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Long-term patterns in remotely-sensed vegetation productivity for a transboundary conservation area in Southern Africa

By
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A Thesis submitted in partial fulfillment of the degree Bachelor of Science in Applied Geography and for graduation summa cum laude from the Department of Geography and Geosciences

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LAY SUMMARY

I used a satellite-derived data product to analyze trends in vegetation productivity from 1981-2015 in a large area of protected lands in Southern Africa. I analyzed the spatial distribution of trends of greening and browning of vegetation across the study area and discussed the implications of those trends in the context of the local communities who rely on the natural resources of the area. I found that there are diverse trends across the study area, and areas of similar trends tend to be spatially clustered. These trends are likely linked to changes in factors associated with climate change and will likely continue in coming decades, making the continued monitoring of these trends important to understand the effects of climate change on the livelihoods of the inhabitants of Southern Africa.
ABSTRACT

In the past century, researchers have observed changes in vegetation productivity and structure in savannas across the world. These changes, caused by shifts in precipitation patterns, fire patterns, soil nutrients, herbivory, and land management decisions, are important to understand because they affect availability of natural resources, which in turn affects the livelihoods of local populations. This study centers on the Kavango-Zambezi Transfrontier Conservation Area (KAZA), a transboundary conservation area that spans five countries in Southern Africa comprised of large areas of protected land. Using the Normalized-Difference Vegetation Index (NDVI), I tested a 35-year remotely-sensed time series for intra- and inter-annual vegetation patterns in KAZA between 1981 and 2015, including analyses for three communities in the region. A Mann-Kendall test for monotonic trends and a Sen’s Slope test were conducted to analyze inter-annual trends for significance and slope of change, respectively. Annual green-up time, the onset of the growing season, was also analyzed for spatial patterns. I found a positive overall trend of greening, as well as spatially clustered patterns of greening and browning across the study region, with sub-study area variation discussed at the community level. Annual growing season onset green-up patterns also varied, appearing to be spatially clustered across the region. The patterns found here have implications for stakeholders at the local and regional levels and will continue to develop as the region continues to face social and environmental changes, thus, continued monitoring is advised.
1. INTRODUCTION

Vegetation is an important component of landscape structure in savannas around the world due to its contributions to ecosystem function, biodiversity, and renewable resources for local populations (Scholes and Archer 1997; Rodriguez-Iturbe et al. 1999; Shackleton, Shanley, and Ndoye 2007). In the late 19th century, people began to notice changes in the floral diversity of savannas in the southwestern United States (Van Auken 2000). These observations were later echoed by residents and researchers in savanna areas across the world (Van Auken 2000). These changes were speculated to be a result of increased herbivory, changes in the frequency of fires, and elevated levels of atmospheric carbon dioxide (Van Auken 2000; Archer et al. 2017). Fast forward to more recent decades, areas of savannas traditionally dominated by grassy vegetation have seen increasing proportions of woody biomass, quantified both from the ground and from a remote sensing perspective (Archer et al. 1988; Rodriguez-Iturbe et al. 1999; Stevens et al. 2016). These shifts along the herbaceous to woody continuum, termed woody encroachment, are influenced by both human and natural factors (Brown and Archer 1988; Archer et al. 1988; Mitchard et al. 2009a; O’Connor, Puttick, and Hoffman 2014). Current research shows that these changes have the capacity to severely alter ecosystems biologically by changing the composition of vegetation species distributed throughout affected areas (Angassa and Baars 2000; Ratajczak et al. 2012), chemically by changing the composition of the soil (Berthrong et al. 2012), and hydrologically by slowing groundwater recharge rates (Huxman et al. 2005; Wilcox and Huang 2010). One region that is particularly vulnerable to environmental and climatic changes, including changes in vegetation composition, is Southern Africa (Eriksen and Watson 2009; O’Brien et al. 2009). Vegetative changes in Southern Africa have been linked to instability in food security (Wessels et al. 2007), proliferation of parasites and infectious diseases, such as
malaria (Patz et al. 2000), variability in fire intensity and dispersal (Govender et al. 2006), and impediment of rural economic development (Shackleton et al. 2001; Wessels et al. 2007). Thus, long-term vegetative monitoring is vital to the livelihoods of the inhabitants of Southern Africa.

Historically, studies of vegetation have relied on surveys of vegetation biomass metrics, including leaf area index (LAI), leaf-weight ratio (LWR), leaf-area density (LAD), net assimilation rate (NAR), leaf inclination distribution function (LIDF), and others, at the individual field-plot scale (Watson 1947; Poorter and Nagel 2000; Weiss et al. 2004; Camargo et al. 2015). Similarly, changes in vegetative structure have been studied, quantified, and monitored at the plot level in studies where woody cover, biomass, or tree basal area is studied over a long period of time, a process which is laborious, can take years, and does not provide information about the geographic extent of vegetative changes in savannas (Scholes and Archer 1997; O’Connor et al. 2014). Furthermore, any attempt to scale-up the information or knowledge gained from survey-plot level studies to the landscape level is difficult due to the spatially heterogeneous nature of savanna environments (Scholes and Archer 1997).

Remote sensing, the analysis of the Earth’s surface typically by airborne sensor, provides useful tools for monitoring vegetation at multiple spatial and temporal scales. For example, Ni-Meister et al. (2010) used an active remote sensing technique, Light Detection and Ranging (LiDAR), to study biomass and vegetation structure. Mitchard et al. (2009b) used another active technique, Synthetic Aperture Radar, to quantify woody biomass. In contrast to these active sensors which generate their own source of energy, other studies rely on information from passive sensors, sensors that capture reflected incident energy from the surface of the earth. For example, Mitchard et al. (2009a) used a remotely-sensed index, the Normalized-Difference Vegetation Index (NDVI) from Landsat’s Thematic Mapper (TM) and Enhanced Thematic
Mapper Plus (ETM+) sensors to study changes in vegetative structure in a Central African tropical rainforest. Red (400-700 nm) and near-infrared (NIR) (700-1,000 nm) bands are often used in large spatial-scale quantitative vegetative studies through the Normalized-Difference Vegetation Index (NDVI) in order to quantify vegetative health and spatial extent (Goward et al 1991). NDVI is a particularly useful remotely-sensed index calculated by comparing the radiance of near-infrared light, which photosynthetically active vegetation reflects, to the radiance of red light, which productive vegetation absorbs, over a given parcel of land (Yengoh et al 2015). NDVI is calculated as:

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)}$$

Through this comparison, NDVI captures a “greenness” signal that is a proxy of vegetative health (Yengoh et al. 2015).

Values of NDVI range from -1 to +1, with values near -1 representing areas with little to no productive vegetation and values near +1 representing areas with dense productive vegetation (Yengoh et al 2015) (Figure 2). Remote sensing and NDVI have been used to study trends in a wide range of vegetation-related topics including, but not limited to, desertification (Piao 2005), deforestation (Danano et al. 2018), droughts (Yengoh et al. 2015), topsoil salinity (Yengoh et al. 2015), and wildfires (Yengoh et al. 2015). The use of remote sensing to analyze vegetation patterns over a variety of spatial and temporal scales provides important information regarding regional scale dynamics, which have implications for local-scale resource use (Tatem et al. 2013).

Remote sensing techniques have been explored as a tool for studying vegetative structure and productivity at a large spatial scale (Mitchard et al. 2009a; Mitchard et al. 2009b; Ni-Meister 2010). While many sensors capable of studying vegetation exist, large scale studies often rely on
data products derived from sensors with a coarse (>1 km pixel size) spatial resolution, typically because these sensors have a large footprint, long temporal continuity, and easily accessible data (Yengoh et al. 2015). A frequently used large-scale NDVI product is the Global Inventory Monitoring and Mapping Studies (GIMMS3g) product (derived from the Advanced Very High Resolution Radiometer [AVHRR]), a robust product to analyze greening trends over time. GIMMS3g is a pre-processed NDVI product, which is correlated with vegetation biomass (Tucker 1979; Hansen and Schjoerring 2003) and is frequently used to monitor vegetative health (Fensholt and Proud 2012; Miao et al 2015). GIMMS3g NDVI is a global-scale eight-kilometer-pixel-size data product that has produced two images per month from 1981 to 2015 (Pinzon and Tucker 2014). While an eight-kilometer pixel size is relatively large, GIMMS3g’s 34.5-year temporal extent makes it ideal for long-term vegetative studies.

In Southern Africa, remote sensing and NDVI has been used to monitor vegetation trends, including woody encroachment (Mitchard et al. 2009a). For example, Mitchard et al. (2009a) used NDVI derived from Landsat images to quantify woody encroachment in a Southern African savanna by measuring NDVI as a proxy for tree canopy area. Mitchard and Flintrop (2013) examined woody encroachment across the African continent using an AVHRR-derived NDVI product by leveraging a dry season NDVI signal to separate a woody savanna signal from a non-woody signal. Studies have shown differences in the NDVI signal between herbaceous and woody vegetation, with areas dominated by wood having a stronger signal during the dry season, whereas areas of herbaceous vegetation tend to turn green only after the onset of the seasonal rains (Archibald and Scholes 2007; Mithard and Flintrop 2013; Brandt et al. 2016). According to ecological studies, trees and shrubs are less dependent on the strict timing of the onset of the rainy season because of their increased capacity for water storage and deeper root systems.
(Woodward 1987; Archibald and Scholes 2007). Generally speaking, woody vegetation has an earlier green up time, while herbaceous vegetation is more closely tied with the seasonal rains (Archibald and Scholes 2007).

Current trends toward less stable precipitation patterns in some areas of savanna (e.g. Batisani and Yarnal 2010), perpetuated by anthropogenic climate change, are establishing trends in vegetation related to changes in the carbon cycle (Dintwe and Okin 2018), fire cycle (Scheiter et al. 2014) and soil composition (Trenberth 2011). Trends in vegetation are important to monitor because they represent changes in tangible natural resources that affect local inhabitants and wildlife. Furthermore, vegetative trends can be used to estimate some future effects of continuing climate change, particularly on vulnerable populations like the rural inhabitants of Southern Africa (Gonzalez et al. 2010).

2. RESEARCH QUESTION AND HYPOTHESIS:

In this project, I examined long-term trends in NDVI for a large transboundary conservation area (the Kavango-Zambezi Transfrontier Conservation Area, KAZA) in Southern Africa using the remotely sensed data product AVHRR GIMMS3g. In doing so, the overarching research question of this project is threefold: 1) What types of statistically-significant long-term trends are observed in the AVHRR GIMMS3g NDVI signal over the past 35 years (1981-2015) for KAZA, 2) how do these trends compare across three community-based organization units in KAZA and 3) are there detectable spatial-temporal patterns in the green-up signal while using an 8-km spatial resolution sensor to analyze spatial patterns of green-up time?

Because of ongoing changes in temperature and precipitation, I hypothesized that there are detectable inter-annual NDVI trends across the study region from 1981-2015. Furthermore, I
hypothesized that spatial patterns of green-up time are detectable with an intra-annual greenness signal associated with green-up time in savannas using the GIMMS$_{3g}$ data product, with areas of later annual green-up time being found towards the south of the study area, and areas of earlier annual green-up time being found further north in the study area, tied to the earlier onset of the seasonal rains.

In analyzing regional-scale trends with a spatially coarse remote sensing product, certain assumptions must be made. The underlying assumptions of this analysis are as follows: 1) there are steady, single-direction changes in vegetative structure across the study area between 1981 and 2015, and 2) these changes are detectable using a remotely sensed NDVI product at an 8 km spatial grain. The limitations of this study are primarily related to the spatial resolution of the dataset, and are as follows: 1) with pixel size of eight kilometers, many small-scale (i.e. field size) geographic areas of vegetation are averaged together, and localized trends will be muted, 2) with an eight-kilometer pixel size, developed land, which presumably has no change in NDVI values, cannot be masked, and will diminish any trends in NDVI from the surrounding areas of savanna, and 3) expansion of human-developed lands such as roads, villages, and agriculture, perpetuated by population growth over the past three decades, will alter NDVI values in unmeasurable ways, adding an element of random.

3. DATA AND METHODS

3.1. Study area

This study was based in the Kavango-Zambezi Transfrontier Conservation Area (KAZA-TFCA) in Southern Africa (Figure 1). The KAZA-TFCA is a transboundary conservation area, comprised of a heterogeneous mix of forest preserves, national parks, game
management areas, world heritage sites, and various other protected areas (Kavango Zambezi Transfrontier Conservation Area 2016). KAZA is geographically positioned around three significant areas: Victoria Falls, which is found near the center of the conservation area, the Okavango river basin, and the Zambezi river basin (Cumming 2008). At 519,000 square kilometers, KAZA is very large, which makes it an ideal size for a study area for regional-scale vegetative studies from a remote perspective (Kavango Zambezi Transfrontier Conservation Area 2016).

The KAZA-TFCA is an important wildlife corridor that hosts a broad array of flora and fauna, not only famously being home to the largest elephant population in Africa, but also including over 100 species of endemic flora (Ziobro 2014). KAZA is also home to two globally threatened large mammals (the black rhinoceros and wild dog), as well as impressive populations of other large mammals, birds, reptiles, and amphibians (Cumming 2008). The region’s rich biodiversity is of great cultural, ecological, and economic value and makes significant contributions to the livelihoods of the 1.5 million local inhabitants in the form of natural resources, cultural preservation, and economic development generated from tourism (Cumming 2008; Ziobro 2014). Thus, the long-term effects of climate change as they relate to changes in ecological structure are of particular import to the KAZA-TFCA region.
KAZA-TFCA also contains communities, and some results here are also discussed in the context of three specific sub study-area communities within the KAZA-TFCA: the Mashi Conservancy in Namibia, the Chobe Enclave Conservation Trust (CECT) in Botswana, and the Lower West Zambezi Game Management Area (LWZ-GMA) in Zambia. These community-based organizations (CBOs) each include five rural village areas in which household surveys were done in 2017 and 2018 to study vulnerability for part of a larger National Science Foundation project (#1560700). CBOs were given rights by the federal governments to manage localized parcels of land in ways that maximize the volume and use natural resources, encourage sustainable land use practices, and generate income for communities with high-value wildlife.
and tourism assets (Twyman 2000; Jones and Murphree 2004). In Namibia, communities are allowed to define their own CBOs and the boundaries of their land, while in Zambia and Botswana, those powers are vested in higher levels of government (Jones and Murphree 2004). Variation in the devolvement and management success varies across the CBOs and country context but, importantly for this study, the CBOs represent three areas within KAZA in which the broad scale, remotely sensed trends overlap locations where household surveys from another study (NSF #1560700) provide insight on local livelihood decisions and natural resource use. The analysis in that study provides important context to the resulting larger-scale spatial patterns identified in this study.

3.2. Data

3.2.1 AVHRR

The Advanced Very-High Resolution Radiometer (AVHRR) is an Earth-observing sensor deployed on the National Oceanic and Atmospheric Administration (NOAA) series of meteorological satellites. The first AVHRR sensor was launched in 1978, with the next generation sensors AVHRR/2 and AVHRR/3 being launched in 1981 and 1998, respectively (NOAA 2017). AVHRR collects data at a 1.1 km spatial grain (before distribution, the data is resampled to a 4 km spatial grain to assist with data processing circa 1980s), with a swath width of over 110° and a revisit time of approximately one day. The sensor includes a 0.58 - 0.68 μm red band and a 0.725 - 1.00 μm near-infrared (NIR) band that are often used for quantitative vegetative studies (Goward et al 1991; NOAA 2017).
3.2.2 *GIMMS*$_{3g}$ *NDVI*

NDVI combines reflectance values of red light, which healthy vegetation absorbs, with reflectance values of NIR light, which healthy vegetation reflects, from which the ratio of \([\text{NIR}-\text{Red}] / [\text{NIR}+\text{Red}]\) allows it to be used as a proxy for the greenness of vegetation (Tucker 1979; Yengoh et al. 2015) (Figure 2). NDVI is a useful index for long-term vegetative studies because of the extensive period of time in which the requisite data, red and NIR bands, have been recorded (Rouse et al. 1973). Several sensors, including AVHRR, Landsat’s Thematic Mapper, the Moderate Resolution Imaging Spectroradiometer (MODIS), and the Satellite pour l’Observation de la Terre (SPOT), have multi-decadal, global-scale records including red and NIR bands capable of producing NDVI (Yengoh et al. 2015). As with most remotely-sensed metrics, there are some limitations associated with the use of NDVI. Pixel saturation is an issue that has been raised regarding the usefulness of NDVI because in some densely vegetated areas, NDVI has been found to become saturated, not accurately discriminating differences between various pixels with lush vegetation (Heute, Liu, and van Leeuwen 1997). In this study, though, NDVI saturation is less of a concern because vegetation in savannas is sparse enough as to not saturate the pixels and at an 8-kilometer spatial grain, some areas of dirt, buildings, and/or waterways are likely to be enveloped in every pixel, which further prevents the pixels from becoming saturated.
Figure 2: NDVI in Southern Africa. Green colors represent areas with high values for NDVI (representing areas of dense vegetation), while red colors represent areas with low values for NDVI (representing areas with little to no vegetation [for example, the image above includes a large portion of water]). The image on the right represents a pixel with a high NDVI value (dense vegetation); the image on the left represents a pixel with a low NDVI value (sparse vegetation).
GIMMS$_{3g}$ is an NDVI product derived from the AVHRR sensor. AVHRR images a given footprint once nearly every 24 hours. Each image recorded is radiometrically processed to ensure accurate temporal continuity of data. The processing of data to create the GIMMS$_{3g}$ product includes atmospheric corrections (for aerosols and cloud coverage), inter-sensor adjustments (radiometric adjustments to ensure compatibility of data recorded by different sensors), and adjustments for the time of day that each image was taken (some data were captured at varying times each day due to orbital drift among the satellites that house the AVHRR instruments) (Pinzon and Tucker 2014). Some data values recorded by AVHRR are poor quality and are set to “null” data values in the GIMMS$_{3g}$ product processing because of calibration errors including but not limited to excessive cloud coverage, snow coverage, excessive aerosol interference, and other sensor errors (Pinzon and Tucker 2014). Additionally, the data originally recorded by AVHRR at a 1.1 km spatial grain and distributed by NOAA at a 4 km spatial grain have been resampled to an 8 km spatial grain to maintain geospatial continuity across sensors (Pinzon and Tucker 2014). Reflectance values from each pixel were then averaged together to create a bimonthly composite: one composite for the first half of each calendar month, and one composite for the second half of each month (Pinzon and Tucker 2014). This data set contains 34.5 years of data, ranging from July of 1981 to December of 2015, at the temporal scale of 24 observations per year, for a total of 828 observations per pixel across the entire time series (Pinzon and Tucker 2014).

The GIMMS$_{3g}$ data product is particularly valuable due to its long temporal coverage. Because of the processing of the AVHRR data to ensure cross-sensor data continuity included in the GIMMS$_{3g}$ product, NDVI values dating back to the launch of AVHRR/2 in 1981 can be analyzed in tandem with NDVI values recorded by AVHRR/3 through 2015. While newer
sensors such as the Sea-Viewing Wide Field-of-view Sensor (SeaWiFS), the Moderate Resolution Imaging Spectroradiometer (MODIS), and the Visible Infrared Imaging Radiometer Suite (VIIRS) provide data that are more spatially, spectrally, and radiometrically accurate than AVHRR, the data continuity provided by the AVHRR GIMMS3g product is invaluable (Pinzon and Tucker 2014). This temporally-extensive continuity of data is the rationale for the use of the GIMMS3g data product in this study. The data was downloaded from NASA EcoCast’s website.

3.3 Methods

3.3.1 Trend Analysis

A trend is defined as a smooth long-term movement in a time series that can be represented by a mathematical function found to generate values consistent with observed values (Kendall and Buckland 1982). A trend analysis is comprised of statistical tests that examine a time series for a statistically significant trend that can be represented by a regression. Trend analyses search for a relationship between a variable and time. If there is a significant relationship, then a trend exists. If there is no significant relationship, then the time series is said to be stationary (ITRC 2013). For each analysis, a threshold for statistical significance is set based on a desired confidence interval. If a value for a statistic has a corresponding p-value greater than the defined threshold, the data series is not considered to be distinguishable from a random distribution of data values and is deemed to be not statistically significant (Kendall and Buckland 1982). Conversely, if an output has a corresponding p-value less than the defined threshold, the trend is considered to be distinguishable from a random trend and should be deemed statistically significant (Kendall and Buckland 1982).
To analyze the signal in vegetation greenness using NDVI over time and to identify patterns of greening or browning on the landscape, I conducted a trend analysis across the 35-year time series, from 1981 through 2015, to identify both positive and negative NDVI trends across KAZA on a pixel-by-pixel basis. All trends were analyzed for statistical significance using a nonparametric Mann-Kendall test for monotonic trends and Sen’s Slope test for the magnitude of the slope. Nonparametric tests were selected because they do not rely on the form of the underlying data distribution, which is of import to vegetative studies in regions that experience seasonal shifts because vegetative health and productivity oscillates regularly with the changing of the seasons, which means that parametric tests would face complications in distinguishing long-term inter-annual trends (Kendall and Buckland 1982; Eastman et al. 2009). Null data values were filled using linear interpolation. Any pixels with null values >50% of the time series were excluded from this study.

3.3.2 Mann-Kendall

The Mann-Kendall test was selected because it is frequently used in vegetation studies (Fensholt et al. 2012; Tushaus et al. 2014). This test examined the entire time series on a pixel-by-pixel basis for the presence of a single directional trend. An output Tau value between -1 and +1 gives information with values close to -1 indicating a negative NDVI trend, values near 0 indicating no trend, and values near +1 indicating a positive NDVI trend (Tushaus et al. 2014).

Mann-Kendall is calculated as:

\[ S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \text{sgn}(x_j - x_i) \]

(Mann 1945; Kendall 1957; Gocic and Trajkovic 2013)
where \( n \) represents the number of data points, \( x_i \) and \( x_j \) represent adjacent data values in the time series \((j > i)\), and \( \text{sgn}(x_j - x_i) \) is the sign function:

\[
\text{sgn}(x_j - x_i) = \begin{cases} 
+1, & \text{if } x_j - x_i > 0 \\
0, & \text{if } x_j - x_i = 0 \\
-1, & \text{if } x_j - x_i < 0
\end{cases}
\]

(Mann 1945; Kendall 1957; Gocic and Trajkovic 2013)

Then, variance was calculated and used to test each trend for statistical difference from zero. Only pixels that were >50% within the study area boundaries were analyzed. This analysis was conducted using the R statistical computing environment version 3.4.1 (R Foundation 2018) (see Appendix A).

### 3.3.3 Sen’s Slope

The Sen’s Slope test was selected to quantify the magnitude of the change in each pixel across the entire time series. This analysis was conducted using Sen’s method, according to the following equation:

\[
d_k = \frac{x_j - x_i}{j - i}
\]

where \((1 \leq i < j \leq n)\), \( d \) is the slope, \( x \) denotes the variable, \( n \) is the number of data, and \( i \) and \( j \) are consecutive values in the time series (Sen 1968). For each pixel, the \( n \) values of \( d \) are ranked from least to greatest, and the median value is selected to represent the slope of the time series (Sen 1968; Gocic and Trajkovic 2013). To test the median value for statistical difference from zero, I calculated the confidence interval of \( d_{\text{median}} \) using the variance of the entire time series. Only pixels that were >50% within the boundaries of the study area were analyzed. This analysis
was conducted using the R statistical computing environment version 3.4.1 (R Foundation 2018) (see Appendix B).

3.4 Intra-annual analysis

To analyze the remotely-sensed data intra-annually, I followed a method according to Whitecross et al. (2016) to detect an annual “green-up” signal on a pixel-by-pixel basis to examine spatial patterns of where, across KAZA, I might identify earlier versus later timing in the “greening” signal. To calculate the “green-up” signal, I first calculated for each year the range of NDVI and then identified the first observation point that exceeded 20% of that range above the minimum NDVI value for a given year. For the purpose of this analysis, each “year” began with the first bimonthly GIMMS3g observation of August, which provides ideal timing: after full senescence of the previous year, but prior to the onset of the rains for the next year. By choosing this time point, there may be a detectable signal in NDVI that suggests pixels with a woodier landcover than herbaceous vegetation (Helman et al 2015). So, for example, in the final output map for a given year, a hypothetical “green-up” pixel with a value of “2” would represent a pixel in which the 20% range threshold above the minimum NDVI for that year was exceeded during the August 16-31 observation period of that year, while a hypothetical pixel with a value of “3” would represent a pixel that exceeded the 20% above annual minimum NDVI threshold during the September 1-15 observation period of that year. For each pixel, the mean and standard deviation were calculated to analyze various patterns of green-up timing across the study region. The mean was calculated to compare green-up times in various locations across the study area. This statistic expresses the average time of greening per pixel. Pixels with low means should be interpreted as areas that green relatively early, while pixels with higher means should be
interpreted as areas that green relatively late. The standard deviation, which represents the variability of annual greening time, was calculated to compare degrees of variability in green-up time in various locations across the study area. Pixels with relatively low standard deviations should be interpreted as areas with very consistent annual green-up timing, while pixels with relatively high standard deviations should be interpreted as areas with more variable annual green-up timing. Near the borders of KAZA, only pixels with an area of >50% within the study area boundaries were analyzed. This analysis was conducted using the R statistical computing environment version 3.4.1 (R Foundation 2018) (see Appendix C).

4. RESULTS

4.1 Inter-annual trends in NDVI

4.1.1 Mann-Kendall and Kendall’s Tau

The Kendall's correlation coefficient Tau ranges from -1 to +1. Tau values of -1 and +1 indicate consistent negative and positive trends, respectively, while a 0 represents no trend. The statistical significance of the trends was assessed by comparing the statistical significance of each pixel’s series of data to a random distribution for every pixel. According to the Mann-Kendall analysis described above, 41.35% of pixels across KAZA experienced a statistically significant trend, marked by p-values of <0.05 (Figure 3). Of those, 67.47% experienced a positive trend in NDVI, noted in green. These areas tended to be clustered along the southern boundary of KAZA. Conversely, 32.53% of pixels with a significant trend had a negative trend in NDVI, marked by a negative value for Tau. These areas were clustered in portions of central, northern, and eastern KAZA. A graphical example of one pixel with a strong trend (p<0.05) across the time series and one pixel with no trend (p>0.05) across the time series is highlighted below in Figure 4.
Figure 3: Mann-Kendall trend analysis in KAZA. Pixel values denote Kendall's Tau of NDVI against time, estimating the presence of a monotonic single direction trend in the time series. Green colors represent positive trends and purple colors represent negative trends. Significant trends (p values < 0.05) are denoted with a hashmark.
Figure 4: Graphical representation of 35-year time series of NDVI encompassed in single pixels. The graph on the left represents a pixel with no statistically significant trend (p>0.05), represented by no clear adherence to a trend line. The graph on the right represents a pixel with a very statistically significant trend (p<0.05), represented by clear adherence to a trend line.
4.1.2 Sen’s Slope

In the context of this study, Sen’s Slope, a measure for the linear rate of change, models how the value of NDVI changes over time by outputting the median slope of adjacent observations. It indicates the magnitude of change by selecting the median change between adjacent observations in the time series. For example, a hypothetical pixel with a Sen’s Slope value of $2 \times 10^{-4}$ would represent a trend of an approximate $4.8 \times 10^{-3}$ point increase in NDVI per year, calculated by the Sen’s Slope value ($2 \times 10^{-4}$) multiplied by the total number of observations in the time series (828) divided by the total number of years in the time series (34.5). Within KAZA, 46.11% experienced a statistically significant slope according to Sen’s method, marked by p-values of $<0.05$ (Figure 5). Of those areas, 42.40% experienced an increase in NDVI, marked by a positive value for Sen’s Slope. Similar to the Mann-Kendall analysis above, these areas experiencing a significant positive slope tend to be spatially clustered along the southern boundary of KAZA, with a notable cluster also surrounding the Cubango River delta in central KAZA. Conversely, 57.60% experienced a decrease in NDVI, marked by a negative value for Sen’s Slope. These areas tend to be clustered in parts of central, northern, and eastern KAZA.
Figure 5: Sen’s Slope linear rate of change in KAZA. Pixel values represent the magnitude of change in NDVI over time. Green colors represent a positive slope (increasing NDVI/time) and purple colors represent a negative slope (decreasing NDVI/time). Significant trends (p-values <0.05) are denoted with a hashmark.
4.2 Trends in CBOs

Land governed by three community-based organizations (CBOs) was also tested for significant trends using the Mann-Kendall method described above (Figure 3) and the Sen’s Slope method also described above (Figure 5). Only pixels that were >50% within each CBO boundary were analyzed. The three CBOs also vary significantly in size, with the Lower-West Zambezi Game Management Area (LWZ-GMA) being the largest at 45,095 km² (including 230 GIMMS3g pixels), the Mashi Conservancy being the smallest at 439 km² (including 5 GIMMS3g pixels), and the Chobe Enclave Conservation Area being 1,563 km² (including 20 GIMMS3g pixels). These differences in size should be considered while interpreting the results of these analyses because of the greater or lesser influence that individual data points that are analyzed may hold in each CBO. For example, since the Mashi Conservancy only contains 5 GIMMS3g pixels, the significance of one more or less pixel would increase or decrease the total area noted to experience a trend by 20%, whereas in the LWZ GMA, the significance of one more or less pixel would alter the total area marked as experiencing a trend by only $4 \times 10^{-3}$%.

In the LWZ-GMA, 45.2% of the area experienced a statistically significant trend, marked by p-values <0.05 according to Mann Kendall’s method. Of those areas, 58.7% of pixels experienced a positive trend, marked by a positive value for Kendall’s Tau. Conversely, 41.4% pixels experienced a negative trend, marked by a negative value for Kendall’s Tau. 46.1% of the LWZ-GMA experienced a statistically significant slope according to Sen’s method, marked by p-values <0.05. Of those areas, 59.4% experienced an increase in NDVI. Conversely, 40.6% of significant pixels experienced a decrease in NDVI. The average absolute value of significant slopes was $4.1 \times 10^{-5}$. In the LWZ-GMA, most of the positively trending areas are clustered in the north, while the negatively trending pixels tend to be clustered in the southern portion of the
CBO, near the five villages. It is worth noting that the locations of most of the statistically significant data points, according to both tests, are located in remote areas of the CBO, with the areas immediately surrounding the five villages experiencing fewer and milder trends.

In the Mashi Conservancy, no pixels experienced a significant trend according to Mann-Kendall’s method, marked by p-values <0.05. The lack of a detectable single-direction trend can likely be attributed to the large spatial grain of the data analyzed (8 km) relative to the small size of the CBO. 20.0% of the area experienced a significant slope according to Sen’s method, marked by p-values <0.05. This area trended negatively, marked by a slope < 0. The average slope of this area was -6.10^{-5}. The Mashi Conservancy is located near the center of KAZA, in a section of the region where trending areas are sparse.

In the Chobe Enclave Conservation Trust (CECT) 35.0% of the area experienced a significant trend according to Mann-Kendall’s method, marked by p-values <0.05. Of those areas, 57.1% trended positively, marked by a positive value for Kendall’s Tau, while 42.9% trended negatively, marked by a negative value for Kendall’s Tau. 35.0% experienced a significant slope according to Sen’s method, marked by p-values <0.05. Of those areas, 28.6% saw an increase in NDVI, marked by slopes > 0, while 71.4% saw a decrease in NDVI, marked by slopes < 0. The average absolute value of significant slopes was 5·10^{-5}. In the CECT, the portions experiencing positive trends in NDVI include areas surrounding two of the five villages, while the areas around the other three are experiencing no trend. Generally, the CECT is in a portion of KAZA where trending areas of vegetation are sparse, though the CECT as a whole has generally experienced a mild positive trend in NDVI.
4.3 Spatial-temporal patterns and variability in intra-annual NDVI

Generally, areas of early or late green-up times (Figure 6) tend to be spatially clustered, with patterns of early greening occurring in northwestern and southern portions of KAZA. Areas of late greening can be found clustered in southwestern, northern, and eastern portions of KAZA. All three of the CBOs are located in areas that, on average, see a relatively late green-up times. Variability in green-up times (Figure 7) also appears to be spatially clustered, although these clusters tend to follow a latitudinal gradient, with areas in the north of KAZA seeing less variability in the onset of the growing season, while areas in the south see more variability. A notable exception is the Cubango River delta, located in south central KAZA, which tends to see a stable green-up time. Most of the LWZ-GMA, located in northern KAZA, which sees a relatively late green-up time particularly in the southern portion near the five villages, has a relatively stable seasonal green-up time, while the CECT, located further south, sees more variability and an earlier green-up time. The Mashi conservancy sees some variability in green-up time, though it does see more stability than the CECT, as well as a late green-up time, relative to both of the other CBOs.
Figure 6: Average annual greening time 1981-2015. Pixel values represent the average timing of the first “green” observation per season. Blue colors represent relatively early green-up times, while brown colors represent relatively late green-up times.
Figure 7: Standard deviation of annual greening time 1981-2015. Blue colors represent areas with low inter-annual variability in green-up timing, while brown colors represent areas with relatively high inter-annual variability in green-up timing.
5. DISCUSSION

5.1 Usefulness of spatially coarse remotely sensed data

While finer spatial scale data is often preferable for shorter term, smaller spatial scale studies, often only spatially coarse datasets give relatively long temporal continuity of data for large spatial scale studies like this one. Though for continental and global scale analyses spatially coarse data might be useful, by today’s standards for remotely-sensed data, an 8-kilometer pixel size is considered to be very coarse (Yengoh et al. 2015). My findings here, that the 8-kilometer GIMMS$_{3g}$ product was able to detect a significant trend in over 40% of pixels in the study region, further support the existing evidence that some remotely-sensed data of a coarse spatial scale can be used to study long-term changes in vegetation. Yengoh et al. (2015) found that remote sensing products rarely meet all requirements for spatial, spectral, and temporal resolutions, making it important to consider tradeoffs between different remotely-sensed datasets for a particular study. Generally speaking, global-scale remotely sensed data from the 1970s and 1980s are only available at a coarse spatial scale due to the technological limitations of the time (Yengoh et al. 2015). The usefulness of spatially coarse remotely-sensed data in vegetation monitoring found here supports future long-term research into vegetative trends because of the large body of data available at a coarse spatial scale, dating back to the launch of the first Earth-observing satellites in the second half of the 20th century.

5.2 Changes in vegetation across community-based organizations in KAZA

Based on my results, it seems that the Lower West Zambezi Game Management Area has seen more changes in vegetative productivity (greenness) than the other two CBOs. Over 40% of the pixels in the LWZ-GMA were marked with a significant trend, more than both of the other
CBOs. Further, the average slope of the trend among those pixels is notably higher than the other two CBOs, meaning that the residents of the Lower West Zambezi Game Management Area CBO can expect to need to adapt or continue to adapt their lifestyles to changing vegetation faster than residents of the other two communities. The area immediately surrounding the cluster of villages in the LWZ-GMA has seen decreasing NDVI, meaning those areas are losing productive vegetation to use as natural resources. This could be due to overuse of resources related to the proximity to the villages, or other factors could be causing the decrease in productive vegetation. The other two CBOs, the Mashi Conservancy and the Chobe Enclave Conservation Trust, have seen more subtle inter-annual changes in NDVI, representing smaller changes to the amount of productive vegetation in their areas.

Changes to vegetation structure and productivity at the community scale are difficult to interpret from trends captured at an 8-kilometer spatial grain. While through this analysis, some trends are found in each of the three CBOs, any speculation surrounding the specific causes or implications of these trends for each CBO would be dependent on further research.

5.3 Changes in vegetation across KAZA

Vegetative changes in Southern Africa, including the ones analyzed here, have been linked to phenomena that can severely affect the livelihoods of regional populations, including instability in food security (Wessels et al. 2007), proliferation of parasites and infectious diseases, such as malaria (Patz et al. 2000), variability in fire intensity and dispersal (Govender et al. 2006), and impediment of rural economic development (Shackleton et al. 2001; Wessels et al. 2007). According to the Mann-Kendall trend analysis, over 40% of KAZA is experiencing a trend that is significant at the 95% confidence interval. Specifically, about 28% of KAZA is
experiencing a positive trend in NDVI, meaning that the vegetation in those areas is becoming greener. These areas of positive trends tend to be located in the southern portion of KAZA, as well as the Cubango River delta. Some of these areas facing trends of increasing NDVI, including the Cubango River delta, might be influenced by recent increases to the frequency and magnitude of flood events in some parts of the region, which has been linked to anthropogenic climate change (Douglas et al. 2008). Changing patterns of precipitation and flooding have been linked to changing patterns of vegetation and ecosystem diversity in Southern Africa (Sithole and Murewi 2009). Thus, as patterns of precipitation and flooding continue to change, the region may continue to see changes to vegetation and ecosystem structure and diversity. Additionally, about 13% of KAZA is experiencing a negative trend in NDVI, meaning that the vegetation in those areas is becoming less green. Those areas tend to be clustered in central and northern KAZA, and those trends could also be linked to instability in precipitation and flooding.

While overall, the vegetative trends from this remote sensing analysis are not extremely strong, directional trends do exist, suggesting vegetative patterns that will potentially affect the livelihoods of the local inhabitants who are stakeholders in the inventory of natural resources. Additionally, further research could find patterns of stronger trends at a smaller spatial scale. Shifting patterns in vegetation at the regional scale have been linked to changes in the chemical composition of the soil (Berthrong et al 2012), changes in local and regional hydrology by slowing groundwater recharge rates (Huxman et al 2005; Wilcox and Huang 2010), and changes in the variety and distribution of fauna (Dewalt et al. 2003). The implications of the vegetative trends found here could be any combination of these, though more research is needed to determine the precise ways in which they will continue to affect the populations who rely on KAZA for natural resources.
Changing patterns of vegetative structure and productivity are likely related to changing climate conditions (e.g. Fuller and Prince 1996; Tchebakova et al. 2009; Zhao et al. 2011). Continuing changes to seasonal patterns in the inter-tropical convergence zone (ITCZ) (e.g. Byrne and Schneider 2016; Staten et al. 2018) bring instability in both the timing and intensity of the seasonal rains. These changes in precipitation can be expected to continue affecting vegetation growth both inter- and intra-annually. Inter-annually, the timing and intensity of precipitation influences the spatial distribution of various species of vegetation, affecting regional biodiversity and ecosystem diversity, as discussed by Midgley and Bond (2015) in the context of anthropogenic climate change. Intra-annually, the timing of the onset of the seasonal rains influences growth patterns, including the timing of the onset of the growing season. Dunning et al. (2016) further discusses issues with wild plant and agricultural cultivation due to factors related to changes in the timing of the beginning of the rainy season.

Inter-annual patterns in the timing of the onset of the growing season can be observed at the community scale by referencing Figure 7 above, the standard deviation of the first observed “green” pixel per year. In the Chobe Enclave Conservation Trust, the standard deviations are noticeably higher than those of the other two CBOs, particularly in the eastern portion of the community near the villages. The implications of this variability lie in difficulties during the planting season faced by the rural inhabitants who rely on the land for subsistence agriculture. The Lower West Zambezi Game Management Area has seen more stability in the timing of the onset of the growing season, particularly in the southeastern section of the community near the villages. In the Mashi Conservancy, the timing of the growing season has been somewhat less consistent than in the LWZ-GMA, though it has been more stable than that of the Chobe Enclave Conservation Trust. All three of these CBOs can expect to see increased variability in the timing
of the onset of the growing season because of changes in precipitation patterns associated with anthropogenic climate change.

The ways in which these trends affect regional stakeholders will continue to change concurrently with the changing demographics of the region. Population growth in Southern Africa has been significant, with the region growing quickly at a rate of 2.5% per year between 2005 and 2010, compared to 1.2% in Southeast Asia or 0.1% in Europe (Stock 2012). Zimbabwe, for example, saw its population increase twenty-fold between 1900 and 2000, 70% of which was growth in rural areas (Murphree 2004). Zimbabwe had an estimated population of 16 million in 2016, a number that is projected to continue to grow to over 22 million in 2030 and reach 33 million in 2050 (Nyoni and Bonga 2017). Population growth, especially at this rate, places significant strain on natural resources at the regional scale (Murphree 2004). Murphree (2004) noted that these pressures are particularly evident in areas of small-scale agricultural production, adding stress to typical crop rotational cycles.

Members of local communities, though, are not the only stakeholders in the preservation of wild land who might be affected by these trends in vegetation. Between 1980 and 2010, the urban middle class in Southern Africa grew at a rate 20% faster than population growth, a trend that is expected to continue at least through 2040 (Tschirley et al. 2015). Murphree (2004) described differences between the attitudes of rural inhabitants and those of urban populations as they pertain to protected lands. Murphree found that generally, members of rural communities tend to value protected lands for their natural resources, as well as the intrinsic value that they find in wildness and native flora and fauna. Urban populations, on the other hand, were found to value protected lands more for recreational and cultural reasons. Thus, it stands to reason that as the demographics of greater Southern Africa continue to change, attitudes toward protected lands
will mirror that change, likely shifting toward more value on cultural and recreational aspects. Accordingly, the trends in vegetation found here can be expected to have changing implications through the coming decades. Furthermore, these changing attitudes could be expected have implications on land management decisions at spatially small and large scales (e.g. Vaske and Donnelly 1999), which makes continued vegetative monitoring advisable.

6. CONCLUSION

Vegetation is an important component of savanna environments for its use as natural resources for humans as well as its roles in ecosystem functions. Anthropogenic climate change, along with some natural factors, has caused continuous changes in vegetation in Southern Africa related to changes in fire patterns, land use decisions, precipitation patterns, and flood frequency and intensity. These changes are affecting the livelihoods of local inhabitants who rely on the vegetation for natural resources, many of whom are particularly vulnerable to changes in resource availability due to socioeconomic factors.

Using the 35-year remotely sensed data product GIMMS3g, I detected inter-annual vegetative trends that appeared to be spatially clustered, with areas of increasing and decreasing amounts of green vegetation. Additionally, using the NDVI product, I was able to identify spatial-temporal patterns of vegetative green-up time, indicating the onset of the growing season. These patterns also appeared to be spatially clustered, with earlier and more consistent green-up occurring in the northern portion of the study region, while areas in southern KAZA experience more variability in the timing of vegetative green-up. These trends affect stakeholders at the local and regional levels, and trends toward instability in vegetative patterns will likely continue
concurrently with climate change, thus, monitoring of vegetation in the region at multiple scales should continue through coming decades.
References


APPENDIX A – R SCRIPT TO PRODUCE MANN-KENDALL ANALYSIS

#### AVHRR Trend Analysis, both Mann Kendall and Sen's Slope - annual time step ####

## set working directory
setwd("~/Desktop/data")

## load packages
library(raster)
library(rgdal)
library(sp)
library(trend)
#install.packages("zoo")
library(zoo)

#read the stacked, QA stacked, Southern Africa GIMMS3g time series into R
ANN_data <- brick("gimms_SAgimms_v1_qa81_15.dat")

#subset to area of interest
shp = readOGR("shps/KAZA/", "kaza")

#### TRENDS IN DATA ####

#mktrend is a function to calculate the man Kendall (mk) trend over all pixels in the GIMMS3g data (x.ts) and kicks out four variables for assessment in raster format

mktrend <- function(x) {
  #x[ x < -3.3e+38 ] <- NA
  x.ts <- ts(data=x, start=c(1981,13), end=c(2015,24), frequency=24) #ts is a time series obj fxn

  if (sum(is.na(x.ts)) >= 414) {
    # summing up all the NA values in a vector and if >= 414 (half of N=828) then it doesn't calculate
    return(c("S"=NA,"varS"=NA,"tau"=NA,"p.value"=NA)) # different outputs from calculation
  } else {
    mk <- mk.test(as.ts(na.approx(zoo(x.ts)))) #zoo takes the two closest values and linearly interpolates between them to fill in NA values of time series, needed for MK
    p <- c(mk$estimates, "p.value"=mk$p.value)
    return(p)
  }
}

mkout <- calc(ANN_data, fun=mktrend)
## AVHRR Trend Analysis, both Mann Kendall and Sen's Slope - annual time step

### set working directory
```r
setwd("~/Desktop/data")
```

### load packages
```r
library(raster)
library(rgdal)
library(sp)
library(trend)
library(zoo)
```

#read the stacked, QA stacked, Southern Africa GIMMS3g time series into R
```r
ANN_data <- brick("gimms_SAgimms_v1_qa81_15.dat")
```

### subset to area of interest
```r
shp = readOGR("shps/KAZA/", "kaza")
```

### TRENDS IN DATA####

#senslope is a function to calculate the Sen’s Slope over all pixels in the GIMMS3g data (x.ts) and produces four variables for assessment in raster format
#Computes Sen's Slope for linear rate of change and corresponding confidence intervals, interpolates like MK test with "zoo"
#Sen's Slope is calculated as the median from all slopes
```r
senslope <- function(x) {
  #x[ x < -3.3e+38 ] <- NA
  x.ts <- ts(data=x, start=c(1981,13), end=c(2015,24), frequency=24) #ts is a time series obj fxn
  if (sum(is.na(x.ts)) >= 414) { # summing up all the NA values in a vector and if
    return(c("slope"=NA,"p.value"=NA)) # different outputs from calculation
  } else {
    s <- sens.slope(as.ts(na.approx(zoo(x.ts)))) #zoo takes the two closes t values and linearly interpolates between them to fill in NA values of time series, needed for MK
    p <- c("slope"=s$estimates[[1]], "p.value"=s$p.value)
    return(p)
  }
}
```

sout <- calc(ANN_data, fun=senslope)
APPENDIX C – R SCRIPT TO PRODUCE GREEN-UP ANALYSIS

### AVHRR Green-Up Analysis ###

## set working directory
setwd("C:/tmp")

## load packages
library(raster)
library(rgdal)
library(trend)
library(zoo)

#read the stacked, QA stacked, Southern Africa GIMMS3g time series into R
ANN_data <- brick("gimms_SA_gimms_v1_qa81_15.dat")

#subset to area of interest
shp <- readOGR(".", "kaza")

#### EXAMINATION OF DATA ####

r <- rasterize(shp, ANN_data)  # rasterize the shapefile of the study area
ANN_data[ANN_data <- 3.3e+38 ] <- NA  # replacing the long no data values with NA

#### GREENUP IN DATA ####

## For testing:
x <- as.numeric(ANN_data[150,150])
x <- as.numeric(x)

greenup <- function(x) {
  #x[ x <- 3.3e+38 ] <- NA
  x.ts <- ts(data=x, start=c(1981,12), end=c(2015,24), frequency=24)
  years <- 1981:2014
  d <- as.numeric(rep(NA,length(years)))
  names(d) <- years

  if (sum(!is.na(x.ts)) > 0.75*length(x.ts)) {
    ## This can fail when there are leading, missing values:
    #x.ts <- na.approx(x.ts, na.rm=F)  #linear interpolation for missing values
    xs <- na.spline(x.ts, na.rm=F)  #fit a spline for having missing data at beg of ts
APPENDIX C - CONT'D

x.ts <- ts(data=x, start=c(1981,12), end=c(2015,24), frequency=24)

for (i in seq_along(years)) {
  w <- window(x.ts, start=c(years[i],15), end=c(years[i]+1,14))

  if (sum(!is.na(w)) > 0.75*length(w)) {
    r <- range(w)
    for (j in seq_along(w)) {
      if (w[j] > (0.2 * (r[2] - r[1]) + r[1])) { #actual analysis part
        d[i] <- j
        break
      }
    }
  }
}

return(d)

}  
gout <- calc(ANN_data, fun=greenup)

plot(gout$X1981, main=1981, zlim=c(0,20))
plot(shp, add=T)
plot(gout$X2014, main=2014, zlim=c(0,20))
plot(shp, add=T)
mean_gout <- (calc(gout, mean))
plot(calc(gout, mean))
plot(shp, add=T)
plot(calc(gout, sd))
plot(shp, add=T)
plot(calc(gout, sd)/calc(gout, mean))
plot(shp, add=T)
writeRaster(gout, file="../tmp/greenupAuga.dat", NAflag=-9999, format="ENVI", overwrite="TRUE")