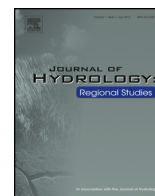




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A multi-scale analysis of Namibian rainfall over the recent decade – comparing TMPA satellite estimates and ground observations

Xuefei Lu^a, Lixin Wang^{a,*}, Ming Pan^{b,c}, Kudzai F. Kaseke^a, Bonan Li^a^a Department of Earth Sciences, Indiana University-Purdue University Indianapolis (IUPUI), Indianapolis, IN 46202, USA^b Department of Civil and Environmental Engineering, Princeton University, Princeton, NJ 08544, USA^c State Key Laboratory of Hydraulics and Mountain River Engineering, Sichuan University, Chengdu, China

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ABSTRACT

Study region: Namibia.

Study focus: The lack of ground observations has long been a major obstacle in studying rainfall patterns in many dryland regions, particularly in the data scarce African continent. In this study, a continuous 6-year (2008–2013) daily record of ground observations collected from Weltevrede Farm at the edge of the Namib Desert was used to evaluate TRMM Multi-satellite Precipitation Analysis (TMPA, 0.25° resolution) daily rainfall estimates of this area. A Mann-Kendall trend analysis was conducted using all the available annual TMPA satellite data (1998–2015) to examine long-term trends in rainfall amount, intensity, frequency and seasonal variations over four locations across a rainfall gradient.

New hydrological insights for the region: The agreement between ground and satellite rainfall data was generally good at annual/monthly scales but large variations were observed at the daily scale. Results showed a spatial variability of rainfall trends across the rainfall gradient. We observed significant changes in frequency along with insignificant changes in intensity and no changes in total amount for the driest location, but no changes in any of the rainfall parameters were observed for the three wetter locations. The results also showed increased rainfall variability for the driest location. This study provided a useful approach of using TMPA data associated with trend analysis to extend the data record for ecohydrological studies for similar data scarce conditions. The results of this study will also help constrain IPCC predictions in this region.

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1. Introduction

Rainfall is one of the main components of hydrologic cycle and the major source of water for natural vegetation as well as agriculture and livestock production in dryland regions (Wang and D'Odorico, 2008). About 90% of the world's dryland population is in developing countries (Wang et al., 2012), where the vast majority of drylands consist of rangelands (Millennium Ecosystem Assessment, 2005) (i.e., 69%). Dryland rangelands support approximately 50% of the world's livestock and its production is particularly vulnerable to climate variability, of which rainfall is the most important component (Millennium Ecosystem Assessment, 2005). African rangelands are of critical importance since they cover 43% of Africa's inhabited surface

* Corresponding author.

E-mail address: lxwang@iupui.edu (L. Wang).

and are home to 40% of the continent's population (AU-IBAR, 2012). Though the proportion of rainfed cropland is not as significant as rangeland, rainfed agriculture is most prominent in some regions of Africa such as Sub-Saharan Africa where more than 95% of the cropland is rainfed (Rockström et al., 2010). Changes in rainfall amount, intensity and rain patterns could significantly affect dryland agriculture leading to decreased resource productivity and production (Daryanto et al., 2016). Erratic rainfall patterns in Nigeria, for example, made it difficult for farmers to plan their operations and resulted in low germination in cropping season, reduced yield and crop failure (Oriola, 2009). Study of maize production in Zimbabwe also indicated that more accurate climate predictions would be valuable in crop management decisions in that it reduced risk in agricultural production associated with rainfall variability at the site level (Phillips et al., 1998).

However, most areas of Africa lack sufficient observational data to study long-term rainfall trend and variability. Apart from the scarcity of data, an additional complication is that, in many regions of Africa, discrepancies exist between different observed rainfall data sets (Barros, 2014). Intergovernmental Panel on Climate Change (IPCC) has predicted a likely decrease in annual rainfall over parts of the western and eastern Sahel region in northern Africa as well as a likely increase over parts of eastern and southern Africa during the period of 1951–2010 (Barros, 2014). Particularly, a reduction in late austral summer rainfall has been observed and projected over western parts of southern Africa extending from Namibia, through Angola, and towards Congo during the second half of the 20th century (Barros, 2014). As shown in the IPCC AR5, signal of future change in precipitation is not obvious (less agreement) until the middle of the 21st century over southern Africa. IPCC prediction using General Circulation Models (GCMs) is run at a coarse spatial resolution of 150–300 km while the rainfall process has a much higher spatial variability, and thus high-resolution data is needed for better prediction. IPCC prediction has great uncertainty and ground data is therefore very important to constrain the model prediction for the future.

Rain gauges have historically been considered the most accurate form of local rainfall measurement (Villarini et al., 2009). However, they can only capture the variability of small areas and therefore in many cases, precipitation estimates from rain gauges are subject to uncertainty when representing the entire observation site. Errors and omissions or power outages from the recording devices, human operators, and data transmission could also cause valuable data to be lost, damaged, or altered and result in poor data quality (Kneis et al., 2014). In many regions of the world, rain gauge data is difficult to access due to technical or administrative reasons (Kneis et al., 2014). Particularly in many remote parts of developing countries, ground-based rainfall measurements are rare or nonexistent. Radar and satellite-based rainfall estimates have been shown to provide a potential solution to the limitations of rain gauge data (Ward and Trimble, 2003). But satellites do not measure rainfall directly, so combining of ground observations with radar and satellite remote sensing of rainfall estimates (e.g., using ground observations to correct satellite data bias) could be a viable approach to produce a consistent, long sequence of climate data records (Villarini et al., 2009).

Although previous studies have documented some characteristics of Namibia rainfall (Eckardt et al., 2013), rarely have they looked at how well satellite-based rainfall data is correlated with ground-based observations. More importantly, no attempt has been made to comprehensively analyze the long-term changes in rainfall in Namibia, where the rainfall is highly variable both spatially and temporally with the greatest rainfall variation coefficient over Southern Africa (Eckardt et al., 2013). A normal rainy season spans from October to April (Foissner et al., 2002), and October, as the transition month from dry season to wet season, is characterized by very high inter-annual rainfall variability (Eckardt et al., 2013). There hasn't been a rainfall observation site from the Namibia Meteorological Services at the edge of the Namib Desert, so the ground rainfall measurements from this region are very valuable. Moreover rainfall in this region could be highly localized with large inter- and intra- annual variation as the area is located right on the steep rainfall gradient from the desert interior to the Namibian highland (Eckardt et al., 2013; Kaseke et al., 2016). As a result of strong the NE-SW rainfall gradient across, Southern Africa rainfall events mainly occur in the north-eastern, northern and central parts, and the southern parts of Namibia are largely hot and dry having only isolated rainfall occurrences, and ultimately the west Namib coast is hyper-arid (Eckardt et al., 2013). Therefore, another focus of this study is to evaluate the rainfall pattern changes at different locations along the rainfall gradient; and for each location, the detailed rainfall trend analyses will be conducted (e.g., total rainfall trend, rainy season rainfall trend, the average rainfall depth per storm, and the average storm frequency).

In this study, we compared the TRMM Multi-satellite Precipitation Analysis (TMPA) satellite data with available ground observations from the local rain gauges. The TMPA satellite estimates were then used to resolve the spatial and temporal distributions of rainfall over the study area. TMPA satellite is a US-Japan joint mission launched in November 1997 (Simpson et al., 1988), and its primary goal is to measure precipitation in the Tropics where surface observations are scarce (Bowman, 2005). It operates in a low-inclination (35°), low-altitude orbit (Bowman, 2005), and the primary merged microwave-infrared product is computed at finer scale with the 3-h, $0.25^\circ \times 0.25^\circ$ latitude–longitude resolution (Huffman et al., 2007). In this study, we aim to address the following questions: 1) are satellite based rainfall data useful to study the rainfall characteristics at regions with the lack of ground observations traditionally? 2) if so, what are the temporal scales at which the satellite rainfall data are comparable with ground observations? and 3) are there any significant long-term changes in rainfall characteristics over multiple locations in Namibia across a rainfall gradient?

2. Methods

To examine the spatial variations and assess the long-term rainfall trends as well as long-term rainfall variability, we analyzed TMPA rainfall estimates from four locations across a rainfall gradient (Fig. 1). The four locations are Farm 1 and Farm 2 within the Weltevrede Guest farm, the Gobabeb Research and Training Center (GRTC, TMPA pixel centered at 23.625°S ,

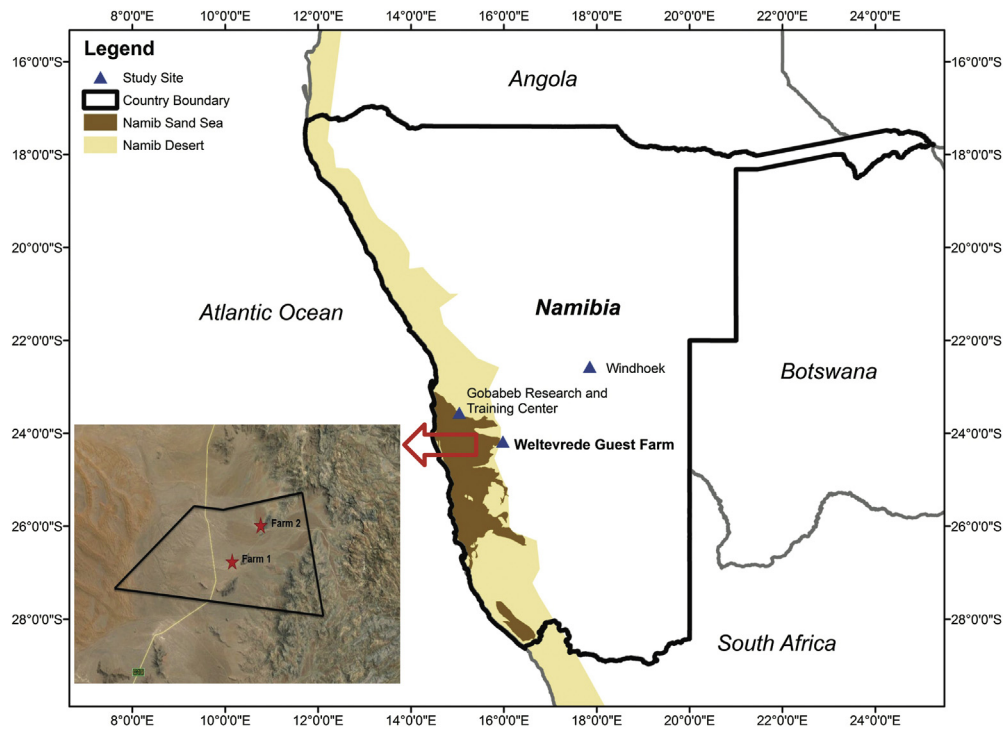


Fig. 1. Locations of the Weltevrede Farm (Farm 1 and Farm 2), Gobabeb Research and Training Center (GRTC), Windhoek (WDH) and the surface rain gauges. Black lines indicate the boundary of the Weltevrede Farm. The map was generated using ArcGIS for Desktop 10.3.1 (<http://www.arcgis.com>).

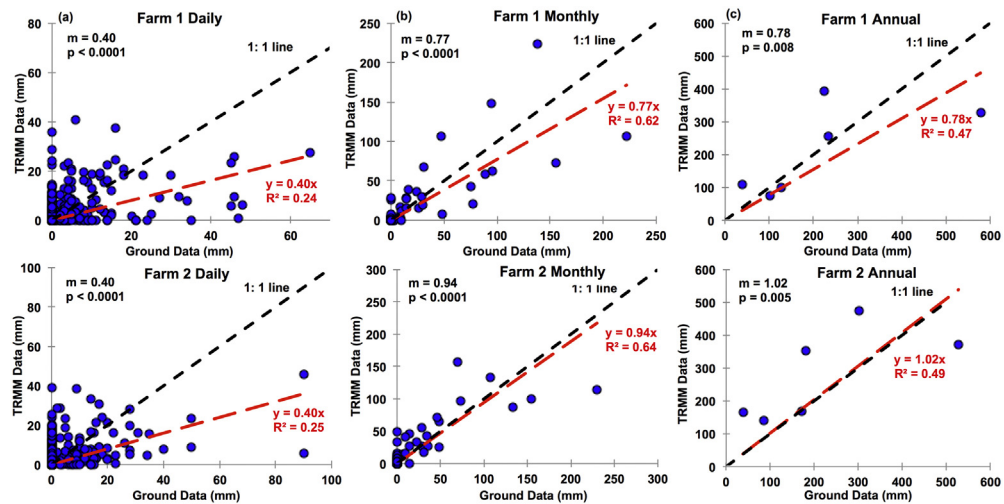


Fig. 2. Data validation of Tropical Rainfall Measuring Mission Multi-satellite Precipitation Analysis (TMPA) data set. Scatter plots of daily (a) (n=2192), monthly (b) (n=72), and annual (c) (n=6) rainfall from TMPA and gauged estimates at Farm 1 (Top Panel) and Farm 2 (Bottom Panel) for the period of January 1, 2008 to December 31, 2013. m is the slope coefficient.

15.125°E) located within hyper-arid Namib Desert (long-term annual average rainfall <60 mm) (NMS, 2015), and Windhoek (WDH, TMPA pixel centered at 22.625°, 17.125°E) that is subject to a long-term annual average rainfall up to 400 mm (NMS, 2015). The time period covered is January 1, 1998 to December 31, 2015 (17 years) and TRMM mission ended in April 2016.

In the Weltevrede Guest Farm site, we have ground rainfall records at two locations for validation of TMPA data. The Weltevrede Guest Farm is located in the escarpment of the southern Namib Desert, and is characterized by semi-desert and savanna transition in biomes (Foissner et al., 2002). The farm is next to the road C19, around 300 kilometers southwest of Windhoek, and bordered on three sides by the Namib Naukluft Park (24°10'S, 15°58'E, Elev. 1087 m) (Fig. 1). It is nestled amidst rugged mountains, shifting dunes, harsh gravel plains, dusty prehistoric riverbeds and camelthorn trees. The farm covers an area of about 11.6 km² and there are two local rain gauges situated at Farm House (Farm 1) and Brine Tank (Farm

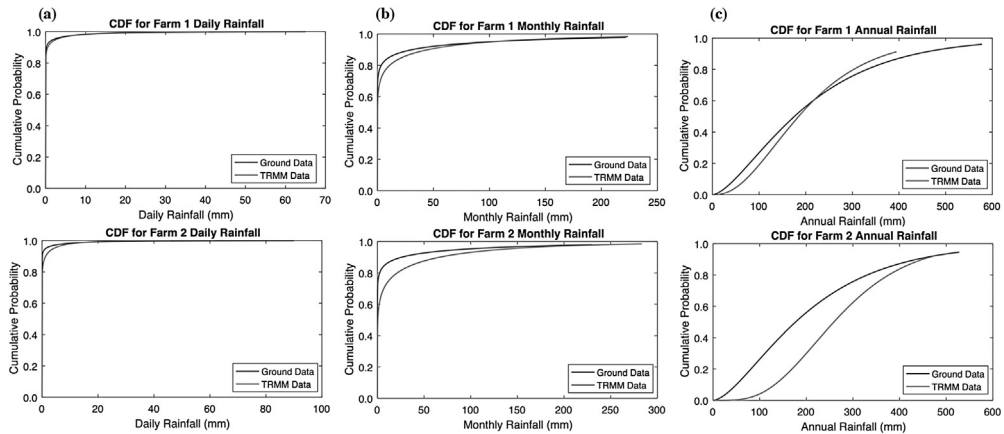


Fig. 3. Cumulative distribution functions (CDFs) of daily (a), monthly (b), and annual (c) rainfall from Tropical Rainfall Measuring Mission Multi-satellite Precipitation Analysis (TMPA) and gauged estimates at Farm 1 (Top Panel) and Farm 2 (Bottom Panel) for the period of January 1, 2008 to December 31, 2013.

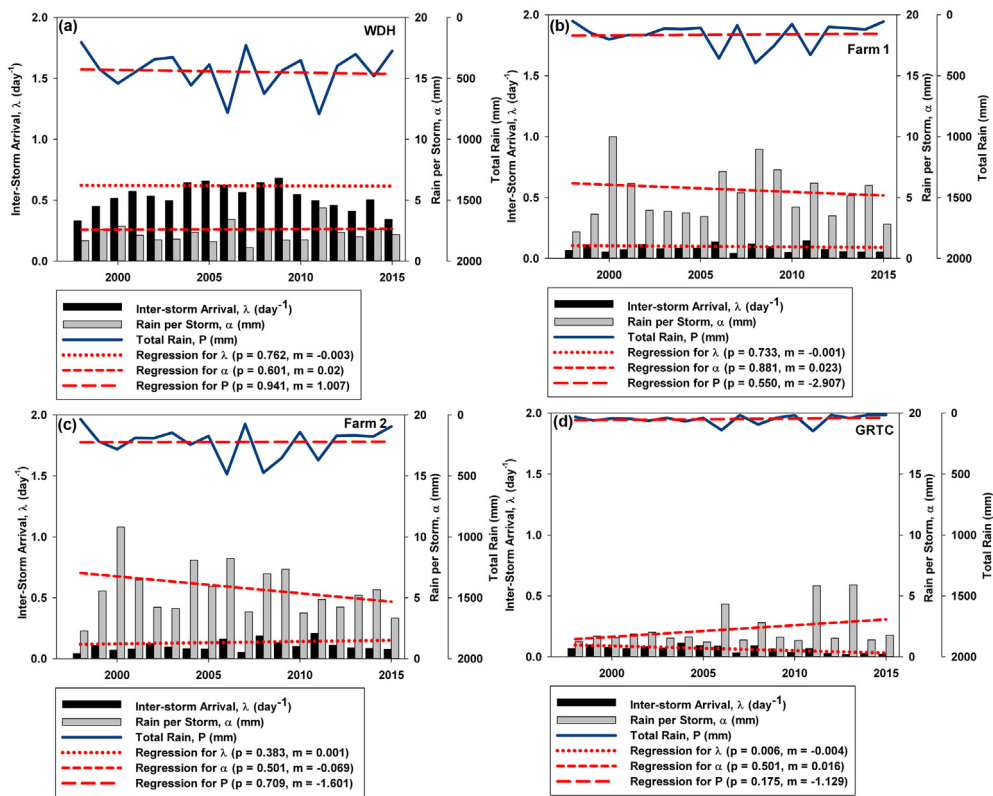


Fig. 4. Time series of annual rainfall (mm), average rain depth per storm (mm) α , and the average storm arrival rate (day^{-1}) λ for (a) Windhoek (WDH), (b) Weltevrede Farm Location 1 (Farm 1), (c) Weltevrede Farm Location 2 (Farm 2), and (d) Gobabeb Research and Training Center (GRTC). Record length = 17 years, and m = Sen's slope.

2), respectively (Fig. 1). Most of the rain falls in summer, and only very rare rainfall occurs through the winter. The two rain gauges within the Weltevrede Guest Farm are the only two sites with available ground record to validate the TMPA data. A major limitation is that although the ground observations collected from the Weltevrede Farm are likely very reliable since local farmers tend to take rainfall measurements faithfully, we have to assume they are the “correct” values. A similar approach has been used in other data scarce regions, such as the central Kenyan highlands (Franz et al., 2010).

This study uses version 7 of the TMPA 3B42 data product, which is composed of instantaneous precipitation retrievals from the Precipitation Radar (PR) and TRMM Microwave Imager (TMI), and a combined algorithm (referred to as COMB) that have been area averaged onto a $0.25^\circ \times 0.25^\circ$ grid (~ 25 km) at the finest scale of 3-h interval (Huffman et al., 2007). The

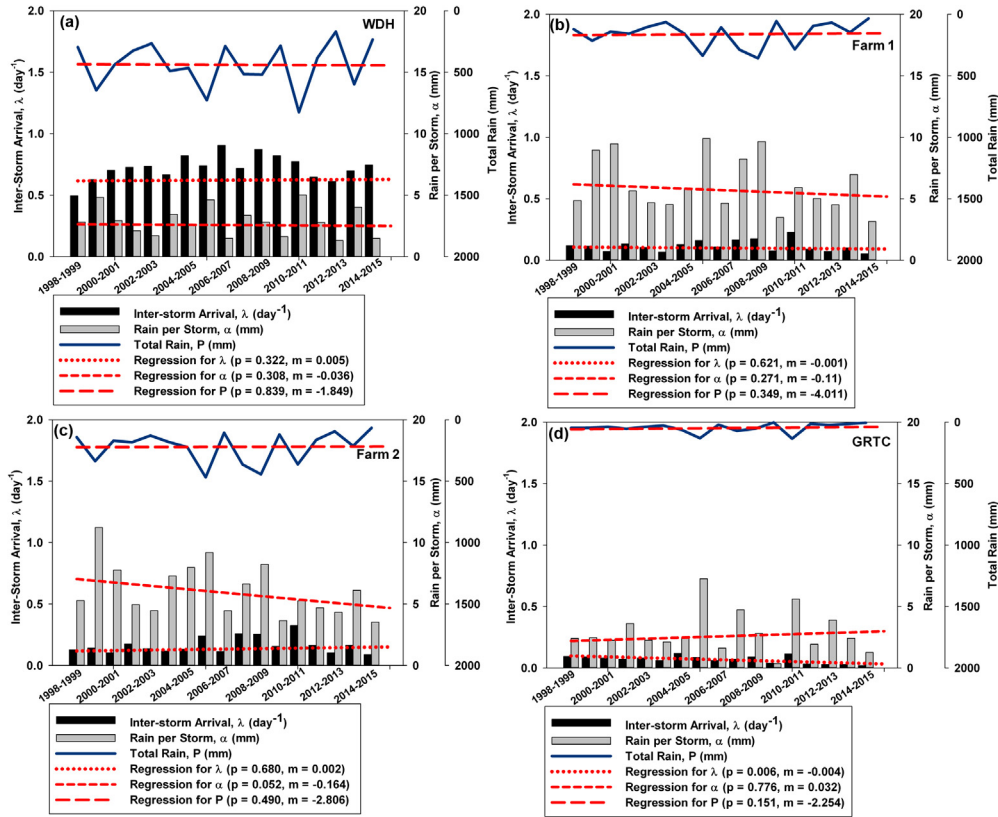


Fig. 5. Time series of seasonal precipitation (mm), the average rain depth per storm (mm) α , and the average storm frequency (day^{-1}) λ for (a) Windhoek (WDH), (b) Weltevrede Farm Location 1 (Farm 1), (c) Weltevrede Farm Location 2 (Farm 2), and (d) Gobabeb Research and Training Center (GRTC). Rainy season is from October to April, record length = 17 years, and m = Sen’s slope.

raw TMPA data was averaged into daily time-scale to match the ground record. For the Weltevrede Guest Farm, Farm 1 is located within the TMPA pixel centered at 24.125°S and 15.875°E; and Farm 2 is within the immediate next pixel (24.125°S, 16.125°E). The quality of TMPA rainfall estimates was evaluated by comparing 6-year daily, monthly and annual data with ground observations from rain gauges at Farm 1 and Farm 2 shown in Fig. 1. Furthermore, the cumulative distribution functions (CDFs) of TMPA rainfall data and ground observations were compared.

Trend analyses were analyzed using non-parametric rank based statistical test, namely Mann-Kendall (MK) test to detect monotonic trends. The MK test has been widely used to assess the significance of trends in hydro-metrological time series including rainfall. Based on the null distribution of the MK test, the critical regions of the MK statistic S can be approximately given by

$$|S| > z_{1-\beta/2} \sqrt{V(S)}, \tag{1}$$

where β is the preselected significance level, $z_{1-\beta/2}$ are the $1 - \beta/2$ quantiles of the standard normal distribution, and $V(S)$ is the sample variance of the MK statistic S . In this study, the significance level is set to be 0.05. In this study, besides the total rainfall amount, we also analyzed the temporal trends of two important hydrological parameters decomposed from the total rainfall: the average rainfall depth per storm, α (mm), and the average storm frequency or average inter-storm arrival rate, λ (day^{-1}) using the Mann-Kendall statistical test (Franz et al., 2010).

Three measures of the rainfall variability in annual rainfall were analyzed including the standard deviation, the coefficient of variation (CV), and precipitation variability index (PVI). PVI is a new dimensionless index defined as the standard deviation of the ratio (R_i) between a time series of cumulative precipitation measurement (C_i) and a time series of cumulative mean precipitation rate (E_i) (Gu et al., 2016) (Eq. (2)). From the measured daily precipitation p_j , a time series of cumulative rainfall C_i (Eq. (4)) and mean precipitation rate \bar{p} (Eq. (5)) were computed. The time series of cumulative mean E_i then were computed based on mean precipitation rate \bar{p} (Eq. (6)), and R_i is the ratio of the cumulative precipitation to the cumulative mean (Eq. (3)). \bar{R} is the average of R_i over n . Study shows that PVI can simultaneously capture the characteristics of both intensity

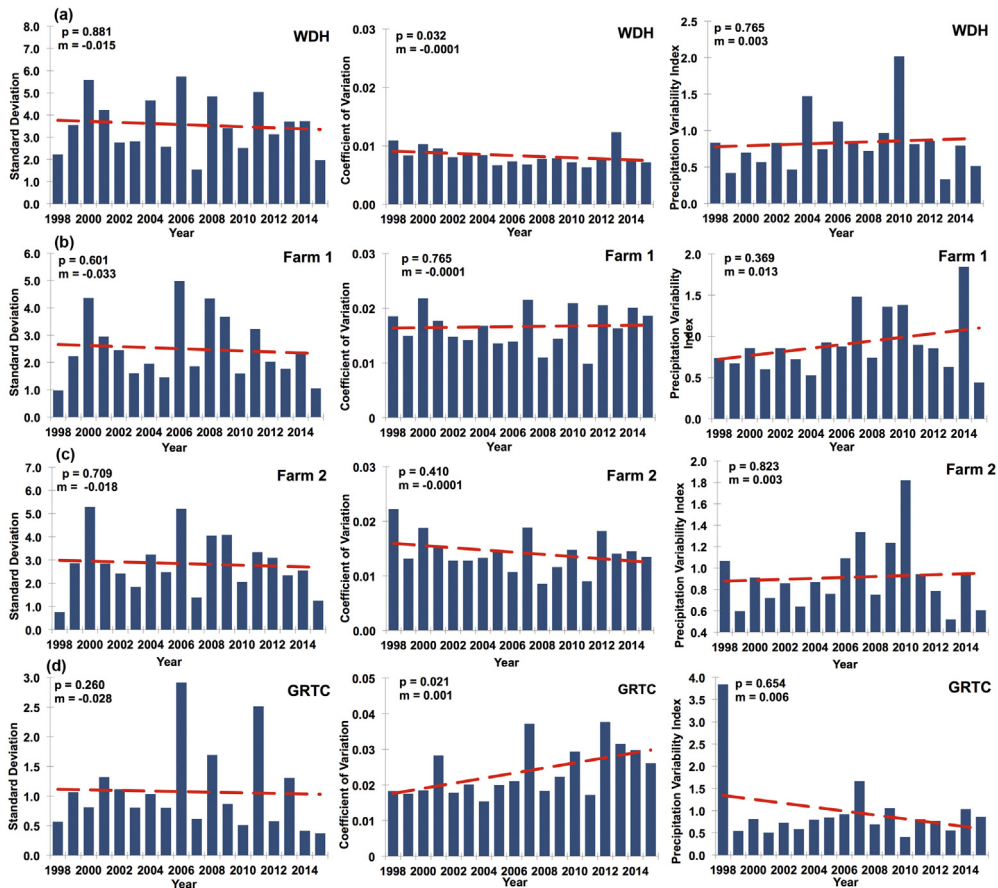


Fig. 6. Time series of standard deviation, coefficient of variance (CV), and precipitation variability index (PVI) of annual rainfall (mm) for (a) Windhoek (WDH), (b) Weltevrede Farm Location 1 (Farm 1), (c) Weltevrede Farm Location 2 (Farm 2), and (d) Gobabeb Research and Training Center (GRTC). Record length = 17 years, and m = Sen's slope.

distribution and event spacing of precipitation, whereas the commonly used index such as CV can only quantify intensity distribution (Gu et al., 2016).

$$PVI = \sqrt{\frac{\sum_{i=1}^n (R_i - \bar{R})^2}{n}}, \quad (2)$$

where

$$R_i = \frac{C_i}{E_i}, \quad (3)$$

$$C_i = \sum_{j=1}^i p_j, \quad i = 1, \dots, n, \quad (4)$$

$$\bar{p} = \frac{\sum_{i=1}^n p_i}{n}, \quad (5)$$

$$E_i = i\bar{p}, \quad i = 1, \dots, n. \quad (6)$$

3. Results and discussion

3.1. TMPA data validation using two ground gauges

A significant issue with comparing satellite and rain gauge data is that the satellite data are estimates of area-averaged precipitation amount while rain gauges make point measurements (Bowman, 2005). For example, TMPA might observe

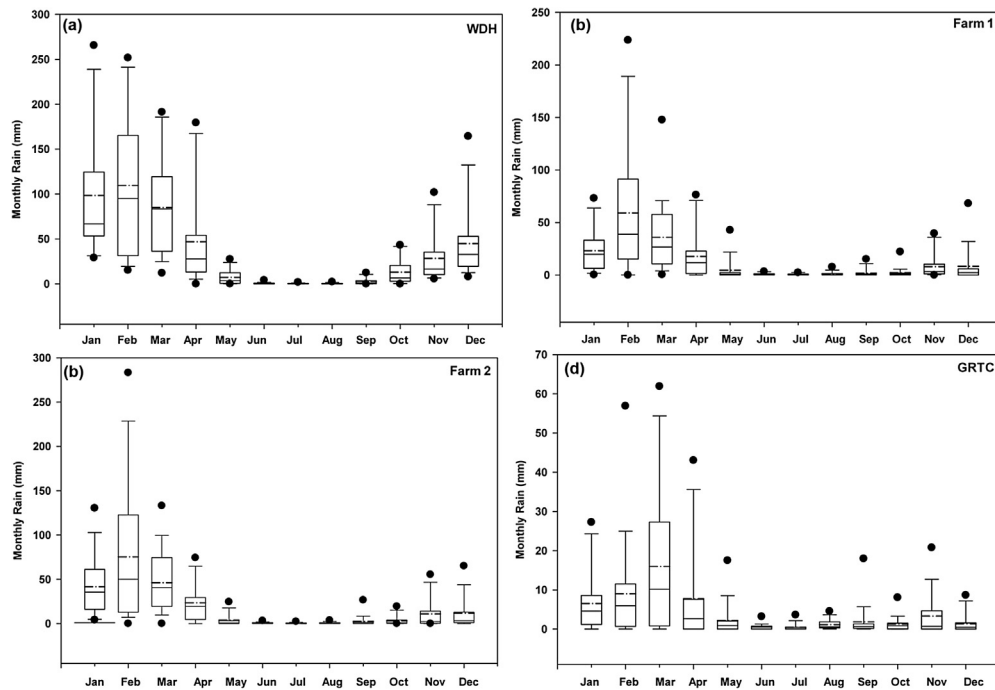


Fig. 7. Seasonality of annual precipitation (mm) for (a) Windhoek (WDH), (b) Weltevrede Farm Location 1 (Farm 1), (c) Weltevrede Farm Location 2 (Farm 2), and (d) Gobabeb Research and Training Center (GRTC). Median represented by dark solid line, box represents the 1st and 3rd quartile range. The boxes are drawn with widths proportional to the square roots of the number of observations in the groups. The whiskers extend to the most extreme data point which is no more than two times the inter quartile range from the box. Circles represent outliers.

rainfall in the area surrounding a rain gauge while it is not raining at the gauge itself. Conversely, the gauge sometimes observes a localized heavy rainfall, but TMPA tends to average the localized high measurements with the nearby lower measurements in order to obtain the area-averaged estimates, and consequently reduce the reliability of data. Prior to using TMPA satellite data to study long-term rainfall patterns in the studied areas, it is therefore necessary to make quantitative estimates on how well the TMPA data represents rainfall characteristics as compared to ground observations. In this study, data from two locations (Farm 1 and Farm 2 rain gauges) were used to evaluate the TMPA retrievals at daily, monthly, and annual time scales. TMPA data was compared with *in-situ* rain gauge measurements for a 6-year evaluation period from 1 January 2008 to 31 December 2013. Fig. 2 shows results of the evaluation for Farm 1 and Farm 2. The performance of the satellite data varies between the two locations, and generally, the bias of the satellite data in measuring daily mean values is larger than that of monthly and annual values. The results showed that the monthly and annual estimates correlate relatively well for both locations with R^2 of 0.47–0.64 (Fig. 2), with the daily estimates having the lower agreements ($R^2 = 0.24$ –0.25). Our R^2 values were lower than other studies conducted in wetter environments such as the La Plata Basin in South America (Su et al., 2008), and the Upper Midwest and far Northeast over the United States (Ebert et al., 2007). In general, at daily time scales, there were a number of high intensity rain days (e.g., 30 mm day^{-1}) on which rainfall was considerably higher for ground observations relative to TMPA data. The opposite was observed on a number of low intensity rain days (e.g., $<10 \text{ mm day}^{-1}$) on which the rainfall was considerably higher for TMPA data relative to ground observations.

The rainfall pattern of rain gauge Farm 2 was generally well reproduced by TMPA data, with a slope of 0.94 and 1.02 at monthly and annual scales, respectively (Fig. 2). However, the satellite data tended to slightly underestimate the mean precipitation amount at Farm 1 (Fig. 2). Satellite data averages the estimates of rainfall amount over a $25 \times 25 \text{ km}$ area, which may induce bias by averaging localized high measurements with nearby lower measurements. According to the Namibia Meteorological Services (NMS), total rainfall is the lowest along the arid west coast, increasing towards the east and north, with extreme variability experienced across the central and northern Namibia (Eckardt et al., 2013). The Weltevrede Guest Farm is located across a steep rainfall gradient from the desert interior to the Namibian highlands, with the eastern part less arid than the hyper-arid western part. This may be responsible for the mismatch between Farm ground observations and satellite data.

Fig. 3 shows the CDF comparisons for daily, monthly and annual rainfall at Farm 1 and Farm 2. As seen from Fig. 3, the ground observation CDFs for Farm 1 generally agreed well with the TMPA data, but the discrepancy became larger for Farm 2 data, particularly at annual scale. A close examination showed that the Farm 2 gauge is allocated to the TMPA pixel immediately next to Farm 1. However, the Farm 2 gauge is actually located at the edge of two pixels and thus may be influenced by its neighboring pixel. This point is illustrated in see Supplementary Fig. S1 (in the online version at DOI: <http://dx.doi.org/10.1016/j.ejrh.2016.07.003>) that shows the CDFs for ground observations from Farm 2 were closer matched

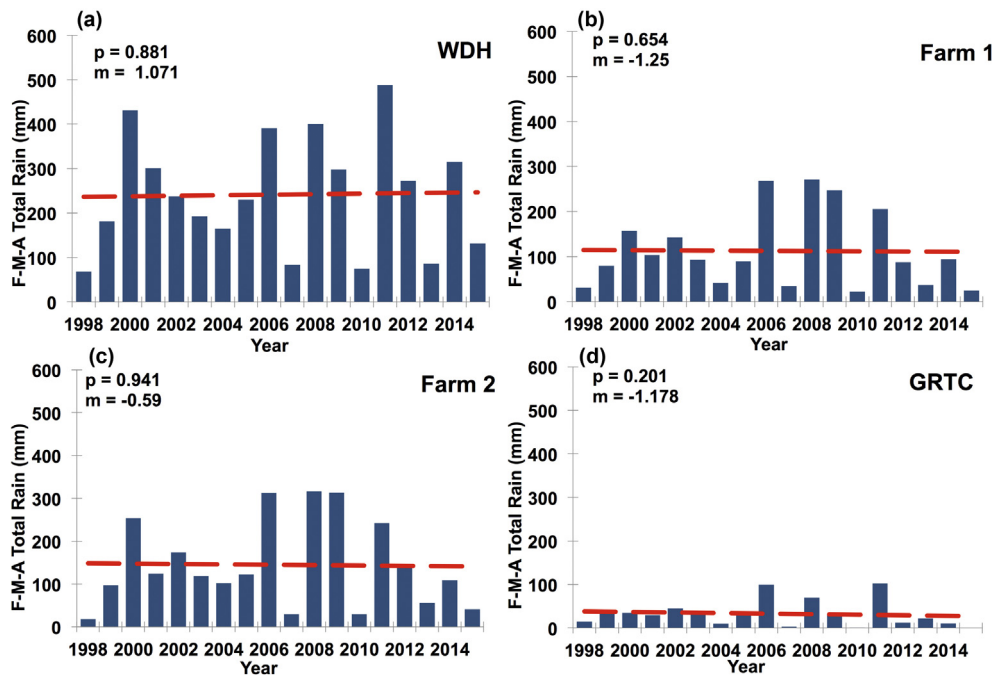


Fig. 8. Time series of late summer (February–March–April) precipitation (mm) for (a) Windhoek (WDH), (b) Weltevrede Farm Location 1 (Farm 1), (c) Weltevrede Farm Location 2 (Farm 2), and (d) Gobabeb Research and Training Center (GRTC). Record length = 17 years, and m = Sen's slope.

to TMPA data from the same pixel as Farm 1. So considering the results from both scatter-plots (Fig. 2) and CDF analyses (Fig. 3), using the uncorrected TMPA data for the trend analysis is a viable approach without introducing additional bias.

In this study, two factors limit the amount of data available for our analysis; one is the relatively short period for which the TMPA rainfall estimates are available (17 years because TRMM mission ended in April 2016), and the other is the limited availability of rain gauge data. Previous study has found that the gaps in the data available at the NMS are serious enough to place the required level of confidence in the analysis results in doubt (Ministry of Agriculture, 1999). Therefore the ground observations that we collected from Weltevrede Farm could help improve the rainfall analysis in this region. In addition, although the number of rain gauge is limited in this study, our validation results are in agreement with other studies that indicate even if the network density is high, TMPA achieves reasonable performance at monthly scale but not at daily time scales (Ebert et al., 2007; Huffman et al., 2007; Su et al., 2008).

3.2. Mann-Kendall trend analysis

Namibia's climate is characterized by hot and dry spells with scarce and unpredictable rainfall, and is second in aridity only to the Sahara within Africa (Foissner et al., 2002). The combination of a cold, subantarctic upwelling ocean current on the Atlantic coast and a hot subtropical interior have led to 69% of the country being semi-arid, and 16% being arid, where the average rainfall of under 250 mm per year is coupled with annual mean evaporation of up to 3700 mm (Foissner et al., 2002). Besides, the rains have been erratic in recent years with many parts of country enduring severe drought, which poses a threat to rangeland owners and crop farmers (Haeseler, 2013).

Trend analyses were conducted for both annual and rainy-season rainfall for total rainfall, frequency (λ), rainfall intensity (α) and rainfall variability parameters. Annual rainfall did not show any significant trend for all the four locations (Fig. 4). However, some location differences in the patterns of trends were observed for the α and λ parameters. There was a significant decreasing trend for λ ($p = 0.006$, Fig. 4), along with increasing trend for α at GRTC, which is located in the hyper-arid central Namib subject to a mean annual rainfall of about 20 mm per year. The changes in rainfall frequency became less significant at Farm 1 ($p = 0.733$, Fig. 4) and Farm 2 ($p = 0.383$, Fig. 4) where the mean annual rainfall was much more than that of the Namib Desert. There was no significant change in either frequency or rainfall intensity at Windhoek ($p > 0.05$, Fig. 4), the wettest station among the four stations. Trend analyses of all the rainfall variability parameters (standard deviation, coefficient of variation, and precipitation variability index) did not reveal significant change in any of the locations for the annual rainfall ($p > 0.05$, Fig. 6) except for the coefficient of variation of GRTC with increased variability.

The spatial patterns of trends in total rainfall, frequency and rainfall intensity for rainy season were similar to those for the annual ones. A decreasing trend in λ and increasing trend in α was observed at GRTC; the changes were significant in

frequency (λ) ($p = 0.019$, Fig. 5), but not in intensity (α) ($p > 0.05$, Fig. 5). The total rainfall, α and λ did not change significantly in either Farm sites or Windhoek station ($p > 0.05$, Fig. 5).

Although IPCC's model projection has found there is likely a drying trend in annual average rainfall over mid to late 21st century (with large uncertainty), our trend analysis did not show any significant changes in total rainfall amount for all sites over the period of 1998 to 2015. Even though our TMPA rainfall estimates were limited to a relatively short period, the TMPA data has a much finer spatial resolution than those of GCMs for IPCC predictions.

3.3. Rainfall seasonality and erratic rain pattern with extreme rainfall events and droughts

Typically there are two seasons in Namibia: cool and dry winter (May to September), and hot and rainy summer (October to April). Rainfall in all the four locations was highly seasonal in occurrence, with 99% or more of the annual rains occurring during the rainy season. More than 55% of annual rain fell in late summer – February, March, and April but was highly dependent on location. The lowest proportion was seen in Windhoek (55%), which had the highest total annual rainfall, while the other three locations saw more than 65% of the annual rains during the late summer period.

The seasonality pattern derived from TMPA data showed the total rainfall was generally higher in February but with greater inter-annual variation (Fig. 7). There were two rainfall peaks during the rainy season: the strong one in February or March, and the weak one in the early summer (November or December). These summer rainfall peaks are most likely associated with Tropical Temperate Troughs (TTTs), the most significant southern African summer rainfall producing systems that link an easterly wave in the tropics to a westerly wave in the south through a trough and cause cloud band and precipitation (Eckardt et al., 2013; Kaseke et al., 2016). Moreover, a reduction has been reported in late austral summer precipitation (February–March–April (FMA) response) associated with an upward trend in tropical Indian Ocean sea surface temperature (SST) (Hoerling et al., 2006; New et al., 2006). Our trend analysis, however, did not show any significant changes in late summer precipitation in any of the sites (Fig. 8).

The results showed an increase in extreme precipitation such as heavy rainfall and drought over our study area. Particularly, the extreme rainfall events seemed to increase in recent years with higher monthly peak rainfall amount in February, and more storm events in the peak month. In addition, the 2013 drought of Namibia has been captured in both rain gauge data and TMPA satellite rainfall estimates, which is consistent with the findings from NMS that reported the rainy season from October 2012 to April 2013 was very dry over the north, middle and the south of the country. The increased frequency of major storms caused damage to farmland, crops and livestock, as well as the roads. In the 2013 drought of Namibia, for example, water shortage during the main cropping season (November to June) resulted in the death of several thousand livestock and crop failure, and severely affected the local agrarian economy (Haeseler, 2013).

4. Conclusions

In this study, we evaluated the feasibility of utilizing satellite-based rainfall estimates for examining the changes in rainfall patterns in data scarce dryland regions. The TMPA satellite data were evaluated against the ground observed rain gauge data. In general, the TMPA estimates agreed well with the rain gauge data at monthly and annual time scales. The agreement between TMPA and gauge precipitation estimates became lower at daily time scale, particularly for high intensity rain ($>30 \text{ mm day}^{-1}$) and low intensity rain ($<10 \text{ mm day}^{-1}$).

One of the most important findings from this study is the difference in trends of rainfall amount, frequency and intensity between drier and wetter regions. In a very arid and hot GRTC area, though the total rainfall amount does not change, there is a decrease (significant) in frequency (λ) of storm accompanied by an increase (non-significant) in storm intensity (α). However, neither of these two indices shows significant changes at Windhoek, a much wetter site. The Weltevrede Farm, as located in the transition zone from the dry Namib Desert to less arid highland (Windhoek), shows less significant results comparing to GRTC. The results also show increased rainfall variability for the driest location as indicated by the increasing trend of coefficient of variation. In addition, the long-term rainfall pattern and late summer precipitation (FMA response) based on TMPA satellite derived rainfall dataset, are contrary to the IPCC predictions (with large uncertainties) of a drying trend in Namibia, again emphasizing the spatial variability of dryland rainfall and the necessity of obtaining ground observations in data scarce regions. This study provides rare long-term ground observations of rainfall record at a daily scale from a data scarce region. More importantly, this study provides a useful approach of using annual TMPA data associated with trend analysis to facilitate the understanding of temporal and spatial rainfall variations in the areas of Africa where the *in situ* observations are scarce.

Acknowledgments

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at <http://dx.doi.org/10.1016/j.ejrh.2016.07.003>.

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