An assessment of remote sensing-based drought index over different land cover types in southern Africa

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Abstract

An understanding of meteorological drought and land-cover interaction play a crucial role in vegetation vulnerability studies. A better understanding of drought and land-use land cover interaction also help in land use planning as well as reducing biodiversity loss. However, the is paucity of information on the impacts of meteorological drought on land-cover types. Understanding the drought and LULC interaction is more important especially on 'social pixels or 'village pixels' which represent rural communities We analysed the drought and land use interaction using and Globcover data and VCI for the 2015-16 season. The 2015-2016 season was chosen because it was a major disaster which forced SADC to declare a regional disaster to appeal for funding. We also developed a novel land use cover 'social pixel' based on the global livestock density (cattle and goat density>900per 10sq km). We used the Kruskal-Wallis test to evaluate whether there is a significant difference of drought impact among the land cover classes. We also analysed the drought frequency based on the drought occurrence maps (1998-2018) Our results reveal that the evergreen forests and the flooded vegetation were the most severely affected. (VCI 18.05 and 18.05 respectively) Despite, the village pixels having a higher mean VCI compared to the evergreen forest and flooded vegetation, the lowest VCI values were recorded in this land-cover, indicating the vulnerability of rural communities to droughts. With regards to drought recurrence (1998 to 2018), the crop and grassland land cover recorded the highest drought frequency whilst the forest had the least drought frequency.

Drought impact, land-cover, land use, southern Africa, google earth engine.

INTRODUCTION

Drought impact assessment on land cover types is crucial for various agricultural and environmental applications (Baniya et al., 2019). Drought is complex phenomenon and is regarded as one of the serious natural hazards (Wilhite, 2000). Drought monitoring and assessment is also complicated the by fact that there is no universal definition. A number of definitions' have been proposed with most definition regarding it as diminished precipitation, soil moisture, plant vigour, ecological and socio-economic status (Kogan et al., 2019). In this study, we regard drought as a period when rainfall is below the historical mean. The simultaneous analysis of drought impact is on multiple landcover types at regional scale is crucial for quantifying the environmental impacts of droughts especially in the context of climate change (Vicente-Serrano, 2007). This is more critical because vegetative drought impacts can influence regional landcover type (Tollerud et al., 2018)stability and transformation.

Within the semi-arid regions rainfall and temperature negatives anomalies are the main drivers of drought (Nicholson, 1990). Global climate models suggest a decrease in rainfall in southern Africa (DAI). This projected decrease will intensify drought occurrence and degradation of land (Vicente-Serrano, 2007) impacting crops and livestock (Ayanlade et al., 2018). A number of studies have also reported the impacts of drought on single landcover types (natural vegetation and crops) e.g. (Tollerud et al., 2018; Kuri et al., 2019; Gidey et al., 2018; Kogan, 1995).Other studies (e.g. Mupangwa, W., Walker, S., Twomlow, S., 2011. Start, end and dry spells of the growing season in semi-arid southern Zimbabwe. J. Arid Environ. 75, 1097–1104., Kuri,) have highlighted the devastating impacts of drought on rural communities who normally depend on agriculture for survival (Ayanlade et al., 2018) Very few studies have focused on the analysis of drought impacts on landcover types which are dominated by rural communities ('social pixels').

The analysis of drought and land use interactions especially focusing on village pixels is important considering that more than 57% of the southern African people live in rural areas (Dalal-clayton 1997). Most of these rural population survive on the ecosystem services with little adaptive capacity to weather impacts which makes them vulnerable to drought (Cooper et al. 2008). The monitoring and assessment of drought impact at village pixel is therefore crucial. Up to now no attempt has been made to understand drought in social pixels this is largely due to the absence of the land cover type which represents the social pixels / rural communities. There is therefore need to include the social pixels when analysing drought and land use and landcover interaction as it helps in land use planning and reducing biodiversity loss (DOI:10.1007/s10661-011-2514-8). The drought and landcover interactions are made possible thanks to the availability of drought indices.

A number of studies have employed a suite of meteorological drought indices to analyse drought with the standardized precipitation evapotranspiration index (SPEI) (REF XX), the standardized precipitation index (SPI) [23] and the Palmer drought severity index (PDSI) [29,30]. SPI and SPEI can be computed at multiple time scales (1-48 months) which makes them suitable for assessing the vegetation response to drought. SPEI has a further advantage of incorporating the contributing of evapotranspiration on drought severity. One of the drawbacks of the PDSI is that it lacks the multiple time scale component which makes it less attractive in assessing vegetation response to drought. In addition, the traditional approaches of quantifying drought impact on vegetation are mainly based on crop yields and point data (Vicente-Serrano, 2007). The problem of these approaches is that they are limited in space and times and are mostly suited for localised application. Furthermore, when using these methodologies, it's difficult to differentiate vegetative drought impacts among landcover types (Vicente-Serrano, 2007)

The use of remote sensing provides a potential solution as it provides both vegetation and rainfall indicators relevant for drought monitoring (XXXXX). The main advantage of remote sensing is that it provides a wide coverage as well as huge historical archive of data (REF). This makes it ideal for regional assessments of drought impact on vegetation. (Kogan, 1995, 1998; McVicar and Jupp, 1998). The Normalised difference vegetation Index (NDVI) is the most commonly used remote sensing index for vegetation monitoring are. NDVI has been successfully used in a number of drought assessment studies and projects as a proxy of vegetation vigour and leaf area index which is a proxy for productivity (Tucker, C. J.: 1979, Red and photographic infrared linear combinations for monitoring vegetation, Remote Sensing Environ. 8, 127–150.). NDVI is widely used to monitor vegetation status and is highly correlated to biomass. Tucker, C. J., Vanpraet, C. L., Boerwinkel, E., and Gaston, A.: 1983, Satellite remote sensing of total dry accumulation in the Senegalese sahel, Remote Sensing Environ. 13, 461–474.) and the spatio-temporal variation in NDVI are mainly influenced by variations in weather conditions (Eastman, J. R. and Fulk, M. A.: 1993, Long sequence time series evolution using standardized principal component analysis, Photogrammet. Eng. Remote Sensing 53, 1649–1658; Ichii, K., Kawabata, A., and Yamaguchi, Y.: 2002, Global correlation analysis for NDVI and climatic variables and NDVI trends: 1982–1990, Int. J. Remote Sensing 23, 3873–3878..)

Nicholson (1990), further notes that the changes in the vegetation greenness (NDVI) over time may be attributed to the plant's response to the variation in the climate. This makes NDVI useful for drought monitoring and impact assessment. (Tucker and Choudhury, 1987; Groten and Ocatre, 2002).

However, due to the fact that NDVI is also influenced by relief, ecosystem characteristics, underlying geology and phenology (Di et al., 1994i From vicente 2007), NDVI on its own is not useful for comparing drought impact of vegetation (Vicente-Serrano, 2007). In this regard to analyse the impacts of drought, on vegetation NDVI values are stratified to remove the contribution of environmental conditions in the analysis (Vicente-Serrano, 2007). To address the limitation of NDVI Kogan (1990) – From Vicente 2007) developed the Vegetation Condition Index (VCI) which applies a geographic filter to remove the influence of ecosystem and topography on NDVI. (Vicente-Serrano, 2007). The resulting VIC has values ranging between 0 (minimum NDVI) and 100 (maximum NDVI) and is widely used for monitoring the impact of weather on plants across diverse vegetation landscape (Vicente-Serrano, 2007).

Despite the availability of freely available remote sensing data , there is paucity of information on drought and land use landcover interactions at sufficient resolution to capture the smallest landcover units especial crops. In most cases the spatial resolution is used is coarse (eg kuri 1km SPOT VGT-crop. e.g. (Vicente-Serrano, 2007) analysed drought impact on vegetation in the Iberian Peninsula between 1987 and 2000 using coarse AHVVR and SPEI; Nicholson, S. E., Davenport, M. L., and Malo, A. R.: 1990, A comparison of the vegetation response to rainfall in the Sahel and east Africa, using normalized difference vegetation index from NOAA-AVHRR, Climatic Change 17, 209–241.). The problem of the coarse resolution data in vegetative drought impact analysis is that it results in mixed landcover types and averaging results at biome level result in misleading results. ~~In addition most of the regional studies are based on land use and landcover type (e.g, , focused on grassland………..). Furthermore, these studies use different methodologies which make it difficult to compare the get a regional picture.~~

~~Furthermore, most of these studies analysed the drought and landcover interaction for the entire Southern Africa (e.g. XXXXX) which does not produce accurate information compared to summarising the analysis at ecoregion level as recommended by (Tollerud et al., 2018)~~

High to medium data eg based on SENTINEL or LANDSAT is only used for small areas (e,gXXXx). This is mainly due the high computing power needed to process data for large areas as well as the lack of computer programming skills. Google Earth Engine (GGE) offers an opportunity to analyse data at regional resolution and at mdium resolution (e.g JF Pikel calculated global water occurrence at 30m resolution , XXXXXX, --------------) GGE is-------------Despite the usefulness of GGE, no study to the best of our knowledge has taken advantage to analyse drought impacts on land cover types using medium resolution data.

This study capitalises on the freely available remote sensing datasets and the computing power of Google Earth Engine (GEE). The objective of this paper is to assess the spatial variations in vegetative drought impact as well as vegetation response to drought impact using the 2015/2016 season. The 2015-2016 season was one of the most severe droughts in the history of southern Africa (Ref XX). The study also analyses drought frequency on the land cover types based on the NDVI data from between 1998-2018. We focused the analysis on 7 landcover types (Figure 1a) and a novel land cover type “social pixel” or “village pixel” derived from the livestock density gridded data. In this study we tested if there is a significant difference in the median drought impact (mean VCI) among the land cover types. Specifically, the study focuses on the following questions: which land cover has the highest drought severity and frequency? How does the land cover types respond to drought impact?

Method

Study area

The study area is located in the Southern Hemisphere and is bounded by the following coordinate 6^{o}N to 35^{o}S and longitude 10^{o}E to 41^{o}E. ~~The total surface area of the study area is XXXXX and~~ The most dominant land cover type in the study area is grassland which is mainly concentrated on the southern half of the region (Figure 1). Th forests land cover type is mainly located in the Northern parts of the region. ~~XXXXXX which accounts for XX%.~~ The vegetation development in the study area is mainly determined by precipitation availability. Most parts of the study area receive summer rainfall between October and April. The Cape province of South African receives winter rainfall typically between May and Sep (REF XXX) The highest rainfall values are recorded in the northern parts of the region mainly covering the forest areas. And the lowest rainfall values are mainly located in the southwestern parts of the study area mainly covering the grasslands

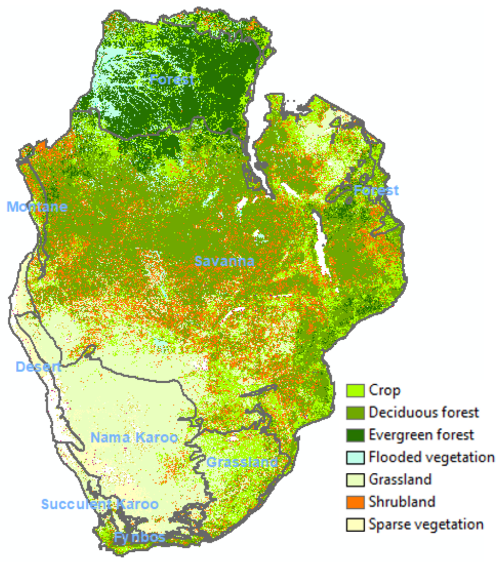


Figure 1a) Location of the study area land-cover distribution

The rainfall variability is mainly controlled by the El Niño Southern Oscillation (ENSO) which is triggered by variations in the sea surface temperatures in the equatorial Pacific ocean. (Unganai and Kogan, 1998). The El Niño (i.e. warm phase of the ENSO) result in below average precipitation over southern Africa while the La Niña (i.e. cold phase of ENSO) results in heavy rains 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 & Vincent, 2017).

Input data

Normalised difference Vegetation Index (VCI)

In this study we analysed the vegetative drought impacts using the 10 day and seasonal NDVI data based on the SPOT and Probav sensor. This data is produced every 10 days using the Maximum value composite (MVC) to reduce the impacts of cloud cover. The data is produced at a spatial resolution of 1km and is available from 1998 to present and is available from Copernicus website (https://land.copernicus.eu/global/products/ndvi).

NDVI provides information about vegetation greenness and is computed using the NIR and RED bands as NDVI = (NIR - RED) / (NIR + RED), where NIR is the near-infrared reflectance and RED is the visible-red reflectance (Tucker, 1979; Tarpley et al., 1984) -from Kuri. The NDVI is commonly used in many environment related studies ranging from ecosystems dynamics, landcover change, drought monitoring and for operational applications such as crop monitoring (https://landval.gsfc.nasa.gov/ProductStatus.php?ProductID=MOD13&_ga=2.246197761.426756091.1573011879-682554445.1570634039). To minimize the effects of cloud contamination inherent in NDVI data, we applied a Savitzky–Golay smoothing filter (5 window filter, 5th order polynomial) following (Cho, Ramoelo and Dziba, 2017). The resultant smoothed NDVI was used to calculate Vegetation Condition index (VCI).

~~In this study we analysed vegetative drought impacts using 16 days Moderate Resolution Imaging Spectroradiometer (MODIS) Normalized difference Vegetation Index (NDVI) data. MODIS (or Moderate Resolution Imaging Spectroradiometer) is a key instrument aboard the Terra (10:30 am overpass) and Aqua (1:30 pm overpass) satellites. (https://earth.esa.int/web/guest/missions/3rd-party-missions/current-missions/terraaqua-modis). NDVI provides information about vegetation greenness and is computed using the NIR and RED bands as NDVI = (NIR - RED) / (NIR + RED), where NIR is the near-infrared reflectance and RED is the visible-red reflectance (Tucker, 1979; Tarpley et al., 1984) -from Kuri. The NDVI is commonly used in many environment related studies ranging from ecosystems dynamics, landcover change, drought monitoring and for operational applications such as crop monitoring (https://landval.gsfc.nasa.gov/ProductStatus.php?ProductID=MOD13&_ga=2.246197761.426756091.1573011879-682554445.1570634039)~~

~~The 16 days MODIS NDVI data is maintained by the NASA EOSDIS Land Processes Distributed Active Archive Center (LP DAAC) at the USGS Earth Resources Observation and Science (EROS) Center, Sioux Falls, South Dakota (https://lpdaac.usgs.gov/data/data-citation-and-policies/). The MODIS NDVI is calculated using TERRA and Aqua's daily atmosphere corrected, bi-directional surface reflectance's which are free of cloud shadow, aerosols and water pixels. The daily NDVI images are then subsequently aggregated at 16 days intervals to eliminate low quality observations (https://landval.gsfc.nasa.gov/ProductStatus.php?ProductID=MOD13&_ga=2.246197761.426756091.1573011879-682554445.1570634039).~~

~~Since both Terra (10:30 am overpass) and Aqua (1:30 pm overpass) are identical and captures the earth almost at the same time, data from these two sensors are used in the NDVI algorithm to minimise the impact of cloud contamination. https://landval.gsfc.nasa.gov/ProductStatus.php?ProductID=MOD13&_ga=2.246197761.426756091.1573011879-682554445.1570634039).~~

~~This MODIS NDVI dataset is available from 18 February 2000 at a spatial resolution of 250m and was accessed via Google Earth API (https://code.earthengine.google.com/). Advantages of the GGE API processing no need to download. A number of validation campaigns based on both airborne and field measurements have show a close correlation between the MODIS NDVI with the the land surface biophysical properties over most biomes (CAN GIVE EXAMPLES) https://landval.gsfc.nasa.gov/ProductStatus.php?ProductID=MOD13&_ga=2.246197761.426756091.1573011879-682554445.1570634039).~~

Vegetation Condition Index (VCI)

For the purposes of assessing the drought impact on the different landcover types, we computed the Vegetation condition Index (VCI) at 10 day (dekad) and seasonal intervals following (Kogan 1990). $VCI = ((NDVI_i - NDVI_{min,i}) / (NDVI_{max} - NDVI_{min})) \times 100\%$ (eq1).

Where $NDVI_i$ is the 16day or seasonal vegetation index, $NDVI_{max,\,i}$ $NDVI_{min,i}$ is the long-term maximum and minimum calculated for each pixel for each 10 day and season from the NDVI time series data. The resulting VCI ranges from 0 (extreme drought i.e. minimum drought) and 100 (no drought i.e. maximum NDVI) (Kogan, 1995) with cut for drought represented with VCI values below 40 (e.g. Kogan, 1997; Dutta *et al.*, 2015) The resultant VCI was then masked out to remove non drought pixels (i.e. VCI >40) .

Standardised Precipitation Evapotranspiration Index (SPEI)

We used SPEI to assess the vegetation's response to drought for each land cover type. The main advantage of SPEI over SPI is that it can be calculated at different time scales (REF XX) and capture both the contribution of rainfall and temperature in drought impact (REF).The SPEI data was downloaded from https://digital.csic.es/handle/10261/153475 website. The SPEI data is provided at multiple time-scales (1-48 months) at a spatial resolution of 0.5^0 (Vicente-Serrano et al., 2013). The SPEI algorithm uses precipitation together with the potential evapotranspiration based on the FAO Penman-Monteith method which is widely accepted in calculation of evapotranspiration which uses many inputs than the Thornthwaite algorithm which only use temperature (Sheffield et al., 2012).

Land use Landcover data

To analyse the influence of land cover type on drought we used, the Globcover 2009 which is available in Google Earth GGE. (Image ID ESA/GLOBCOVER_L4_200901_200912_V2_3). The Globcover 2009 was developed by European Space Agency (ESA) based on the ENVISAT's Medium Resolution Imaging Spectrometer (MERIS) Level 1B data. This data is provided at a spatial resolution of 300m resolution with 22 land cover classes defined with the United Nations (UN) Land Cover Classification System (LCCS (2010 and UCLouvain http://due.esrin.esa.int/page_globcover.php). We first masked out built up, water and irrigated crops from the land cover map.

The basic pre-processing of the Globcover data (i.e. clipping global landcover data to the study area ~~and masking out of the out built up, water and irrigated crops~~) was done in google earth engine platform. To simplify the analysis of drought impact on landcover classes, the original 21 land cover classes (Table 1) was reclassified to 11 classes as shown in (Table 2) using the reclass function in GGE. These new classes were then used for assessing drought impact on vegetation. The resulting landcover data for was then exported to geotif for further possessing and analysis.

Table 1: Original Globcover landcover classes

Value	Label
11	Post-flooding or irrigated croplands (or aquatic)
14	Rainfed croplands
20	Mosaic cropland (50-70%) / vegetation (grassland/shrubland/forest) (20-50%)
30	Mosaic vegetation (grassland/shrubland/forest) (50-70%) / cropland (20-50%)
40	Closed to open (>15%) broadleaved evergreen or semi-deciduous forest (>5m)
50	Closed (>40%) broadleaved deciduous forest (>5m)
60	Open (15-40%) broadleaved deciduous forest/woodland (>5m)
70	Closed (>40%) needleleaved evergreen forest (>5m)
90	Open (15-40%) needleleaved deciduous or evergreen forest (>5m)
100	Closed to open (>15%) mixed broadleaved and needleleaved forest (>5m)
110	Mosaic forest or shrubland (50-70%) / grassland (20-50%)
120	Mosaic grassland (50-70%) / forest or shrubland (20-50%)
130	Closed to open (>15%) (broadleaved or needleleaved, evergreen or deciduous) shrubland (<5m)
140	Closed to open (>15%) herbaceous vegetation (grassland, savannas or lichens/mosses)
150	Sparse (<15%) vegetation
160	Closed to open (>15%) broadleaved forest regularly flooded (semi-permanently or temporarily) - Fresh or brackish water
170	Closed (>40%) broadleaved forest or shrubland permanently flooded - Saline or brackish water

180	Closed to open (>15%) grassland or woody vegetation on regularly flooded or waterlogged soil - Fresh, brackish or saline water
190	Artificial surfaces and associated areas (Urban areas >50%)
200	Bare areas
210	Water bodies
220	Permanent snow and ice
230	No data (burnt areas, clouds,)

Table 2: Reclassified Globcover landcover classes

Original classes	new class	Name
11	1	Irrigated cropland
14, 20, 30	2	Crops
40,70, 90	3	Evegreen forest
50,60,100	4	Deciduous forest
110,120,130	5	Shrubland
140	6	Grassland
150	7	Sparse vegetation
160,170,180	8	Flooded vegetation
190, 200	9	Bare and artifical areas
210	10	Water bodies
220, 230	11	Ice and no data

Livestock density (consider using pop density)

We used the livestock (cattle and goats) density gridded data to compute a novel 'social pixels' a unique land cover type representing rural communities or 'village pixels which is also part of the communal rangelands. The livestock density data for goats and cattle is based on the African model and is provided on a spatial resolution of 10 km for year 2000 data which is adjusted to FAOSTAT values (Robinson TP, Wint GRW, Conchedda G, Van Boeckel TP, Ercoli V, Palamara E, Cinardi G, D'Aietti L, Hay SI, and Gilbert M. (2014) Mapping the Global Distribution of Livestock. PLoS ONE 9(5): e96084. doi:10.1371/journal.pone.0096084).

The goats and cattle density data were downloaded from the FAO geoportal; http://www.fao.org/geonetwork/srv/en/

~~Link to cattle density:~~

~~http://www.fao.org/geonetwork/srv/en/resources.get?id=47949&fname=AFCattle1km_AD_2010_GLW2_01_TIF.zip&access=private~~

~~Link to goat density: http://www.fao.org/geonetwork/srv/en/resources.get?id=48049&fname=AFGoats1km_AD_2010_v2_1_TIF.zip&access=private~~

We defined the village pixels as areas with cattle and goat density > 400 per 10km. The resultant village pixel mask landcover (Figure 2) corresponds very well with the general rural population ~~density map (Figure XX) in terms of the general~~ patterns which makes it useful for understanding drought impacts on communities 'social pixels' i.e rural communities . ~~as well as how it the vegetation within the village pixels respond to drought.~~ The resultant village pixel land cover was then used in the drought impact analysis together with other landcover units from the Globcover map.

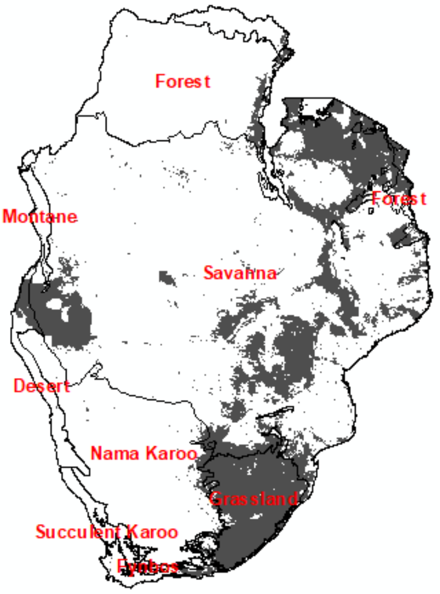


Figure 2: Village pixels based on cattle and goats density data

Data Analysis

Calculation of drought frequency

We calculated drought frequency using seasonal (October - April) VCI data from 1998 to 2018. In order to match the resolution of the landcover data, we first resampled all the VCI dataset to match the globcover spatial resolution of 300m. To characterise the drought impact on landcover we only considered vegetation pixels under drought (i.e. VCI< 40). We masked out the built-up areas, irrigated crops, water bodies and bare soil from the analysis. The resultant VCI maps showing only drought conditions were then used to compute the number of times each landcover pixel was affected by drought conditions over the 20 year period (1998 to 2018). We also computed the percentage area covered by drought (1998-2016)

Drought Impact analysis

To assess drought impact across land cover types we used the dekadal (10day) VCI for 2015-16 season. A total of 21 dekadal VCI images were used in the analysis. We chose the 2015-2016 season because it was one of the driest since the 1980s, with severe consequences on vegetation (Archer et al., 2017). The analysis was restricted to drought pixels (VCI<40) non drought pixels were not considered in the analysis. We then extracted the median VCI for each landcover and village pixel to assess the drought impact for each land cover type

Since, the median VCI for the landcover types did not follow the normal distribution and thus violates one of the assumptions of Analysis of variance (ANOVA), the Kruskal-Wallis test (Wallis, K. (1952). Use of ranks in one-criterion variance analysis. Journal of the American Statistical Association, 47, 583-621.) was used to test whether there is no significant difference ($p<0.05$) in drought impact among the vegetation classes following recommendation by (Vargha and Delaney, 1998). The Kruskal Wallis test extends from the Wilcoxon Rank-Sum test which to deals with 2 samples and is used in place of one-way ANOVA since the data was not normally distributed. (http://www.real-statistics.com/one-way-analysis-of-variance-anova/kruskal-wallis-test/

~~In addition, we also computed the seasonal NDVI's coefficient of variation (CoV) (1998-2019) to ascertain if there and any variation in drought impact due to plants activity (represented by NDVI) and temporal variability (represented by Cov) following (Vicente-Serrano, 2007)~~

$$\mathrm{CoV} = \frac{\sigma_x}{\bar{x}}$$

~~Where X is the average NDVI and Xs is the standard deviation of the NDVI data~~

Vegetation response to drought

To determine the landcover type's response to drought we sued the correlated the NDVI data for 2015-2016 season with monthly SPEI data at different time-scales (i.e. 1,3,6,9,12, 18 and 24 months). To facilitate the correlation, we first resampled the SPEI to match the 1km resolution of the NDVI. From the resulting correlation maps from the different time scales we created a composite map and computed a map showing the SPEI time-scale at which maximum correlation between NDVI and SPEI is found (i.e. time lag of vegetation response to drought impact).

Results

Figure 3 show the long-term average NDVI (1998-2018) over the study area. Areas of low vegetation activity are mainly found in the southwestern part of the region covering the grassland, sparse vegetation and some parts of the shrubland. Dense vegetation activity (high NDVI) is mainly over the forest biomes. ~~The NDVI profiles for the landcover units is shown in figure XXX~~

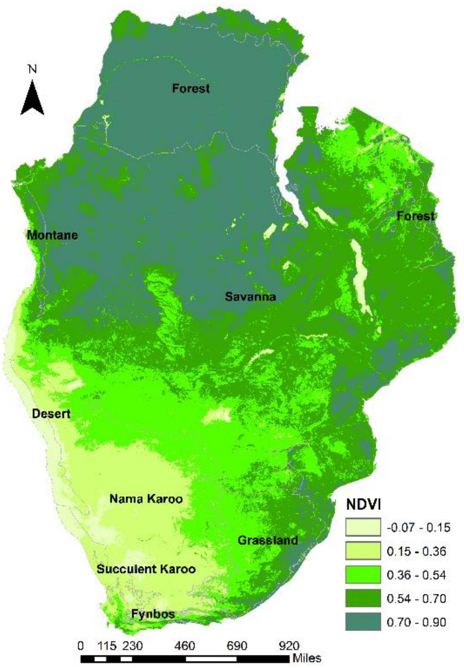


Figure 3 show the long-term average NDVI (1998-2018)

Temporal trends of drought impact

Figure 4 show trends the mean seasonal VCI for all the southern landcover types (1998-2017). The main drop in VCI (drought) was recorded in 2015-2016 and 2016-2017. These periods coincided with the major droughts that affected the Southern African region. On particular interest is the 2015-16 drought which caused widespread crop failure across many major countries which forced many countries to declare drought disasters (Archer et al., 2017). These findings validate the utility of VCI for characterising drought impacts on vegetation.

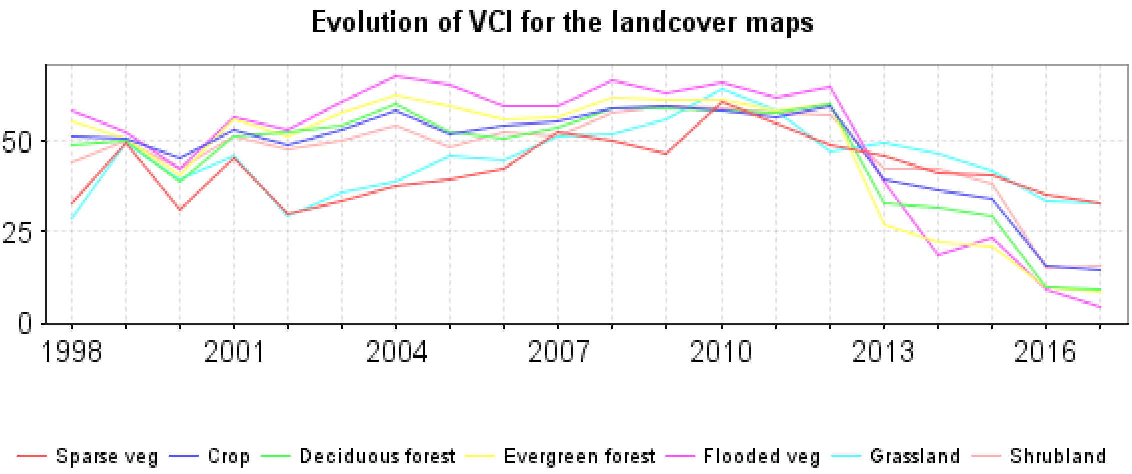
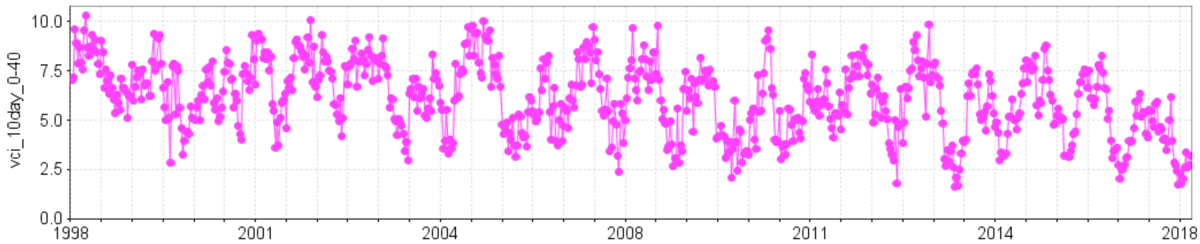


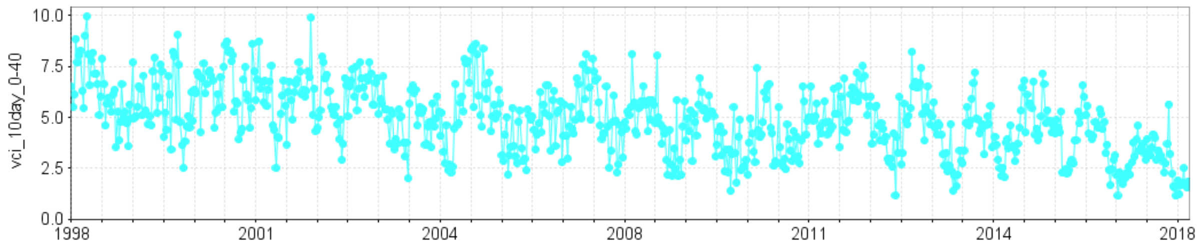
Figure 4: VCI trends based on seasonal mean VCI (1998-2018)

Figure 6 provides more details of the VCI trends at dekadal interval focussing only on pixels affected by drought extreme drought (i.e. VCI<30). It can be seen that there is a general declining trend of VCI with most landcover units recording lowest VCI is between 2015 and 2018.

Crop

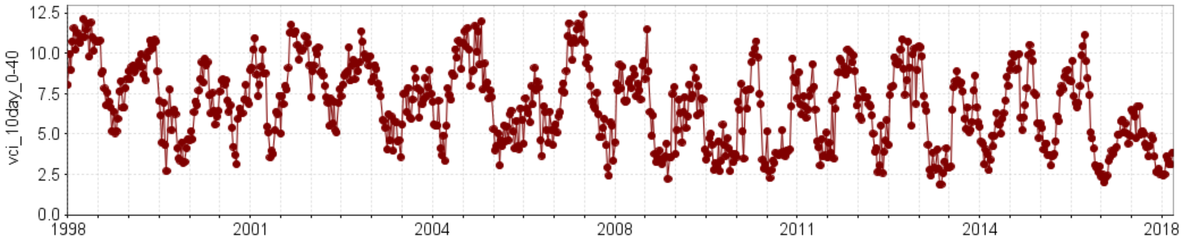


Evergreen forest

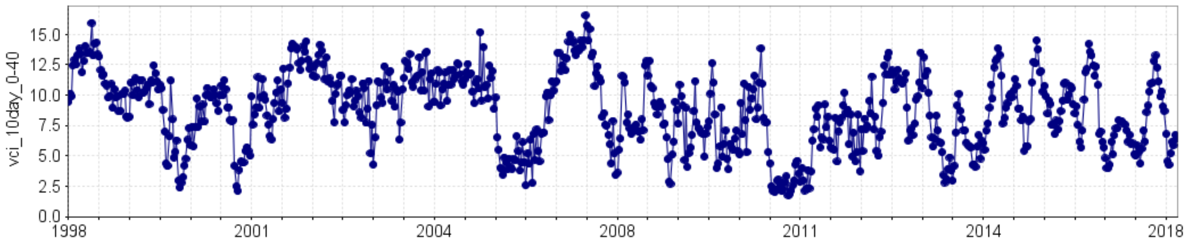


Deciduos forest

Shrubland

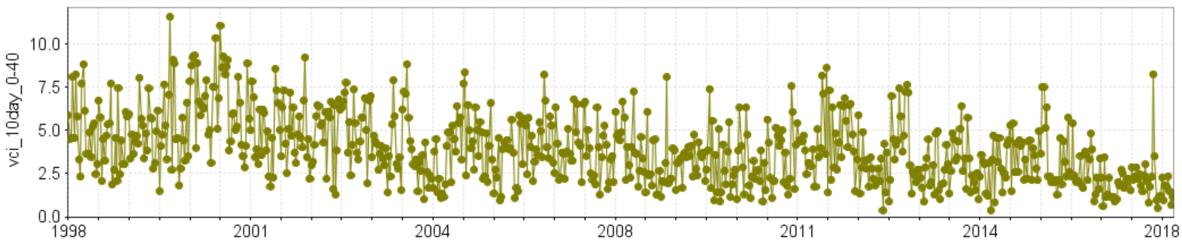


Grasslands



Sparse vegetation

Flooded vegetation



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Drought impact analysis

The results of drought impact for the different landcover types are shown in figure 6 based on the dekadal mean VCI for the 2015-2016 season. The village pixel landcover type recorded the lowest VCI during the 2015-2016 drought season. This was followed by the flooded vegetation. It is reasonable to hypothesise that the village pixel landcover type is vulnerable to drought impact.

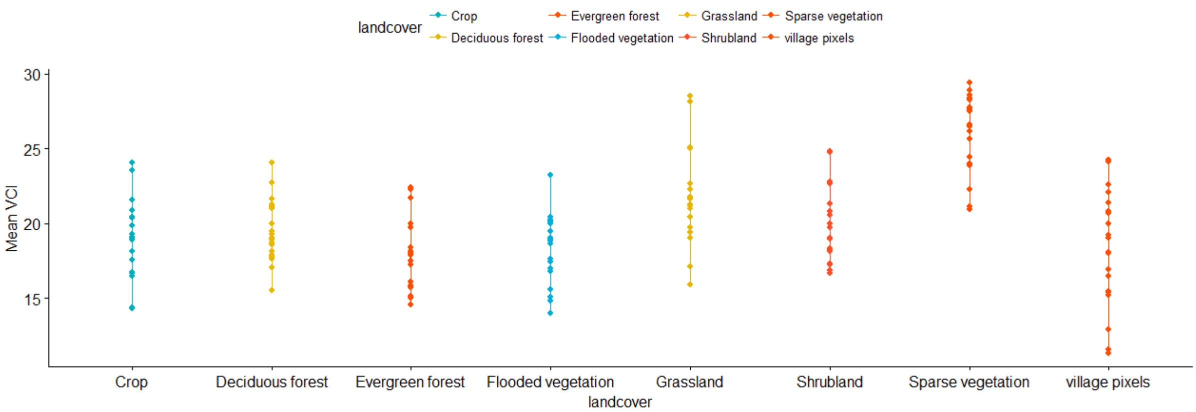

Figure 6: Drought impact during the growing season (October 2015- April 2016).

The box plots (Fig 7) provide a summary of the drought impacts (median VCI) based on the dekadal VCI images. The Kruskal-Wallis test show significant difference in drought impact a mong the landcover types and vegetation pixels (p-value = 4.256e-11) confirming the fact tha t drought impact of vegetation is not the same across the landcover types. The low VCI values across all the landcover also shows that fact that the 2015-2016 was the most severe drought a s reported by (Archer et al., 2017).

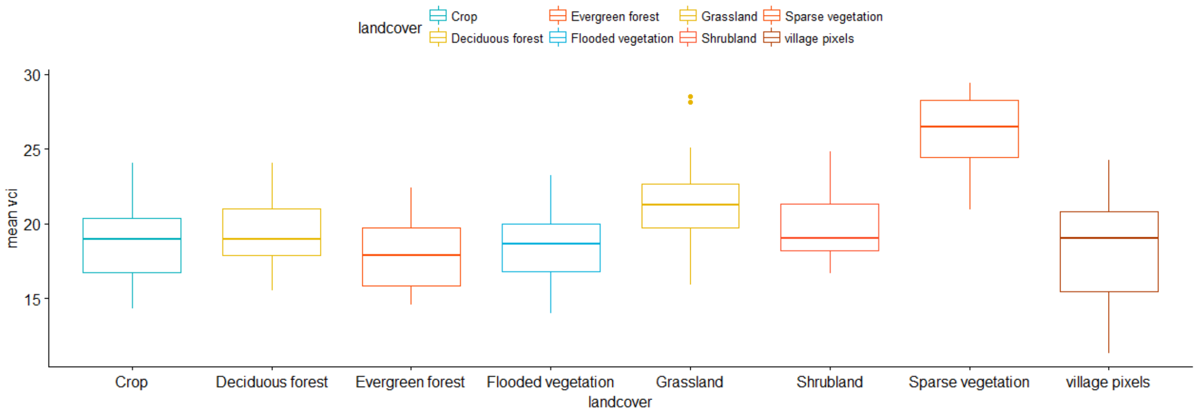

Figure 4: Box-plots showing mean drought impacts among landcover types and vegetation pixels.

The mean VCI for the landcover types is presented in Table 3. The lowest VCI values are recorded over the evergreen forest (VCI =17.89) and the flooded vegetation (VCI=18.05). On the other end the highest VCI value of 26 was recorded over the sparse vegetation.

Table 3: Mean VCI for 2015-16 season

landcover	mean VCI
Crop	18.77
Deciduous forest	19.36
Evergreen forest	17.89
Flooded vegetation	18.05
Grassland	21.47
Shrubland	19.8
Sparse vegetation	26.04
village pixels	18.31

~~This finding is lowinteresting given that the evergreen forest has deep root system and is located in an area with high rainfall (REF XXX) recorded severe drought impact compared to and sparse vegetation, which is predominantly dry is located over the South western part of the study area which is arid.~~

~~The quick response of the forest to drought (i.e. 3 months) Table XX explains why the low VCI compared to other classes~~

Vegetation response to drought per landcover type

Table 4 present a summary of the response of the land cover types to drought. Our findings show that most landcover types generally the respond to drought impacts at time scales ranging from 2 months to 8 months. Croplands and responds to drought at short time scales (2 months) whereas flooded vegetation responds at medium time scales (8 months). These results are consistent with the findings of (Vicente-Serrano, 2007) and explains why the evergreen forest is among the landcover classes with the lowest VCI values

Table 4: Landcover response to drought (time-lag of drought impact on landcover)

Landcover	Time-lag of drought impact (month)
Crop	2
Evergreen forest	3
Deciduous forest	4

Shrubland	5
Grassland	6
Sparse vegetation	7
Flooded vegetation	8

Drought Frequency Map

Discussion and conclusion

In this study we analysed the drought impacts on vegetation using VCI widely used as a proxy for vegetation greenness (Kogan et al., 2019; Liu and Kogan, 1996; Unganai and Kogan, 1998). Due to the fact that NDVI is not comparable across different geographical areas (Vicente-Serrano, 2007), we computed the VCI which enabled the quantification and comparison of drought impacts on different vegetation types using the Globcover land cover data. To analyse drought trend and frequency analysis, we used VCI data from 1998 to 2018. For assessing the drought impacts on the land cover units, we specifically select the 2015-2016 season which was one the major drought with severe impacts on crops natural vegetation and livestock (Archer et al., 2017). ~~This forced many countries to declare disasters as early as in February and forced SADC to declare a regional disaster~~.

We also developed a novel landcover "social pixels" based on livestock density. The inclusion of the "social pixel" is novel and important since it provides a new insight into drought impacts on rural communities. The cattle density map was selected because of the close association between rural communities with livestock especially cattle which is used as draught power to increase farm productivity and their life (Ellis-Jones and O'Neill, 2000; Pearson and Vall, 1998). In addition, the social pixels, which is also part of the communal rangelands provides the rural communities with the ecosystem goods and service which support livelihoods (Cousins, 1999). This makes it important to understand how the drought affects the vegetation in the 'social pixels' which are dominated by the livestock rural and communities / villages.

Our results show that drought impacts are not the same and vary with landcover. The sparse vegetation appears to be the least affected by drought impact during the 2015-2026. This can be explained by the fact that this landcover together with grassland can quickly responds to rainfall after termination of drought (show Spirits maps)

On the other hand, the evergreen forest and the flooded vegetation recorded the lowest mean VCI (drought impact). For the flooded vegetation one possible explanation is that greater parts of the flooded vegetation lie in the arid part of the region (e.g. the Okavango delta) which means more drought impacts when the water which normally floods the vegetation is lost via evapotranspiration. For the forest this could be explained by fact that the forest quickly responds to drought impact (Table 4) (~~REF XX).~~ Deciduous forests on the other hand are less impacted by drought (VCI=19.36) compared to evergreen forest (VCI=17.89). This can due to the fact that, unlike the evergreen forests, deciduous trees normally shed leaves as a copying strategy for minimise drought impacts (Chidumayo)

Despite the fact that the 'social pixel' landcover class had a mean VCI of 18.31, much higher than the evergreen and forest vegetation, it is worrying to note that the the lowest dekadal VCI values were located land cover. This finding is worrying considering the important role of social pixels. The extremely low VCI values (extreme drought) in the 'social pixels' caused severe loss of cattle affecting (e.g. in Zimbabwe-----) forcing many countries to declare a major disaster. The loss of livestock to drought interrupts farming leading to poverty. This has been identified as one of the major challenges hindering economic progress in Sub- Saharan Africa by the Food and Agriculture Organisation (FAO)

(http://www.fao.org/3/a0229e/a0229e04.htm)

Conclusion

The by analysing the drought frequency, drought impact on landcover as well as the response of the vegetation to the drought impact were able. to characterise both the spatio-temporal analysis of drought impact across the landcover classes. The results of this study provides can be used to support land use planning as well as helping to preserve biodiversity loss.

4. Results

4.1. SEASONALITY OF THE NDVI PATTERNS

Figure 4 shows the evolution of the average VCI of the study area between 1987 and 2000. The main decrease was recorded in 1991–1992 and 1995–1996 coinciding with the main drought periods that affected this region (Vicente-Serrano, 2005). On the contrary, between 1987 and 1988 and

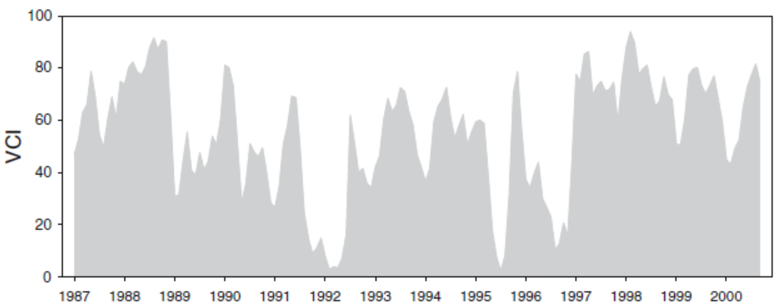

Figure 4. Evolution of the VCI for the whole study area (1987–2000).

Figure 5 shows the spatial and temporal average and standard deviation values of the monthly NDVI for the whole study area. On average, the highest NDVI values were recorded during the spring, with a marked rise occurring in the index between January and April, followed by a slower fall from here to the end of the year. This behaviour is determined by climatic seasonality: in winter, frequent frosts limit vegetation activity **whereas in summer, the characteristic aridity reduces vegetation activity. Spring, due to available water and moderate air temperatures, is the season** most favourable to vegetation activity and is when the highest NDVI values were recorded. The spatial variability in the NDVI (bars of 1 standard deviation values) was higher during the summer than in winter, because the irrigated lands and the active forests present marked differences in their vegetation activity compared to that of the dry-land agricultural areas and the steppes. By contrast, vegetation activity was very low during winter for all land-cover types and, therefore, a low spatial variability was recorded. Marked differences in the average monthly NDVI values as a function of land-cover type were recorded (Figure 6). In April, maximum vegetation activity was recorded primarily in the dry-farming areas (cereals). In areas

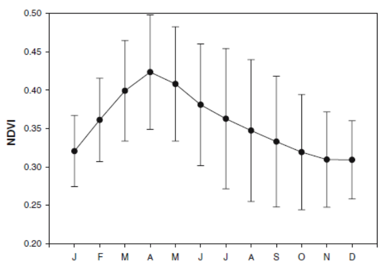

Figure 5. Mean and standard deviation of monthly NDVI values in the whole study area (1987–2000).

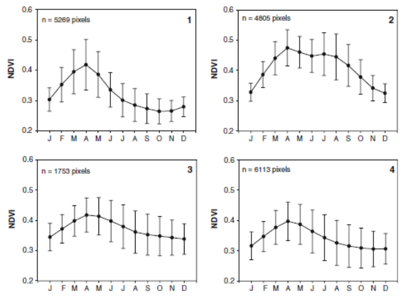

Figure 6. Monthly averages of NDVI in different land-cover types within the study area (1987–2000). 1. Dry farming areas (cereals), 2. Irrigated lands, 3. Coniferous forests, 4. Shrub and pasture-lands.

of shrubs, pasture and coniferous forests, seasonal differences were lower. In irrigated lands, the average NDVI values were higher than those recorded in other land-cover types as vegetation activity remained high during the summer months. The values of leaf area index (LAI) for these land cover types indicate important spatial and seasonal differences. The following values were obtained from MODIS images at a resolution of 1 km_2 (http://www.edcdaac.usgs.gov/modis/mod15a2.asp). The dry farming areas have a LAI between 1 and 2 in spring and values close to 0 after the harvest in summer. The coniferous forests have LAI values between 1.5 and 3 in spring and between 2 and 4 in summer. Finally, the shrub and pasture lands have LAI values between 0.5 and 1.5 in spring and between 0 and 0.5 in summer.

SPATIAL DISTRIBUTION OF CORRELATIONS BETWEEN VCI AND SPI

Figures 7–9 show the spatial distribution of correlations between the monthly series of VCI and the series of SPI_3, SPI_6 and SPI_{12}. The black lines isolate areas with positive and significant correlations (R ‡ 0.53,p < 0.05). For SPI3, large areas to the north of the study area showed Drought impact

The Kruskal Wallis tests show that there is a significant ($P<0.05$) difference in yield among wards with different dry dekad sequences---

The result of the stud

Drought fraction varies spatially as well as temporally, with VegDRI measuring more frequent drought in some ecoregions and land-cover types (Table 1). Averaged over time for 1989–2012 and by ecoregion and land-cover type, the overall VegDRI drought fraction for grassland, shrub/scrub, and nonirrigated cultivated crops was generally less than 20%, with only one exception [grassland in the Northwestern Great Plains (43)]. Cropland had a lower drought fraction (10%–13% for ecoregions with more than 2000 km^2 of crops). Wet conditions occurred less frequently than dry conditions (excluding small areas, wet conditions were ≤15% in grasslands and croplands). Normal conditions were present during ~70% of the study period. Results for grassland in Edwards Plateau (30), scrub/shrub in Northwestern Glaciated Plains (42), and nonirrigated crops in Nebraska Sand Hills (44), Flint Hills (28), and especially Edwards Plateau (30) should be treated with caution, as these cases are represented by relatively small areas.

Table 1. Land-cover area, percentage of area, and percentage in drought, normal, and wet conditions (1989–2012) for the Great Plains ecoregions.

			Land cover		
Ecoregion No.	Ecoregion name	Description	Grassland	Shrub/ scrub	Nonirrigated cultivated crops
6	NCA3 Great Plains	Area (km^2)	795 940	481 762	469 368
		Percent of ecoregion area	34%	21%	20%
		Total percent drought	19%	20%	13%
		Total percent normal	69%	67%	75%
		Total percent wet	12%	13%	12%
46	Northern Glaciated Plains	Area (km^2)	13 504	—	91 432
		Percent of ecoregion area	10%	—	68%
		Total percent drought	11%	—	10%
		Total percent normal	76%	—	79%
		Total percent wet	13%	—	11%
42	Northwestern Glaciated Plains	Area (km^2)	89 162	2378	69 659
		Percent of ecoregion area	51%	1%	40%
		Total percent drought	17%	17%	11%

DISCUSSION POINT

-Importance of grasslands= highest cattle density mostly cattle esp on the southern part of the biome—talk about the grazing and degradation

Discussion

Land–atmosphere feedbacks enhance the importance of drought impacts on vegetation. Climate-forced changes in vegetation produce feedbacks to the atmospheric system because of modifications in biogeophysical properties. When vegetation is water stressed, albedo increases and latent energy flux decreases, which may decrease atmospheric instability, convection, and cloud development. Human-forced LULC changes further complicate these land–atmosphere interactions (Pielke 2001; Pielke et al. 2011; Mahmood et al. 2014). Studies have shown that human-forced change in LULC modified regional long-term temperature, precipitation, humidity, and in some cases, atmospheric circulation (Foley et al. 2005; Wang et al. 2009; DeAngelis et al. 2010; de Noblet-Ducoudré et al. 2012; Brovkin et al. 2013; Kumagai et al. 2013; Mahmood et al. 2014; Lawrence and Vandecar 2015).

The NCA3 regions provide a useful way to summarize climate effects within administrative boundaries

Great Plains average drought values were similar to those of the major Great Plains ecoregions, except for the northwestern and southeastern ecoregions Comparisons of ecoregions within the Great Plains highlight the similarity between nearby ecoregions and spatial autocorrelation. Ecoregions that are in close geographical proximity tend to have correlated droughts, whereas more distant ecoregions become increasingly different (Figure 8)

. Drivers of differences in drought between LULC types

Across the Great Plains, drought was detected by VegDRI more frequently in grassland and shrubland land-cover types than in nonirrigated cultivated cropland (Table 1). This result suggests that cropland could be less sensitive to drought than grassland (at least for the drought severity seen during the study period). However, attribution is difficult because there are a number of processes that could contribute to differences in VegDRI drought detection among the land-cover types.

For one, crops are more intensively managed than grassland or shrubland, and managers could be taking actions that reduce the impact of drought on their crops, such as planting more drought-tolerant crops or cover crops during dry periods. Installation of tile drainage may have influenced the frequency of wet periods in VegDRI (particularly in the Northern Glaciated Plains). Although previously not common in the study area (Pavelis 1987), tile drainage has increased in the northern Great Plains in recent years (Cihacek et al. 2012). Management actions might also influence the drought signal measured by the satellite record. For example, fallow land has a different phenological pattern of NDVI than cropped land (Wardlow et al. 2007).

Another potential factor for drought differences among grassland, shrubland, and cropland is preferential site selection for cropland. Land-use decisions are made by managers based on many variables, including expected yields, so cropland is likely to be different from grassland in soil, climate, topography, drainage, and other factors. These factors could contribute to the lower drought frequency observed in croplands in the VegDRI time series, since locations that are less affected by drought are presumably more likely to be converted to cropland.

It is also possible that these observed differences in VegDRI are attributable to the analysis procedure. Since NLCD land cover and ecoregion are inputs to VegDRI, it is conceivable they are affecting drought index values in a way that is detected by this analysis. Also, since VegDRI is a measurement of the anomaly compared to average conditions, it is possible that the difference between the study period (1989–2012) and the averaging period (1989–2008) could affect the drought index.

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