Geospatial analysis of meteorological drought impact on Southern Africa biomes

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Abstract

Within Southern African biomes, droughts are recurrent with devastating impacts on ecological, economic, and human wellbeing. In this context, understanding the drought impact on vegetation is of extreme importance. However, information on drought impact on natural vegetation at the biome level is scanty and remains poorly understood. Most studies of drought impact on vegetation have largely focussed on crops. The few existing studies on natural vegetation are based on experiments and field measurements at individual tree level which are not representative of biomes. In this study, we mapped the spatial extent and severity of drought using the Standardized Precipitation Evapotranspiration Index (SPEI) and then quantified the drought impact on Southern African biomes using the Vegetation Condition Index (VCI) for the period 1998 to 2017. To compare drought impact across the biomes, we computed the percentage area of the biome with seasonal VCI <30. The drought trend for each biome was computed for each pixel using a linear regression model in R software using the seasonal VCI images from 1998 to 2017. Our result showed that extreme drought impact on vegetation was mainly confined to the southwestern biomes (i.e. the Nama karoo and desert biomes) with most drought occurring during the first half of the season. We also observed an increasing trend of VCI (1998 to 2017) across all biomes and this increasing VCI trend might be explained by woody encroachment which is prevalent in the Savannah and Grassland biomes. The results of this study provide baseline information on drought hotspots.

Key words: VCI; Southern Africa; Drought, Spatio-temporal trends; Biome, SPEI.

1. Introduction

Southern African biomes provide important ecological services particularly to rural populations in the region (Small, Munday, and Durance 2017). These biomes are however increasingly coming under pressure from climate change-induced droughts (Dai 2013). A number of studies on drought have reported an increasing trend in meteorological drought occurrence over Southern Africa (Rouault and Richard 2005; Trenberth et al. 2013). Simultaneously, the Southern African countries are also experiencing rapid population growth which puts more pressure on vegetation resources (CARIAA 2015). In addition, the Southern African biomes support several wildlife National Parks, e.g. Central Kalahari Game Reserve in Botswana, Kruger National Park in South Africa, Gonarezhou National Park in Zimbabwe. As such, monitoring the spatial distribution of drought impact on vegetation can provide the National park authorities with important information for drought early warning systems (Kusserow 2017) which can help to minimize drought impact on the wildlife.

The determination of drought impact on vegetation at sub-continental scales and over diverse landscapes is complex due to the differences in elevation, soil, climate, and geology (Kogan 1990). As such, these landscape differences should be accounted for in order to accurately assess meteorological drought impact on vegetation (i.e. weather impact on vegetation) (Kogan 1990). This calls for robust drought indices which can accommodate landscape variations and are also standardized to enable the comparison of drought impact across the diverse vegetation landscapes. Traditionally, most studies of drought impact on vegetation are based on precipitation anomalies derived from meteorological ground stations. The resultant drought impact on vegetation is viewed as proportional to the water deficit (Gouveia et al. 2017). The most frequently used rainfall based drought indices are, (i) Standardized Precipitation Index (SPI); (ii) Palmer Drought Severity Index (PDSI); (iii) Aridity anomaly index (Leelaruban et al. 2009); and (iv) Standardized Precipitation Evapotranspiration Index (SPEI). The advantage of SPEI is that it incorporates the estimate of the effects of evapotranspiration in drought assessment (Bento et al. 2018; Barbosa et al. 2019). The general weakness of meteorological drought indices is that they do not provide direct information on drought impact on vegetation. As such, rainfall-based meteorological indices need to be complemented by vegetation-based drought indices which capture the direct impact of drought on vegetation (Zou et al. 2020).

The availability of remotely-sensed satellite data has given rise to a suite of vegetation-based indices which provide direct information on vegetation health condition (Bajgain et al. 2015). Among the satellite-based vegetation indices, the Normalized Difference Vegetation Index (NDVI) is the most commonly used spectral index for monitoring vegetation condition. The NDVI values range from −1 to 1, with low NDVI values indicating a weak level of photosynthetic activity which translates to low productivity (Unganai and Kogan 1998). Thus, NDVI is useful for the assessment of the intra-annual and inter-annual weather-related drought impact vegetation (Peter 2006; Leelaruban et al. 2009).

However, previous studies have noted some limitations of NDVI (e.g. sensitivity to atmospheric contamination, saturation in high biomass areas) (Spanner et al. 1990). The development of other alternative indices to NDVI (e.g. the Enhanced Vegetation Index (EVI) and the Soil-Adjusted Vegetation Index (SAVI)) aimed at minimizing the NDVI shortcomings still presents a challenge. For example, Eumetrain (2010) noted that EVI produces accurate results than NDVI in areas with high biomass due to the fact that it does not saturate easily. However, in an effort of trying to correct for biomass saturation, the main disadvantage of EVI is that it tends to portray relatively low values in sparsely vegetated areas (Eumetrain, 2010). Notwithstanding the limitations of NDVI described above, NDVI remains the most widely used indicator for drought monitoring (Carlson and Ripley 1997; Tucker et al. 1981; Kuri et al. 2014; Chikodzi and Mutowo 2014; Barbosa et al. 2019).

In drought monitoring studies, the current NDVI is usually compared to the long-term average, maximum, or minimum (e.g. the Vegetation Condition Index (VCI)) as a way of quantifying drought impacts on vegetation (Ansari et al. 2014). The concept of VCI is that the maximum vegetation is associated with optimal weather and the minimum vegetation activity is associated with dry and hot weather (Kogan 1990). Therefore, the maximum and the minimum NDVI defines the upper (favorable weather) and the lower (unfavorable weather) limits of the ecosystem resources in response to extreme weather conditions, i.e. the pixel's 'carrying capacity' (Kogan 2002). VCI therefore provides a quick overview of how well the vegetation is growing and helps to identify potential drought hotspots which might need further attention (Kogan 2002). VCI has been tested in different parts of the globe (Africa, America, Europe, and Asia) for a drought impact assessment on vegetation (Unganai and Kogan 1998; Zribi et al. 2016; Kogan 1997).

Within the Southern African region, most recent studies of drought impact on vegetation are localized and focus mainly on crops (Kuri et al. 2018; Chikodzi and Mutowo 2014; Unganai and Kogan 1998). Consequently, the drought impact on natural vegetation in Southern African biomes is still a research challenge. Therefore, the main objectives of this study were to: (i) analyze the meteorological drought trends and the associated impact on vegetation across the Southern African biomes over a 20-year period (1998 to 2017), and (ii) determine drought hotspots, i.e. identification of biomes which are frequently affected by drought.

2. Materials and methods

The study area covers Southern African biomes and lies between 6° N and 35° S and between 10° E and 41° E (Figure 1). The study area is covered by eight biomes with the Savannah covering the greater part of the area. One of the key phenomena regulating precipitation and the resultant droughts in Southern Africa is the variation in the ocean temperatures (Morioka, Tozuka, and Yamagata 2011; Reason 2001), the so-called El Niño-Southern Oscillation (ENSO) (Lindesay 1988). Greater parts of Southern Africa, with the exception of the Western Cape of South Africa, receives rainfall mainly between October and April (Daron 2014). The Southern tip of Africa receives winter rainfall which occurs between May and September. The average annual rainfall for Southern Africa varies between 100 and 2500 mm. The rainfall is highly variable and the Southern African region is frequently affected by drought with the recent 2015–2016 being the most severe since the 1980s (Archer et al. 2017).

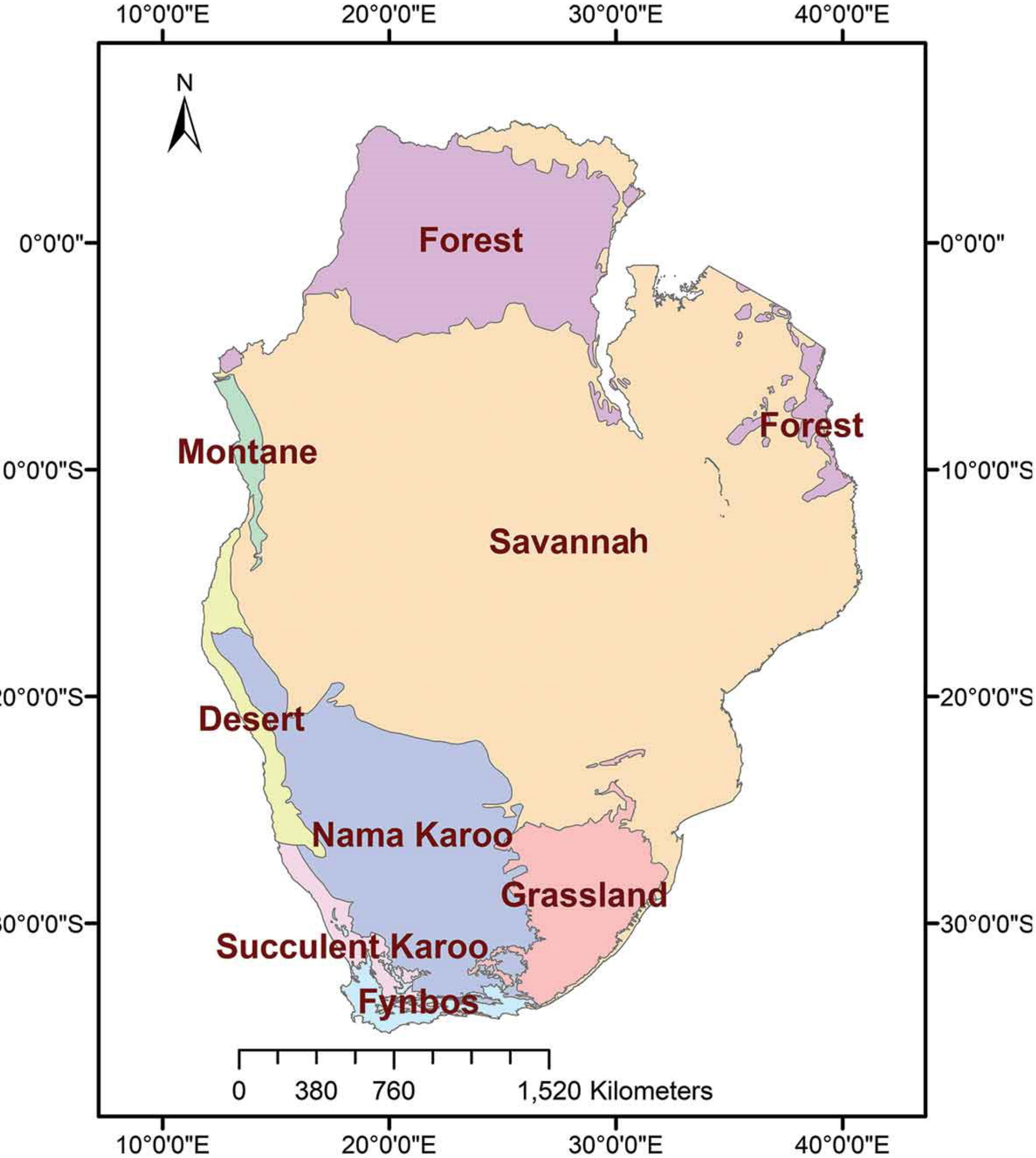

Figure 1. Study area showing Southern African biomes based on Rutherford biome classification method (Mucina and Rutherford 2006)

2.1. Input data and preparation

In this study, we used remotely sensed NDVI and SPEI data. The drought impact on vegetation was analyzed at dekadal (10 days) and seasonal time-scales to capture both the intra-seasonal and inter-seasonal variability of drought impact on vegetation. The VCI seasonal computations were done using the following months: (a) May–September for the Fynbos biome which receives winter rainfall and (b) October–April for the rest of the biomes which receives summer rainfall.

2.1.1. NDVI data

We used the Satellite Pour l'Observation de la Terre vegetation (SPOT VGT) & Project for On-Board Autonomy – Vegetation (PROBA-V) Normalized Difference Vegetation Index (NDVI) data (1998–2017) to calculate VCI which was then used for assessing the drought impact on vegetation. The NDVI data were downloaded from the Copernicus website (https://land.copernicus.eu/global/products/ndvi). The SPOT VGT& PROBA-V is provided by Vision on Technology (VITO) as a 10-day synthesis at 1 km spatial resolution. Daily near-infrared bands (R_{NIR}) and red bands (R_{Red}) are used to compute daily NDVI which is later aggregated at the end of 10 days (dekad) using the maximum value composite (MVC) technique.

The NDVI is calculated as

$$\mathrm{NDVI} = \frac{R_{\mathrm{NIR}} - R_{\mathrm{Red}}}{R_{\mathrm{NIR}} + R_{\mathrm{Red}}} \tag{1}$$

where R_{NIR} is the near-infrared reflectance and R_{Red} is the visible-red reflectance (Vicente-Serrano 2007). The NDVI data is provided together with a status map which provides information on the quality of the NDVI (e.g. shadow and cloud effect). This status map is used for masking out contaminated NDVI pixels (Wolters et al. 2016). To reduce the impacts of cloud contamination, we filtered the NDVI data using a Savitzky–Golay smoothing filter (five window filter, 5th order polynomial) following Cho, Ramoelo, and Dziba (2017) using Timesat software (Jonsson and Eklundh 2002). The filtered NDVI was then used to compute the VCI for assessing the impact of drought on vegetation.

2.1.2. Calculation of vegetation condition index (VCI)

In order to accurately assess the drought impact on vegetation at different time-scales, we calculated dekadal and seasonal VCI over a 20-year period (1998 to 2017). The VCI was computed using the Monitoring for Environment and Security in Africa (MESA) Drought Monitoring Software (DMS). The VCI compares the NDVI of a given period and pixel (NDVI) with its minimum ($\mathrm{NDVI}_{\mathrm{min}}$) and maximum ($\mathrm{NDVI}_{\mathrm{max}}$) and is calculated as

$$\mathrm{VCI} = \left(\frac{\mathrm{NDVI} - \mathrm{NDVI}_{\mathrm{min}}}{\mathrm{NDVI}_{\mathrm{max}} - \mathrm{NDVI}_{\mathrm{min}}}\right) \times 100 \tag{2}$$

where NDVI is the 10 day or seasonal NDVI value, $\mathrm{NDVI}_{\mathrm{max}}$ and $\mathrm{NDVI}_{\mathrm{min}}$ are the long-term maximum and minimum, respectively, calculated for each pixel for each dekad or season from the NDVI time-series data. The resulting VCI values are fixed in the range of 0 to 100. According to the United Nations Platform for Space-based Information for Disaster Management and Emergency Response (UN-SPIDER) VCI values, less than 40 are indicative of drought impact on vegetation (UN-SPIDER, 2017). VCI values less than 30 represents moderate to extreme drought conditions (Kogan 1997). Based on this formulation, we mapped the vegetation affected by drought as pixels with VCI < 30, i.e. moderate to extreme drought impact.

2.1.3. Standardized precipitation evapotranspiration index (SPEI)

We used the SPEI data to map drought severity and extent across the biomes. The SPEI data used are provided on a 0.5° spatial resolution and the data is available from 1900 to 2015. For this study, we only used the data starting from 1998 to match the start date of the NDVI data. The SPEI data were downloaded from http://digital.csic.es/handle/10261/153475 website. SPEI is a robust drought indicator which takes into account the impact of both rainfall and an estimate of evapotranspiration in determining drought. The SPEI values are interpreted using the classification shown in Table 1 (Mckee *et al*., 1993).

Table 1. Standardized precipitation evapotranspiration index (SPEI) classification based on (Mckee *et al*., 1993)

SPEI value	Category
>2	Extremely wet
1.5 to1.99	Very wet
1.0 to1.49	Moderately wet
-0.99 to 0.99	Near normal
-1.0 to -1.49	Moderately dry
-1.5 to -1.99	Very dry
<-2	Extremely dry

To analyze the spatial extent and severity of meteorological droughts at a seasonal timescale, we developed 6-month SPEI maps covering the October–March period for each year. In order to evaluate the part of the season with the most severe meteorological droughts, we generated SPEI maps for the first half of the rainfall season (October–December) and the second half of the season (January–March).

2.2. Drought impact and trends analysis

To analyze the spatial extent of the vegetation affected by drought, we computed the percentage area of each biome affected by drought during the rainfall season. We only have focussed on vegetation pixels with moderate to extreme drought conditions (i.e. VCI <30) as defined by UN-SPIDER (2017).

2.2.1. Intra-annual analysis

To understand the intra-annual variability of drought impact on vegetation, we extracted dekadal mean VCI values for each biome during the summer-growing season (October–April) and the winter growing season (May–September) using the Software for the Processing and Interpretation of Remotely Sensed Image Time Series (SPIRITS). The SPIRITS software can be downloaded from the European Commission website (https://mars.jrc.ec.europa.eu/asap/download.php). We then created a temporal matrix of VCI in order to show the dekadal trends of drought impact on vegetation over a 20-year period (1998 to 2017).

2.2.2. Inter-annual analysis

To establish the general trend of drought impact on vegetation, we computed a pixel-wise linear regression model in R software using seasonal VCI values for each biome (R Core Team 2018). The linear regression is computed using Equation (3):

$$y = \beta_0 + \beta_1 X + \varepsilon \tag{3}$$

where y is the seasonal (October–April) or (May–September) VCI value from 1998 to 2017; X is the year (1998 to 2017); β_0 and β_1 are the intercept and slope of the seasonal VCI, respectively; and ϵ is the error term, the component of y which is not accounted for by the regression model (R Core Team 2018). In order to determine the magnitude of the VCI change, we calculated the average slope in R software and multiplied it by the number of the years from 1998 to 2017 (i.e. 20 years). To determine the statistical significance of the trends ($\alpha = 0.05$), we calculated the p-value using the R software.

3. Results

3.1. Spatio-temporal patterns of meteorological drought

Figures 2, 3, and 4 shows the spatio-temporal patterns of meteorological droughts from 1998 to 2015. At the seasonal timescale, (Figure 2) the meteorological drought spatial extent (SPEI <-1) does not match the spatial extent of moderate to extreme drought (i.e. VCI <30) (Figure 6). This is mainly due to the fact that a single event of heavy rainfall can offset the negative water balance. However, such events might have a limited impact on vegetation recovery from drought especially if the rainfall is not well distributed.

According to the data presented in Figures 3 and 4, the first half 2015 to 2016 rainfall season comes out as the driest, with severe drought conditions covering the central and southern half of the study area.

The spatio-temporal extent of vegetation affected by drought (i.e. VCI <30) (Figure 6) is closely linked to meteorological droughts occurring during the early part of the season (October–December). The second half of the season (January–March) is generally characterized by wetter conditions (Figure 4).

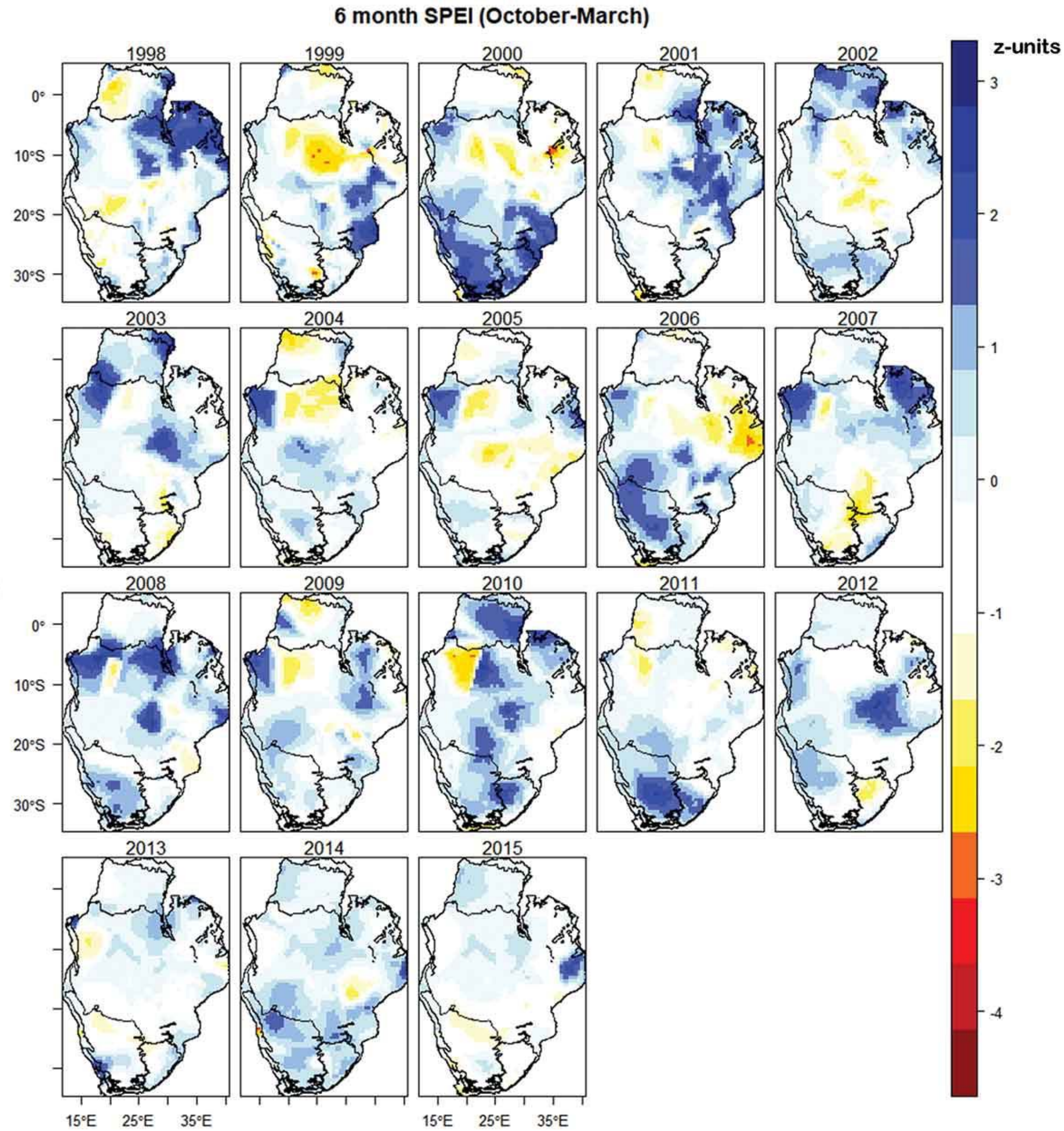

Figure 2. Spatio-temporal patterns of 6-month SPEI covering (October to March)

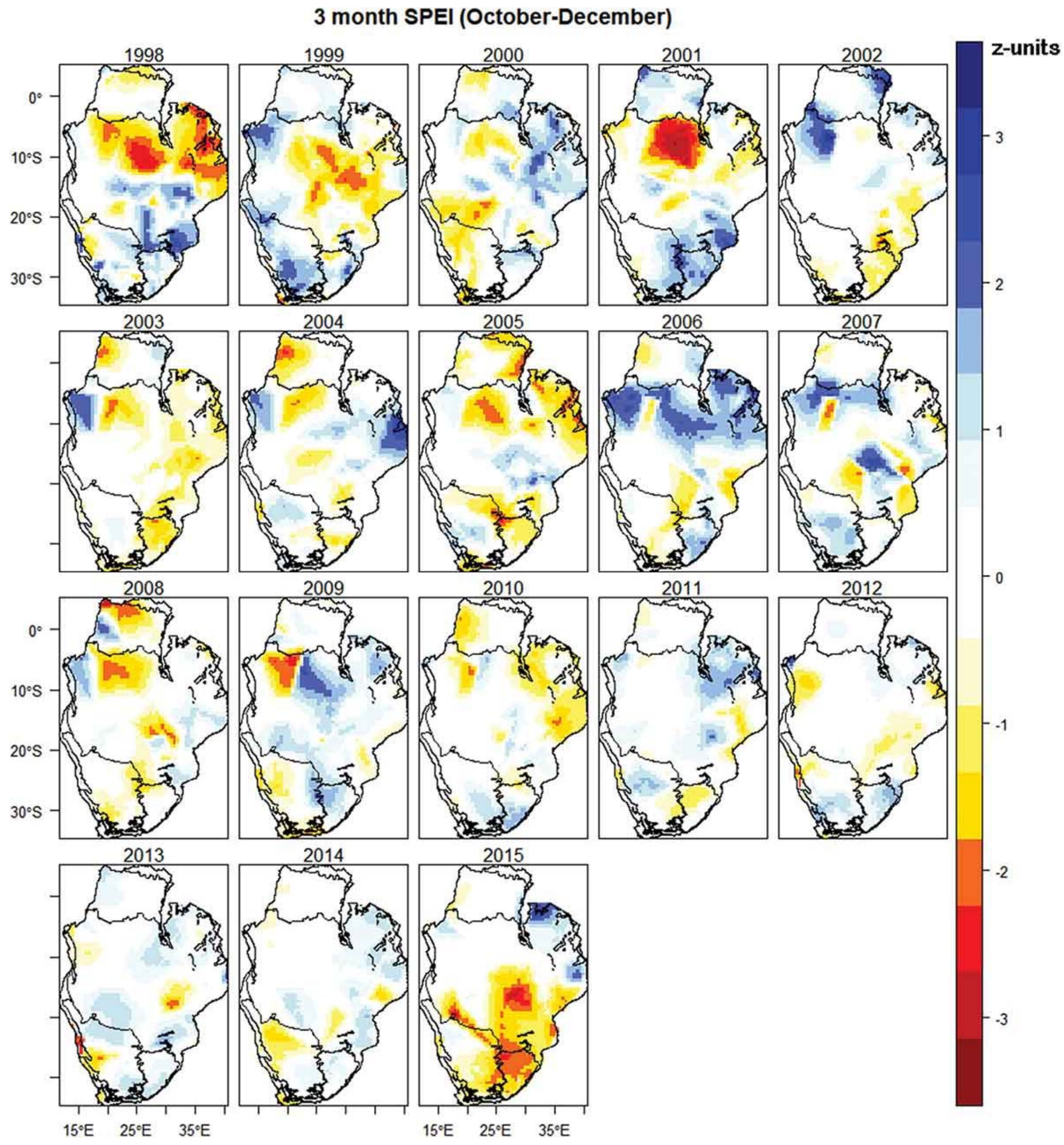

Figure 3. 3-month SPEI for October–December period

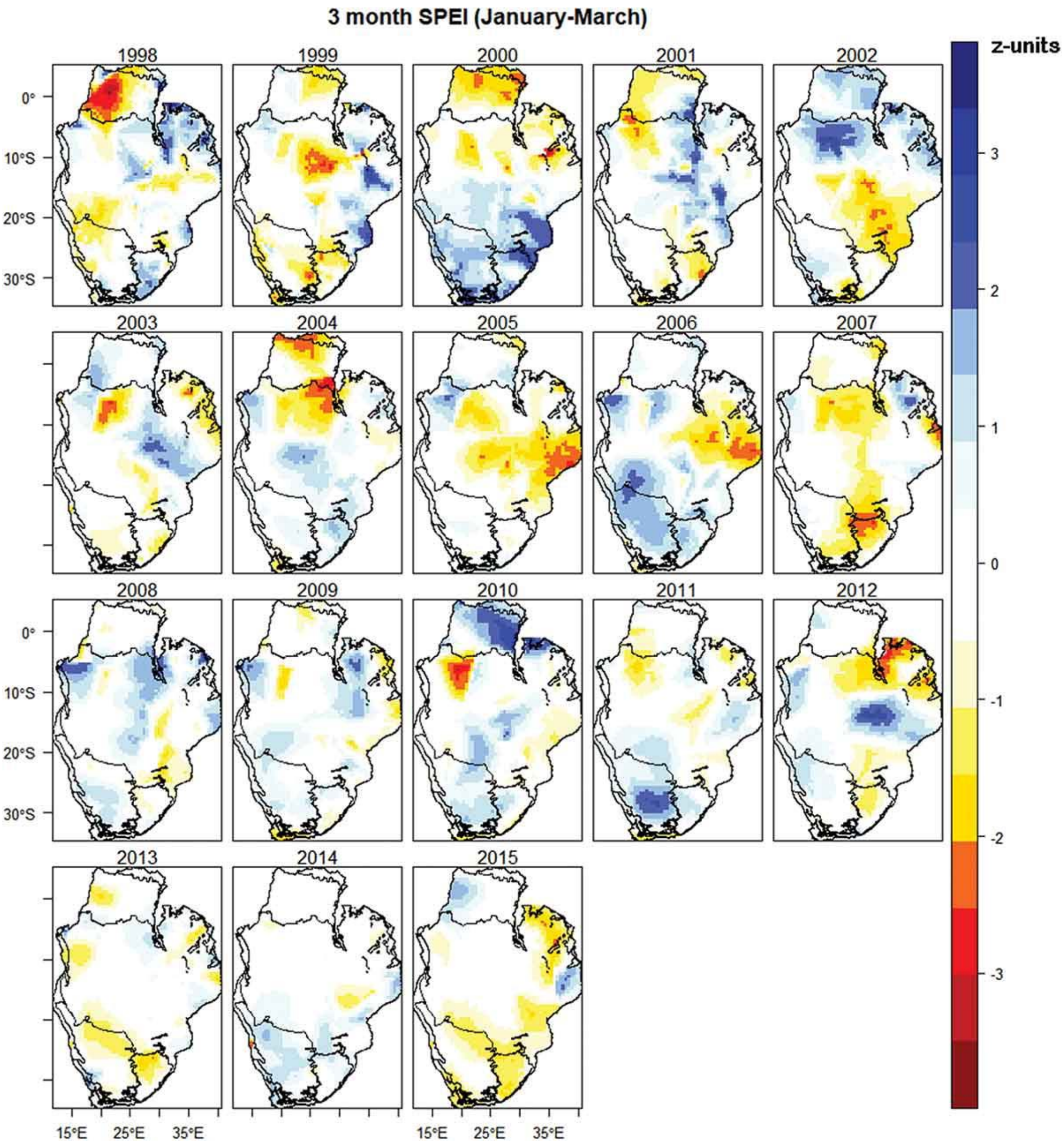

Figure 4. 3-month SPEI for January–March period

3.2. Intra-annual drought impact trends

The VCI matrix (Figure 5) shows the intra-annual drought impact from 1998 to 2017 based on dekadal VCI data. The Forest, Savannah, and Montane biomes were the least affected biomes by drought. Even the most recent drought impact of 2014 to 2015 and 2015 to 2016 seasons was not pronounced in these three biomes (Figure 5). Extreme drought impact on vegetation conditions was mainly restricted to the southwestern biomes, i.e. the Nama karoo and Desert biomes.

Figure 5. Temporal variation of drought impact on vegetation based on dekadal VCI

3.3. Inter-annual drought impact on vegetation based on the seasonal average VCI

The seasonal spatio-temporal patterns of drought impact on vegetation are illustrated in Figure 6. The yellow to red color depicts the increasing drought impact on vegetation based on the VCI. The patterns and the spatial extent of the drought impact closely resemble the 3-month SPEI (Figure 3) for October to December period which covers the early part of the season. This suggests that droughts occurring during the first half of the season have more impact than droughts occurring during the second half of the season.

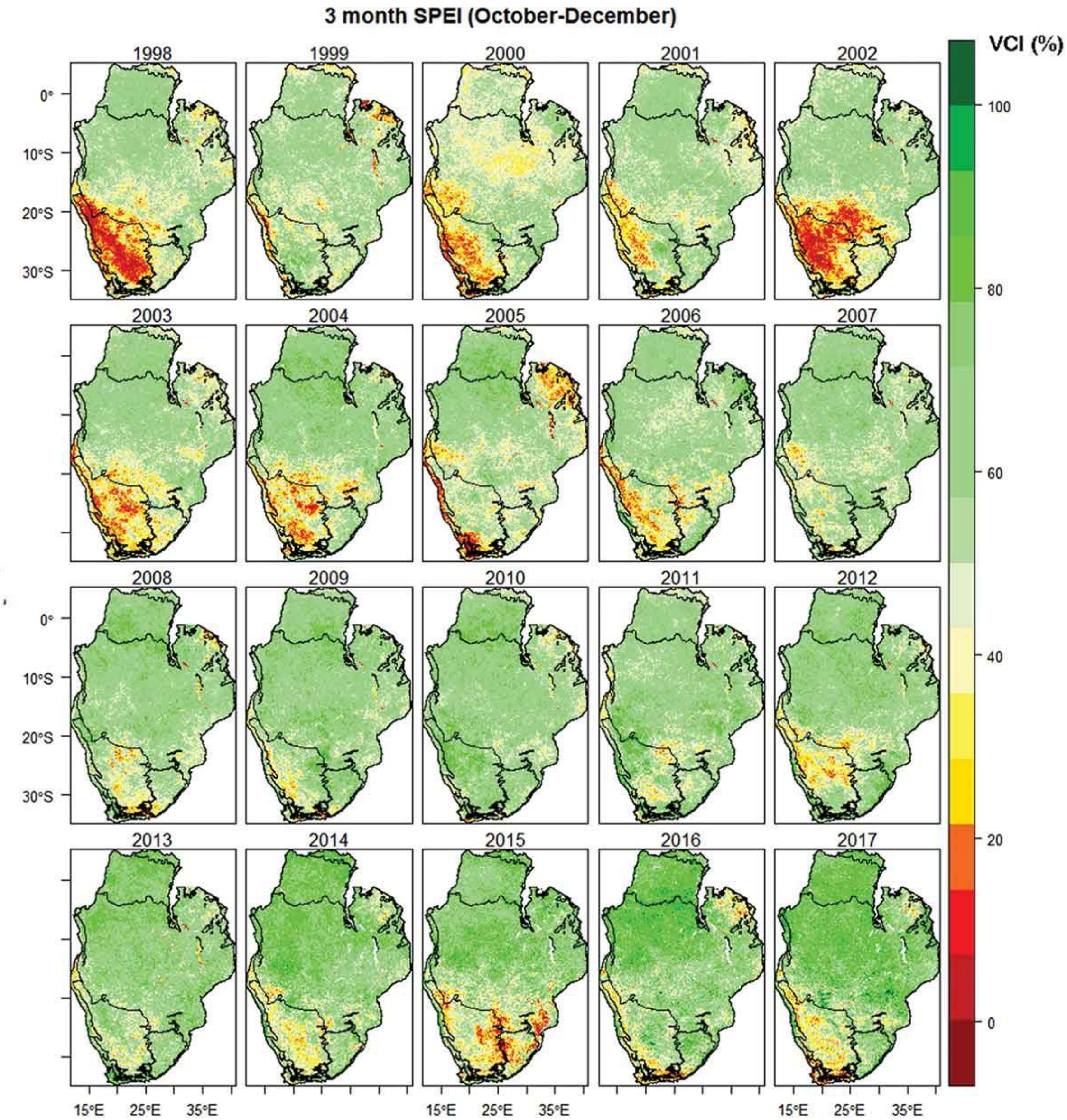

Figure 6. Seasonal VCI trends. Yellow to red depicts increasing impact of drought on the vegetation. Note: the year indicates the start of the season for summer rainfall region e.g. 1999 represents season 1999 to 2000

The year indicates the start of the season for summer rainfall region, e.g., 1999 represents season 1999 to 2000.

From the VCI time-series images, the rainfall seasons 1998 to 1999, 2000 to 2001, 2002 to 2004, and 2014 to 2017 seasons had severe drought impacts on vegetation. Table 2 shows a summary of the seasonal drought impact on vegetation based on the percentage area of the biome with moderate to extreme drought conditions (i.e. VCI <30). We observed that in general, the water-limited biomes (i.e. desert and Nama karoo) recorded the highest number of seasons with more than 20% of the biome's vegetation area affected by drought. Within

Table 2. Percentage of biome area affected by drought (VCI<30) during the rainfall season

	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Number of seasons with >20% of biome area affected by drought
Fynbos	16	43	19	33	18	28	19	30	8	9	22	19	32	2	4	2	7	28	25	70	8
desert	59	53	91	45	29	64	49	90	41	12	13	26	4	21	37	32	26	13	25	22	16
Forest	2	5	14	5	2	2	1	5	1	1	1	0	1	1	1	0	0	0	1	0	0
Grassland	32	15	13	6	40	45	14	17	22	4	17	8	3	6	5	3	10	58	11	7	4
montane	12	3	46	17	8	8	1	41	0	1	14	6	0	49	2	19	1	1	2	2	3
Nama karoo	93	19	68	46	91	82	69	27	56	17	32	21	2	16	47	15	41	53	25	47	13
Savanna	16	9	24	11	17	12	10	16	7	5	3	2	3	4	5	2	4	9	4	3	1
Succulent karoo	78	51	92	39	58	68	64	93	10	4	6	8	18	3	2	3	20	19	38	71	8
Total	2306	2197	2367	2203	2265	2312	2231	2324	2151	2060	2161	2099	2073	2113	2115	2089	2123	2196	2147	2239	

the Fynbos biome, the 2017 drought was the most severe with 70% of the biome's vegetation area affected by drought

The year 2000 to 2001 season drought had the worst impact on the vegetation compared to the 2015 to 2016 season which recorded the worst meteorological drought since the 1980s (Swemmer et al. 2018). During 2000 to 2001 drought, three biomes (Desert 91%, Forest 14%, Savannah 24%) recorded the highest area affected by drought compared to any other year (Table 2). This finding is consistent with the results of Abbas, Bond, and Midgley (2019) who also noted insignificant tree mortality during 2015 to 2016 season drought.

3.4. Inter-annual drought impact trends

Figure 7 shows the inter-annual VCI time-series aggregated at the biome level. Based on inter-annual trend analysis of seasonal VCI, we observed a general increase in the biome seasonal VCI over time especially after 2006 to 2007 season across all biomes (Figure 7). The increase in VCI translates to a reduction in drought impact on vegetation. As observed at the intra-annual timescale (Figure 6), the Karoo and Desert biomes were also the worst affected by drought at the inter-annual timescale. On the other hand, the forest, Savannah, and montane biomes were the least affected by the past droughts.

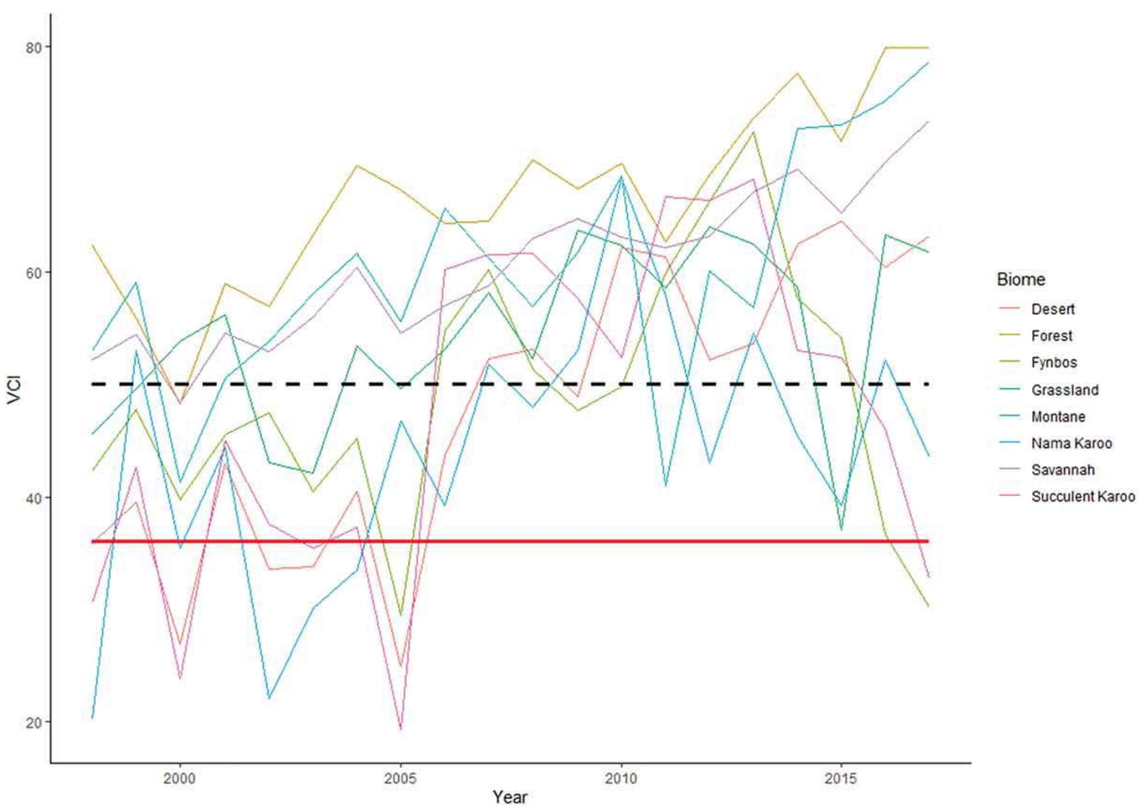

Figure 7. Seasonally averaged VCI time-series for biomes. The red line show cut-off for moderate to extreme drought (VCI<30) and black-dotted line show cut-off for no drought conditions (VCI>40)

The results from the pixel-wise linear regression analysis generally showed a significant increase (p-value < 0.05) of VCI across the biomes especially over the Savannah biome

(Figure 8). We also observed a decreasing trend of VCI mostly around major cities (Figure 8 (a)). However, this decreasing trend is not statistically significant (Figure 8(b)).

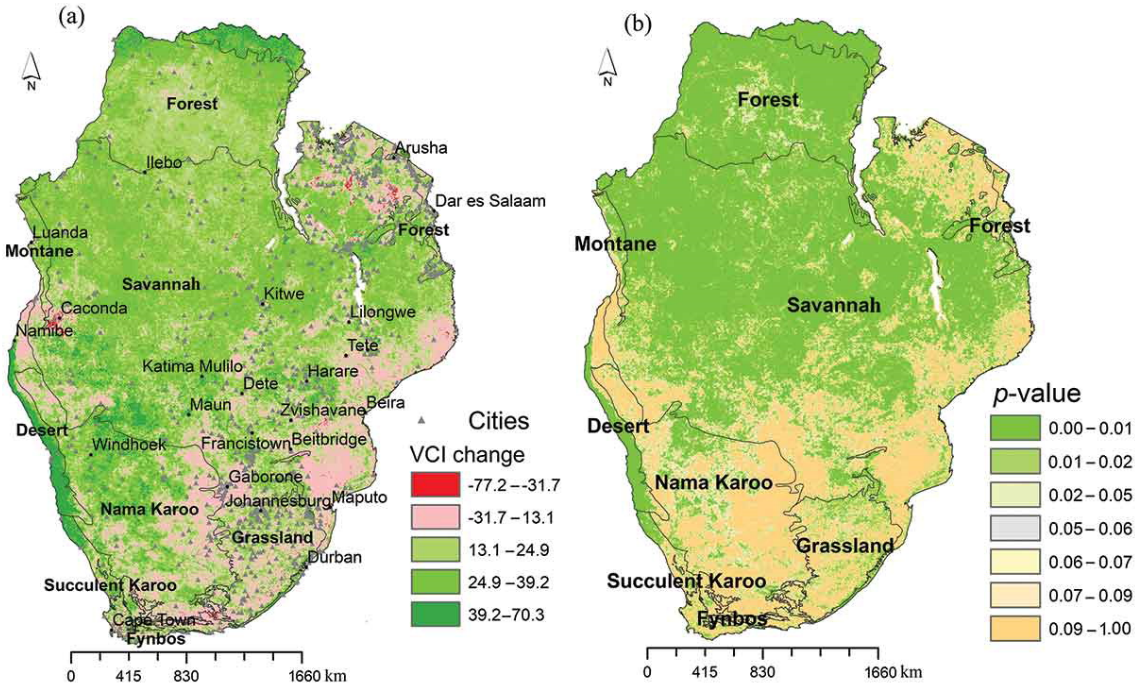

Figure 8. A) VCI changes based on pixel slopes during years 1998 to 2017. b) Map of *p*-values (*p*-value < 0.05

4. Discussion

The VCI has been widely applied in drought monitoring studies worldwide. Unlike other meteorological drought indices, VCI provides a direct measurement of drought impact based on the vegetation's photosynthetic activity (Kogan 1995). The main advantage of VCI is its ability to characterize drought conditions across diverse landscapes.

Within the Southern African region, although there have been some exceptions, most El Niño years result in severe drought conditions mostly during the mid to late part of the season (Dec–Jan–Feb). Meque (2015) noted that this period has the highest correlation between the El Niño–Southern Oscillation (ENSO) index and the SPEI and consequently any rainfall deficit during this period has a severe impact on vegetation. However, based on the seasonal VCI (Table 2), the major El Niño event of the 2015 to 2016 season generally had less impact on vegetation compared to the other years. This is finding is unusual considering the fact that 2015 to 2016 season drought was the worst since the 1980s (Archer et al. 2017). The year 2015 to 2016 drought only severely affected the grassland biome more than any other year, with 58% of the grassland biome affected by drought. These results are consistent with the findings of Swemmer et al. (2018) who also noted that 2015 to 2016 season drought had less impact on vegetation. In addition, Abbas, Bond, and Midgley (2019) in a study entitled 'The worst drought in 50 years in a South African savannah: Limited impact on vegetation' also noted insignificant tree mortality during 2015 to 2016 season drought. In fact, the study recorded an increase in tree numbers in 2016 and 2017 relative to the 2012 census which was not a drought year (Abbas, Bond, and Midgley 2019).

In terms of drought impact, the Montane and Forest biome had the least area affected by moderate to extreme drought (i.e. VCI<30) (Table 2). This is probably due to the fact that the Forest biome has deep root systems which enables it to withstand drought impact (Pasho et al. 2011; Xu, Wang, and Zhang 2016). In addition, the soil type of the Forest and Montane biomes has a higher proportion of clay (39% and 26%, respectively) (Harvest Choice 2011). This enables water retention which can support the vegetation during extended periods of droughts. The low percentage area of vegetation affected by drought during 2015 to 16 seasons in the Desert (13%), succulent karoo (19), and Fynbos (28%) biomes can be explained by the plant's efficient mechanisms which allows the vegetation to adapt to drought conditions which for example allows them to go dormant during drought period (Gouveia et al. 2017). In contrast, the grassland biome had the largest area affected by drought (58%). This is mainly due to the low levels of the plant's roots which means that a small reduction of soil moisture has a severe impact on the vegetation (Gouveia et al. 2017). This is further exacerbated by the fact the grassland biome has the highest livestock density. Browsing by livestock helps to reduce the vegetation cover and exacerbates the meteorological drought impact on vegetation.

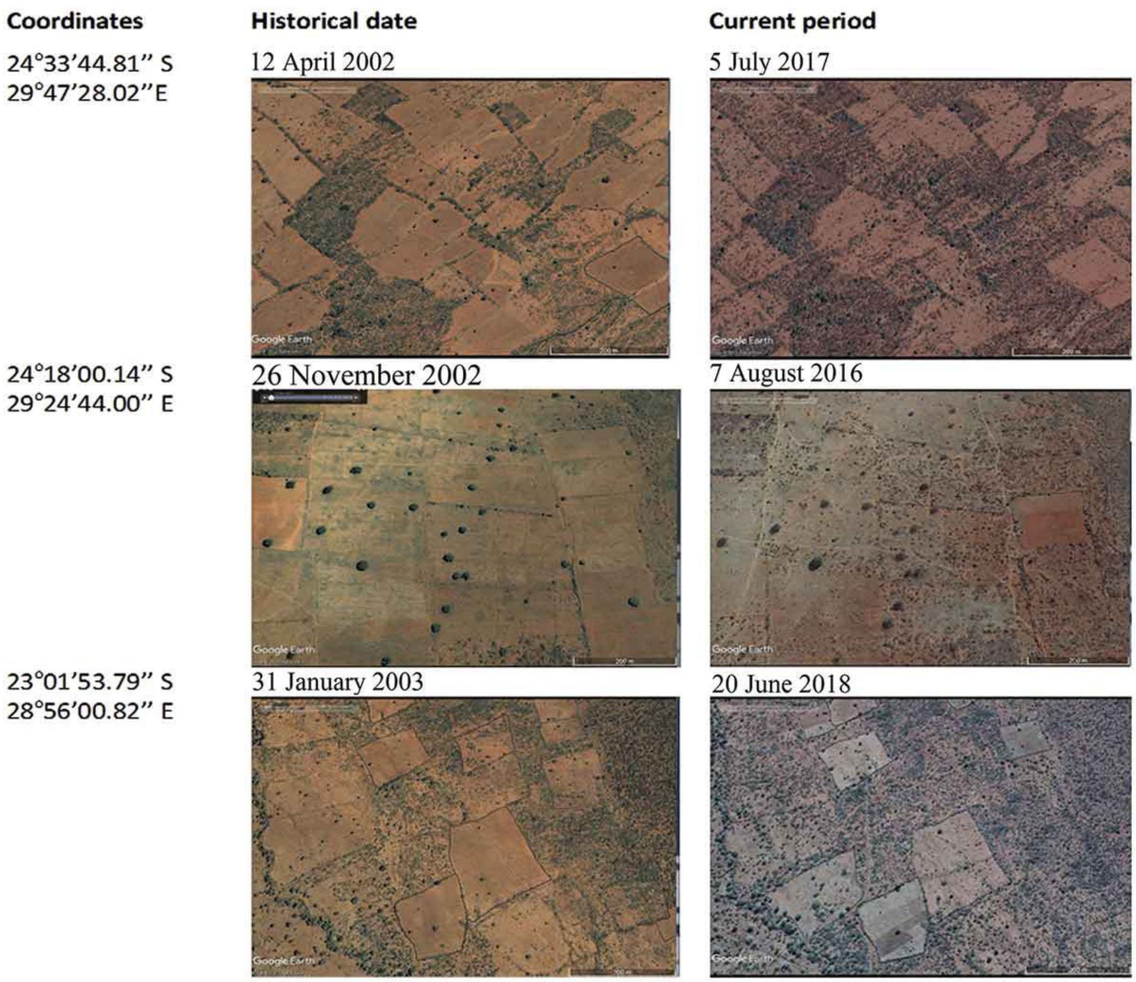

Figure 9. True color composite maps showing bush encroachment in agricultural fields. Map extracted from (Cho and Ramoelo 2019)

The analysis of VCI trends across Southern African biomes revealed an increasing trend of VCI especially over the Savannah biome, translating to a reduction in the intensity of drought impact on the vegetation. A plausible hypothesis to explain this is that the proportions of tree cover have been increasing over time. This phenomenon is referred to as woody encroachment and it is widespread in the Grassland and Savannah biomes (Luvuno et al. 2018). The causes of woody encroachment are widely debated. Cho and Ramoelo (2019) argued that Savannah woody encroachment (Figure 9) occurs as more agricultural land is left to fallow due to erratic and declining rainfall.

The resultant trees that grow as a result of woody encroachment (Figure 9) always green up in anticipation of the rainfall season and have a deep root system which can sustain the plants during extended drought periods (Cho, Ramoelo, and Dziba 2017). This possibly explains the increasing trend of VCI across most biomes and the low drought impact on vegetation during 2015 to 2016 season drought. However, this increasing tree cover in Savannah could unsettle the ecological benefits offered by the grass/tree mosaic of Savannah biome, e.g. the reduction of palatable forage which reduces the livestock carrying capacity.

In this study, we only have focussed on the impact of meteorological drought on the Vegetation Condition Index. However, other factors for example wildfires, herbivory, and human influence also affect the Vegetation Condition Index and these factors need to be investigated in future studies. For example, Bond and Keeley (2005) noted that the wildfire helps to maintain biome distribution and plant structure especially in biomes with recurrent wildfire outbreaks. In this regard, the drought impact on vegetation cannot be understood without understanding the ecology of wildfire (Bond and Keeley 2005).

5. Conclusion

We examined the impact of droughts on Southern African biomes over a 20-year period based on VCI. The year 2014 to 2016 period was a major drought and is well documented (Swemmer et al. 2018) and was captured in the study. This demonstrates the utility of VCI for capturing drought impact on vegetation. The majority of meteorological droughts occurred during the early part of the season (October–December) and most of the drought impact on vegetation was mainly restricted to the biomes on the south and southwestern part of the study area. In terms of the drought impact trends, we observed a general decline of drought impact across all biomes between 1999 and 2017, especially over the Savannah biome. This is despite the fact that the rainfall has been declining over most parts of the Southern African region (Marumbwa, Cho, and Chirwa 2019). As with most studies, our study laid the foundation for future work. Future studies should also focus on drought impact on landscape phenology and the time lag of vegetation response to drought impact.

Disclosure statement

The authors declare no conflict of interest.

Authors contribution

Study conception and design: Marumbwa, Cho

Acquisition of data: Marumbwa

Analysis and interpretation of data: Marumbwa

Drafting of the manuscript: Marumbwa

Supervision: Cho and Chirwa

Critical revision: Cho, Marumbwa

Additional information

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