Analysis of spatio-temporal rainfall trends across southern African biomes between 1981 and 2016

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A b s t r a c t

Southern African biomes experience significant changes in the distribution of rainfall that are linked to El Niño–Southern Oscillation. As such, an understanding of the spatio-temporal rainfall trends is key in predicting rainfall patterns as well as validation of climate change projections. Currently, the available information on rainfall trends in southern Africa is scanty with most studies focusing either on the spatial or the temporal dimension at localised levels. The novelty of this study is its regional aspect (i.e. all of southern African arid and semi-arid biomes) and the simultaneous integration of space and time in rainfall trend analysis through the use of space time rainfall cube. In this study, we simultaneously examined spatial and temporal rainfall trends based on the space-time rainfall cube derived from 1981 to 2016 CHIRPS satellite rainfall data. The space time rainfall trend analysis revealed a significant ($P < 0.05$) decrease of rainfall across most biomes particularly in the northern parts of the savanna biome and southwestern biomes (i.e. karoo, desert and fynbos). Statistically significant ($P < 0.05$) rainfall increase was observed in the central parts of the region mostly within the savanna biome. In terms of the magnitude of rainfall change, some of the areas experienced as much as 12 mm rainfall decrease in the mean annual rainfall while others recorded an increase of 14 mm. Our results provide baseline information for climate change adaptation and ecosystem conservation.

Keywords: Rainfall trend; Southern Africa; Biome; Climate change, Drought

1. Introduction

The United Nations has identified global climate change as a key challenge of the 21st century (Davis-Reddy and Vincent, 2017) with serious threats to ecosystems and society (Gosling et al., 2011). Within southern Africa, severe and widespread droughts have occurred during 1982–1984, 1991–1992, and recently the 2015–2016 season drought was the driest since the early 1980s with critical impacts on ecosystems and food security (Archer et al., 2017). Furthermore, most parts in Africa are projected to have a possible decrease in rainfall as a result of global warming (Mazvimavi, 2010).

The global warming effects together with expanding population and the resulting increased pressure on ecosystems could lead to negative impacts on southern African societies which are predominantly rural and survive on natural ecosystems (Dalal-Clayton, 1997). Studies claim that global warming will result in extreme weather events (droughts and floods) (Fauchereau et al., 2003). However, the magnitude of these extreme events is not known (Kusangaya et al., 2013). This is despite the fact that these extreme events often have devastating consequences on society for example the cyclone Idai which started on the 14th of March 2019 affected Mozambique, Zimbabwe and Malawi killing more than 1000 people and destroying more than 50 000 houses (Reliefweb, 2019). The recent 2015/2016 drought season which caused severe crop and ecosystem failure in the southern African region (Archer et al., 2017) also points to the region's vulnerability to the effects of global warming. It is therefore imperative to assess the historical rainfall trends in order to understand future rainfall trends so that societies can be better prepared especially in the case precipitation decrease.

The literature on historical rainfall trends in southern Africa is scanty and fragmented and based on point level analysis (Kusangaya et al., 2013). The paucity of this literature was raised as a major concern in the second assessment report of the Intergovernmental Panel on Climate

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Change (IPCC) which noted insufficient studies on observed historical trends in climate extremes (Toggweiler, 2001). Most of the available studies on rainfall trends are at country and river basin level e.g. Kampata et al. (2008) found no evidence of significant trends in the annual rainfall at individual stations of the Zambezi basin in Zambia. Mazvimavi (2010) also found no evidence of significant trends in rainfall on all 40 weather stations used in Zimbabwe. Fauchereau et al. (2003), did a similar study over southern Africa (1950–1988) and found no significant changes in the late (January–March) season rainfall.

A comprehensive review of rainfall trend studies covering southern Africa was done by Kusangaya et al. (2013). Most of the studies highlighted in the review are based on rain gauge data for example Nicholson (1993) used rain gauge data to analyse rainfall trends for the African continent between the 1970–1990 period. The results of the study showed negative rainfall trends across the whole African continent except for East Africa. However, the rainfall geographical regions used to analyse rainfall trends do not coincide with southern African biomes. A study by Shongwe et al. (2009) revealed decreasing rainfall trend in the southwestern parts of southern Africa and increasing rainfall trend in the northern parts of the region mainly covering northernmost parts of Zambia, Malawi and Mozambique. A similar study on rainfall trend analysis (1961–2000) based on ground rainfall station data by New et al. (2006) in Southern Africa also found negative rainfall trends across most rainfall stations. A study by Joubert et al. (1996) revealed a declining trend of rainfall for southern Africa. However, this decline was not statistically significant. Statistically significant rainfall decrease in areas between the equator and 20° South latitude was reported by Morishima and Akasaka (2010) between 1979 and 2007 period.

The major weakness of previous studies on rainfall trend is that they do not simultaneously consider space and time in the trend analysis and they are restricted to the location of rain gauges which are limited in spatial coverage (Chikodzi and Mutowo, 2014). By considering time separately in rainfall trend analysis, the existing studies fail to detect rainfall trend clusters which are slowly emerging whilst considering space separately might detect less relevant rainfall trend clusters, i.e. those that have been in existence over a long time, rather than emerging ones (Neill et al., 2005). Furthermore, the analysis of rainfall trends at administrative or river basin level does not always reflect southern Africa's main rainfall zones. In addition, such analysis cannot be extrapolated to the southern African regional level mainly due to the use of different methodologies and datasets.

Global circulation models provide an alternative source of regional information on rainfall trends. However, the problem with these models, is that they do not accurately model regional trends and different models sometimes show conflicting results of rainfall trends. For example, Dai (2013) in a study entitled "Increasing drought under global warming in observations and models" reported an increase of drought risk due to precipitation decreases over Africa. On the other hand, Trenberth et al. (2013) found no significant increase in drought trends. The differences in the results of these two studies are partly attributed to different methodologies used (Seneviratne, 2012).

In this regard, the aims of the study are to: (i) investigate the intra-annual and inter-annual rainfall patterns over the southern African biomes, (ii) determine if there is any significant trend in the annual rainfall amounts over space and time and (iii) compute, on a pixel level the magnitude of the rainfall change (total increase or decrease of rainfall (mm)) over a 36-year period (1981–2016) across southern African biomes. We hypothesize the presence of negative rainfall trends across southern African biomes due to increased frequency and intensity of droughts.

2. Methods

The study area, southern African biomes lies between latitude 6°N to 35°S and longitude 10°E to 41°E (Fig. 1). In terms of precipitation, the southern African rainy season is between October and April for summer rainfall biomes i.e. desert, karoo, forest, montane savanna and grassland, with peak rainfall received between December and February. The fynbos biome receives winter rainfall between May and September.

The El Niño Southern Oscillation (ENSO) controls inter-annual rainfall variability over southern Africa. The ENSO phenomenon is triggered by variations in sea-surface temperature (SST) in the equatorial Pacific (Unganai and Kogan, 1998). The El Niño (i.e. warm phase of the ENSO) results in below average rainfall over greater parts of the region while the La Niña (i.e. cold phase of ENSO) results in above average rainfall which normally leads to flooding. Some of the strongest El Niño events in southern Africa are 1982/83 and 2015/16 rainfall seasons which resulted in severe droughts (Davis-Reddy and Vincent, 2017). These two ENSO phases do not necessarily occur in a sequence and have been reported to occur every three to seven years (OCHA, 2019). In terms of duration, El Niño events rarely go beyond one year whilst La Niña events can go up to three years (OCHA, 2019) reaching peak during November to February for the summer rainfall regions and March to June for the winter rainfall regions.

Most of southern Africa's summer rainfall is also associated with latitudinal movement of the Inter-Tropical Convergence Zone (ITCZ) and Congo air boundary (CAB) (Junginger and Trauth, 2012). CAB is a belt of converging airstreams that create a belt of low pressure which results in high rainfall (Marchant et al., 2007). During summer, the ITCZ and CAB moves southwards causing widespread rainfall especially when the ITCZ and CAB converge (Nash and Endfield, 2002). The dry season occurs when the ITCZ and CAB move northwards (Unganai and Kogan, 1998).

Also important in regulating southern African rainfall is the Indian Ocean Dipole (IOD), which refers to the difference in sea surface temperatures in the eastern and western part of the Indian ocean (Marchant et al., 2007). The western Indian Ocean is characterised by abnormally warm (SSTs) whilst and the eastern Indian Ocean is characterised by abnormally cold SSTs (Marchant et al., 2007). During the positive IOD warmer sea surface water moves towards the western Indian Ocean which increases rainfall over Africa and causes drought in Australia. The negative IOD has an opposite effect, strong winds push warm water

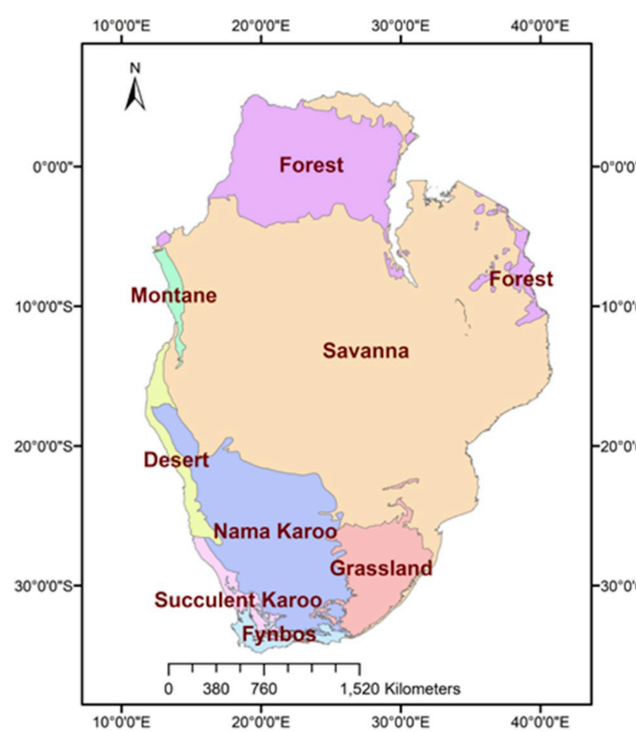

Fig. 1. Location of study area showing southern African biomes used in the rainfall trend analysis.

towards Australia which result in less rainfall over Africa (Marchant et al., 2007). Unganai and Kogan (1998) noted that southern Africa's climate is also governed by the semi-permanent subtropical high-pressure systems and by the downward leg of the Hadley cell which results in low rainfall. As a result greater parts of southern African biomes are semi-arid (Unganai and Kogan, 1998) with recurrent droughts.

2.1. Rainfall data

The study investigated the spatio-temporal rainfall trends over southern African biomes using Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS) v2 satellite rainfall data covering the period 1981–2016. The CHIRPS rainfall data is generated by the U.S. Geological Survey Earth Resources Observation and Science Center in collaboration with the Santa Barbara Climate Hazards Group at the University of California (Funk et al., 2014). These data are available online at: http://chg.geog.ucsb.edu/data/chirps/. CHIRPS rainfall is developed by blending satellite based and climate models rainfall estimates, precipitation climatology and rainfall data from meteorological stations (Funk et al., 2014). The resultant data is provided at pentad, dekadal and monthly temporal resolution on a 0.05° spatial resolution and is available from 1981 to present. The main advantages of the CHIRPS satellite rainfall data is that it incorporates more meteorological station rainfall data than other satellite rainfall estimates products which help to improve its accuracy (Shukla et al., 2014). The CHIRPS data set has been shown to correlate with other global data sets such as the Global Precipitation Climatology Project (GPCP) (Shukla et al., 2014).

The rainfall trend was analysed at biome level (Fig. 1). Biomes generally follow the main climatic regions (Mucina and Rutherford, 2006) which makes them ideal for rainfall trend analysis. The biome data used in the study is based on the Terrestrial Ecoregions of the World data developed by Olson et al. 2001. These data can be downloaded freely from the WWF website (https://www.worldwildlife.org/publications/terrestrial-ecoregions-of-the-world).

2.2. Rainfall trend analysis

In this study, the seasonal rainfall trends were analysed using October to April for the summer rainfall biomes and May to September period for the Fynbos biome which receive rainfall in winter. For October to April season, we divided the rainfall season into two main parts as follows; (a) the early part of the rainy season, October-November-December (OND), and (b) the mid to end of the rainfall season, January-February-March (JFM). The rationale behind splitting the season into two parts is that most parts of the vegetated landscape of southern Africa are predominantly deciduous with vegetation greening up during the October to December period (Chidumayo, 2001; Cho et al., 2017). Thus the variations of OND rainfall will have an impact on the early stages of vegetation development, while the JFM rainfall variations will impact the final phases of vegetation development (Mazvimavi, 2010). The division of the rainfall into two parts also help to capture trends that may not be identified in the total annual precipitation.

2.2.1. Intra-annual and inter-annual patterns

In the context of rainfall trend analysis, intra-annual refers to rainfall variation that occur at a time scale of 1 year and inter-annual refers to rainfall variation across the years. In order to understand intra-annual historical rainfall trends, the rainfall z-score (standardised difference) were computed from 10 day (dekadal) and seasonal rainfall data. The z-score defines the number of standard deviation (anomaly) from the average i.e. dekadal or seasonal long-average (1981–2016). Z-score values can either be positive or negative, indicating whether the parameter i.e. rainfall is above or below the dekadal or seasonal long-term average and by how many standard deviations. Standard deviation within the range of 1 to −1 is considered to be within the normal range. The rainfall z-score for each biome was computed using the following (Eq. (1))

$$Z_{ij} = \frac{x_{ij} - \overline{x}_i}{\sigma_i} \tag{1}$$

Where Z_{ij} is the z-score; $x_{ij}$is the raw input value to be standardised; $\overline{x}_i$ is the mean of the population and $\sigma_i$is the standard deviation.

2.2.2. Spatio-temporal trends

To test the hypothesis of the presence of negative rainfall trends, a space-time cube approach was used which enables the detection of statistical hot (wet spells i.e. high rainfall clusters) and cold spots (dry spells i.e. low rainfall clusters) (Gates, 2017). A space time cube is a 3 dimensional data structure which is based on geographic coordinates (x and y) and z coordinate representing time (Abdrakhmanov et al., 2017). The space-time cube approach is important in rainfall trend analysis and it was successfully used to analyse the anthrax epidemic among livestock in Kazakhstan over the period 1933–2016 (Abdrakhmanov et al., 2017). The same approach can be applied to spatio-temporal rainfall analysis. Analysing rainfall data over space and time can show previously unknown trends (Gates, 2017) and provide answers to questions such as: where are the space-time drought hot spots located?; are these hot spot patterns or trends new, intensifying, persistent, or sporadic hot-spot patterns? (ESRI, 2018).

The rainfall space-time trend was analysed based on a space-time rainfall cube covering 125 × 125 km using the emerging hotspot tool in ArcGIS software (ESRI, 2018). Each cube (bin) represents the rainfall station location, time and the rainfall value. The rainfall space-time cube approach enables the detection of rainfall trend clusters through time and shows areas or clusters with increasing or decreasing rainfall. The emerging hotspot tool was used because of its ability to simultaneously handle space and time in trend analysis. This tool takes as input a space-time Network Common Data Form (NetCDF) cube and then identifies trends in data using Mann-Kendall trend test (ESRI, 2016). The resulting trends from the emerging hotspot tool are classified either as new, intensifying, diminishing, and sporadic hot and cold spots (Fig. 4) (ESRI, 2018). The Mann-Kendall trend test, is a nonparametric test which is used for detecting trends in time series data and is extensively used in rainfall and river discharge time series data (Kendall, 1945). The Mann-Kendall trend test correlation coefficient, tau which ranges from −1 and 1 provides the direction and strength of the trend in a time series. The advantages of the Mann-Kendall test over the Spear-man's rho test is that it less affected by small numbers of extreme outliers and it can also work with missing data (Croux and Dehon, 2010).

We first calculated the intensity of clustering for both high and low rainfall values based on the Getis-Ord Gi* statistic for each rainfall cube representing location of a weather station. The Getis-Ord Gi* statistic, introduced by Getis and Ord provides an indication of where observations with either low or high values cluster. Locations of high spatial associations or clustering will have positive z-score (Songchitruksa and Zeng, 2010). On the other hand, negative z-score provides an indication of clustering of low values.The trends for the dry and wet spells clusters were then evaluated using the Mann-Kendall trend test to detect whether a decreasing or increasing trend is present in the rainfall space time cube (Kendall, 1945; Gates, 2017). The resultant map of the rainfall trends with the associated z-score and p values is shown in Fig. 5.

2.2.3. Quantification of the magnitude of the trend (rainfall increase or decrease)

A pixel-wise Mann-Kendall tau correlation coefficient was calculated first to establish the direction of the rainfall trends. To quantify the magnitude of the trend i.e. total decrease or increase of rainfall (mm) over time, a pixel-wise linear regression was computed using time (years) as independent and annual rainfall as dependent variables. Here, the slope of the regression which gives the increase or decrease of rainfall was computed using a linear model and raster package within the statistical software environment (R Core Team, 2018). The resultant average slope map was multiplied by the number of years (1981–2016) i.e. 36 years to determine the magnitude of the trend.

3. Results and discussions

3.1. *Intra-annual and inter-annual rainfall trends*

Fig. 2 displays the intra-annual variability based on 10-day rainfall z-scores for the 36-year period (1981–2016) aggregated over the biomes. Negative Z-scores, representing below normal rainfall were mostly recorded in recent years, (i.e. between 2014 and 2016 seasons) mostly in the arid and semi-arid biomes. These negative z-score values (i.e. dry spells) mainly occur between the October to December period for most biomes except the montane biome (Fig. 2).

A summary of the inter-annual rainfall trends is presented in Fig. 3. At the annual time scale and during the October to December period (Fig. 3a and b), a negative rainfall trend is observed in all biomes except for the savanna, nama karoo and montane biomes which show an increasing rainfall trend. More biomes (grassland, desert, nama karoo, savanna and montane) show an increasing rainfall trend during the January to March period (Fig. 3c). This might be attributed to the fact that this is the period when most cyclones in southern Africa to occur. At the annual time scale, the succulent karoo biome has the steepest decrease of rainfall (slope = −0.04991) (Fig. 3a). This is followed by the forest biome (slope = −0.04947) (Fig. 3b). The observed increasing rainfall trend at the annual time-scale in the nama karoo biome (Fig. 3a) is not statistically significant for greater part of the biome (Fig. 6a).

3.2. *Spatio-temporal analysis*

The analysis of the rainfall space-time cube showed a decreasing rainfall trend (dry spells, blue colour (Fig. 4) across all the arid biomes. These biomes are located in the south and southwestern parts of the region covering mostly the karoo, desert, fynbos biomes and western parts of the grassland biome. The decreasing trend is also observed in the forest biome during the late part of the season (i.e. January to March period). Clusters of increasing rainfall trend (wet spells, brown colour) are mainly found in the montane, grassland and in the western and central parts of the savanna biome. No significant trend in the space time rainfall cube was observed over greater parts of the savanna and the forest biome (Fig. 4a).

The intensification of the dry spells (clusters of low rain) was observed over the fynbos and karoo biomes (Fig. 4). This area has been noted by the South African National Biodiversity Institute (SANBI) as an area of high concentrations of taxa of conservation concern (SANBI, 2017). The other concern is the persistent dry spells mainly over the forest biome during the January to March period (Fig. 4c, blue colour).

Table 1 show the summary of the space-time rainfall trends for all biomes. What is of more concern is the intensification of the dry spells for all the three periods. This trend has negative consequences on the vegetation development especially for the south western biomes.

To get an insight into the evolution of space-time rainfall trends shown in Fig. 4, a 3-dimensional map of the space-time rainfall cube (Fig. 5) was generated. The space-time rainfall cube enabled the simultaneous observation of the spatio-temporal trends of wet and dry spell clusters over southern African biomes. Intense clusters of dry spells were mainly observed over the desert and karoo biomes (Fig. 5).

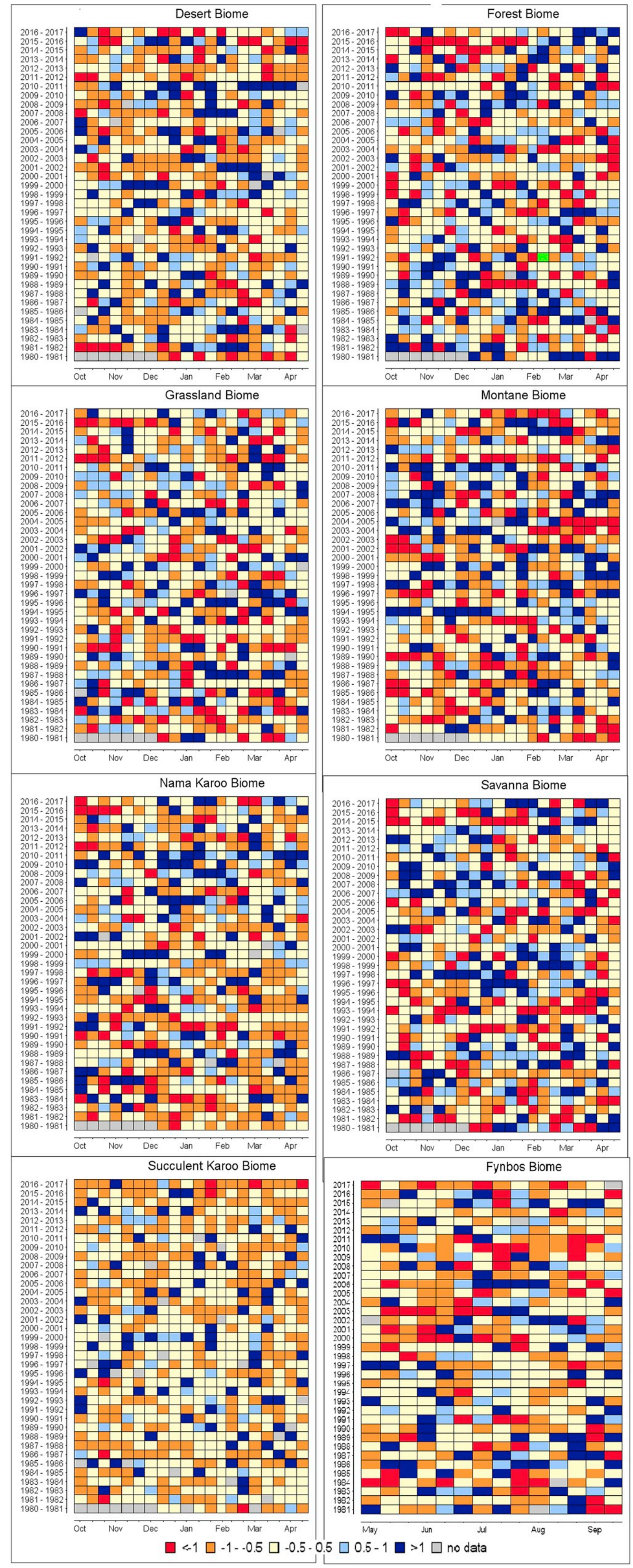

Fig. 2. Intra-annual rainfall trends based on 10-day rainfall z-scores.

3.3. *Magnitude of rainfall change*

Results of the pixel-wise Mann-Kendall trend analysis are presented in Fig. 6a. A Statistically significant ($p < 0.05$) negative rainfall trend was mainly observed over desert, succulent karoo, fynbos, northern parts of the savanna and western parts of the grassland biome. A statistically significant increasing rainfall trend was observed mainly over central part of the southern African region covering the savanna biome. No statistically significant trend was observed for the montane biome.

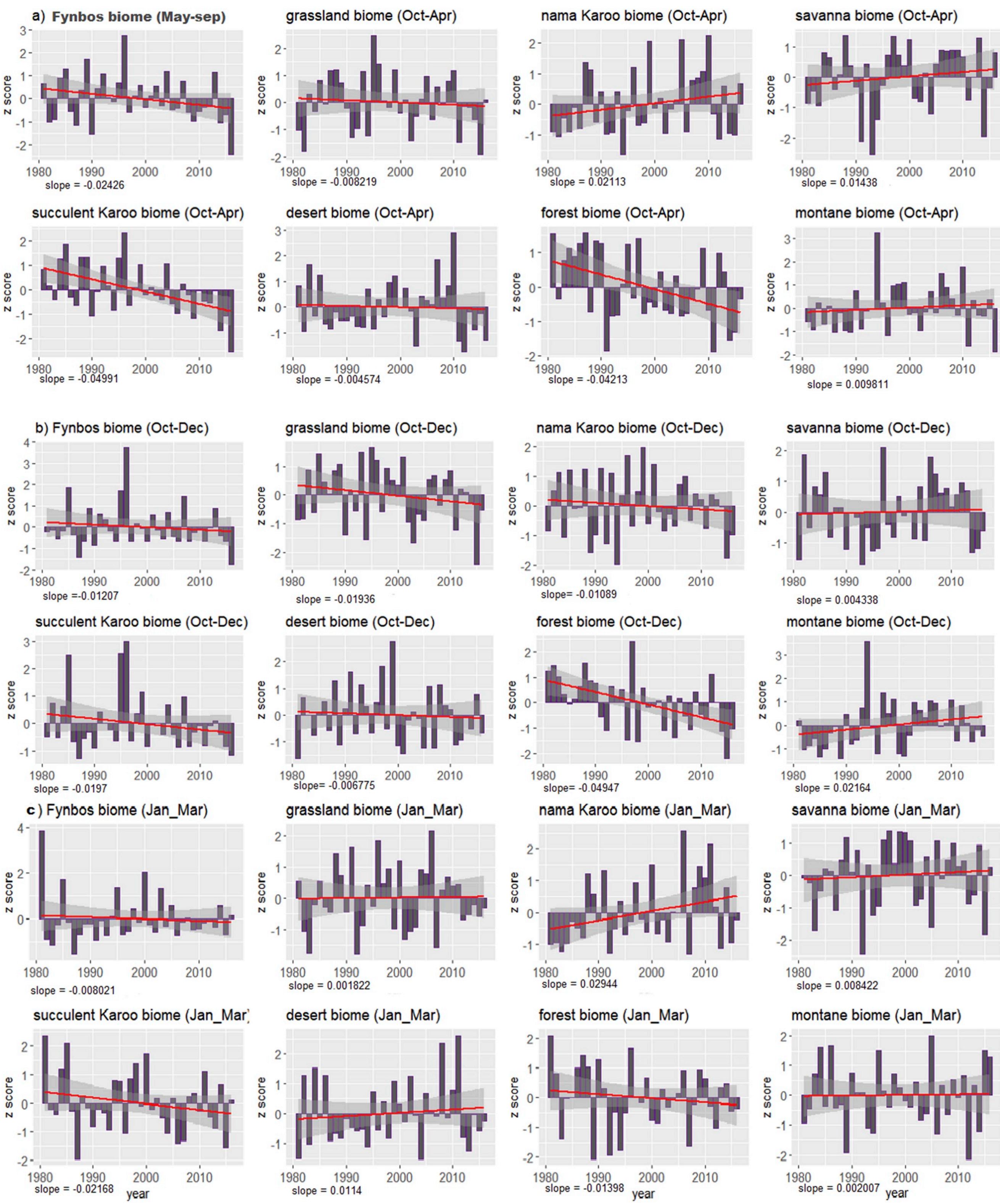

Fig. 3. *Inter-annual trends for: (a) annual rainfall (October-April for summer rainfall biomes and May-September for winter rainfall biomes); (b) early rainfall season (October-December) and (c) mid to late rainfall season (January-March).*

The results from the pixel-wise linear regression showed a decrease in mean annual rainfall up to 441 mm and an increase up to 508 mm between 1981 and 2016 (Fig. 6b). The highest statistically significant decrease is observed over the northern parts of the southern African region bordering the savanna and forest biome (Fig. 6b). The highest increase in rainfall change (over a 36-year period) is observed over the central parts of the region might be explained by the fact that this is area which is mostly affected by the tropical cyclones which have been on the increase in recent years.

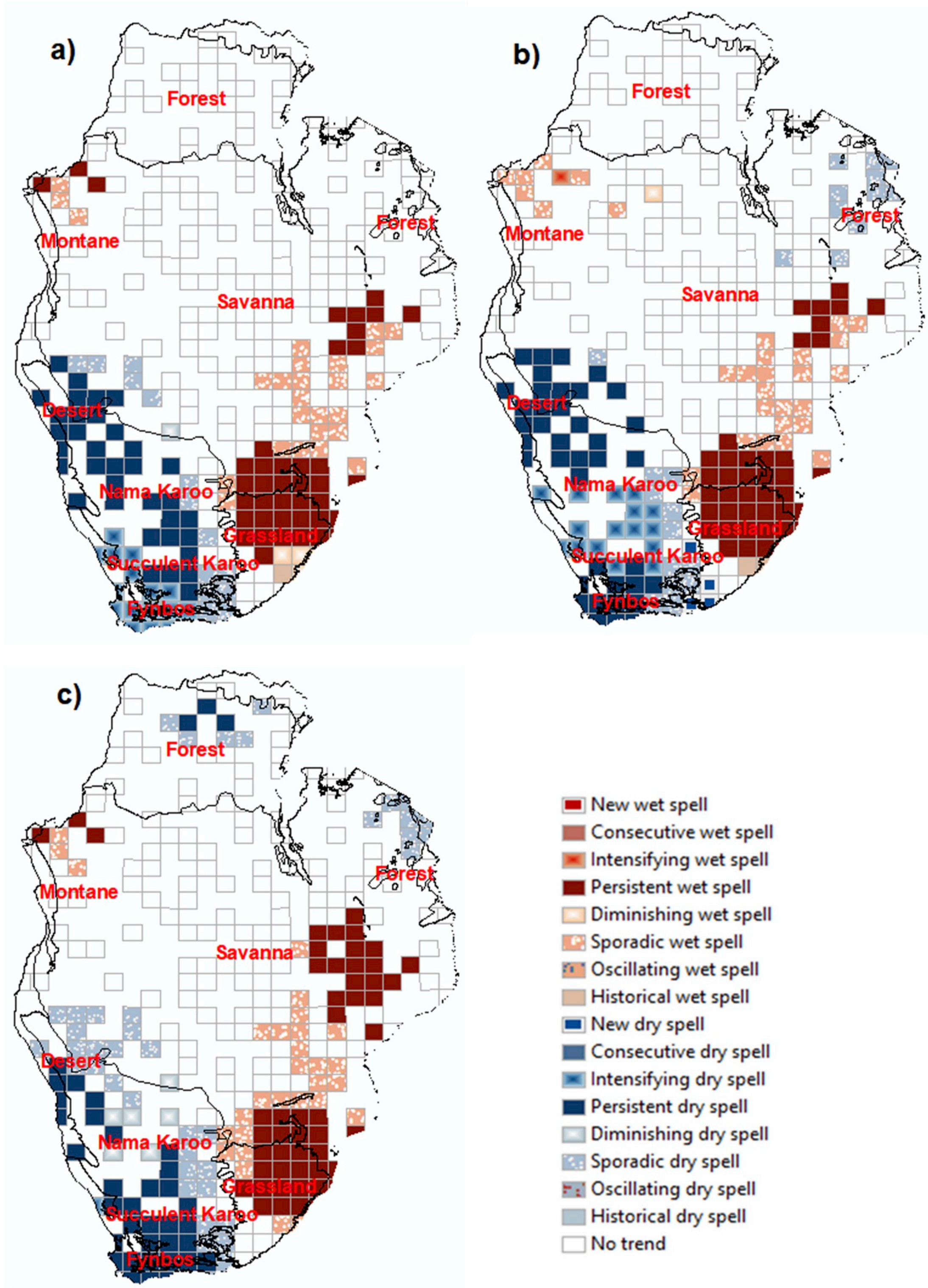

Fig. 4. Space-time rainfall trend based on 125 × 125km grid for: (a) annual rainfall (October–April for summer rainfall biomes and May–September for winter rainfall biomes); (b) early rainfall season (October–December) and (c) mid to late rainfall season (January–March).

4. Discussion and conclusion

Historical rainfall trend information is important in many areas such as health, farming, ecosystems, hydrology, etc. CHIRPS satellite rainfall data was used to determine rainfall trend over a 36-year period for eight southern African biomes. The results of the Mann-Kendall trend analysis revealed a negative rainfall trend mainly over the forest biome and southwestern parts of the region (i.e. fynbos, desert and karoo biomes). Increasing rainfall trend was mainly observed in the central parts of the region and western parts of the savanna biome. Our results are in line with the findings of Shongwe et al. (2009) who observed declining rainfall trends over the southwestern parts of the Southern African region and increasing trends in northern part of Mozambique, Zambia and Malawi.

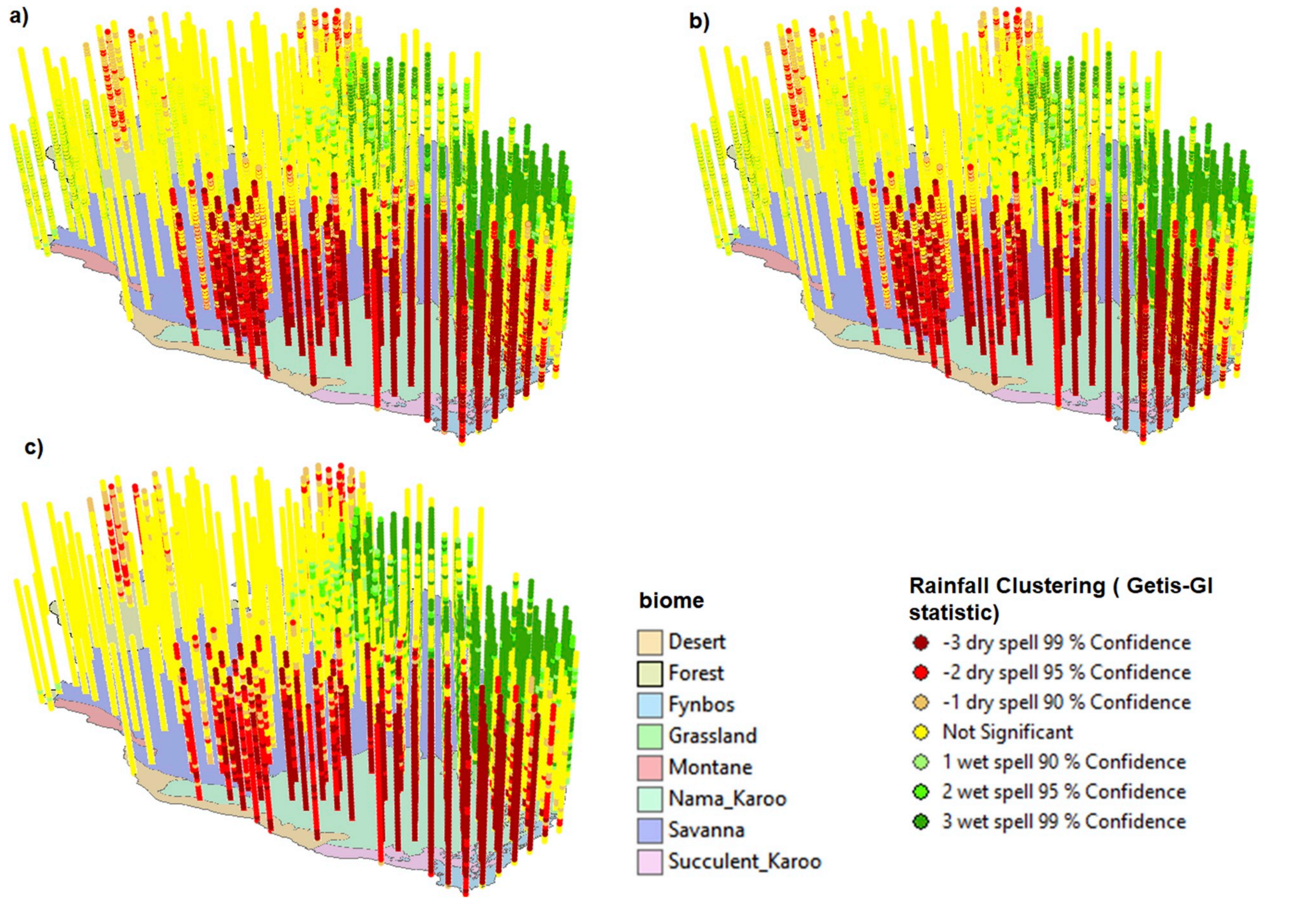

Fig. 5. 3-dimensional visualisation of the rainfall space-time cube.

Table 1
Regional summary of space-time rainfall trends.

Annual rainfall	Wet spell	dry spell	October to December season rainfall	Wet spell	dry spell	January to March season rainfall	Wet spell	dry spell
New	0	0	New	0	5	New	0	0
Consecutive	0	0	Consecutive	0	0	Consecutive	0	0
Intensifying	0	17	Intensifying	1	16	Intensifying	0	2
Persistent	41	36	Persistent	33	39	Persistent	48	38
Diminishing	4	1	Diminishing	1	0	Diminishing	0	6
Sporadic	26	16	Sporadic	12	26	Sporadic	10	39
Oscillating	0	0	Oscillating	0	0	Oscillating	0	0
Historical	1	0	Historical	1	0	Historical	0	0

Most of the areas with negative rainfall trend have been reported by Sloat et al. 2018 to have a high coefficient of variation of rainfall (CVP) (unreliable rainfall patterns). The rainfall decline is largely attributed to the effects of warm phases of the El Niño-Southern Oscillation (ENSO) which result in drought conditions over southern Africa (Gaughan and Waylen, 2012). In recent years (2014–2017), El Niño events have been on the increase with the 2015–2016 El Niño being the strongest since the 1970s (weathertrends360, 2015). This explains the declining rainfall trends across the southern African biomes. It is also important to note that increasing rainfall trend observed mostly over the Nama karoo biome is not statistically significant at 5% significance level. One possible explanation might be the reliability of rainfall as reported by Sloat et al. 2018.

Declining rainfall trends will have negative impacts on the southern African population due to the low adaptive capacity (Kusangaya et al., 2013). For example, within the fynbos biome, the decline in rainfall activity has already led to water restrictions by the Cape town municipality in South Africa following the 2015–2017 drought (Western Cape Government, 2019). The declining rainfall in the southern parts of the grassland biome which mainly covers greater parts of South Africa has a negative impact on livestock production. Within the grassland biome, livestock grazing is key for local communities as well as the beef industry. Sloat et al. (2018) in a study entitled "Increasing importance of precipitation variability on global livestock grazing lands" assessed the inter- and intra-annual precipitation-based threats to global rangelands based on rainfall concentration index, NDVI, coefficient of variation of rainfall (CVR) and livestock density data. The major finding of the study was that areas with unreliable rainfall, i.e. high CVR such as the grassland and savanna biome have low carrying capacity than less variable regions. The study further reports globally the rangelands have a CVR of 0.27, which is 25 percent more than all land surfaces combined (Patel, 2019). This high CVR coupled with the declining rainfall trends reported in this study affects the livestock carrying capacity (Patel, 2019).

For management purpose, since most severe rainfall decreases were observed in northern parts of savanna and western parts of grassland biomes which are predominantly used for grazing (Patel, 2019),

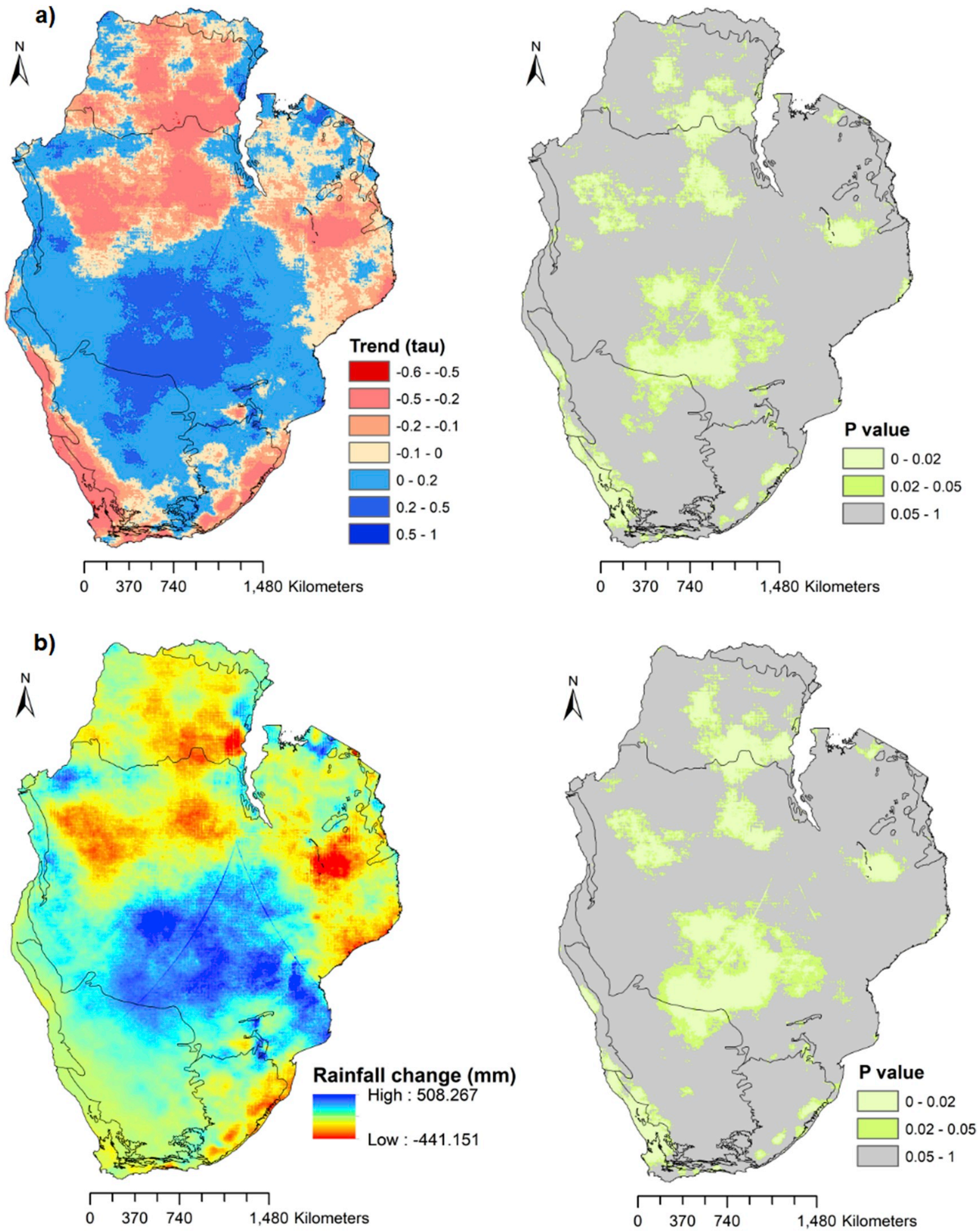

Fig. 6. a) Annual rainfall trend based on Mann-Kendall tau and associated p values b) the magnitude of annual rainfall changes i.e. rainfall increase (+) or decrease (−) in mm and associated p values.

destocking is recommended. In addition Sloat et al. (2018) recommends the efficient use of these biome's grazing landscape as well as the avoidance of cultivation in these marginal landscapes. Results from this study provide baseline data for climate change mitigation programmes as well as mapping drought hotspots. Future studies should focus on rainfall trend analysis based on day-count indices e.g. number of days with rainfall amount higher than 1 mm as recommended by World Meteorological Organisation.

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Authors contribution

Study conception and design: Marumbwa, Cho.
Acquisition of data: Marumbwa.
Analysis and interpretation of data: Marumbwa, Cho.
Drafting of manuscript: Marumbwa.
Supervision: Cho and Chirwa.
Critical revision: Cho, Marumbwa.

Declaration of competing interest

The authors declare no conflict of interest.

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