four location in Kenya: (a) Kisumu, (b) Dagoretti, (c) Mombasa, and (d) Marsabit for period 1998-2016.

Table 1. Brief description of four quasi-global daily gridded remotely sensed rainfall datasets evaluated in this study. The spatial coverage is longitude 34° E - 42° E and latitude 5° S - 5° N and temporal coverage is from 1998-2016.

Abbreviation	Full name and details	Provider	Spatial resolution	Spatial Coverage	Temporal Resolution	Temporal Coverage	Retrieval algorithms	Datasets Calibrated	Reference	Web Links
PERSIAN-CDR	Precipitation Estimation on Remotely Sensed Information using Artificial Neural Network [PERSIAN] Climate Data Record [CDR]	NOAA-NCDC	0.25°	60° S – 60° N	6hr	1983 (delayed)-present	MW,IR, RG	GPCC monthly	Ashouri et al., (2015)	http://chrs.web.uci.edu
CHIRPS V2.0	Climate Hazards Infrared Precipitation Station	NOAA-CPC	0.05°	50° S - 50° N.	24hr	1981-present	MW, IR,RG	Daily gauge	Funk et al., (2015)	http://chg.ucsb.edu/data/chirps/
ARC2	African Rainfall Climatolo	NOAA-CPC	0.1°	40° S - 40° N: 20° W -	24hr	1983-present	IR, REF2	GTS of 24-hour data	Novella N and Thiaw	https://iridl.ldeo.columbia.edu/SOURCES/.NOAA/.NCEP/.CPC/.FEWS/.Africa/.DAILY/.ARC2/

	gy Version 2			55° E					W, (2012)	
TMPA 3B42	Tropical Rainfall Measuring Mission Multi-Satellite Precipitation Analysis version 7	NASA/JAXA	0.25°	50° S - 50° N.	3hr	1998-present	MW,IR, RG	GPCC monthly	Huffman et al., (2000)	https://mirador.gsfc.nasa.gov/

Notes: RG, rain gauges (used for biased correction); MW, Microwave imager; IR, Infrared; REF2, Rainfall Estimation version 2.

Table 2. Description of the regions selected for satellite and in situ data comparison

Region	Station	Longitude	Latitude	Elevation(m)	Climatic zone
1	Kisumu	34.58	-0.1	1208	Humid
2	Dagoretti	36.75	-1.3	1798	Moderate warm
3	Mombasa	39.62	-4.03	55	Fully Humid
4	Marsabit	37.98	2.32	1345	Arid and Semi-arid

Table 3. Monthly statistical parameters obtained from the validation of ground based vs remotely sensed precipitation over four locations in Kenya.

Station (Zones)	Model Name	Slope	RMSE	R	STDE	Bias
Kisumu(1)	Chirps	0.12	78.03	0.48	1.08	-19.85
	ARC2	0.30	60.53	0.69	1.03	-12.73
	Persiann-cdr	0.29	110.79	0.65	0.79	-82.13
	TMPA	0.44	57.18	0.83	1.09	-38.49
Dagoretti(2)	Chirps	0.59	70.23	0.68	1.14	8.29
	ARC2	0.52	68.68	0.80	1.15	37.72
	Persiann-cdr	0.32	90.54	0.50	1.15	39.46
	TMPA	0.64	53.88	0.87	1.13	26.99
Mombasa (3)	Chirps	0.71	80.92	0.62	0.86	-18.93
	ARC2	0.81	36.13	0.92	1.14	17.66
	Persiann-cdr	0.69	56.78	0.80	1.15	25.42
	TMPA	0.79	44.83	0.86	1.03	17.63
Marsabit (4)	Chirps	0.61	80.22	0.60	0.98	-14.46
	ARC2	0.42	64.42	0.78	1.85	26.83
	Persiann-cdr	0.27	74.92	0.79	2.90	32.42
	TMPA	0.53	54.15	0.87	1.64	23.47

Seasons	Regions	CHIRPS			ARC2			PERSIANN-CDR			TMPA		
		CC	RMSE	BIAS	CC	RMSE	BIAS	CC	RMSE	BIAS	CC	RMSE	BIAS
JF	Lake	0.89	28.03	48.2	0.77	82.51	-42.13	0.98	20.78	14.27	-0.28	104.56	102.91
	Highlands	0.41	115.63	13.64	0.84	35.44	26.87	0.13	148.47	13.69	0.82	35.64	42.18
	Coastal	0.72	76.22	72.77	0.82	70.52	49.25	0.79	79.52	67.07	0.64	111.18	6.64
	ASALs	0.98	15	21.59	0.66	92.78	-21.33	0.67	89.09	-16.38	0.32	138.54	9.65
MAM	Lake	0.69	33.2	126.5	0.5	71.64	52.79	0.84	52.46	128.8	-0.16	77.66	208.68
	Highlands	0.03	110.1	203.33	0.8	62.68	-10.91	-0.27	170.47	60.25	0.72	56.6	33.81
	Coastal	0.28	86.85	198.98	0.75	62.36	62.29	0.64	69.17	98.84	-0.86	149.68	129.26
	ASALs	0.95	18.36	37.91	0.46	100.92	-16.26	0.49	110.69	-52.25	-0.54	138.09	65.74
JJAS	Lake	0.83	34.44	91.82	0.74	72.23	-74.82	0.91	62.15	0.66	-0.08	87.42	139.36
	Highlands	0.44	115.52	4.95	0.84	41.27	19.64	0.49	114.57	13.84	0.82	40.43	29.97
	Coastal	0.62	80.4	111.2	0.82	60.53	30.67	0.77	72.16	27.88	-0.82	165.25	37.72
	ASALs	0.98	10.62	8.92	0.71	83.98	-22.69	0.71	84.71	-21.48	0.68	134.2	-1.54
OND	Lake	0.81	31.5	90.33	0.68	74.91	7.18	0.83	76.16	145.03	-0.11	84.16	155.73
	Highlands	0.22	104.53	102.66	0.84	46.69	-5.61	-0.57	113.84	114.37	0.76	38.97	37.87
	Coastal	0.5	81.98	131.65	0.81	57.95	41.48	0.66	75.92	64.07	-042	159.23	64.19

	0.96	17.61				0.39	115.07	-	-0.26	145.49
ASALs	27.44		0.35	115.96	9.81	9.53			65.17	

Table 4. Seasonal statistical parameters obtained from the evaluation of in situ against SPEs over four locations in Kenya during 1998-2016. Notes: CC, Correlation Coefficient; RMSE, Root Mean Square Error.

Table 5. Annual statistical parameters obtained from the validation of ground based vs remotely sensed precipitation over four locations in Kenya.

Station (Zones)	Model Name	Slope	RMSE	R	STDE	Bias
Kisumu(1)	Chirps	1.02	28.20	0.91	0.88	-18.75
	ARC2	1.05	25.95	0.89	0.85	-11.63
	Persiann-cdr	1.22	90.89	0.81	0.66	-81.66
	TMPA	0.81	39.83	0.93	1.14	-36.35
Dagoretti(2)	Chirps	0.92	13.26	0.98	1.07	8.92
	ARC2	0.51	48.72	0.96	1.89	36.36
	Persiann-cdr	0.55	57.09	0.69	1.25	37.93
	TMPA	0.64	36.78	0.95	1.47	27.62
Mombasa (3)	Chirps	0.51	25.93	0.98	0.80	-19.42
	ARC2	0.81	22.07	0.98	1.22	17.17
	Persiann-cdr	0.78	36.71	0.87	1.12	24.17
	TMPA	0.81	26.14	0.94	1.16	17.13
Marsabit (4)	Chirps	1.17	19.77	0.98	0.84	-14.36
	ARC2	0.51	39.37	0.96	1.88	26.94
	Persiann-cdr	0.31	51.03	0.91	2.91	32.15
	TMPA	0.53	34.09	0.97	1.65	23.37

HIGHLIGHTS

- Four Satellites derived Precipitation Estimates (SPE): TMPA V7 3B42, PERSIANN-CDR, CHIRPS, and ARC2, are assessed over four homogeneous zones in Kenya.
- Variations of SPE products are based on complex geomorphology of different climatic zones.
- All SPE products depict bimodal pattern of climatology with west-east gradient representing heavier to lighter precipitation events
- Most SPE products unsatisfactorily capture light precipitation of values >2.5 mm/day but the improvement increases with increase in precipitation across diverse topography
- Monthly analyses reveals good statistical agreement with reference datasets by TMPA, ARC2, and CHIRPS despite underestimation of precipitation in most regions.