VARIABILITY AND CHANGE IN A DRYLAND SYSTEM: CLIMATE-LAND INTERACTION IN THE OKAVANGO-KWANDO-ZAMBEZI CATCHMENT OF SOUTHERN AFRICA

By

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To my parents, Ron and Karen Brown

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Southern Africa is one of the most uncertain regions in the world with respect to projections of climate change and the response of land-use/land-cover dynamics. How vegetation phenology, structure, and composition will change with increased climate variability, more or less rainfall, changes in seasonality of rainfall, or changes in temperature is complicated by local land-use decisions for agriculture, ranching, and settlement. Before competing and interacting drivers of climate and land use may be disentangled, effects of water availability, arguably the most limiting factor in savanna environments, must be accounted for in landscape change. This dissertation asks the question of how spatial and temporal patterns of precipitation in part of southern Africa affect the seasonal and long-term response of different savanna vegetation types. I use geospatial analyses and field measurements to examine the relationship between vegetation productivity and rainfall variability at a regional catchment scale and within a local protected area to better understand long-term change across different savanna vegetation types.

The first part of this study describes and explains the long-term pattern of total annual precipitation and changes from one period (1950-1975) to another (1980-2005) across sub-catchments of three rivers, the Okavango, Kwando, and Zambezi (the “OKZ” system). Results indicate decreasing precipitation patterns and increased dry years and warm phase ENSO in the last quarter of the twentieth century. The second part develops an empirical model of the relationship between seasonal rainfall and vegetation productivity response. Results show at the landscape level that intra-annual rainfall across wet season months is strongly associated with beginning of dry season vegetation productivity, as measured by the Normalized Difference Vegetation Index (NDVI). The relationship between wet season months of rainfall and NDVI varies by savanna vegetation type. The model is also used to correct for seasonal precipitation effects on vegetation productivity in order to identify areas of longer term land-cover change attributed to other savanna processes. This research contributes to savanna ecological theory through investigation of precipitation-vegetation dynamics for a semi-arid region. The conclusions emphasize the changing nature of precipitation patterns over the second half of the 20th century and the importance of inter-annual variability in seasonal rainfall on savanna vegetation types.

CHAPTER 1
INTRODUCTION

General Introduction

Forty percent of the Earth's land surface is covered by dryland areas, including arid, semi-arid, and dry sub-humid regions (Reynolds et al. 2007). Drylands' most important limiting resource is water availability (Walker et al. 1981), which interacts with other factors to control vegetation structure and other ecosystem characteristics, and the ability of humans to exploit the system (Scholes and Walker 1993). Water is not the only limiting resource in controlling ecosystem dynamics but is a necessary component of every physiological process (Rodriguez-Iturbe 2000). While precipitation is only a surrogate for water availability in drylands, (Archibald and Scholes 2007), the limited availability of water means any subtle shift in precipitation will affect all ecosystem aspects.

In dryland systems, average rainfall and its variability influences the rates and dynamics of transitions among various tree-grass states (Frost et al. 1986; Allen and Breshears 1998; Sankaran et al. 2005; House et al. 2003). At tropical and subtropical latitudes, the seasonal rainfall amount is largely controlled by the movement of the Inter-Tropical Convergence Zone (ITCZ), the global low-pressure system that defines the alternating wet/dry seasons (Scholes and Archer 1997). Other parts of the water cycle, such as soil moisture, evapotranspiration, and flooding also contribute to dryland vegetation growth but are dependent on the quantity, timing, and frequency of rainfall. In the same way, other biotic factors (ex. fire, herbivory) that contribute to driving landscape dynamics are also dependent on the underlying hydro-metrological factors to maintain co-existence of grasslands and woody vegetation in dryland areas (Sankaran

et al. 2005; Wang, Rich, and Price 2003; Breshears and Barnes 1999). The dependence of other ecosystem processes on the initial input of water into the system makes precipitation dynamics and their inter- and intra-annual effects on tree-grass cover an essential component to understanding savanna environments.

Overarching Research Question and Study Objectives

The research question of this dissertation project is how does precipitation variation at several spatial and temporal scales influence vegetation response in the dryland system of the Okavango-Kwando-Zambezi River basins? Before examining other forcing factors in dryland environments, one must first understand past and current precipitation patterns, and how their variability influences land-cover dynamics. This is due to the dominating influence rainfall has in dryland water budgets (McCartney 2000) and how its timing and duration have important implications for agriculture and water resource management. Inter- and intra-annual precipitation patterns also strongly influence the continuum of tree-grass cover in savanna ecosystems (Scanlon et al. 2005; Sankaran et al. 2005; Scholes et al. 2002). This dissertation includes a set of complementary articles that address different spatial and temporal aspects of precipitation variability and how it correlates to land-cover dynamics in three catchments in the Kavango-Zambezi Transfrontier Conservation Area (KAZA), a rural but important socio-ecological system in southern Africa. The area is both regionally important for conservation efforts that cross national boundaries and locally important for its perennial water sources and charismatic wildlife, the basis for increasing conservation-based tourism that benefits local communities. To investigate seasonal and longer-term precipitation patterns in the Okavango-Kwando-Zambezi (OKZ) catchment a spatio-temporal, multi-scale analysis is used to identify the effects of precipitation on

vegetation patterns at both a regional catchment level (~693,000 km2) and within a local protected area (1,300 km2). The overall objective of this research is to contribute to the broader knowledge of how dynamics of human and environmental factors interact in dryland socio-ecological systems by accounting for precipitation-vegetation relationships in the OKZ catchment. Four questions comprise my focus:

1. What are the spatial and inter-annual precipitation patterns in the Okavango-Kwando-Zambezi (OKZ) catchment of southern Africa?
2. What is the variation in vegetation productivity response to seasonal precipitation patterns in the OKZ catchment?
3. What is the relative importance of seasonal precipitation in regulating savanna vegetation in the Kalahari sand woodlands of Caprivi?
4. After controlling for seasonal effects, what temporal and spatial trends are detectable in vegetation in the Kwando Core Area of Bwabwata National Park from 1984 to 2007?

Linking Objectives to Theory

Climate-land Interactions for Coupled Human-Environment Systems

The ability to detect and monitor landscape dynamics is a fundamental task of global environmental change studies (Turner et al. 1990; Lambin and Geist 2006; GLP 2005). Land-change science focuses on global environmental change through a coupled human-environmental systems approach with emphasis on understanding linkages across ecosystems, climate, and social dimensions of land-use and land-cover change (Rindfuss et al. 2004; Turner, Lambin, and Reenberg 2007). Within this framework, the Global Land Project Science Plan and Implementation Strategy document emphasizes the need to understand climate-land interactions better, especially directional trends in distribution, variability, and average rainfall at local and regional scales and its effects on vegetation (GLP 2005). Variability and shifts in

precipitation influence changes of ecosystem structure and function but adequate data on the response of ecosystems to changing rainfall patterns is still lacking (GLP 2005; Goward and Prince 1995; IPCC 2007; Zhang 2005).

Shifting Dynamics of Dryland Environments

Specifically in arid and semi-arid southern Africa, land cover is characterized by a continuous gradient of tree-shrub-grass ratios that results from interaction of multiple ecological factors over space and time (Skarpe 1992). These dryland areas have a range of land-cover types which include grasslands, shrublands, savannas, xerophytic woodlands, and hot and cold deserts (Puigdefabregas 1998) and lack of water is an important limitation for growth. A variety of terms describe this continuum of variable and diverse ecosystems comprised of different proportions of mixed woody and herbaceous species (House et al. 2003; Breshears and Barnes 1999). I adopt the definition of a mixed woody-herbaceous system from House et al (2003) which refers to such systems as ‘tree-grass’ or ‘savanna’ systems. Woody vegetation is a mix of shrubs and trees with range of density and canopy cover while grass includes grass, forbs, and sedges. Savanna systems exist along this continuum but a useful distinction can be made between ‘wet’ and ‘dry’ savannas. The designation is based on grassland productivity in dry savannas responding strongly to increased annual rainfall whereas the relationship is much weaker in wet savannas (Scholes and Walker 1993)**.** The transition where this relationship weakens occurs around 500-700 mm/yr rainfall although soil type decreases (sandy) or increases (clays) the exact leveling off of the curve between these two different savanna systems (Accatino et al. 2010; Scholes and Walker 1993). Vegetation type also changes along this savanna gradient with a higher

woody to grass cover ratio in areas with higher mean annual rainfall (Sankaran, Hanan, and Scholes 2007).

Effects of Precipitation on Dryland Ecosystems

Changes in climate will influence changes in land cover and significant shifts or changes in climate patterns (in this case, rainfall) can contribute to change in vegetation ratios along the tree-grass continuum. The shifts in average rainfall or frequency and timing of rainfall will alter competitive advantage of either woody or grass species (House et al. 2003) and changes in rainfall average and/or variation may affect system drivers, such as soil moisture or fuel load, in determining woody-to-grassland ratios in dryland ecosystems. The next few sections describe how I studied the changes in long-term precipitation patterns for the past half century in the OKZ catchment in southern Africa and use a multi-scale approach to identify and examine the effects of seasonal rainfall on vegetation dynamics for the OKZ catchment in southern Africa. The dissertation is arranged as a series of three stand-alone but related articles that will be published in peer-reviewed journals.

Spatial and Temporal Precipitation Patterns, 1950-2005

The first article, presented in Chapter 2, describes and explains the long-term pattern of total annual precipitation and how it has changed from one period (1950-1975) to the next (1980-2005) across and within sub-catchments of three rivers, the Okavango, Kwando, and Zambezi (the “OKZ” system). The controlling effects of variable precipitation on vegetation responses underlie the modifying effects of disturbances such as fire, herbivory and limited resource availability (Nemani et al. 2003). Shifts in timing, distribution, and frequency of rainfall influence ecosystem function, composition, and structure (Huxman et al. 2005). In southern Africa wetter

conditions persisted throughout the mid-20th century but during the 1980s and into the 1990s there has been a drying trend across Africa (Nicholson 2001). This phenomenon corresponds to a global climatic regime driven by a shift in the Pacific atmosphere and ocean in the late 1970s (Hare and Mantua 2000; Chavez et al. 2003) which has been linked to increases in El Niño-Southern Oscillation warm periods (El Niño events) and changes in teleconnection patterns of southern African rainfall (Mason 2001; Fauchereau et al. 2003).

This chapter provides a spatio-temporal descriptive analysis to determine if similar patterns of changing precipitation exist for the OKZ catchment pre/post the late 1970s climate shift. Using a monthly precipitation modeled dataset (0.5^{o} x 0.5^{o}) to quantify rainfall patterns (Matsuura and Willmott 2007), I show that the late 1970s shift in rainfall is significant for a large portion of the OKZ basin and that precipitation and ENSO patterns differ before and after the climate shift. Annual precipitation totals to each individual basin were calculated and number of wet (upper tercile) or dry (lower tercile) years experienced in two periods, 1950-75 and 1975-2005 are compared to those expected at random using the hypergeometric distribution. Rainfall correspondence to, and the frequency of, El Niño Southern Oscillation (ENSO) events within these periods was also investigated.

Results from this chapter indicate decreasing precipitation patterns and increased dry years and warm phases of ENSO across all three sub-catchments in the last quarter of the twentieth century. Knowledge of the historical spatio-temporal shifts in precipitation plays a direct role in decisions made on the ground regarding agriculture, wildlife, and resource management. An explanation of inter-annual precipitation patterns

provides important information for local collaboration between national parks and communities about decisions concerning water access and usage between wildlife and humans.

Vegetation Response to Seasonal Precipitation

Chapter three also examines precipitation patterns at the regional OKZ catchment scale but at a monthly time step by investigating the response of vegetation productivity to the timing of wet season rainfall. The relationship between plant phenology and seasonality of precipitation in drylands is not straightforward (Archibald and Scholes 2007). In dryland regions a pulse system dictates the cycling of nutrients in which temporary water availability strongly drives biogeochemical processes (Scholes and Walker 1993). In semi-arid savannas, woody plant growth typically greens up just prior to first rainfall as storage of previous season nutrients and carbohydrates make them less dependent on the timing of rainfall (Sekhwela and Yates 2007; Shackleton 1999; Do et al. 2005). In contrast, grasslands are more limited by water availability and have a more tightly coupled response to rainfall (Prins 1988; Archibald and Scholes 2007). And although less attention has been given to beginning of dry season vegetation productivity, the status of beginning of dry season vegetation influences the availability of water resources and other important forage materials for wildlife, therefore affecting wildlife movement and distribution throughout the dry season.

Timing in seasonal rainfall will affect system drivers, such as soil moisture or fuel load, in turn influencing the tree-grass ratios in semi-arid dryland ecosystems. This is an important consideration for a region where large proportions of the human population and economy are dependent upon wildlife tourism. This study uses MODIS NDVI as a proxy for vegetation gross primary productivity (GPP) to investigate the response of

GPP of different savanna vegetation types to month-to-month precipitation variability. I focus on the effects of monthly wet season rainfall on vegetation status at the beginning of the dry season across the OKZ catchment over the years 2000-2009. I estimate monthly precipitation using the Tropical Rainfall Monitoring Mission 3B43 dataset and use the MODIS 13A1 VI product. A time-series model that estimates beginning of dry season vegetation productivity from the prior rainy season (October – April) using geographically weighted regression (GWR) determines within-wet season rainfall influence on beginning of dry season GPP.

Results show at the landscape level intra-annual rainfall variability accounts for significant amounts of beginning dry-season vegetation GPP variation and overall has a stronger effect for areas with greater grassland proportion and dry, deciduous woodlands. The tighter association of grassland and open canopy woodlands (specifically Mopane woodland) to end of wet season monthly rainfall (February – April) highlights the importance of both beginning and end of the rainy season for understanding the effects of future climate change.

Detecting Seasonality in Dryland Savannas

Detecting and accounting for inter-annual variability in seasonal precipitation on vegetation with remotely-sensed imagery is important for identifying long-term trends in land-cover change. This is especially important for ecosystems with strong photosynthetic response to wet and dry seasons such as those in southern Africa. The seasonal response of vegetation productivity prevalent in African savannas may obscure detection of long-term change that results from decadal climate shifts or from anthropogenic land-use decisions.

The fourth chapter applies the empirical model developed in Chapter 3 to examine local-scale vegetation patterns in a core area (1,300 km2) of Bwabwata National Park in Caprivi, Namibia. The main focus of this chapter is to account for seasonal precipitation effects on gross primary productivity (GPP) at the beginning of dry season for the southern African savanna landscape, as estimated by the Normalized Difference Vegetation Index (NDVI). Beginning of dry season productivity is important to savanna ecosystem phenological patterns due to water availability and the importance of both grass and woody species for wildlife forage pattern and livestock feed (Chase and Griffin 2008; Paterson et al. 1998). Four discrete time steps across the study period that correspond to the Landsat TM-derived NDVI provide a twenty-three year period (1984-2007) to examine the vegetation change. To correct for seasonal precipitation effects, I estimate NDVI from the downscaled Geographically Weighted Regression (GWR)-derived relationship between MODIS (or Moderate Resolution Imaging Spectroradiometer) NDVI and the Tropical Rainfall Monitoring Mission (TRMM)-estimated precipitation. The estimated NDVI, calculated for each TM image year, is then subtracted from the observed TM-derived NDVI resulting in a new, precipitation-corrected (PC)-NDVI value, or residual (Evans and Geerken 2004). The PC-NDVI corrects for seasonal effects on the landscape and thus, any trend (positive or negative) through time present in the PC-NDVI values indicates change in NDVI not due to seasonality.

Findings emphasize the importance of inter-annual variability of seasonal precipitation effects on land-cover change in savanna ecosystems. The minimal change in PC-NDVI across the four TM dates indicates the regional model, parameterized for a

savanna land cover using the prior wet season months, accounts for a large portion of variability in NDVI for the local study area. However, temporal clusters of PC-NDVI and image differencing identify areas in which PC-NDVI varies over space and time. The trends remaining in vegetation productivity after accounting for seasonal effects are then attributed to longer-term climate or anthropogenic drivers on the landscape.

Importance of the Study

The three papers complement one another by providing an in-depth examination of spatio-temporal precipitation changes and subsequent effects on savanna vegetation productivity in a southern African dryland catchment. The process of this dissertation project has been couched within an interdisciplinary context largely driven by an U.S. National Science Foundation Integrative Graduate Education and Research Traineeship (IGERT) with a theme of adaptive management, water, watersheds, and wetlands. The IGERT program emphasizes collaboration and cross-disciplinary efforts to tackle research questions larger than the scope of just one discipline. As such, this dissertation research builds upon an understanding of the larger socio-ecological system with four field seasons working with academic, governmental, and local collaborators who made it possible to capture a more holistic understanding of the OKZ system. In addition, coursework that spanned physical and social subject matters, all related to the theme of water, allows for greater breadth of my own understanding in directing this research toward not only a theoretical contribution to knowledge but also an applied understanding of the OKZ catchment in which adaptive management is important to the process of land-use and management decisions for conservation and development trade-offs.

Successful management of this semi-arid savanna system requires recognition and understanding of ecosystem processes that operate on multiple scales. While local level processes such as fire and grazing affect vegetation structure, the response of vegetation productivity to climate variability also must be taken into account for conservation management decisions. Adaptive management incorporates a learning-by-doing approach that provides a flexibility necessary when managing natural resources such as water and wildlife that demand larger spatial extents than provided by protected or political boundaries alone (Agrawal 2000; Walters and Holling 1990). Additionally, incorporating the capacity to learn in managing this socio-ecological system will provide a stronger management framework to deal with the uncertainly of climate change. While the adaptability of system dynamics is mostly a function of the social element (Walker et al. 2004), to respond to change and uncertainty people must first know how the physical environment responds to stress and change over space and time.

This research contributes to savanna ecological theory by testing hypotheses that relate to precipitation-vegetation dynamics for semi-arid dryland regions but examines this relationship for the beginning of dry season, a lesser studied but still critically important to phenological patterns in savanna ecosystems. This study also contributes to land change science by providing a multi-scale approach to understanding land-use/land-cover dynamics for an area undergoing extensive and rapid changes in both the conservation and development sectors. Lastly, this study contributes an applied understanding to historical environmental change for three dryland catchments necessary to look at future projections of climate change and variability and its effect on semi-arid dryland vegetation both at the local and regional scale.

CHAPTER 2
SPATIAL AND TEMPORAL PRECIPITATION VARIABILITY IN THE OKAVANGO-KWANDO-ZAMBEZI CATCHMENT, SOUTHERN AFRICA

Changes in precipitation patterns strongly influence ecologic, hydrologic, and socio-economic components of a system making their quantification critical in water-limited environments such as African savannas (Frost et al. 1986; Scholes and Archer 1997). Modeling and observational studies over the recent decades suggest that there has been a drying trend over much of the African continent (Giannini et al. 2008). Specific to southern Africa, multi-decadal trends highlight declining mean annual precipitation (MAP), increasing variability and drier conditions, and an increased number of warm phase El Niño Southern Oscillation (ENSO) events (Mason 2001, 1996; Nicholson and Entekhabi 1987; Giannini et al. 2008). The relationship between observed precipitation patterns and associated climate drivers vary at different spatial and temporal scales (Nicholson and Kim 1997) which has important effects for savanna ecosystems where variable precipitation patterns influence both wildlife movements and agricultural land-use decisions. This paper examines precipitation patterns from 1950-2005 and investigates changes in rainfall patterns and associations to the El Niño Southern Oscillation (ENSO) pre/post the late 1970s climate shift for the Okavango-Kwando-Zambezi (OKZ) catchment in southern Africa.

Regionally, southern Africa is one of the most sensitive areas to precipitation shifts and variability (Mason et al. 1996; Archibald and Scholes 2007; IPCC 2007) and a large degree of uncertainty exists about future rainfall distribution, frequency and variation (Flato 2001; Gordon et al. 2000). Along with ENSO, the most important underlying mechanisms driving rainfall patterns in southern Africa are the migration of the inter-tropical convergence zone (ITCZ), and sea surface temperatures (SSTs) in the Indian

and Atlantic Oceans (Nicholson 1997c; Nash and Endfield 2008; Mason 2001). The ITCZ controls seasonal rainfall but global climate teleconnections related to ENSO and SSTs of the Indian and Atlantic oceans will influence the inter-annual and inter-decadal variability in rainfall (Richard et al. 2001; Mason 2001; Nicholson 2001; Rouault et al. 2003; Hirst and Hastenrath 1983; Reason and Rouault 2002).

ENSO refers to the irregular shifts in Pacific sea surface temperatures and atmospheric conditions and is the major inter-annual influence on rainfall in the tropics (Curtis 2008). Its effect on southern African rainfall patterns is modulated by SSTs from the Atlantic and Indian Oceans (Nicholson 1997a; Paeth and Friederichs 2004; Mason and Jury 1997; Jury, White, and Reason 2004). In recent years there has been an increase in the number of warm phase ENSO events (Mason 2001). This phase often is associated with drier conditions in southern Africa (Mason 2001; Mason and Jury 1997; Jury, White, and Reason 2004; Alemaw and Chaoka 2006). If a warm phase occurs during an already dry year conditions will be exacerbated and the drought may persist into subsequent years (Nicholson, Leposo, and Grist 2001; Nash and Endfield 2008). However, the strength of association varies making an understanding of the association between ENSO phase and rainfall patterns critical to natural resource management (Richard et al. 2001).

One possible explanation to recent multi-decadal changes in southern Africa rainfall patterns and potential changes in ENSO phase frequency is a shift in the background state of the coupled ocean-atmosphere system in the tropical Pacific during the late 1970s (Graham 1994; Meehl, Hu, and Santer 2009; Mason 2001). Main characteristics of the shift included altered patterns in sea surface temperatures

(increase in SSTs > 0.75^{o}C) and an eastward shift in convection patterns in the near-equatorial Pacific (Graham 1994). The slowly varying pattern of sea surface temperatures, known as the Interdecadal Pacific Oscillation (IPO) (Power et al. 1999), has a concurrent effect on the underlying processes of ENSO in the Pacific Ocean (Wang 1995). The 1970s shift to warmer SSTs in the tropical Pacific is coincident with a strengthening of winter circulation patterns in the North Pacific affecting climatological, hydrological and biological components of the system (Graham 1994; Francis et al. 1998; Nitta and Yamada 1989), and with altered relationships between ENSO and precipitation patterns over Australia (Power et al. 1999). Similar changes in frequency, intensity, duration of ENSO, air temperatures and rainfall patterns since the 1970s have been noted by Mason (2001) and Nicholson (1997b) over southern Africa.

This study examines the spatial and temporal trends in precipitation over the Okavango-Kwando-Zambezi (OKZ) catchment (693,000 km^2) which includes three inter-connected yet distinct catchment areas. Included in the three-catchment area is the future Kavango-Zambezi Transboundary Conservation Area (KAZA) that spans five southern African nations attempting to achieve regional-scale conservation through cooperative management of shared natural resources (van Aarde and Jackson 2007). The need to understand how southern African rainfall varies across large geographical but politically connected landscapes is even more critical for such transboundary conservation initiatives that are becoming more common in southern Africa (Wolmer 2003). As geographically extensive as these areas may be, their boundaries often exclude important hydro-meteorological processes that operate at larger regional scales and contribute important inputs to the system from beyond conservation limits. The

KAZA region provides a vital wildlife corridor to which surface waters generated by precipitation upstream constitute an important water source in an otherwise water-limited ecosystem. Wildlife patterns are dictated by changes in both local rainfall patterns, and those throughout the basin, which influence availability and accessibility to forage and surface water (Chase and Griffin 2009). If there has been a change in rainfall average, frequency, and distribution over the last half century, then we expect to observe a corresponding increase in El Niño years, increased frequency in dry years, and decrease in MAP in the Okavango-Kwando-Zambezi catchment. Additionally, we expect that the association between local and regional input to be less strong in more recent years due to an increase in the variability of climate patterns across southern Africa.

Materials and Methods

Study Region

The Okavango-Kwando-Zambezi (OKZ) catchment (693,000 km^2) encompasses the vast majority of KAZA, the politically defined conservation area that includes parts of Angola, Zambia, Namibia, Botswana, and Zimbabwe (Figure 2-1). The main KAZA areas in the OKZ basin are the Caprivi Region of Namibia, northern Botswana, and western Zambia. KAZA is set to become the largest transfrontier conservation area in Africa connecting multiple protected areas and thus has considerable potential to sustain increased wildlife densities and diversity (O'Connell-Rodwell et al. 2000). The region possesses one of the largest free ranging populations of elephants left in Africa, to whom the three perennial rivers constitute a critical source of water in an otherwise water-limited ecosystem (Craig 1997). Moreover, most human settlement also occurs along these water courses thereby increasing the potential conflicts as wildlife

congregates near these perennial water sources especially during the dry season (Chase and Griffin 2009). The highest human populations are located in the lower OKZ basin particularly along rivers in the Caprivi Region (20,000 km^2) of Namibia (O'Connell-Rodwell et al. 2000; Mendelsohn and Roberts 1997).

The majority of the headwaters of all three catchments are located in Angola although a good portion of the Zambezi lies in western Zambia. The upper catchment is characterized by Miombo woodland in areas receiving > 1000 mm/year of rainfall and with a canopy flush that occurs a few weeks before the first rains (Frost, 1996). The lower catchment is of a more mixed composition of tree-shrub-grass and a sub-parallel system of drainage lines (Omirumbas) that run along a NW-SE gradient (Thomas et al. 2000). The region experiences natural variability in precipitation with a gradient of decreasing rainfall from north to south. Kalahari sandveld characterizes a large portion of the region's soil and subtle variations in vegetation type traverse a gradient that corresponds to the N-S rainfall regime (Dube and Pickup, 2001). However, variation in soil type exists with upland areas in Angola and Zambia defined by a range of ferralsols to sandy arenosols for mid-elevation regions and the lower, flatter areas of the catchment contain clay-enriched gleysols (Batjes 2000).

Datasets

The boundaries of the OKZ catchment provide the limits within which comparisons of mean annual precipitation across and within three sub-catchments are completed. Digital elevation model (DEM) data from the World Wildlife Fund HydroSHEDS project delineate the catchment (Lehner, Verdin, and Jarvis 2006). HydroSHEDS data products have a spatial resolution of 15 arcseconds and were processed using the ArcHydro data

model and toolset (Maidment 2002) to extract drainage networks and sub-catchment extents.

To examine long-term precipitation patterns, we used a gridded monthly time series of modeled rainfall across the OKZ catchment (Matsuura and Willmott 2007). The Willmott-Matsuura (WM) dataset was developed at the Department of Geography and the University of Delaware and is based on an earlier global mean monthly precipitation dataset (Legates and Willmott 1990). The WM dataset improves upon the Legates and Willmott dataset with a refined Shepard interpolation algorithm and an increased number of neighboring station points included in analysis (Fekete et al. 2004). The WM dataset uses a spatial interpolation of monthly total precipitation station values created a 0.5^{o} x 0.5^{o} degree latitude/longitude grid with grid nodes centered on 0.25 degree which results in a total of 232 points for the OKZ catchment. We chose the Matsuura and Willmott dataset over other global modeled datasets (Kalnay et al. 1996) because of its finer spatial resolution and inclusion of more recent years. Existing meteorological station data alone did not provide sufficient spatial or temporal extent and satellite-based estimates (ex. Tropical Rainfall Monitoring Mission (TRMM)) did not provide the necessary longitudinal history for analysis. The WM model output accuracy for global precipitation patterns compares favorably to five other monthly precipitation datasets (Fekete et al. 2004) and the finer spatial resolution and inclusion of more recent years made it the most appropriate dataset for this study.

Statistical Examination of Precipitation Patterns

To identify any temporal shifts in precipitation patterns across the OKZ catchment we use progressive windows comparing consecutive 5 and 10 year blocks of time from 1950-2005. Comparisons were conducted for the two sample blocks using a Mann-U

Whitney test. The nonparametric test was applied cell-by-cell. In order to further test the presence of the postulated climate shift in the late 1970s (Mason and Jury 1997; Mason 2001; Chavez et al. 2003; Graham 1994), estimated basin-wide precipitation input data from 1950-2005 are separated into two periods (P1: 1950-1975 and P2: 1980-2005) excluding the latter half of the 1970s.

Correlations comparing overall precipitation input (1950-2005) for each sub-catchment spatially identify the strength of association between catchments in the OKZ basin. We used Pearson's product-moment correlation coefficient (Pearson's r), a correlation that assumes a linear relationship between the variables of interest, in this case the precipitation input for each sub-catchment (Burt and Barber 1996). In addition, visual comparisons of patterns in P1 and P2 in the OKZ basin are made by investigating the number of years in each period experiencing above/below median rainfalls. Similar comparisons are possible for rainfalls in cold and warm phases of ENSO.

After describing spatial and temporal change for the OKZ basin, we use the hypergeometric distribution (Agresti 2007; Mason and Goddard 2001) to determine the likelihood of experiencing any number of above or below median rainfall events in P1 and P2 under the null hypothesis of no significant change in characteristics between the two time periods. The observed number of above and below median rainfall years within a given time period can then be tested against this null hypothesis of randomness. The test which has no underlying assumption of normality has been used successfully to look at rainfall distributions and probabilities globally (Mason and Goddard 2001) and for other regions in Africa (Owusu, Waylen, and Qiu 2008). The hypergeometric distribution test can be stated as such:

$$p(x) = \frac{\binom{k}{x}\binom{N-k}{n-x}}{\binom{N}{n}}$$

Where N is the population of total annual precipitation inputs (N=55); the time period from 1950-2005), n is the subset of estimated available years for each time period (n=25), and k represents the number of years in the population that are considered a success (for example, the number of years experiencing below median rainfall in the N; N/2). The equation returns the probability, p(x) of experiencing x dry (wet) years at random.

The same analysis is performed for El Niño and La Niña years to determine the correspondence between phases of ENSO and wet and dry years respectively (Grimm et al., 2000). Years which correspond to warm phase and cold phase events are identified by the Center for Ocean-Atmospheric Prediction Studies (COAPS) at Florida State University (http://www.coaps.fsu.edu/jma.shtml). The statistical null hypothesis states that there is no significantly greater number of El Niño (La Niña) years occurring in the driest (wettest) third of all years than one would expect at random. Similarly, we hypothesize that there is no significantly lesser number of El Niño (La Niña) years occurring in the wettest (driest) third of all years than one would expect at random. Significance is a discrete p-value determined by the hypergeometric distribution probability of x or more (x or less) events occurring outside what is expected at random.

Lastly, as water resources available to the KAZA conservation area include the local precipitation and regional waters imported from the respective upstream sub-

catchments, it is important to focus on these different patterns of precipitation across and within the sub-catchments and to examine the association between regional and local input (Figure 1). By comparing precipitation input between local and regional areas of each catchment we determine a general idea of how synchronized hydrological and meteorological droughts (floods) are in the area. A Chi Square test of independence is used to examine the relationship between "wet", "normal", and "dry" years between the local and regional study areas. For examinations of Periods 1 and 2, where the expected sample size falling into each possible combination of categories is less than 5, we use Fisher's exact test (Fisher 1970). Associated probabilities for above and below median precipitation values are also analyzed in each catchment. We use regional sub-catchment estimates of spatially-averaged total precipitation as a substitute for discharge due to the lack of longitudinal discharge measurements across all three basins. The analysis is completed for the entire time period (1950-2005) and repeated for purposes of comparison between P1:1950-1975 and P2:1980-2005.

Results

Climate Shift

Results of the application of the Mann Whitney test to compare differences in mean values of precipitation using a 5-year progressive window (water years 1950-2005) are shown in Figure 2-2. There were no significant differences in mean values for the 10-year progressive window. Figure 2-2 values highlighted in white and grey are grid points that had a p-value < 0.05 and 0.10, respectively. The comparison between years 1975-79 and 1980-84 showed the largest number of grid points in which the mean value differed significantly from each other. Of the total 232 grid points that comprise the OKZ basin, 32% are significant ($p < 0.05$) for the 1975-79 and 1980-84 period. The next

largest number of grid points to have significant difference between time steps was 21% between 1965-69 and 1970-74. Other paired comparisons show no change (ex.1950-54 to 1955-59) or regional differences (ex. 1955-59 to 1960-64) but only the late 1960s and late 1970s time periods show a difference across all three catchment areas. Excluding the time period 1975-79, allows comparison of changing precipitation patterns before and after the shift which clearly manifests itself in the study area.

Spatial and Temporal Patterns

Figure 2-3 indicates that the two more western catchments (the Okavango and the Kwando) experience similar magnitudes and variabilities of estimated annual basin inputs, while the Zambezi exhibits a slightly out of phase temporal pattern and increased level of precipitation input. Correlations calculated for the entire time period between the three catchments showed a significant positive association for all comparisons. The positive association was strongest between the Kwando and Okavango catchments (64%) and weakest between the Okavango and Zambezi catchments (44%). Period 1 and Period 2 did not show statistically significant results suggesting that precipitation between time periods is not temporally associated. Warm and cold phase ENSO periods identified in Figure 2-3 also suggest a reduction in the number of cold phase years since 1980.

Variability, calculated by the coefficient of variation, is relatively higher for more semi-arid regions in the southern part of the OKZ catchment (Figure 2-4). The NE-SW gradient of increasing variability (exception is a small area in upper northeastern area) in the OKZ basin is coupled with a decreasing gradient of overall less MAP input (Figure 2-5). Breaking down the MAP input by P1 and P2 suggests, in general, more rainfall fell overall in the OKZ catchment during P1 (Figure 2-5a). A noticeable shift in P2 isolines

indicate less total annual rainfall occurred in the OKZ basin in recent decades. The majority of the OKZ basin shows a decline (P2 – P1) in total median rainfall. Areas experiencing higher rainfall in P2 are limited to the most northeasterly extreme of the Zambezi.

The difference in median rainfalls between cold and wet phase of ENSO (La Niña – El Niño) shown in Figure 2-6 illustrates a much larger range (more marked impact on variability) since 1980. Higher values identify areas with bigger extremes between amount of rainfall during an ENSO event (LN-EN) while lower values are areas that do not differ as strongly in total median rainfall during El Niño (warm) and La Niña (cold) years. During P1 (1950-1975) the largest difference in La Niña and El Niño occurs in the lower catchment areas of the Okavango and Kwando, while the difference is much more pronounced across the entire area including the Zambezi in Period 2: 1980-2005 (Figure 2-6a and 2-6b). The largest difference of ENSO events across the two time periods (LN-EN 1950-1975 minus LN-EN 1980-2005) occurs in a broad arc stretching across the uppermost reaches of the Okavango and Kwando catchments and through mid-portions of the Zambezi catchment (Figure 2-6c) . Positive values identify regions with increased variability in ENSO periods during P2 while negative values indicate areas with less variability in ENSO during P2. The KAZA area itself seems to be sensitive to changes in ENSO phase during both periods, but more so during the second. The change appears most marked over the Zambezi section and upper Okavango portions of the OKZ basin.

Basin Level Analysis

Figure 2-7 displays the differences in mean annual precipitation input for each sub-catchment of the study area for P1 and P2. In all three sub-catchments the mean annual precipitation was higher in P1 (1950-1975) when compared to P2 (1980-2005).

In addition to experiencing less rainfall overall, the more recent decades also exhibit an increase in the number of "dry" years (years in the long run lowest tercile), while the total number of wet years has decreased for each basin (Figure 8). Application of the hypergeometric distribution indicates that the number of dry and wet years in each basin over each separate time period is different than that expected at random. The opposite patterns in dry and wet year frequency for P1 and P2 respectively complements findings on total annual precipitation input declining in each sub-catchment.

Observations of figures 2-3 and 2-8 prompt the related questions of whether the numbers of years experiencing various ENSO phases changed in the late 1970s, and also whether the severity of the association of ENSO events to wet and dry years. Table 2-1 shows the probability that the concordance between the historic (1950-2005) number of warm and cold phase events and dry and wet years is *not* random The likelihood of experiencing a dry year during an El Niño event is significantly greater than random for the two most western catchments, the Okavango and the Kwando, but not in the Zambezi. Only in the Kwando catchment is La Niña events associated with significantly fewer dry years than expected at random. Wet years are significantly more likely to occur simultaneously with cold phase (La Niña) events.

The associations may be further broken down to see if similar associations are present pre/post mid-1970s, although levels of significance may drop in association with

the smaller sample sizes in comparison to the previous analyses. Table 2-2a shows that the number of dry years increases (decreases) coincident with El Niño (La Niña) events in all three basins from P1 to P2. For the driest third of all years, in P1 the probability of experiencing an El Niño or La Niña event does not fall outside the number of events one would expect at random with the exception being La Niña events in the Kwando catchment (Table 2-2a). In P2, there is a much stronger association than expected at random between dry years in the Okavango and Kwando catchments and El Niño events. However, there is no such relationship for the Zambezi and none of the three catchments seem to be associated with La Niña events aside from what we would expect at random.

Considering the highest third of all years (Table 2-2b), the only association that falls outside that expected at random for P1 is that between the Kwando catchment and La Niña events indicating more wet years than random. In Period 2, a pattern emerges across all three catchments with El Niño events eliciting fewer wet years than expected at random. Again, no such relationship in P2 for any catchment seems to be associated with La Niña events aside from what we would expect at random.

Cell by Cell Analysis

A cell-by-cell analysis is employed to determine how patterns of association are changing between phases of ENSO with dry (wet) years within the basins themselves and also provides a more refined spatial depiction of the relationship between ENSO and mean annual precipitation. Figure 2-9 shows the cell values with associations between warm phase and dry conditions that have significantly greater numbers of association than random. A significance level of 0.059 level is employed as this is the closest that the discrete hypergeometric distribution comes to providing the more usual

level of 0.05. The significance level corresponds to the likelihood of experiencing 4 or more warm phase ENSO events in the lowest historic tercile during one of the time periods. Only 4 grid cells in the Angolan Highlands are significant during Period 1 (Figure 2-9a). However, a more extensive and coherent pattern is present in Period 2 (figure 9b) over much of the lower catchment area including precipitation directly into the central region of KAZA itself. There is no statistically significant relationship ($p < 0.059$) for either time period for cold phase ENSO and dry years.

The same analysis is done for the highest (wettest) climatological third of all comparable seasonal totals and correspondence to warm or cold phase ENSO across the two time periods. Figure 2-10 identifies the cell values with associations between warm phase and wet conditions (panels a and b) that have a significantly *lesser* number of associations than random ($p < 0.069$). One grid cell is highlighted in P1 (Figure 2-10a), located in the Angolan highlands. However, a large portion of the southern half of the OKZ basin shows a relatively strong response of less number of warm phase ENSO events concurrent with the “wettest” tercile of MAP. Spatially, emphasis is on the Okavango and Kwando catchment regions. The cell values with associations between cold phase and wet conditions (Figure 2-10c and 2-10d) that have significantly more numbers of association than random show P1 has a minimal association between cold phase ENSO and wet conditions. However, a strong geographic pattern exists in P2 covering much of the central region of the OKZ basin. This area encompasses part of all three basins and emphasizes the importance of wet years coincident with cold phase ENSO.

Local versus Regional Input

Table 2-3 suggests that precipitation input to the entirety of each sub-catchment fluctuates in a similar fashion to that portion of the sub-basin falling within the KAZA region itself. When the entire time period (1950-2005) is considered, this similarity of behavior of both local precipitation and exotic waters brought into the KAZA by the rivers could have severe consequences for the management of water resources in the parks. The indications are that the congruity of meteorologic and hydrologic droughts and flooding have increased in the latest decades, and that this may be particularly strong and persistent as one moves eastwards in the KAZA area.

Table 2-4 summarizes the observed relative frequencies with which combinations of above/below median catchment (horizontal) and local (vertical) are recorded in the three sub-catchments over the time periods considered. All basins and time periods reflect the strong positive associations (large values in the diagonal top left- bottom right) between local and regional conditions. The first column highlights the overall time period (1950-2005) and shows a positive association for all three catchments. The Okavango and Kwando are in the same state (above/below) 68% of the time, while the Zambezi evinces even greater similarities (88%). Examined by Period, two changes are apparent; 1) during period 2 there is a greater tendency for both local and regional inputs to be in the same state, and 2) the most common combination of states switch from simultaneous above median conditions during period 1 to simultaneous below median conditions in Period 2. Thus, while the association remains positive, there is a greater probability that each catchment will experience both below average rainfall as well as below average flow from 1980-2005. Again the Zambezi has the strongest

positive association with 96% of the years from 1980-2005 either having above average rainfall and flow or below average rainfall and flow.

Discussion

Spatial and temporal precipitation patterns in the OKZ basin shows a decrease in total mean annual rainfall between P1 (1950-1975) and P2 (1980-2005). The late 1970s shows the largest percent difference in precipitation input on a cell-by-bell basis (Figure 2-2). The late 1960s is identified as another period of anomalous precipitation patterns but not to the same magnitude as the late 1970s (Nicholson 2000). The late 1970s difference in precipitation corresponds to the time period observed for the global climatic shift that resulted from climate shifts in the northern Pacific basin. The decline between P1 and P2 manifests itself in an increased frequency of dry years and a rise in number of warm phase ENSO events, which are often coincident. Although there is a decline in wet year frequency from P1 to P2, when wetter than average years of rainfall occur they are often coincident with cold phase ENSO events. The distinction of cold and warm phase ENSO associated with either wet or dry years is more apparent in P2 compared to P1. This suggests that ENSO phases are more strongly associated in recent decades with either dry (warm phase ENSO) or wet (cold phase ENSO) years. These findings support the strong relationship previously identified between inter-annual rainfall variability and ENSO for southern Africa (Mason 2001; Mason and Jury 1997; Ropelewski and Halpert 1987) and also indicate that the global climate shift of the late 1970s is detectable within the OKZ catchment.

Both the overall basin calculations and the cell-by-cell analysis indicate increase in number of warm phase ENSO events associated to dry years in P2 for all three OKZ sub-catchments (1980-2005), corresponding to previous findings for other regions in

southern Africa and globally (Mason 2001; Nyenzi and Lefale 2006). The basin scale correspondence is strongest for the increased frequency of warm phase ENSO events during P2 (1980-2005) and occurrence with dry years in the Okavango and Kwando basins. The cell-by-cell analysis also shows the strongest correspondence in P2 but emphasizes not only areas in the Okavango and Kwando, but the entire lower half of the OKZ basin (Figure 2-9b). In addition for P2, the cell-by-cell analysis indicates a decoupling in the strength of warm phase ENSO and wet years (Figure 2-10b) and a stronger association of wet years to cold phase ENSO events (Figure 2-10d) than expected at random.

The change in frequency from P1 to P2 of ENSO phases (more warm phase versus cold phase) and the increased association of warm phase ENSO and dry years coincides with positive (negative) atmospheric temperature fluctuations of recent decades that trigger global warm (cold) phase ENSO events (Tsonis et al. 2005). Tropospheric warming in the latter half of the 20th century could also be a factor in higher frequency of warm phase ENSO events (Flohn and Kapala 1989). Our results for these southern African catchments correlate to the global change in the ENSO signal (Chang et al. 2006) and warming of global ocean temperatures (Levitus et al. 2000), and may be related to a possible enhanced greenhouse effect or just be part of a normal, variable climate pattern (Mason 2001). Regardless of the underlying mechanisms, the varying strength of associations suggests ENSO phases will have a stronger influence in certain part of the OKZ catchment than others. ENSO appears to impact rainfall patterns across the entire OKZ basin, but the association of warm phase

ENSO and dry year appears particularly strong in the more westerly Okavango and Kwando catchments, in recent decades.

Some of the main underlying factors that influence the spatial and temporal rainfall patterns across the OKZ catchment and its association to ENSO are largely related to Atlantic and Indian basin ocean-atmospheric processes (Nicholson 1997a; Jury 2010; Vigaud et al. 2009; Rouault et al. 2003; Hirst and Hastenrath 1983; Nicholson and Entekhabi 1987). Specifically, the association of Atlantic ocean-atmospheric processes on southern African rainfall variability is growing in its importance especially for western and central regions of southern Africa (Vigaud et al. 2009). The periodic appearance of anomalously warm coastal waters off the coast of Angola coincides with increased rainfall over regions of Namibia, Angola and Zambia (Hirst and Hastenrath 1983; Rouault et al. 2003; Nicholson and Entekhabi 1987). The phenomenon of warming waters, Benguela Niños, might be a response to ENSO-like processes in the equatorial Atlantic. However no consistent link between the phenomena in the two ocean basins has been found (Binet, Gobert, and Maloueki 2001). In addition, variability in the intensity of moisture circulation across the South Atlantic, the South Atlantic midlatitude mode, has been observed to influence rainfall patterns in parts of southern Africa (Vigaud et al. 2009). The positive and negative phases of this mode are linked to shifts in intensity of the ITCZ and Angolan low (a strong tropical trough) which in turn affects precipitation in the OKZ basin (Vigaud et al. 2009). There is also a seasonal association for North Atlantic ocean-atmospheric circulation patterns and river flow for the Okavango basin (Jury 2010).

To the east, the Indian basin constitutes the major source of austral summer rainfall (Rouault et al. 2003; Reason 2002; Washington and Preston 2006). There is evidence that Indian Ocean sea-surface temperatures influence rainfall patterns across eastern and central-southern Africa (Goddard and Graham 1999), including large portions of the OKZ basin. Surface moisture fluxes that develop over the OKZ basin therefore reflect a gradient of the influences of circulation in the Atlantic and Indian basins, both of which may act to amplify or dampen the strength and signal of ENSO events. The varying contributions from these two ocean basins may help explain the difference in rainfall patterns and associations with ENSO witnessed between the western and southern regions and the more northeastern area of the study area. The shifts in global climate forcings such as ocean-atmospheric processes and climate phenomenon such as ENSO coupled with local variability (Shongwe et al. 2009) creates inconsistency in rainfall patterns across the OKZ basin having implications for agricultural and wildlife management (Phillips, Cane, and Rosenzweig 1998; Chase and Griffin 2009).

Another important geographic consideration is that of a transitional zone in response to ENSO between the western and southern, and northeastern sections of the OKZ basin . The ITCZ migrates along an asymmetrical loop in southern Africa due to differential heating from topographical changes in the landscape and also from warm eastern coastal waters that encourage convective activity and cold western coastal waters that have the opposite effect (Marchant et al. 2007). Variation in the direction and strength of zonal trade winds also will affect the ITCZ seasonal rainfall distribution patterns (Marchant et al. 2007). Thus rainfall variability in the western and southern

portion of the OKZ basin will be more sensitive to seasonal fluctuations in ITCZ movement. The nature of the seasonal migration of the ITCZ, brings more rainfall for the northeastern section of the OKZ basin where rainfall is more consistent than southern parts of the basin (Figure 4). This is also the area of mixing between the ITCZ and another zone of convergence, the Congo Air Boundary (CAB) (Tyson and Preston-Whyte 2000). The CAB is a complex union of converging air streams that originate from East Africa and the Indian and Atlantic oceans which frequently create low pressure systems and conditions favorable to rainfall (Tyson and Preston-Whyte 2000; Hansingo and Reason 2009). Another layer of complexity involves the Angolan low located in the southern portion of the OKZ basin (Gasse et al. 2008). This local climate feature has also been shown to be influenced by processes occurring in the Atlantic and Indian ocean basins and appears to fluctuate in strength along with the ITCZ, (Vigaud et al. 2009). The limits of all these climatic features coincide at about at about 15-17°S producing a dominance of influence of the Angolan low in the central southern region of the OKZ catchment, and a region of strongest influence of the ITCZ across the northeastern portion of the catchment (Gasse et al. 2008). Inter-annual fluctuations in the exact location of this boundary will affect variability in rainfall patterns across the region potentially creating differing precipitation patterns for various areas of the OKZ catchment. If long-term change in global climate creates permanent shifts in the operation of these local climate features then it is even more imperative that transboundary initiatives are cognizant of precipitation patterns and how such low frequency or global climate change may affect rainfall over the larger region.

Precipitation variability is common in semi-arid environments but increased variability or persistently drier conditions demands effective coping and adaptation strategies (Vetter 2009; Thornton et al. 2004). Those strategies rely on knowledge of spatial patterns of past and present precipitation and how shifts in the underlying climate may influence the timing, distribution, or frequency of rainfall. While the state of local and regional inputs for each sub-catchment remains relatively strong (Table 4), the switch from above median conditions in P1 to below median conditions in P2 suggests that land-use and conservation decisions should be cognizant of the historical shifts in above/below average rainfall and flow in the OKZ basin. Multiple years of drought may contribute to vegetation changes (Ringrose et al. 2007) and negatively influence perennial vegetation which affects rangeland management decisions (Vetter 2009). Fisheries in the lower part of the OKZ basin are affected by spatial variation in rainfall patterns as lake levels may not reflect long-term local climate changes but rather depend on fluctuations in rainfall that occur in a catchment's headwaters (Shaw 1983). The decrease in mean annual rainfall for the OKZ basin and increase in dry years associated with ENSO warm phase events suggests spatial ranges of large mammal species may have decreased to adapt to drier conditions (Chase and Griffin 2009). In addition, effective measures should be developed in response to better understand the effects of ENSO on rainfall variability for crop production as ENSO may have an influence on favorable cropping seasons (Phillips, Cane, and Rosenzweig 1998).

Summary

Unpredictable or inconsistent rainfall patterns will negatively influence marginal landscapes such as savannas where the timing and quantity of rainfall is critical for rural livelihoods. Thus, an understanding of the spatial and temporal patterns of rainfall in the

OKZ catchment is paramount for transboundary management initiatives, with fixed spatial limits, that involve decisions for wildlife and people in such dryland environments. The more recent period (1980-2005) had less overall mean annual precipitation input into the OKZ catchment than the period (1950-1975) before the late 1970s global climate shift. In addition, the number of dry years and frequency of dry years associated to warm phase ENSO events has increased. These patterns suggest short term changes to the shifts in the functioning and response of the catchment to hydro-meteorological patterns from 1950-2005. However, since 2008, the OKZ basin has experienced higher than normal rainfall and increased flooding for all three sub-catchments (Wolski 2010). More research is necessary to determine how short-term variability in rainfall patterns fit within the longer term changes of climate. Climate change is a global phenomenon that impacts the abundance and distribution of flora and fauna across a range of ecological levels, from individual species to entire ecosystems (Walther et al. 2002) making it vital to recognize and incorporate an understanding of spatial and temporal precipitation patterns into management plans for the future KAZA region.

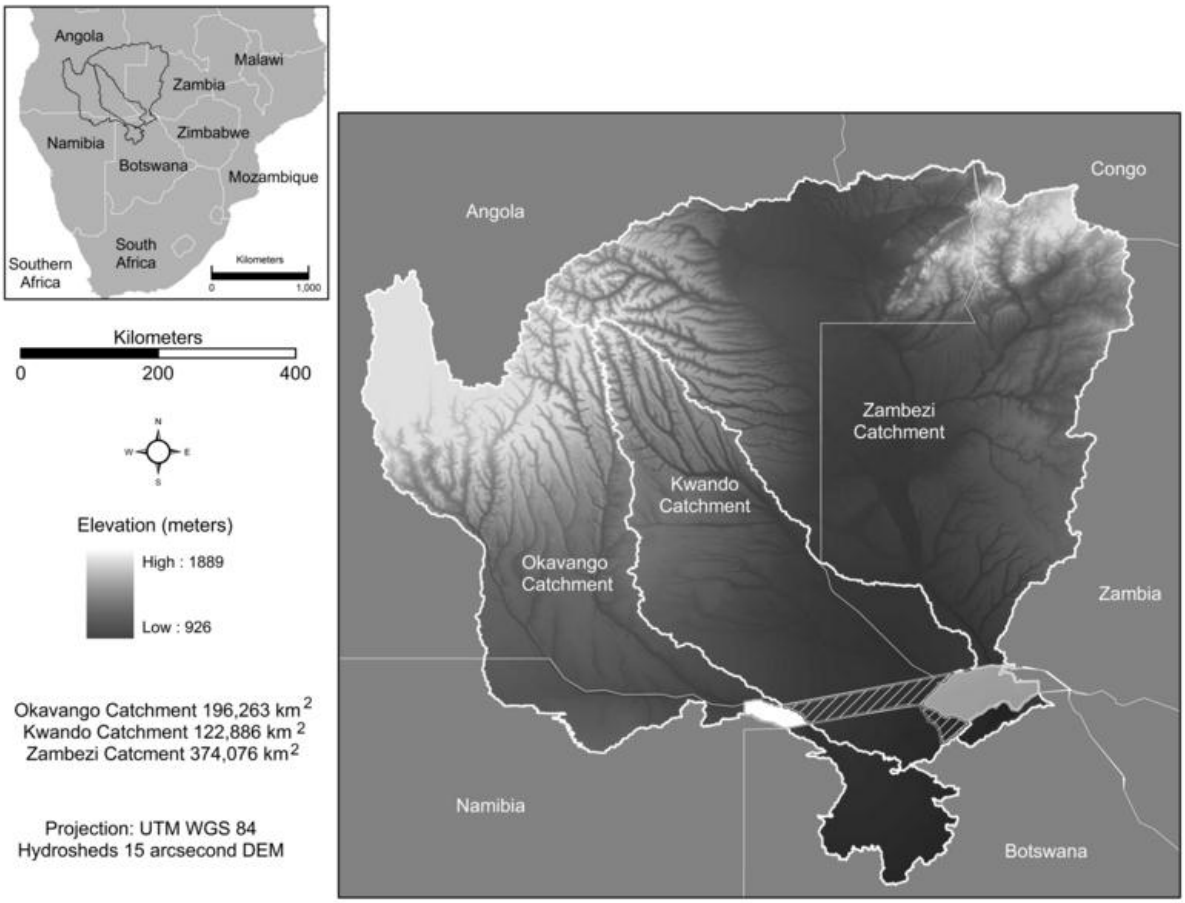


Figure 2-1. Study region in southern Africa outlining the three sub-catchment areas that make up the larger Okavango-Kwando-Zambezi catchment. Local study areas in the Caprivi Region are defined in white (Okavango), stripes (Kwando) and gray (Zambezi).

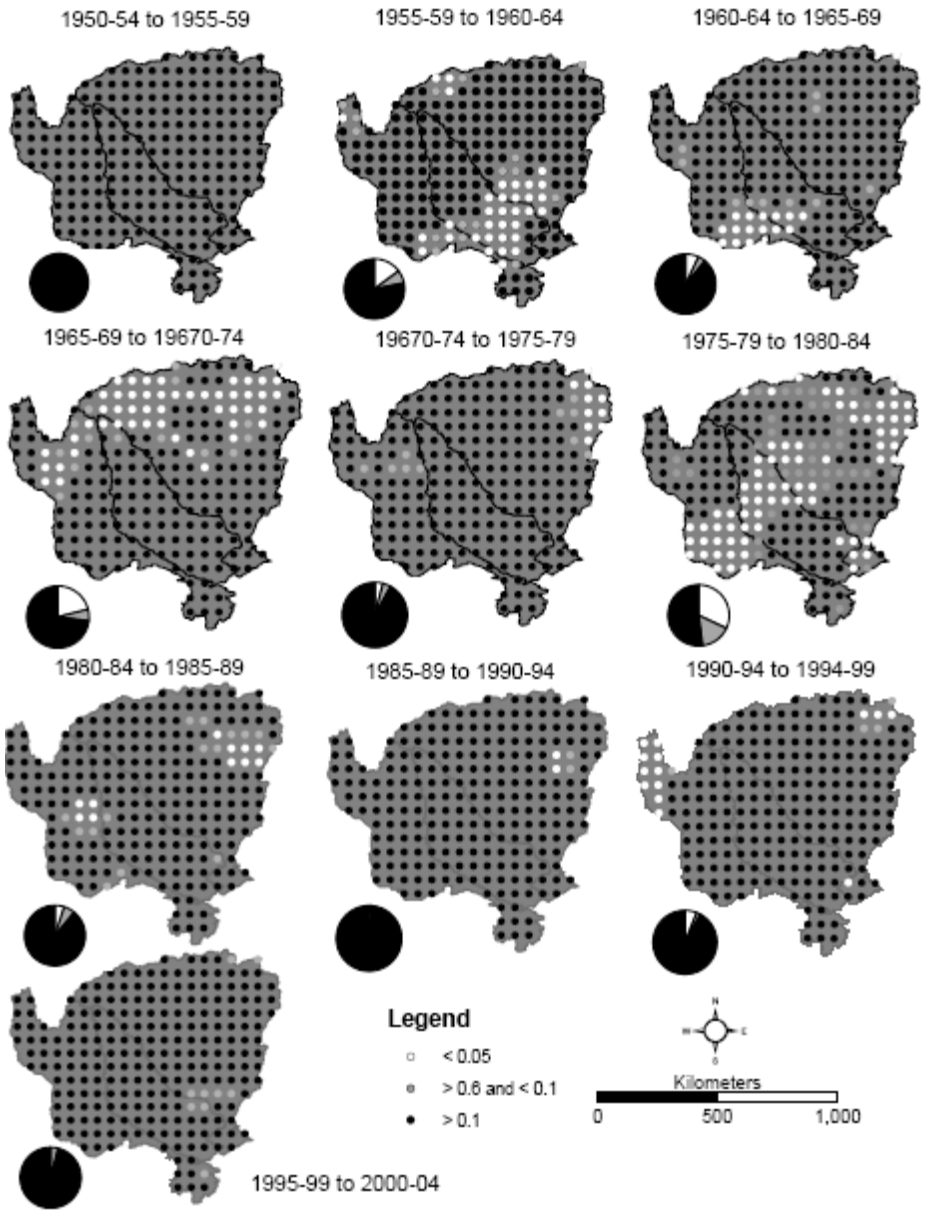


Figure 2-2. Cell-by-cell 10-year moving window analysis which shows the most statistically significant cells that indicate a difference in precipitation input from time 1 to time 2 occurs between the 1975-79 and 1980-84 periods.

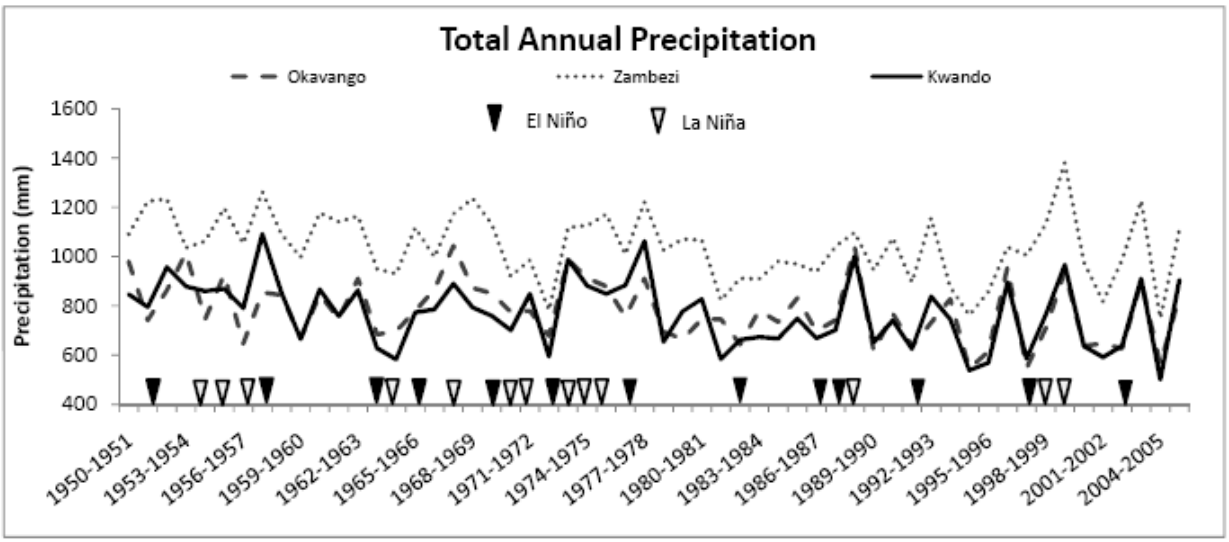


Figure 2-3. Time series of in the Okavango, Kwando, and Zambezi catchments in southern Africa from 1950-2005 (based on water years, October-September) with ENSO warm and cold phases identified in background.

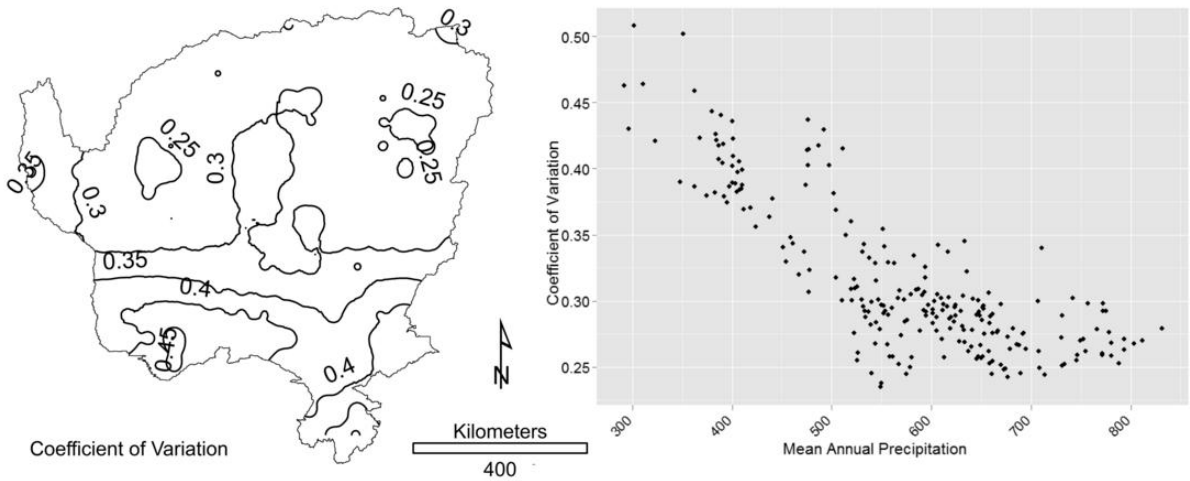


Figure 2-4. Spatial variability across the OKZ basin calculated as the coefficient of variation (CV). The graph shows decreasing CV with increasing mean annual precipitation.

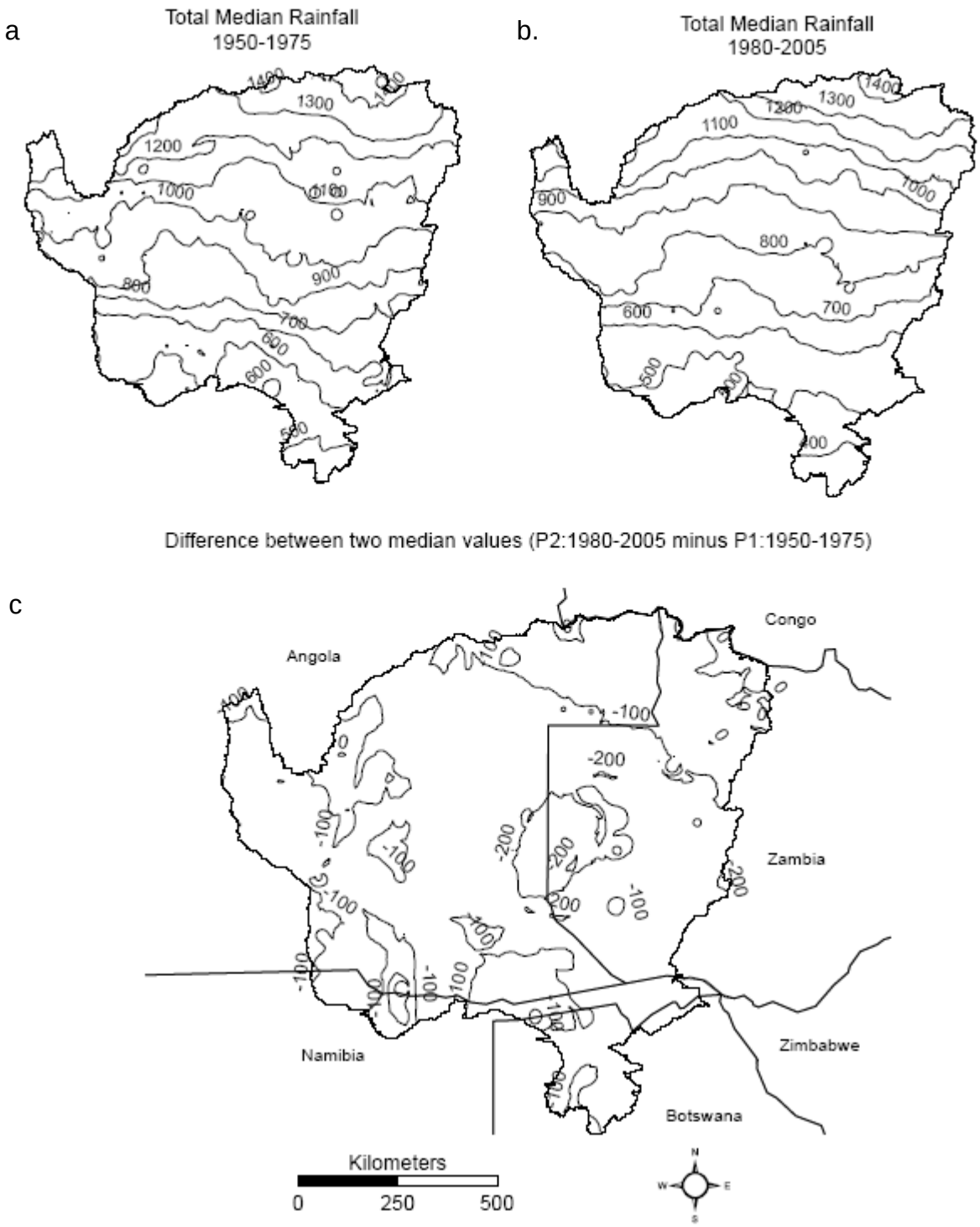


Figure 2-5. The two images on top indicate an aggregated spatial depiction of median annual rainfall from 1950-1975 and 1980-2005 respectively. The bottom image shows the differences between the two time periods (P2 – P1).

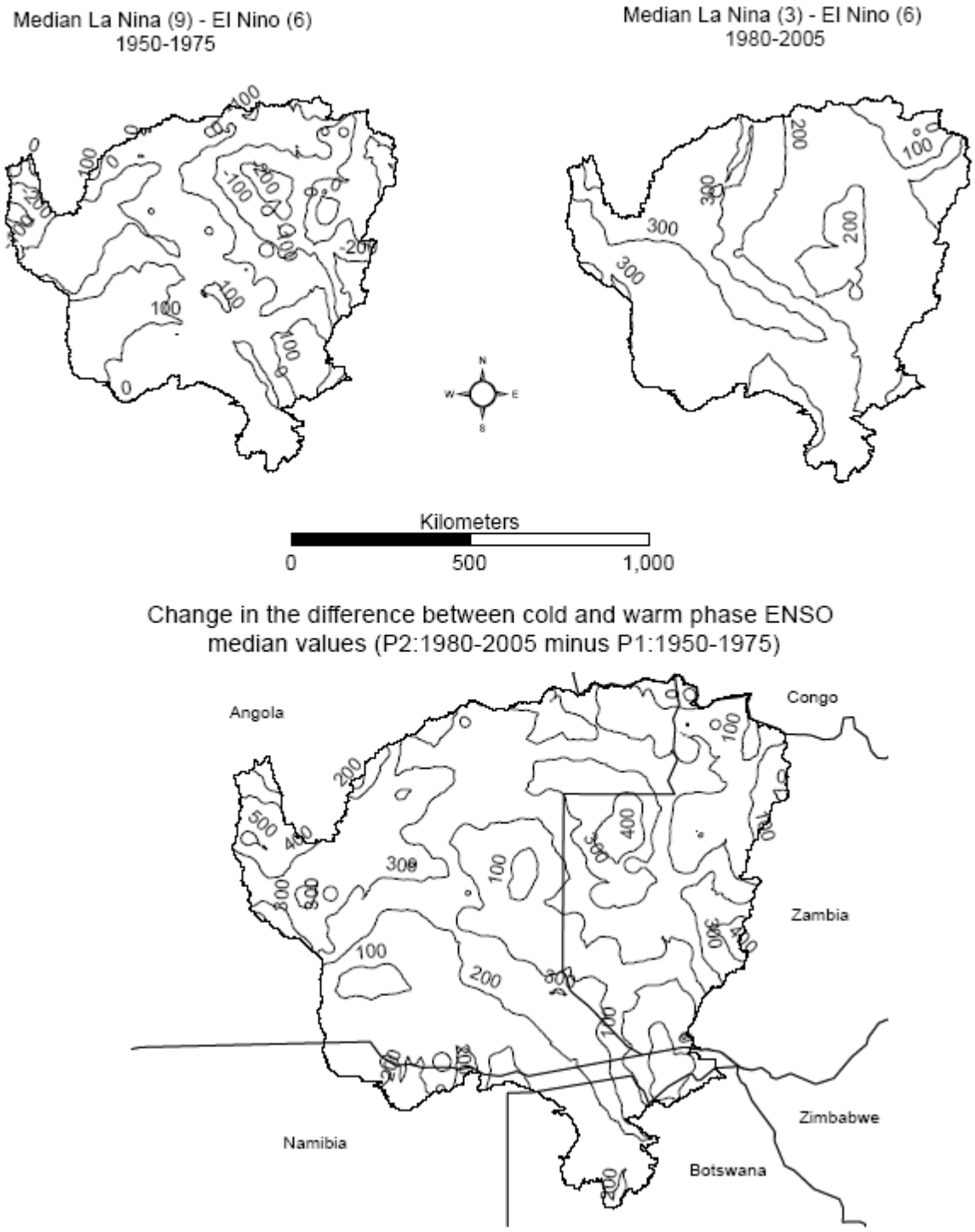


Figure 2-6. The two images on top indicate areas of large change between ENSO phases (La Niña – El Niño) for each respective period. The lower image shows the difference between the two periods. Areas with higher values indicate a larger difference between warm and cold phase ENSO periods in P2: 1980-2005.

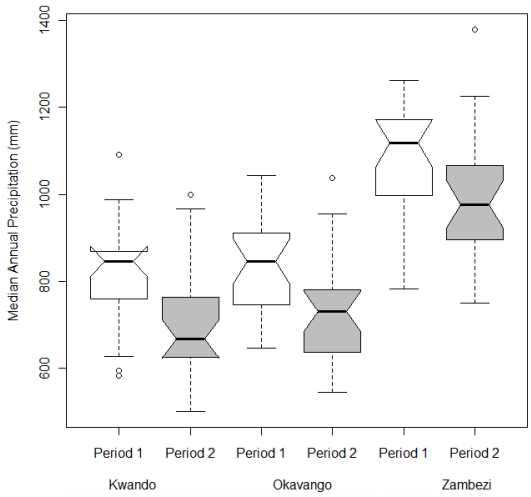


Figure 2-7. Box plot of average annual precipitation input for Period 1: 1950-1975 (white) compared to Period 2: 1980-2005 (gray) for each OKZ sub-catchment.

a. b.

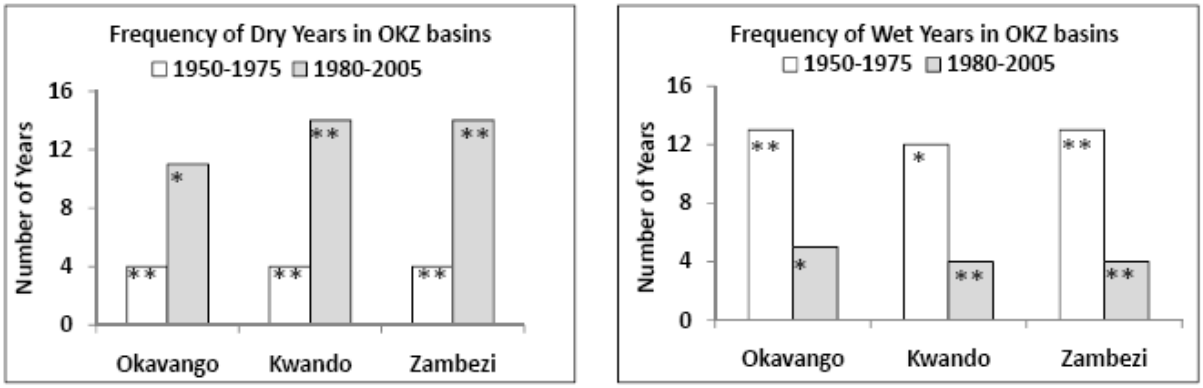


Figure 2-8**.** Shows the frequency of upper and lower climatological third of precipitation data indicating the number of a) dry and b) wet years for each time period and the probability of experiencing more (less) than expected dry (wet) years in Period 1 (Period 2). * Significant at the 0.1 level, ** Significant at the 0.05 level.

Table 2-1. ENSO frequency across a) dry years from 1950-2005 and b) wet years from 1950-2005.

a.

Dry Years: 1950-2005		
Basin	El Niño	La Niña
Okavango	7*	2
Kwando	7*	1**
Zambezi	5	3

b.

Wet Years: 1950-2005		
Basin	El Niño	La Niña
Okavango	2	7**
Kwando	2	9**
Zambezi	4	7**

* Significant at the 0.1 level, ** Significant at the 0.05 level

Table 2-2. ENSO frequency across a) dry years and b) wet years for P1 (1950-1975) and P2 (1980-2005).

a.

Dry Years	P1: 1950-1975		P2: 1980-2005	
	El Niño	La Niña	El Niño	La Niña
Okavango	2	2	5**	0
Kwando	2	1*	5**	0
Zambezi	2	2	3	1

b.

Wet Years	P1: 1950-1975		P2: 1980-2005	
	El Niño	La Niña	El Niño	La Niña
Okavango	2	4	1*	2
Kwando	1	6**	0*	2
Zambezi	4	4	0*	2

* Significant at the 0.1 level, ** Significant at the 0.05 level

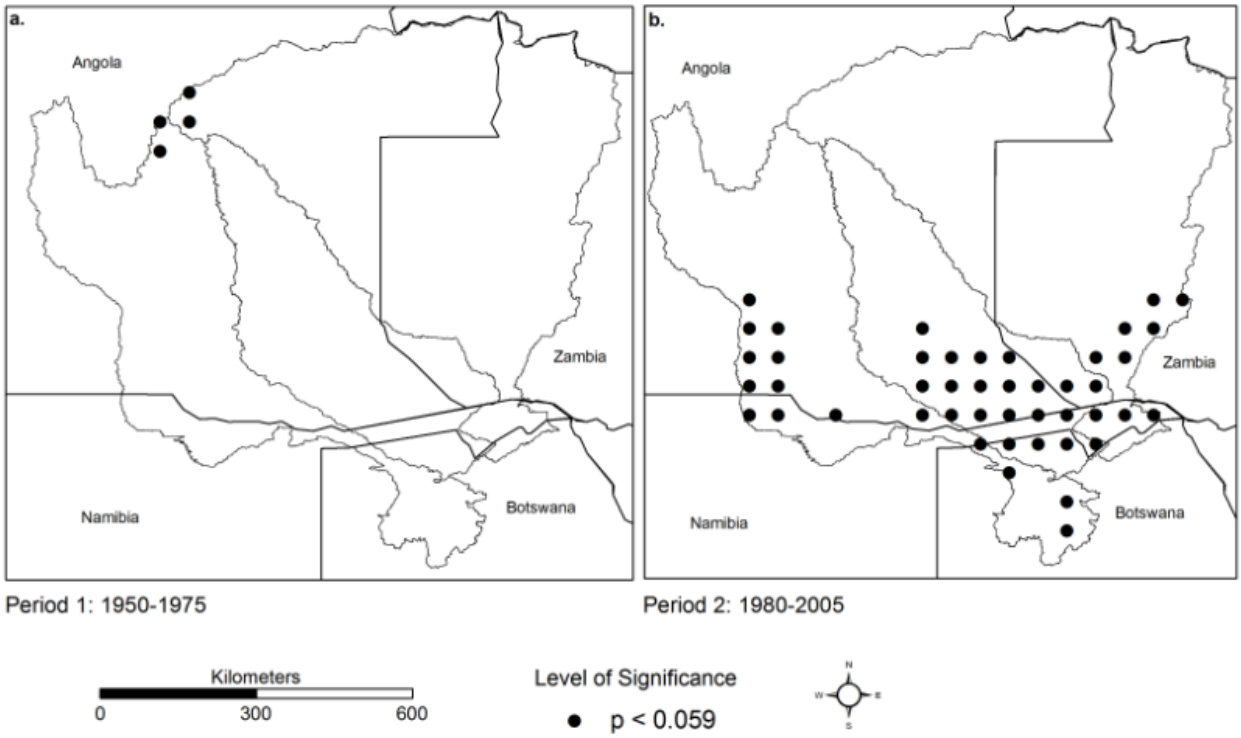


Figure 2-9. Cells reporting statistical significant associations between the concordance (*x or more number*) of warm phase ENSO events and "dry" years during a dry year for Period 1 (1950-1975) and Period 2 (1980-2005), figures a and b respectively. No such associations of significance are detected during cold phases of ENSO.

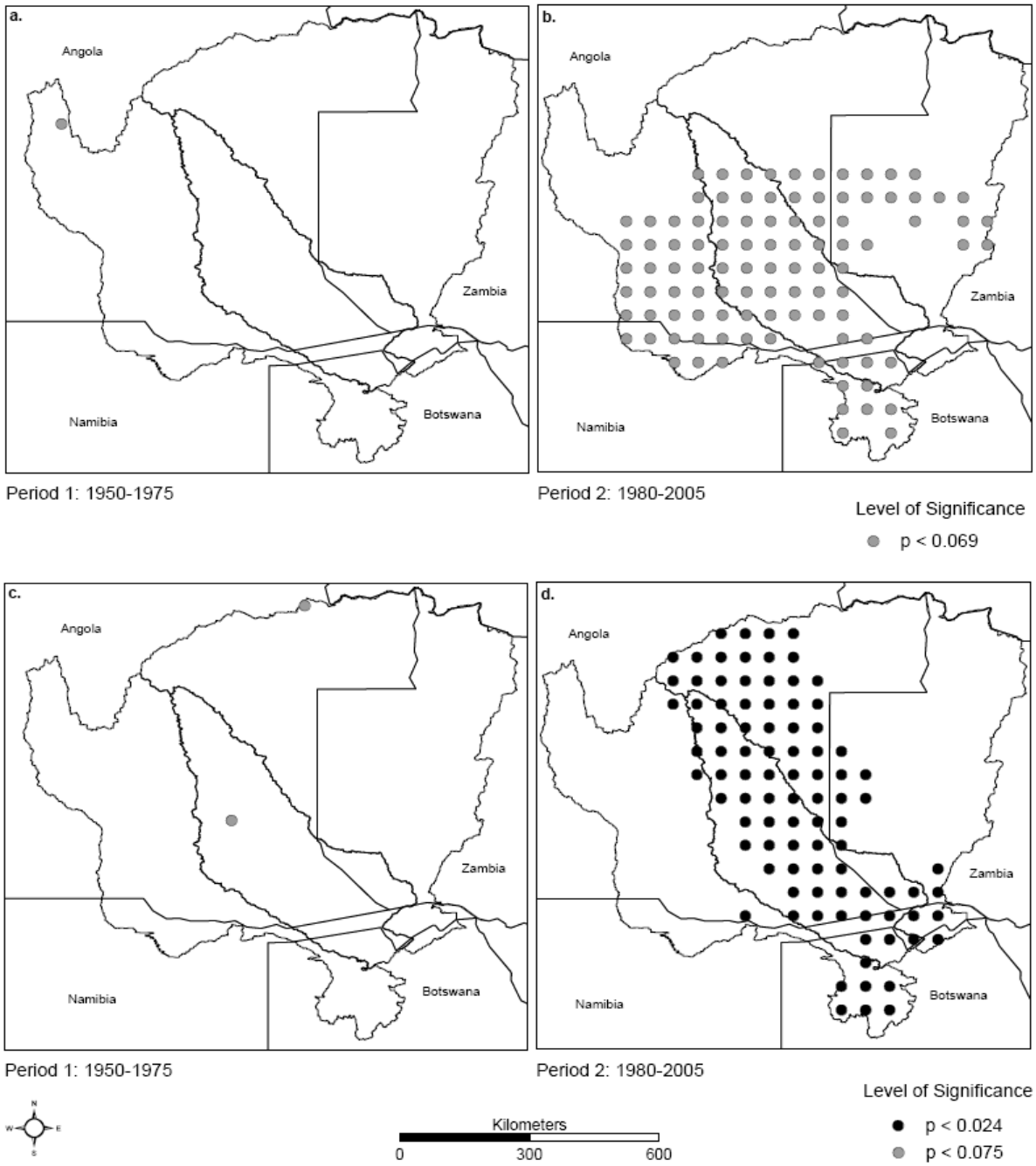


Figure 2-10. Cells reporting statistical significant associations between the concordance of warm phase (panels a and b) and cold phase (panels c and d) ENSO events and "wet" years during a wet year for Period 1 (1950-1975) and Period 2 (1980-2005). Panels a and b show cells display x or less number of expected warm phase events coincident with wet years. Panels c and d show cells that are x or more number of expected cold phase events coincident with wet years.

Table 2-3. Chi-Square results suggest precipitation input within catchments operates similarly for all three catchments across the entire time period but there is less agreement in the Okavango for both P1 and P2, and less agreement in the Kwando for P1.

Basin	n	Chi-Sq Value	DF	Probability	Fisher's Value
Okavango - Median					
P1: 1950-1975	25	3.59	1		0.087
P2: 1980-2005	25	3.59	1		0.087
Total: 1950-2005	55	8.04	1	**	
Kwando - Median					
P1: 1950-1975	25	0.44	1		0.671
P2: 1980-2005	25	10	1	**	0.00365
Total: 1950-2005	55	8.04	1	**	
Zambezi - Median					
P1: 1950-1975	25	11.99	1	**	0.00217
P2: 1980-2005	25	20.3	1	**	0.00004
Total: 1950-2005	55	36.87	1	**	

Table 2-4. Observed relative frequencies between local and regional precipitation input

Local versus Regional Input by Catchment

Okavango Catchment

	Overall: 1950-2005 Regional Input				Period 1: 1950-1975 Regional Input				Period 2: 1980-2005 Regional Input	
Local Input	Above	Below			Above	Below			Above	Below
Above	0.34	0.17	Local	Above	0.54	0.17	Local	Above	0.17	0.12
Below	0.15	0.34	Input	Below	0.12	0.17	Input	Below	0.17	0.54

Kwando Catchment

	Overall: 1950-2005 Regional Input				Period 1: 1950-1975 Regional Input				Period 2: 1980-2005 Regional Input	
Local Input	Above	Below			Above	Below			Above	Below
Above	0.34	0.17	Local	Above	0.44	0.2	Local	Above	0.2	0.09
Below	0.15	0.34	Input	Below	0.2	0.16	Input	Below	0.09	0.61

Zambezi Catchment

	Overall: 1950-2005 Regional Input				Period 1: 1950-1975 Regional Input				Period 2: 1980-2005 Regional Input	
Local Input	Above	Below			Above	Below			Above	Below
Above	0.46	0.04	Local	Above	0.71	0.04	Local	Above	0.24	0
Below	0.05	0.42	Input	Below	0.08	0.21	Input	Below	0.04	0.72

CHAPTER 3
LINKING VEGETATION RESPONSE TO SEASONAL PRECIPITATION IN THE OKAVANGO-KWANDO-ZAMBEZI CATCHMENT OF SOUTHERN AFRICA

Variability in inter- and intra-annual precipitation affects ecosystem structure and function in all climates (Scanlon et al. 2005; Merbold et al. 2009; Huxman et al. 2004). In dryland ecosystems water availability is the most important climate constraint on plant growth (Prince, Goetz, and Goward 1995; Nemani et al. 2003). Dryland areas, including arid, semi-arid, and dry sub-humid regions, cover 40% of the Earth's land surface, including about half of the African continent (Reynolds et al. 2007). Under different scenarios of future climate change, many dryland regions may become even drier and precipitation timing and amount may shift (IPCC 2007). The underlying dryland mechanisms that govern atmosphere-plant-soil processes are strongly influenced by water availability and any subtle shift in precipitation will influence the ability of plants to respond to such change (Scholes and Walker 1993). The relationships between vegetation productivity and precipitation for such regions are determined not only by total rainfall, but also by precipitation timing and variability. An understanding of relationships between current climate variability, especially within seasons, and vegetation processes is necessary before projecting likely impacts of future climate change.

All dryland areas in southern Africa are water-limited for part of the year and the often unpredictable pattern and timing of water distribution plays an important role in the structure and function of savanna vegetation (Scholes and Walker 1993). These ecosystems consist of a mix of tree-shrub-grass vegetation that first appeared with a global expansion of C_4 vegetation about 5-7 million years ago (Cerling et al. 1997) and today exist along the 30°N and 30° S latitudinal belts within a wide range of mean

annual precipitation (MAP) regimes (~200 to ~3000 mm MAP) (Scholes and Archer 1997; Bond 2008). The mixture of continuous grass interspersed with woody vegetation results from interaction of multiple ecological factors (precipitation, soil-nutrients, fire and herbivory) over space and time (Skarpe 1992). Projected anthropogenic climate change, especially in southern Africa, most likely includes drier conditions and increased inter-annual variability (Giannini et al. 2008), which will probably alter tree-grass biomass and cover ratios and subsequently affect other ecosystem processes such as water and nutrient cycles (Archibald and Scholes 2007). Water is not the only limiting resource controlling ecosystem dynamics but is a necessary component for every physiological process (Rodriguez-Iturbe 2000). Across much of southern Africa, there is a strong seasonal response to wet and dry periods (Scholes and Walker 1993). Seasonal rainfall amount in the subtropical drylands is largely controlled by the movement of the Inter-Tropical Convergence Zone (ITCZ) (Scholes and Archer, 1997). Other parts of the water cycle, such as soil moisture, evapotranspiration, and flooding also contribute to dryland vegetation growth but are dependent on the quantity, timing, and frequency of rainfall. In the same way, other biotic factors (ex. fire, herbivory) that contribute to driving landscape change also depend on the underlying hydro-metrological factors to maintain co-existence of grasslands and woody vegetation in dryland areas (Sankaran et al. 2005; Wang 2003; Breshears and Barnes 1999).

A common approach to examine the relationship between precipitation and savanna gross primary productivity (GPP) is remotely-sensed estimates of vegetation productivity (Sjostrom et al. 2009; Sims et al. 2006; Sims et al. 2008; Tucker and Sellers 1986). The Normalized Difference Vegetation Index is ideally suited for semi-arid

regions where the index does not saturate at high foliage biomass (Nicholson and Farrar 1994; Richard and Poccard 1998). NDVI is the ratio of the difference between the NIR and Red band reflectances divided by their sum (Los et al. 2000; Justice et al. 1985; Huete et al. 2002; Cohen and Goward 2004; Tucker 1979).

Despite the fact NDVI measurements are not a pure value of leaf chlorophyll, trends in GPP measured by NDVI are still a valuable proxy for vegetation productivity of different vegetation types (Archibald and Scholes 2007; Chapin, Matson, and Mooney 2002). While other vegetation indices may have advantages over NDVI in dryland areas (Gobron et al. 2000; Leprieur, Kerr, and Pichon 1996), NDVI is one of the few long-term vegetation records available across multiple sensors over many years making it useful for longitudinal vegetation studies (Fisher and Mustard 2007; Brown et al. 2006) and also has a good correspondence with vegetation productivity in semi-arid regions (Martiny et al. 2006). Furthermore, it is well known and so allows us to compare our research findings to a large and significant literature and make useful comparison to similar studies.

Many studies of the precipitation-vegetation relationship in Africa have used NDVI to identify responses of vegetation productivity to inter- and intra-annual rainfall patterns (Martiny, Richard, and Camberlin 2005; Fuller and Prince 1996; Ji and Peters 2005; Richard et al. 2008; Richard and Poccard 1998; Martiny et al. 2006; Nicholson, Davenport, and Malo 1990; Camberlin et al. 2007; Goward and Prince 1995). At the yearly time step, the association between annual NDVI and precipitation for large portions of the African continent shows a correlation with increasing NDVI along a latitudinal precipitation gradient (Martiny et al. 2006; Martiny, Richard, and Camberlin

2005; Camberlin et al. 2007; Richard and Poccard 1998). The strongest association of the NDVI-precipitation relationship exists for semi-arid regions (200-600 mm yr^{-1}) (Martiny et al. 2006; Fuller and Prince 1996). When the relationship is examined on a month-by-month basis, vegetation responds to both increases and decreases of rainfall with a greening or senescence within 0-2 months (Richard and Poccard 1998; Martiny et al. 2006; Nicholson, Davenport, and Malo 1990; Fuller and Prince 1996). Fuller and Prince (1996) used the Global Inventory Modeling and Mapping Studies (GIMMS) Advanced Very High Resolution Radiometer (AVHRR) monthly maximum value composite (MVC) NDVI and found the strongest positive correlation in vegetation response to rainfall to be a 1-month lag in southern Africa. Martiny et al (2006) also use the AVHRR GIMMS but conclude that the lag of vegetation response to rainfall varies depending on rainfall regime with less importance placed on other co-varying factors. Using the peak of the rainy season (February) as the rainfall measurement, they find a one-month lag in the East Kalahari (higher annual rainfall) while there is a two-month lag in the Karoo and West Kalahari (lower annual rainfall). Richard and Poccard (1998) examined Africa south of 15° latitude at a spatial resolution of $1x1^{o}$ identify a 1-2 month lag of AVHRR NDVI to monthly precipitation.

MODIS NDVI is often used to track ecosystem phenology (Archibald and Scholes 2007; Knight et al. 2006; Choler et al. 2010; Huemmrich et al. 2005). Phenology refers to timing of plant production and its response to climate characteristics (White et al. 2009) and differentiating the phenology of tree and grass savanna species is useful for studying biological (Owen-Smith and Cooper 1989), ecological (Shackleton 1999), and hydrological (Borchert 1994) ecosystem processes. However, the relationship between

plant phenology and precipitation seasonality in drylands is not straightforward, as different species respond to timing, frequency, and intensity of rainfall in different ways (Archibald and Scholes 2007). The use of an overall NDVI estimate for savanna vegetation is not sufficient when representing this ecosystem in global climate models (Field et al. 1998), because the level of complexity that results from the mix of different functional groups (grass, trees, shrubs, etc.) is not adequately captured for phenological cycles incorporated into global climate models (Chase et al. 1996). This is especially relevant for unique tree-grass ecosystems where potential for different growth strategies exists year round due to tree and grass response to timing of water availability (Archibald and Scholes 2007).

A wide range of temporal and spatial scales of analysis of NDVI response to rainfall exists (Nicholson, Davenport, and Malo 1990; Richard et al. 2008; Martiny et al. 2006; Fuller and Prince 1996; Richard and Poccard 1998; Fuller 1999; Archibald and Scholes 2007; Zhang 2005). Peak NDVI lags more than 1.5 months after the peak of the rainy season (February) in southern Africa (Martiny et al. 2006). However, the response of savanna vegetation to the onset of the rainy season varies depending on the tree-grass cover ratio (Fuller and Prince 1996). Grassland response to the start of the rainy season (October) is more tightly coupled with precipitation with minimal lag while timing of woody vegetation leaf expansion occurs a couple months prior to the first rains (Fuller and Prince 1996; Archibald and Scholes 2007). In addition, the timing of leaf flush peak at the beginning of the dry season, and leaf fall at the end have large inter-annual variation (Do et al. 2005) with vegetation dormancy occurring with a lag of 3 months after the end of the rainy season (Zhang 2005).

We examine the response of GPP at the beginning of the dry season to monthly variation in wet season rainfall. The identified 0-2 month vegetation response to rainfall suggest that February, March, and April rainfall should have the strongest association to beginning of dry season GPP measured in April for savanna vegetation covers with increased amount of grass cover. Vegetation status at the beginning of the dry season influences the availability of water resources and other important forage materials for wildlife, therefore affecting wildlife species throughout the dry season. This is important for a region where large proportions of the human population and economy are dependent upon wildlife tourism (Barnes, MacGregor, and Weaver 2002). In addition, the structure of the rainy season may influence savanna vegetation covers differently which, in turn, will affect other savanna ecosystem processes (Sankaran et al. 2005; Martiny et al. 2006).

This study investigates the response of photosynthetic activity at the beginning of the dry season to month-by-month precipitation variability in the Okavango-Kwando-Zambezi (OKZ) catchment of southern Africa, using two remotely sensed data sets, MODIS (Moderate Resolution Imaging Spectroradiometer) 13A1 (vegetation indices) and mean monthly precipitation data from the Tropical Rainfall Monitoring Mission (TRMM) (0.25^{o} x 0.25^{o}). We hypothesize that savanna land cover with more grass will show a stronger positive response to precipitation later in the rainy season than vegetation with proportionally more woody plants. The main focus is the regional relationship between mean monthly rainfall and vegetation GPP at the beginning of the dry season across the OKZ catchment. We address the following questions: What is the relationship of GPP measured at the beginning of the dry season to several earlier

months' precipitation? How much variation in GPP is explained by relationships between vegetation and different months of wet season rainfall? And what coupling relationships exist between different vegetation response groups to seasonal precipitation from 2000-2009? Current consensus in the literature emphasizes the complex and distinctly different phenological responses tree and grass species have to inter- and intra-annual precipitation for savanna ecosystems. Being able to differentiate the influence of wet season months of rainfall on vegetation productivity leading into the dry season provides a crucial link to better understanding precipitation-vegetation interaction in savanna ecosystems.

Materials and Methods

Study Region

The study region comprises the Okavango, Kwando, and Zambezi catchments, situated in sub-tropical southern Africa, and cover a total area with an annual precipitation range of 400-2200 mm/yr (Figure 3-1). High variability of intra-annual and inter-annual rainfall across the three catchments varies due to the underlying influence of climatic controls such as the Inter-tropical Convergence Zone (ITCZ) and atmospheric circulation patterns (McCarthy et al. 2000).The lower part of the study region is semi-arid, defined by scarce and typically unpredictable patterns of precipitation while the upper part of the region has a higher average annual precipitation and lower inter-annual variability. The majority of the Okavango and Kwando catchments and all three headwaters are located in Angola although a good portion of the Zambezi catchment is in western Zambia. Soils typically range from ferralsols in upland areas of Angola and Zambia to sandy arenosols in mid-elevation regions, and clay-containing gleysols throughout lower, flatter areas of the catchments (Batjes 2000).

The mid-elevation Kalahari sandveld, which makes up the majority of the region, consists of deep Aeolian sand deposits, longitudinal dunes, pans and fossil valleys with the variations in vegetation type along the north-south, high-low rainfall gradient (Dube and Pickup 2001) .

The OKZ catchment is located in the future Kavango-Zambezi Transboundary Conservation Area (KAZA). KAZA is a politically-defined conservation area that spans Angola, Zambia, Namibia, Botswana, and Zimbabwe. The transboundary conservation area is designed to provide vital wildlife corridors among multiple protected areas. Topography is very flat across the southern portion of the region. The topography of the lower area (especially the Caprivi Strip and northern Botswana) makes it difficult to clearly separate these different catchments because hydrological flows are inconsistent across the flat terrain.

Datasets

The study region was delineated hydrologically into three neighboring watersheds with void-filled Shuttle Radar Topography Mission (SRTM) DEM data as well as derived flow direction and accumulation grids at a spatial resolution of 15 arcseconds from the World Wildlife Fund HydroSHEDS project (Lehner, Verdin, and Jarvis 2006). These data were processed using the ArcHydro data model and toolset (Maidment 2002) to extract drainage networks and basin delineations, which form the basic units for further analyses.

We examined the long- and short-run precipitation patterns across the region using the TRMM 3B43 dataset (version 6). TRMM 3B43 data are best estimates of average daily rainfall rate by month (Kummerow et al. (2000) combining the TRMM instrument rain calibration algorithm estimates (3B42) and several rain gauge data

sources using Huffman et al. (1997) method. Daily instrument data are severely limited in terms of availability and quality in this study region. At a relatively coarse scale of 0.25° x 0.25° TRMM 3B43 data are comparable to rain-gauge estimates and show very little bias in West Africa (Nicholson et al. 2003). The TRMM 3B43 data product has the least bias of any data across both season and region and shows a high degree of association with regional rain gauge estimates (Adeyewa and Nakamura 2003). Average daily rainfall rates by month were converted to total monthly rainfall in millimeters for further analyses.

We use NDVI from MODIS 13A1 data (version 5) with 500 x 500 m spatial resolution to approximate GPP at the beginning of the dry-season (April). The delineated study region includes two full MODIS 16-day composite footprints downloaded from Land Processes Distributed Active Archive Center (LP DAAC) which is a component of NASAs Earth Observing System (EOS) Data and Information System (EOSDIS). Data were acquired for each year 2000-2009 and encompass dates between April 23rd and May 8th for each composite (see Leeuwen et al. 1999 for detailed description of the compositing algorithm).

Data Sampling and Standardization

A temporal and spatial scale mismatch exists between the monthly TRMM precipitation pixels (predictor variables) measured at 0.25^{o} x 0.25^{o} and the MODIS NDVI pixels (response variable) measured at 500 x 500 meters. For any point in time a single TRMM pixel value will overlap many MODIS pixels (~3600). To minimize bias one MODIS pixel per water year was randomly sampled within a single TRMM pixel area, yielding 17,900 data points

Since this research is primarily concerned with terrestrial, semi-arid vegetation we used a 5 kilometer buffer around permanent and seasonally flooded areas to exclude samples that may contain water and riparian vegetation, resulting in a final sample of 15,466 observation points. Although a smaller buffer may be have been sufficient, the 5 km buffer was selected based on field observations regarding the spatial extent of seasonal water presence and flooding-affected vegetation. The buffer safely excluded known perennial water sources and many seasonally flooded areas. These areas become inundated after rainfall events at various lags and were removed from the analysis because of the influence of semi-/permanent water on NDVI estimates.

Modeling Approach

We use geographically weighted regression (GWR) to account for spatial non-stationarity in the relationship between rainfall and beginning of dry-season vegetation productivity to minimize the effect of unmeasured, spatially-varying covariates (Brunsdon, Fotheringham, and Charlton 1998; Foody 2003). GWR extends the traditional regression framework by allowing local model parameters to be estimated at any point within the study area by incorporating a spatial weighting of observations and allowing the estimated models to vary across space (Fotheringham et al. 2000). Observations are weighted by their proximity to the point at which the relationship is estimated so that the weighting of an observation is not constant but varies with each location. GWR models assume that observations nearest the estimation point are more informative than those further away (Charlton et al. 2006).

Sampled NDVI and TRMM data were standardized prior to modeling by subtracting the mean and dividing by the standard deviation. The unitless measures of within-month variation were used to assess relative explanatory power of variability

instead of absolute effects of monthly rainfall. The relationship between April MODIS NDVI (dependent variable) and standardized TRMM values for seven months of preceding rainfall (7 independent variables) varies across space, minimizing the effects of any unmeasured, important covariates while enabling us to compare the relative importance of each month's rainfall for explaining variation in beginning of dry season vegetation productivity. The GWR model that for April NDVI is:

$$NDVI_{Apr}(\mathbf{u}) = \beta_0(\mathbf{u}) + \beta_1(\mathbf{u})\,Rain_{Oct} + \beta_2(\mathbf{u})\,Rain_{Nov} + \ldots + \beta_7(\mathbf{u})\,Rain_{Apr} + e(\mathbf{u})$$

Where $NDVI_{Apr}$ (u) represents modeled NDVI for April at location **u**, and β_0 (u) … β_7 (u) $Rain_{Apr}$ are the intercept and regression coefficients specific for the model at **u** estimated from distance weighted observations nearest to that location and $e(\mathbf{u})$ is the random error term. Locations need not be coincident with observation points, and from the stratified sample across space and time regression surfaces for all eight estimated coefficients were used to predict April NDVI on a 500 x 500m grid for each year 2000-2009.

During estimation GWR requires the choice of a kernel and its associated distance weighting function. The kernel function and associated bandwidth parameter, which may be thought of as a smoothing parameter, (Fotheringham et al. 2002) may be chosen subjectively if a strong theoretical base exists or through more objective quantitative methods that have either a fixed or variable kernel function and bandwidth parameter (Brunsdon, Fotheringham, and Charlton 1998; Foody 2003). We used a Gaussian, fixed kernel with an optimal bandwidth chosen to minimize Akaike

Information Criterion (AIC_c) of the estimated model. The Gaussian, fixed kernel incorporates all observations into each local model calculation but weights each observation by the distance from each regression point according to a Gaussian decay model. To determine the bandwidth parameter used in the weighting decay function, the AIC_c function and global spatial autocorrelation of residuals, measured by Moran's I, were used as diagnostics. These were calculated for the model at bandwidths across a range of 18 to 90 km at equal one km steps. The results were used to identify the bandwidth parameter value with the lowest model AIC_c and that locally minimized spatial autocorrelation. Using this strategy an ideal bandwidth parameter value was identified (39,356 m, see Table 3-1) to use in the weighting decay function.

We calculated the final GWR model in ArcGIS 9.3 using the standardized NDVI to compare the influence of prior monthly rainfall on April NDVI. We conducted post-hoc examinations of local coefficient estimates and determined at the optimal bandwidth that some multicollinearity persisted at the extreme coefficient values, but overall trends showed little correlation and coefficient interpretations are valid.

Model Comparison across Vegetation Classes

The coupling between precipitation and vegetation varies by vegetation type (Archibald & Scholes, 2007). The results of the GWR model create a continuous gradient of coefficients for each rainfall predictor in the model. We extracted and compiled coefficient estimates across the study region and for each class of the White's Vegetation Map (White 1983) (Figure 3-2). The vegetation map, although dated, was tested for accuracy by comparison with 1) training sample data collected during 2006-2009 field seasons and 2) a coarser classification produced by the IGBP classification (Friedl et al. 2010). The land cover groups identified by White's map correspond well

with ground cover observed during ground data collection in 2006-2009. The White and IGBP maps were found to be consistent with each other. We used the White map because it has finer taxonomic resolution. White's map provides a more detailed breakdown of woodland groups, and defines a transition area between upland Miombo woodland and dry deciduous and secondary grasslands in the lower part of the OKZ basin. We extracted sample points of NDVI and precipitation estimates within six vegetation classes: wetter Zambezian Miombo woodland, Zambezian evergreen forest, *Brachystegia* thicket and edaphic grassland,dry deciduous and secondary grassland, edaphic and secondary grasslands, and *Colophospermum mopane* woodland. Herbaceous swamp and semi-aquatic vegetation were excluded from analysis We compared the coefficient values of each predictor month by land-cover type for each classification to determine the relationship between each month's rainfall on NDVI across different vegetation covers. Analyses were conducted in R (2.10.1) and ENVI 4.3.

Results

Spatial and Temporal Relationship between NDVI and Rainfall

Average pixel-by-pixel calculation indicates higher NDVI values in the upper catchment and a gradient of increasing precipitation from southwest to northeast (Figure 3-3). The darker band of values that stretches down the center of the basin is low-lying floodplain region which corresponds to mostly grassland in White's vegetation map. The higher NDVI values correspond approximately to Miombo woodland and dry evergreen forest areas of White's land cover map. These areas in the upland part of the OKZ basin also receive the highest amount of total precipitation during the rainy season (Oct – Apr). While the Okavango Delta area located at the bottom of the OKZ basin also shows

areas with high NDVI, we exclude this area, along with other wetland and riparian areas in the basin, since NDVI values within these areas are highly influenced by basin-wide precipitation and flooding rather than the local precipitation patterns.

Mean April NDVI for each land cover and mean total wet-season precipitation (October – April) for the 9-years covered by the MODIS dataset (2000-2009) is shown in Figure 3-4. Miombo woodland and dry Evergreen forests have the highest, most consistent average April NDVI values (ranges are 0.67-0.71 and 0.68 – 0.65 respectively). In contrast, mean April NDVI in Mopane woodland increases and decreases with average wet season precipitation, ranging from 0.39 to 0.56. Similarly, the dry deciduous and secondary grassland land cover also tends to increase or decrease with corresponding change in precipitation though over a smaller range than mopane woodlands (0.48-0.58). The edaphic and secondary grassland maintains an April NDVI value around 0.55 without as large a range as dry deciduous and secondary grassland. The *Brachystegia* thicket maintains a relatively consistent April NDVI around 0.62 (± 0.015 Std. Dev.) and provides a transition between the wetter Miombo woodland and the drier, more deciduous mix of woody and secondary grassland areas in the OKZ catchment. The different April NDVI patterns across the 10 years indicates that varying amounts of precipitation influence the overall productivity for the beginning of the dry season differently for specific savanna vegetation types.

Model Results

A comparison of the results from a global OLS linear regression with the GWR regression is presented in Table 3-1 and Figure 3-5 to illustrate the effects of spatially co-varying factors such as soil type and dominant vegetation cover. Results of the global ordinary least squares (OLS) linear regression indicate previous months of wet

season rainfall explain 37.7% (adjusted R^2) of the variation in April NDVI. The strength of the relationship between NDVI and rainfall increases substantially with the local GWR model, with rainfall explaining 78.2% (adjusted R^2) of the variation in April NDVI. Table 3-1 shows that the difference between AIC_c values for the global OLS and local GWR model is very large indicating the two models are not equivalent in their explanatory power. Residuals from subtracting the modeled standardized April NDVI predictions from the observed, standardized April NDVI results suggest the GWR model does a better job at reducing spatial autocorrelation (spatial pattern in the residuals) than the OLS model (although it does not completely eliminate it) (Figure 3-5). While not all spatial autocorrelation is accounted for in the GWR model the spatial dependence in model errors is greatly reduced resulting in better predictions of April NDVI than the OLS model while using the same number of wet season precipitation months as predictors in the model.

GWR Results by Land Cover

We sampled the standardized coefficient surfaces for each point of the original random sample within each vegetation type on White's (1983) map (Figure 3-2) and plotted them as "bean" plots (Kampstra 2008) (Figure 3-6). The standardized monthly rainfall coefficients represent the effects of lower or higher than average monthly rainfall on April NDVI. The coupling between rainy season months and vegetation varies by vegetation type. Model estimates across land cover type (Figure 3- 6) suggest vegetation classes with woodland components (Miombo woodland, dry evergreen, and *Brachystegia* thicket) and consequently higher NDVI (Figure 3-4) are less affected by variability in monthly precipitation (i.e. the medians of most predictor coefficients on the bean plots are near zero and the distribution of coefficients indicated by the bean plot

histograms straddle zero evenly). In this study, February precipitation was the most common month associated with April NDVI for all land covers in the OKZ basin although the strength of association varied by vegetation class. Regardless of where along the savanna continuum each land cover is situated, there is a positive effect of February precipitation on April NDVI. The month of February is the only month that shows a positive association for the two higher NDVI classes, Miombo woodland and dry evergreen forest. October precipitation has a slight positive association on the dry evergreen forest but the beginning of the rainy season is not associated with Miombo woodland productivity in April. The *Brachystegia* thicket and edaphic grassland land cover, which provides a transition between the upland Miombo woodland and drier, more deciduous and secondary grassland, shows a slight positive association between April NDVI and February, March and April rainfall. The dry deciduous and secondary grassland land cover shows a disproportionately large positive association with dry season productivity for the same three months when compared to rainfall in the beginning of the wet season. *Colophospermum mopane* woodland is also positively associated with late wet season precipitation, although this particular woodland type is positively influenced by December precipitation and negatively influenced by October precipitation. The edaphic and secondary grasslands on Kalahari sands do not show strong associations between any of the wet season months and April NDVI, except for a slight positive association with February rainfall. This land cover behaves more similarly to the denser woodland and forest covers of Miombo and Evergreen land covers. The strongest association in its April NDVI productivity and precipitation exists with February

precipitation and, to a lesser degree, slight positive associations for all other months minus October and April.

Discussion

Our results indicate that precipitation patterns within the wet season, not just annual or seasonal totals, drive vegetation productivity at the beginning of dry season, with different rainy season months more strongly associated for some vegetation types than others. Specifically, those vegetation types with more mixed tree-grass cover composition rather than woodland-dominated covers tend to have an April NDVI more strongly influenced by February-April months of rainfall. An exception to this was *Colophospermum mopane* woodland which showed more variation in April NDVI response than other woodland-dominated vegetation covers like Miombo woodland and Zambezian evergreen forest.

The end of the rainy season occurs relatively uniformly across the region in April (Zhang et al. 2005). The positive and negative model coefficient patterns for each month for respective vegetation classes (Figure 3-6) identify lags in April NDVI response to the different months of rainfall in the wet season. For example, while most coefficient values for rainfall months are zero for Miombo woodland and Zambezian evergreen forest, February has a positive association with April NDVI. This suggests there is a two-month lag in response of April NDVI to February rainfall. The 0-2 month lag in vegetation response to rainfall agrees in general to the vegetation response to rainfall measured for other parts of the growing season in southern Africa (Martiny et al. 2006; Fuller and Prince 1996; Goward and Prince 1995; Richard and Poccard 1998). This two-month lag after the height of the rainy season most likely results from a set of ecosystem processes that differ at the level of vegetation type (Williams et al. 2009).

Different types of savanna woodland species adapt different coping mechanisms and strategies to deal with the highly variable and seasonal savanna environment (Shackleton 1999; Fuller 1999). For Miombo woodland and Zambezian evergreen forest the minimal effect in February may suggest a short-term storage of water and carbohydrate reserves that are accessed when the rainy season ends and provides an indication to how sensitive the ecosystem may be to within wet season rainfall (Schwinning et al. 2004). However, the effect may be minimal with a stronger, inter-annual effect more dominant on vegetation response depending on number of previous dry years or high water stress prior to rainfall (Richard et al. 2008; Martiny, Richard, and Camberlin 2005). The longer inter-annual lag that may be present depends on ecological processes that influence nutrient and water cycling (Williams et al. 2009; Martiny, Richard, and Camberlin 2005) although further investigation is necessary to determine how vegetation types respond to inter-annual variation within the OKZ basin.

The specific responses of different woodland species to months of wet season rainfall also helps explain the much stronger association in the response of *Colophospermum mopane* April NDVI to wet season rainfall. The strong seasonal response of *Colophospermum mopane* corresponds to previous studies which use field and remotely-sensed data to show the intra-annual rainfall effect on these woodlands (Fuller 1999; Fuller and Prince 1996). *Colophospermum mopane* woodlands in the OKZ basin mostly are found on impervious clay soils that limit the depth of water penetration and are not conducive to water storage (White 1983). The shallow root system of *Colophospermum mopane* woodlands also means this woodland species will compete more with grass species for soil moisture in the top 25 cm of soil. The transition zone of

Brachystegia thicket and edaphic grassland shows precipitation in months during the latter half of the rainy season (Feb-Apr) having a slight association with April NDVI although the higher percent of mixed land cover may dampen the effect observed in more open, less woody land cover classes.

For those vegetation types with higher grass cover (edaphic and secondary grasslands and dry, deciduous and secondary grassland) or more open canopy areas (such as *Colophospermum mopane* woodland), March and April precipitation have similar if not more influence on April NDVI values than does February. *Colophospermum mopane* woodlands also have a negative October coefficient suggesting rainfall at the outset of the wet season suppresses April GPP.

However, the rest of the rainy season months show a positive association to *Colophospermum mopane* April GPP. The difference in association may relate to the highly seasonal nature of *Colophospermum mopane* woodland and their response to variable timing of the onset of the rainy season (Fuller 1999; Veenendaal, Kolle, and Lloyd 2004). For all vegetation types with higher grass cover, the strong one-month and concurrent effect of April and March precipitation on April NDVI may be due to the higher dependence grasslands have on rainfall for seasonal productivity patterns (Scanlon, 2002). The shallow root depth of grass roots suggests these species will be more sensitive to temporal and spatial variations in water availability making the timing of rainfall, rather than total amount, and its effects important on plant productivity (Sher, Goldberg, and Novoplansky 2004).

This study identifies the importance of the precipitation-vegetation relationship for GPP leading into the dry season and also shows that the strength of association varies

depending on the ratio of tree to grass cover. The variation in response across the OKZ basin corresponds to previous findings that study differences in response to rainfall across savanna vegetation types (Fuller and Prince 1996; Archibald and Scholes 2007). Our study complements previous studies that identify the importance of vegetation response to different rainfall regimes (Martiny et al. 2006; Nicholson, Davenport, and Malo 1990) by emphasizing this relationship is further broken down by savanna vegetation type. Timing of wet season rainfall on GPP for beginning of the dry season is a vital component to understanding shifting dynamics of dryland ecosystems (Archibald and Scholes 2007; Scanlon et al. 2005; Fuller and Prince 1996).

Our study complements but differentiates from these previous studies by investigating the NDVI-precipitation relationship leading into the dry season using a GWR model. The GWR model provides a useful statistical tool to minimize the effects of unmeasured, spatially-varying factors and the negative impacts of autocorrelation on conventional models. The focus on April vegetation productivity provides insight to vegetation status leading into the dry season which will affect ecosystem processes such as nutrient cycling, water-energy budgets, and forage availability throughout the dry season. Our findings support the idea that vegetation with shallower root systems utilizes soil water more quickly than vegetation with deeper root systems, more commonly found in more humid regions, which can access sub-surface water months after the initial precipitation event (Porporato et al. 2003). These processes operate at different spatial and temporal scales depending on the composition and structure of the savanna ecosystem. Therefore quantifying the timing of the prior month rains is an

important control of April GPP, therefore dry season vegetation processes for different savanna vegetation covers.

Summary

Findings from this study support our hypothesis that April GPP for savanna vegetation types with higher grass cover positively respond with a tighter coupling to late wet season rainfall. Month-by-month variability affects system drivers, such as soil moisture or fuel load, in turn influencing April GPP differently for various savanna vegetation types. If less rainfall occurs at the end of the rainy season it will most strongly influence GPP for savanna vegetation covers of grassland and open canopy woodlands. As a result, it may cause more frequent and intense fires early in the dry season due to a drier fuel load. The designation of average monthly precipitation is an arbitrary means to identify the effects of rainfall on beginning of dry season productivity and a finer break down in rainfall events may highlight other important interactions between wet season rainfall and vegetation productivity. However, expressing wet-season precipitation by monthly totals shows how months in the beginning, middle and end of the rainy season influence NDVI, and by proxy GPP, at the beginning of dry season.

This study highlights the importance of within-season precipitation variability to vegetation growth for the beginning of the dry season. While a landscape level approach makes detailed analysis of growth patterns of different vegetation types difficult, the analysis of finer taxonomic scale classes of savanna vegetation provides shows how timing of rainfall during the wet season influences vegetation types with different tree-grass ratios along the savanna continuum. Rainfall is only one environmental variable that influences the growth and function of vegetation but is the

most limiting factor in savanna ecosystems. In these water-limited systems, the response of different savanna vegetation types April GPP to the various months of wet season rainfall depends on multiple ecosystem processes that relate to how grassland and woodland species differ in their timing and uptake of available water through the season. We show that intra-annual variability explains a large amount of observed variation of the productivity of vegetation at the beginning of the dry season and that the relative importance of different months on savanna vegetation type varies throughout the wet season. Other studies suggest that altering the seasonal timing of rain will strongly influence its role in ecosystem processes (Schwinning et al. 2004) making the quantification of both beginning and end of the rainy season important for understanding the effects of future climate change.

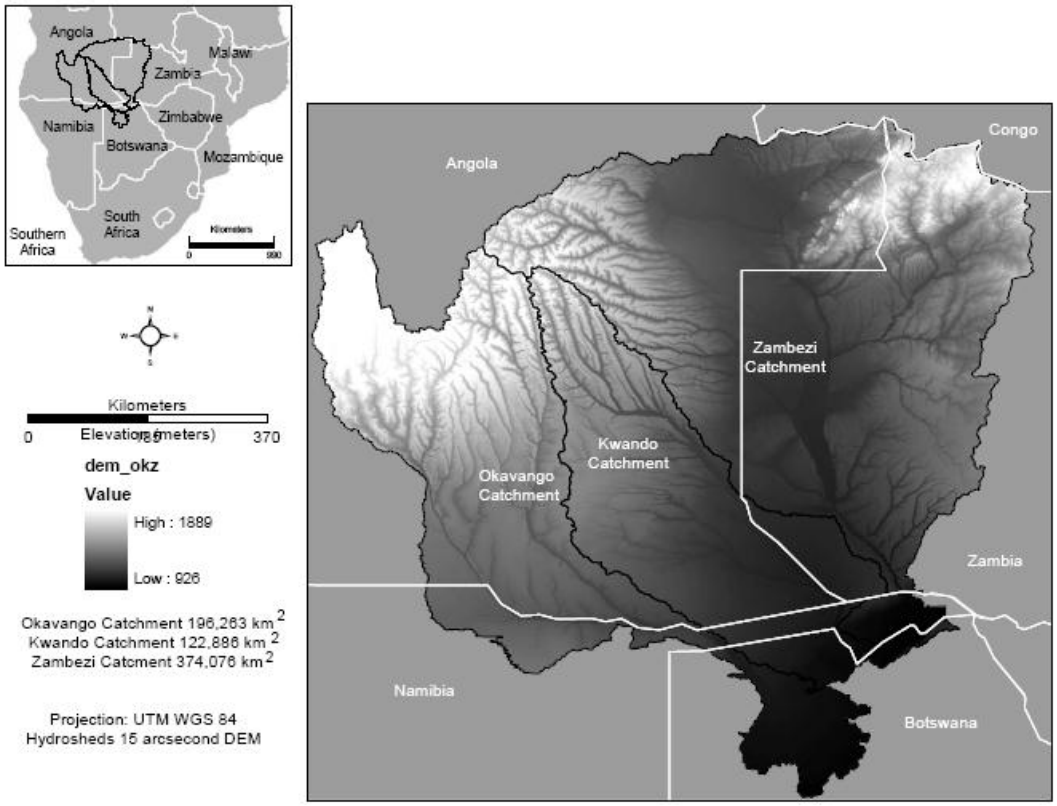


Figure 3-1. Study region depicting the three catchment areas of interest with elevation from a Digital Elevation Model (source: World Wildlife Fund HydroSHEDS proect) with a spatial resolution of 15 arcseconds.

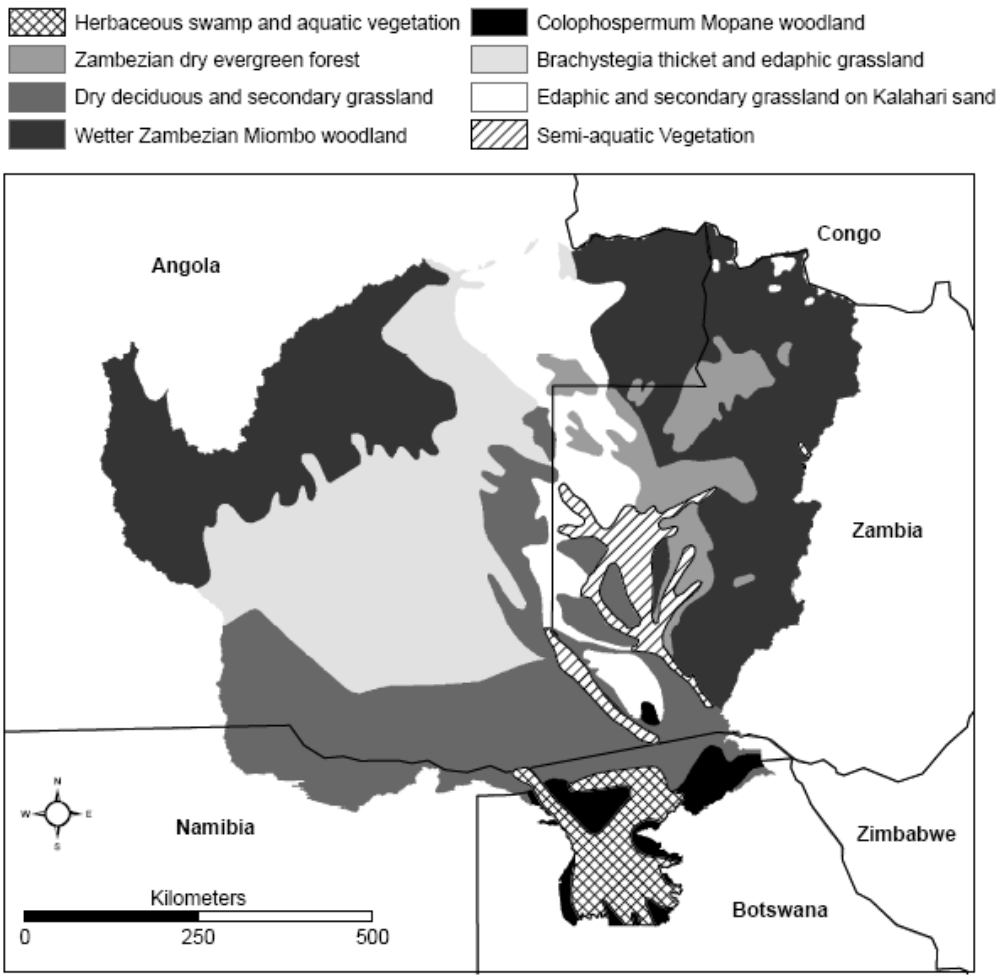


Figure 3-2. White's Vegetation map, created in 1983, that shows a detailed classification of different land covers in the OKZ catchment.

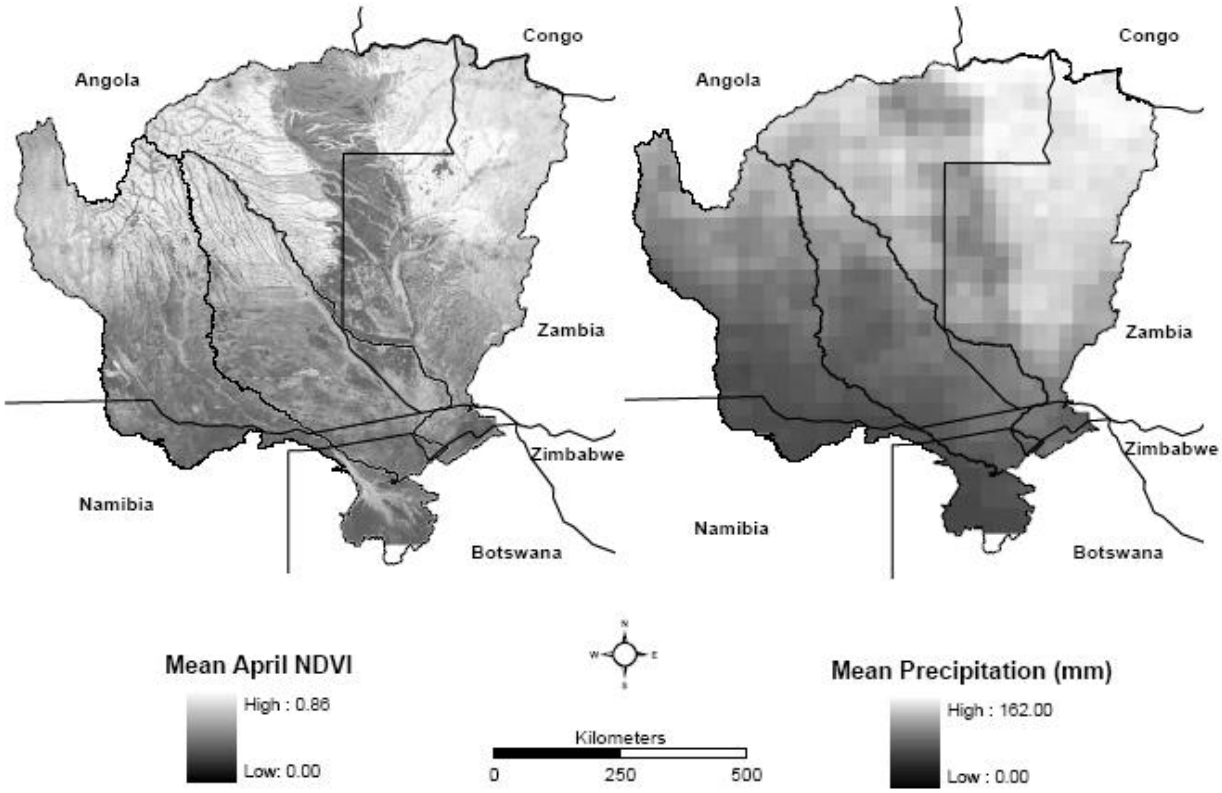


Figure 3-3. Mean values across each grid cell were calculated from each pixel's time series of (a) mean April NDVI and (b) total mean wet season precipitation respectively from 2000-2009. The spatial distribution highlights the highest mean precipitation in the northeast of the OKZ basin and the higher April NDVI values for areas of predominant woodland.

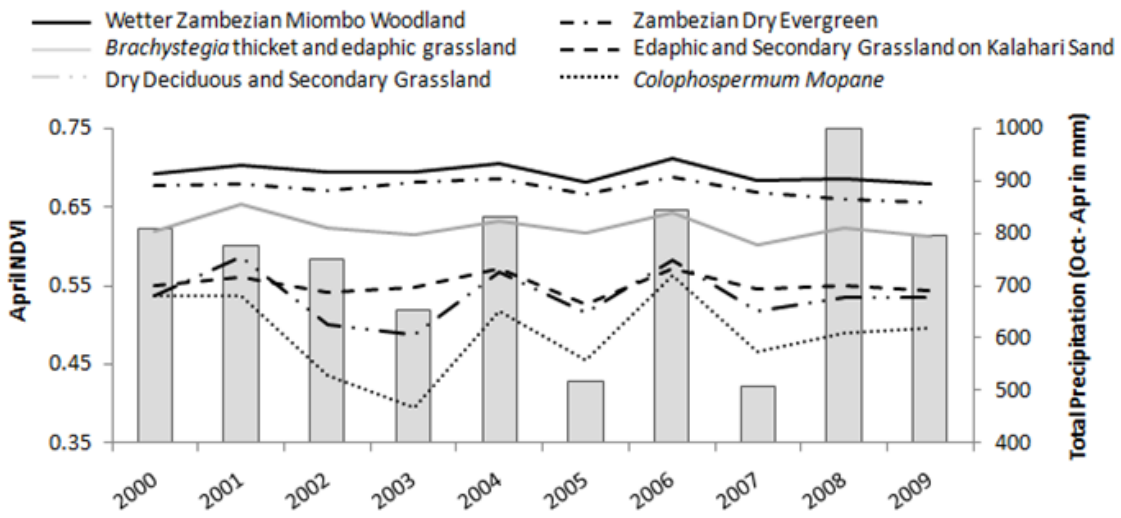


Figure 3-4. Time series of averaged April NDVI for the OKZ catchment plotted against the total average precipitation for each wet season (October – April) across 2000-2009.

Table 3-1. This table compares the global OLS model diagnostics to those of the GWR. GWR fits the data across the catchment much better as indicated by the delta AIC and increase in R2.

Model Type	RSS	R^2	Adj. R^2	Δ AIC_c	Parameters Estimated	Bandwidth
Global OLS	12007.54	0.329	0.329	16646.95	8	N/A
GWR	3656.42	0.795	0.754	0	3015.40*	39,356 m*

* The “parameters estimated” for the global OLS model (8) is the number of predictor variables in the model, for GWR are the “effective number”, an estimate of the number of observations contributing to local model estimates. The bandwidth parameter (here fixed, in m) controls at what distance a gaussian spatial weighting is applied (Fotheringham, 2002).

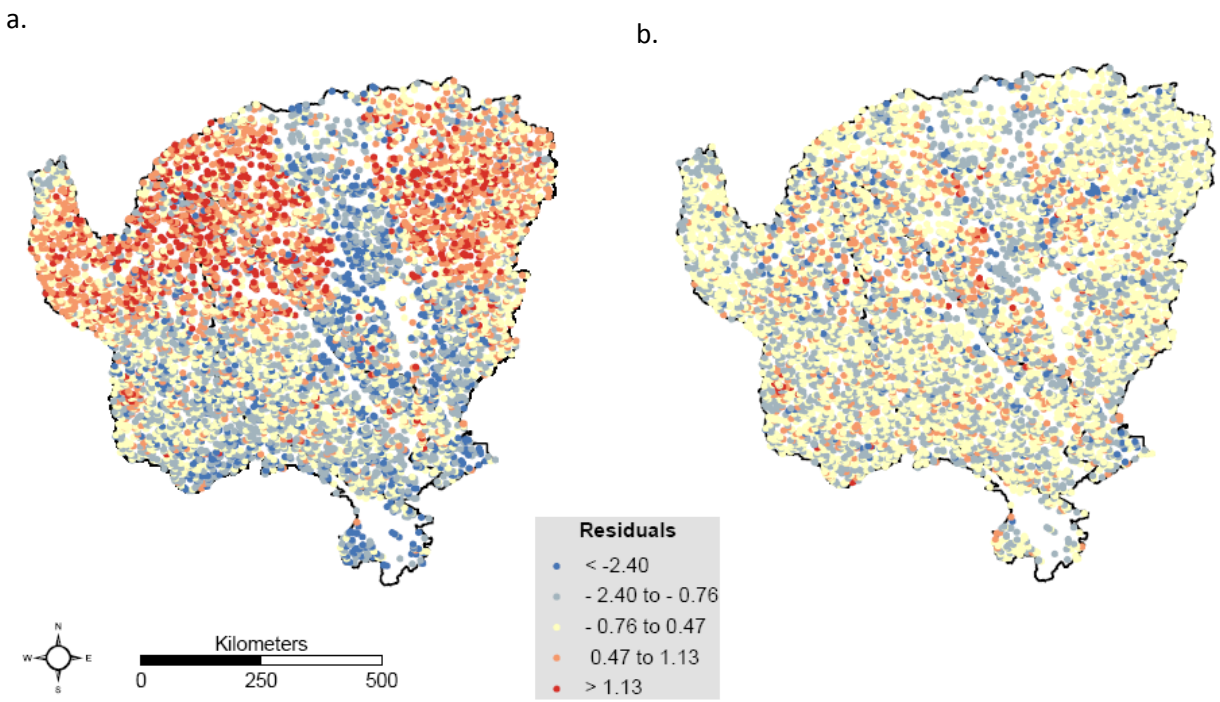


Figure 3-5. Residuals from the estimates of the (a) global OLS and (b) GWR models. Spatial autocorrelation still exists in high/low residuals in the GWR, but is significantly minimized when compared to the OLS.

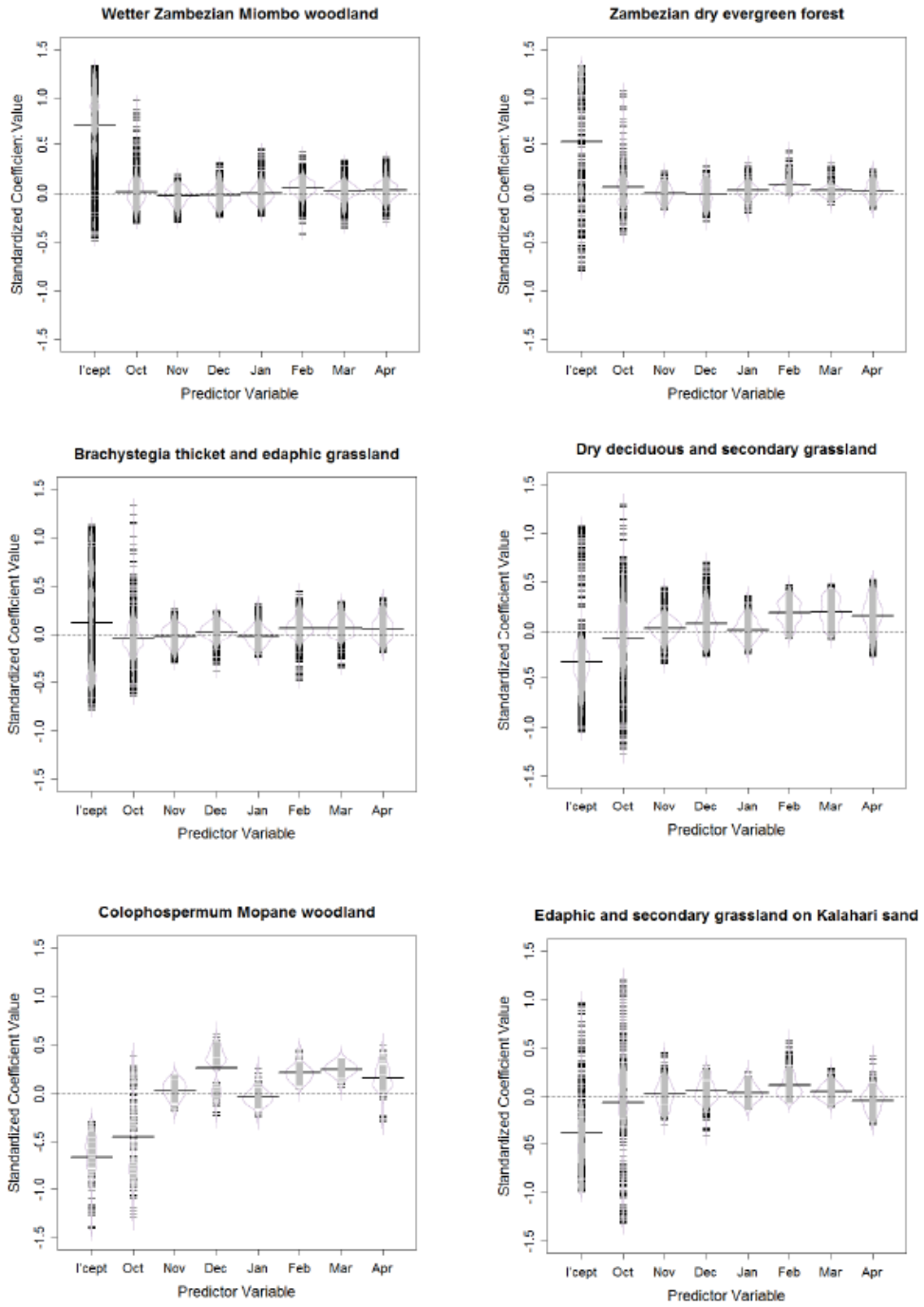


Figure 3-6. “Bean plots” of the GWR coefficients for monthly precipitation variables as predictors of April NDVI for each of White’s (1983) vegetation types. Each sample point has its own GWR model. The median coefficient for the Y-intercepts and each month is indicated by the long horizontal bar above each month (independent variable). Each individual local model is represented by the spread of short horizontal bars above and below the median value and the distribution for each predictor variable shown with vertical histograms.

CHAPTER 4
DETECTING LONG-TERM VEGETATION TRENDS BY ADJUSTING FOR SEASONALITY IN A SAVANNA LANDSCAPE

Savanna ecosystems cover approximately 1/5th of the Earth's land surface and over half of the African continent (Sankaran *et al.*, 2005, Scholes & Archer, 1997), are third only to tropical and temperate forests in terms of global terrestrial carbon sequestration (Field *et al.*, 1998) and woody vegetation in these semi-arid regions are increasingly recognized as a vital component of the global climate system (Dewees *et al.*, 2010, Rotenberg & Yakir, 2010). Many rural communities in these marginal landscapes depend on local natural resources and shifts in the ratio of tree to grass cover across different savanna vegetation types influence local livelihood sustainability (Shackleton *et al.*, 2007). Specifically, if savanna composition and structure changes, the kind of resources available to rural communities will be affected because different savanna woody and grass species are preferred for building materials, firewood, thatching, and medicines (Dewees *et al.*, 2010, Shackleton & Shackleton, 2004) . Determining how best to measure changes in savanna vegetation over time is critical considering the tight dependence on local natural resources and potential contributions of carbon gases to global climate patterns that may result as a consequence of long-term changes in the tree-grass ratio.

Vegetation productivity in arid and semi-arid regions of Africa is influenced by inter- and intra-annual precipitation variation (Hulme *et al.*, 2001, Nicholson, 1986, Nicholson, 2001). Global climate phenomena such as the El Niño-Southern Oscillation (ENSO) and sea surface temperatures in the Atlantic and Indian Oceans regulate the variability in longer-term mean annual precipitation across Africa (Mason, 2001, Nicholson, 1997, Nicholson, 2000). Historical shifts in distribution and frequency of

rainfall influenced the expansion and contraction of desert regions, presence of marshes in the western Sahara, and lake sizes in the Rift Valley (Hulme *et al.*, 2001, Nicholson, 2001). Recent climatic changes include a drying trend over large parts of Africa that, in part, is attributable to anthropogenic climate change (Giannini *et al.*, 2008). These changes include semi-arid savanna ecosystems in southern Africa although separating the influence of variation in rainfall from human-induced changes on vegetation productivity is difficult (Wessels *et al.*, 2007). As such, the strong seasonal response of savanna vegetation to wet and dry periods may obscure detection of long-term change that results from decadal-scale climate shifts or from land-use decisions. Separating the seasonal signal from other factors influencing savanna vegetation dynamics is necessary for identifying long-term vegetation change on the landscape.

This study examines vegetation status at the beginning of the dry season (BDS) in terms of remotely sensed gross primary production (GPP). BDS vegetation status is the basis for support of ecosystem processes through months of no rainfall. Different savanna vegetation types (evergreen and deciduous woodland, thickets, grasslands, etc) behave differently with respect to ecosystem processes making it important to quantify long-term changes in the ratio of trees to grass cover of savanna landscapes (Martiny *et al.*, 2006, Sankaran *et al.*, 2005). The variation in behavior is due to growth strategies that differ between the responses of trees and grasses to timing of water availability (Archibald & Scholes, 2007). Total precipitation during the wet season and the timing of that rainfall affect biological processes of BDS GPP (Schwinning *et al.*, 2004) and must be accounted for when determining long-term landscape change.

Remotely sensed Normalized Difference Vegetation Index NDVI ((NIR-Red)/(NIR+Red)) was originally designed as an index of GPP (Tucker & Sellers, 1986). Previous work using remotely sensed estimates of vegetation productivity describe the strong correlation between precipitation and gross primary production (GPP) especially in dryland regions (Chapin *et al.*, 2002, Nemani *et al.*, 2003, Prince *et al.*, 1995, Tucker & Sellers, 1986). NDVI is ideally suited for semi-arid regions where the index does not saturate at high foliage biomass or leaf-area index (Nicholson & Farrar, 1994, Richard & Poccard, 1998). NDVI is also one of the few long-term vegetation records available across multiple sensors over many years making it useful for longitudinal vegetation studies (Chapin *et al.*, 2002, Cohen & Goward, 2004, Huete *et al.*, 2002, Justice *et al.*, 1985, Los *et al.*, 2000, Tucker, 1979). A relatively strong, albeit slightly non-linear relationship between mean annual NDVI and mean annual rainfall exists for much of southern Africa (Goward & Prince, 1995, Martiny *et al.*, 2006). This relationship also corresponds to an increase in fractional tree cover with increasing mean wet season rainfall along the Kalahari Transect, stretching from central Botswana northward into Angola and western Zambia (Scanlon *et al.*, 2002). It is important to note that the coupling between GPP and precipitation varies by vegetation type (Gaughan et al., *in prep*, Scholes and Archibald, 2007). Change in NDVI over multiple decades may indicate shifts along the tree-grass continuum that, in turn, influence storages and flows of water, carbon, and nutrients affecting spatial and temporal patterns of ecosystem production (Sankaran *et al.*, 2008). However, to detect long-term landscape change with NDVI, the variation in NDVI due to the effect of seasonal precipitation must be controlled.

Various approaches to correct for precipitation effects on NDVI attempt to separate the climate signal from other drivers of land-cover change (Archer, 2004, Evans & Geerken, 2004, Groeneveld & Baugh, 2007, Ji & Peters, 2005, Omuto *et al.*, 2010, Wessels *et al.*, 2007). Evans and Geerken (2004) calculated numerous linear regressions between 8-km AVHRR annual NDVI (1981-1996) and different periods of accumulated rainfall to identify the precipitation-vegetation productivity relationship for a dryland area in Syria. They found the best correlation for March/April maximum NDVI was the accumulation of the previous months of wet season rainfall (September through mid-April) while absolute maximum NDVI best correlated to the preceding four months of rainfall (Evans & Geerken, 2004). Evans and Geerken (2004) also show that stronger correlations exist at the pixel scale compared to a dryland average. Wessels et al. (2007) used AVHRR 1-km, 10-day maximum NDVI composites (∑NDVI) to represent the entire growing season (Oct – Apr) for years 1985-2003 and calculated the relationship to the sum of rainfall during the same period. Then using of a residual trend analysis, Wessels et al. (2007) found that a residual trends approach was more robust than a rain-use efficiency model in detecting trends for degraded areas. Archer (2004) used expert opinion to determine a 2-month lag of average rainfall as the best-correlated rainfall predictor to predict monthly AVHRR 1 km NDVI data from 1984-1997.

After establishing a relationship between measures of accumulated rainfall and NDVI, the use of a residual analysis is commonly used to derive a “detrended” or “corrected” NDVI value. To separate the inter-annual precipitation signal, as defined by a seasonal measure of rainfall from other factors that influence change in NDVI, the difference of the predicted NDVI from observed NDVI ($NDVI_{obs} – NDVI_{pred}$) produces a

residual value that corrects for the precipitation signal. The resulting positive and negative residual trends over time indicate change in NDVI attributed to something other than inter-annual variability in seasonal rainfall (Archer, 2004, Evans & Geerken, 2004, Wessels *et al.*, 2007). The approach, derived in previous studies from a linear regression, assumes that the measure for rainfall is representative of the climate signal, and removes the effect of inter-annual variability on vegetation productivity, isolating other factors driving landscape changes (Archer, 2004). The residual trends analysis is a useful method to account for precipitation effects on NDVI but a more robust, spatially explicit regression approach may be more appropriate for highly heterogeneous landscapes such as semi-arid savannas (Foody, 2003, Omuto *et al.*, 2010).

This study introduces a new, spatially explicit approach using a downscaled Geographically Weighted Regression (GWR) model (Fotheringham, 2002) that is parameterized by the statistical relationship between wet season months of precipitation and vegetation at a catchment level. The GWR model extends the traditional regression framework, creating local model parameters estimated for any point within the study area in which each observation point has its own specific set of coefficient values. The implicit inclusion of spatially co-varying biophysical factors (ex. soil type, elevation, etc) in the GWR model is important due to differences in the NDVI-precipitation relationship across different vegetation and soil types.(Nicholson *et al.*, 1990, Wang *et al.*, 2001). The GWR model includes estimates of local parameters based on a weighting decay function that places more influence on data closer to the observation point at location *i* than data farther away (Harris *et al.*, 2010). In addition, the non-stationarity incorporated within the GWR framework helps minimize spatial autocorrelation in the residuals

(Brunsdon *et al.*, 1998). By allowing spatial non-stationarity in the relationship between rainfall and vegetation productivity the effects of any unmeasured, important covariates are minimized while comparing the relative importance of each month's rainfall for explaining variation in vegetation productivity for a given location. This is important for relationships between the response and predictor variables in environments such as semi-arid savannas where rainfall is highly variable across space and time.

The objective of this study is to account for and remove inter-annual variability in seasonal precipitation that influences the signal of gross primary productivity (GPP) at the beginning of dry season, as measured by NDVI in order to identify longer term land-cover changes. The new method estimates NDVI from the GWR-derived relationship between MODIS (or Moderate Resolution Imaging Spectroradiometer) NDVI and precipitation estimated by the Tropical Rainfall Monitoring Mission (TRMM) (Gaughan et al., *in prep*). The GWR model represents the vegetation-precipitation relationship for the larger catchment region (~700,000 km^2) and extends the traditional regression framework by creating local model estimates that vary across space (Fotheringham, 2002). We apply the GWR regression model within the Kwando Core Area (KCA) of Bwabwata National Park (~1,300 km^2) to determine how well the regionally-parameterized model controls for seasonal precipitation dynamics on NDVI. The KCA provides an ideal landscape that minimizes the effect of human activities on the landscape as the core area management has excluded people since the early 1970s. Our specific questions are: 1) How well does the regional GWR model, parameterized with prior wet season months of rainfall, predict NDVI for the Kwando Core Area? 2) What NDVI changes, not caused by inter-annual precipitation variation, occurred during

the period from 1984 to 2007? 3) Do the GPP trends vary across different vegetation types (indicated by different ranges of NDVI) in the KCA? We expect there to be variability around the mean predicted NDVI values for each year. However, if the magnitude of any one pixel's residual value remains constant over time that suggests prior wet season rainfall is the sole determinant of NDVI for that pixel. If an individual pixel's residual value changes (increase or decrease) across time, that represents a shift in NDVI. The variation in NDVI unaccounted for by seasonal rainfall, as measured by positive or negative changes in the residuals, represents changes due to longer term climate or anthropogenic drivers on the landscape.

Materials and Methods

Study Region

The regional GWR model includes the larger Okavango-Kwando-Zambezi catchment (~700,000 km^2) (Figure 1). The semi-arid savanna that comprises the Kwando Core Area of Bwabwata National Park (BNP) in Caprivi, Namibia is located in the lower, central portion of the OKZ catchment. The protected area is characterized by a predominantly deciduous woodland on the relatively homogenous Kalahari Sand soil (Wang *et al.*, 2007). The larger park area, Bwabwata National Park, was originally known as the Caprivi Game Reserve. The Reserve was established in 1966 and upgraded to a park status in 1968 (Mayes, 2008). The Kwando Core Area (KCA) is one of three areas zoned for conservation and tourism and covers the eastern end of BNP (1,300 km^2). A parallel system of ancient drainage lines, called *omirambas*, cut across the KCA in a west-north-west to east-south-east direction visible on Landsat imagery (Figure 2) (Thomas *et al.*, 2000).

This region has experienced large precipitation fluctuations over the past century. The beginning of the 20th century started with low rainfall, increased precipitation characterized the mid-20th century, while the last quarter of the 20th century experienced annual rainfall values lower than normal (Nicholson, 2001). Statements collected from local informants during the 2007 and 2008 field seasons about the region's environmental history correspond to the above description of southern African rainfall variability described by Nicholson (2001). The wetter conditions mid-20th century followed by drier conditions in the last couple decades were visually apparent to local inhabitants with less than normal mean annual rainfall and less flooding of the Kwando River since the late 1970s. The decrease in rainfall observed at the local level follows a global climatic shift identified in the late 1970s (Chavez *et al.*, 2003), at least until 2009-2010 when very high rainfall has generated severe flooding.

Datasets

Landsat TM data

We used four Landsat-TM derived Normalized Difference Vegetation Index (NDVI) images (April 22, 2007, April 10, 2000, May 9, 1990, and June 10, 1984) for the Kwando Core Area (Figure 2). Image acquisition dates correspond to the beginning of the dry season, with a seven-week differential between the earliest and latest acquired images. Images were georectified to a 1991 Landsat TM image from the NASA Global Land Cover project (http://glcf.umiacs.umd.edu/index.shtml), with a nearest neighbor resampling algorithm using the Autosync function in Erdas Imagine 9.2 (RMSE of < 0.5 pixels, or < 15 m). Images were also calibrated to convert raw digital numbers to at-sensor radiance and surface reflectance estimates using the ENVI 4.3 software calibration tools to control for bias due to difference in acquisition time, sun angle and

sensor geometry. The atmospheric correction algorithm Fast Line-of-Sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) was used to generate corrected estimates of surface reflectance (Berk *et al.*, 1999, Cooley *et al.*, 2002).

Using a RGB 7,5,4 composite, we masked fire scars visibly apparent on the TM images from analysis. Aquatic vegetation and water pixels were masked to minimize the influence of riparian vegetation and water inundation from the Kwando River. From the final processed TM images, NDVI images were used to conduct the residual trends analysis with modeled estimates of NDVI.

While we are not directly comparing the MODIS and TM NDVI values, the derived coefficients from the GWR model were generated using the MODIS NDVI 13A1 product (500 meter, 16-day composite), acquired from GLOVIS (http://glovis.usgs.gov/), as the response variable. The MODIS NDVI product applies a bidirectional reflectance distribution function (BRDF) model to account for anisotropy in surface reflectance values by controlling for view and zenith angles (Leeuwen *et al.*, 1999, Walthall *et al.*, 1985) . The final NDVI 16-day composite minimizes cloud cover and uses quality control flags to exclude missing and “poor” quality pixels values in the final calculation (Leeuwen *et al.*, 1999). The April 23, 2007 MODIS 13a1 NDVI composite was used to check spectral compatibility between MODIS NDVI and TM-derived NDVI for April 2007. Landsat TM-derived NDVI pixels were resampled to match the 500 x 500 meter spatial resolution of the MODIS 13a1 composite NDVI values using a cubic convolution algorithm. Ten percent of the data was randomly sampled and extracted from the two-layer stack of MODIS and TM NDVI bands. The Wilcoxon Signed Ranks non-parametric test was used as a statistical measure to compare the NDVI distributions of Landsat

TM-derived NDVI and the MODIS 13a1 NDVI composite. Equivalent to a paired-samples *t*-test, the Wilcoxon signed rank statistic tests the hypothesis of no difference between measurements taken on the same subject (in this case, pixel value). The test showed non-significance ($p < 0.632$, df = 609) between NDVI estimates on a pixel-by-pixel basis for the April 23, 2007 MODIS13a1 composite image and the April 22, 2007 Landsat TM-derived NDVI image indicating no statistical significance was detectable between the two images. Pre-processing methods differ between the two derived NDVI images which could potentially influence a difference in final NDVI products. However, the use of a paired-samples test has been shown to be a useful diagnostic tool to evaluate the comparability of MODIS and Landsat imagery (Melendez-Pastor *et al.*, 2010). Further analysis in this study uses the GWR-derived coefficient values generated with MODIS 13a1 NDVI to estimate NDVI and compare to observed TM-derived NDVI for the KCA.

Rainfall data

The regional GWR model is parameterized using the TRMM 3B43 dataset (version 6) which includes best-estimated rainfall calculations from a combined instrument rain calibration algorithm (3B42) and rain gauge data sources (Huffman *et al.*, 1997). However, to calculate the GWR model for each TM image acquisition year (1984, 1990, 2000, and 2007) we used the gridded monthly precipitation time series (0.5^{o} x 0.5^{o} grid cell resolution) produced by Willmott and Matsuura (hereafter known as the WM dataset) (Matsuura & Willmott, 2007). Ideally we would use the same precipitation data source at both the regional and local scale but data collection from the TRMM instrument dates back only to 1998. Meteorological station data in the region are sparse and lack of reliable existing records makes the modeled precipitation dataset necessary

for longitudinal analysis. The WM model output accuracy for global precipitation patterns compares favorably to five other monthly precipitation datasets (Fekete *et al.*, 2004) and inclusion of all Landsat time steps made it an appropriate dataset for this study.

Precipitation-corrected NDVI

The GWR-derived relationship between NDVI and seasonal precipitation developed at the regional catchment scale (~600,000 km^2) (Gaughan et al., *in prep*) identifies the strength of association between different wet season months and BDS GPP. The GWR creates location-specific observation estimates that are weighted by a distance-decay function and these estimates will vary depending on which point within the study region the model is being estimated (Fotheringham, 2002). The regional model uses TRMM rainfall estimates across ten years (2000-2009) for each of the seven wet season months (October – April) to predict April NDVI. The years 2000-2009 include wet, normal, and dry years. By stratifying our sampling of MODIS NDVI response and TRMM predictor across years we account for temporal variation in rainfall providing a representative relationship between savanna vegetation and prior wet season rainfall. The derived beta coefficients from the GWR model are used with WM monthly precipitation data to estimate NDVI for each image year (1984, 1990, 2000, and 2007). The coarseness of the WM dataset means only one grid cell of precipitation was included within the boundaries of the KCA. We compared the one-point estimate of monthly precipitation to an inverse distance weighted (IDW) interpolation approach for estimating NDVI. Minimal difference was evident in the mean and standard deviation when comparing the residual of sum squares (RSS) value between the two precipitation

estimation approaches. Thus we determined that the point estimates of monthly rainfall provided adequate predictors for each year of estimated NDVI.

Before estimating NDVI, the GWR model was re-calculated with a spatial resolution of 30 meters to be comparable with the observed TM NDVI images. The estimated model that predicts NDVI is:

$$NDVI_i = \beta_0 (u_i, v_i) + \beta_1 (u_i, v_i)\ Rain_{Oct} + \ldots + \beta_7 (u_i, v_i)\ Rain_{Apr} + e_i$$

Where $NDVI_i$ represents predicted BDS NDVI for each Landsat pixel *i* and its spatial location is represented by coordinates (u_i, v_i) in the KCA. $\beta_0 (u_i, v_i)$, $\beta_1 (u_i, v_i)$ $Rain_{Oct}$ … $\beta_7 (u_i, v_i)$ $Rain_{Apr}$ are realizations of the continuous, estimated coefficient functions of $\beta_{0\text{-}7}$ (u, v) at location *i* and e_i is a Gaussian random error term. The intercept and regression coefficients specific for the model at each point were generated from the regional GWR model coefficients multiplied by each WM monthly predictor value. The total number of months included in the model may vary depending on the TM image acquisition date. For the June 10th, 1984 image we re-estimated the regional GWR model with May and June rainfall as predictors extending the model to include 9 total predictor variables. The model, parameterized with the additional two months of rainfall, provides a better fit to observed June NDVI. However, we did not include May rainfall for the May 9th, 1990 image. While the time difference between the June 1984 image and the other three image dates is not ideal, we assume that by adjusting the GWR model we capture the inter-annual seasonal effects on the landscape and thus control for the seasonal differences one might observe in this environment. The coefficient

values extracted from the GWR model for the KCA correspond broadly to savanna land cover based on the International Global Biosphere Programme (IGBP) global land cover classification map, which defines savanna as lands with herbaceous and other mixed understory cover and a forest canopy cover of 10-30% with height greater than 2 meters (Friedl *et al.*, 2002). We use this designation of savanna to determine how the KCA vegetation cover may vary over time after controlling for seasonal rainfall.

After NDVI was estimated from the down-scaled GWR model, we subtract estimated NDVI ($NDVI_{est}$) from the observed TM-derived NDVI ($NDVI_{obs}$) resulting in a new, precipitation-corrected (PC)-NDVI value, or residual (Evans & Geerken, 2004). The PC-NDVI corrects for seasonal effects on the landscape by removing the variation in NDVI explained by the prior wet season months of rainfall in the model for a given year. As a result, any trend (positive or negative) through time present in the PC-NDVI values indicates change in NDVI not due to seasonal precipitation. If each subsequent year sees an increase in positive PC-NDVI then it suggests a trend towards increased vegetation productivity at the start of the dry season. Likewise, consecutive time steps of increasing negative PC-NDVI suggest a landscape with less vegetation productivity over time at the start of the dry season.

Long-term Land-Cover Change in the KCA

Temporal clusters of the raw PC-NDVI were created using a K-means unsupervised classification method on the stacked multi-temporal PC-NDVI layers. These clusters were then used to identify spatial variation in PC-NDVI change over time by identifying areas on the landscape with similar PC-NDVI trajectories. By clustering similar PC-NDVI values together across the four image dates we examined how spatial patterns of vegetation productivity varied since 1984. Calculations also were completed

to determine which areas in the KCA had a continual increase or decrease in PC-NDVI over the four time steps (1984-1990-2000-2007). These areas in the KCA highlight a one directional (either positive or negative respectively) trend in vegetation productivity over the 23-year period.

However, a continual increasing or decreasing trend in PC-NDVI does not identify pixels that oscillate over time. We also calculate image differences between each PC-NDVI year to identify trajectories of change within the KCA for 1984-1990, 1990-2000, and 2000-2007. Extreme difference in PC-NDVI for two dates is identified by applying a ±2 standard deviation threshold. Other cutoff values were investigated but the ±2 standard deviations, while arbitrary, provides a conservative estimate of "change" that identifies important biological shifts on the landscape. We then conduct a post-classification analysis on the differenced PC-NDVI images to determine the different pixel trajectories over the three differenced time steps. We examine only those trajectories that are > 1% of the landscape. We use ground data along with semi-structured interviews collected within the study area in 2007 and 2008 to help explain the observed changes. Before applying the threshold value the main paved road was masked out of the analysis. We assume that the tar surface would not respond to seasonal precipitation and we wanted to exclude those pixel values from influencing the mean and standard deviation used in the threshold calculation.

Results

PC-NDVI Compared to Observed NDVI

Figure 3a shows the observed TM-derived NDVI and Figure 3b shows the precipitation-corrected NDVI (PC-NDVI) plotted as bean plots (Kampstra, 2008). For each year, ~6,000 sample points are plotted that are equivalent to 30 x 30 meter pixels

in the KCA. Every sample point has a unique GWR model shown by individual black lines in Figure 3a and 3b. The spread of the distribution around those points is indicated by the gray, vertical histograms. The PC-NDVI (residual value) for each year centers on zero suggesting that the pattern of increase-increase-decrease shown for observed NDVI (Figure 3a) is minimized once seasonal effects are accounted for by the previous months of wet season rainfall (i.e. the bean plot medians of each year are near zero and the distribution of PC-NDVI indicated by the bean plot histograms straddle zero evenly). Variation exists around zero as the parameter estimates used in the model describe the relationship of NDVI to rainfall at the larger catchment scale. The distributions around zero, shown by the gray histograms, represent other factors (dominant vegetation type, soil cover, etc) that may influence change in NDVI. This figure indicates that the GWR model controls for the prior wet season rainfall across image dates.

Temporal Clusters of PC-NDVI

The comparison with 3a and 3b shows the importance of seasonality on inter-annual variation in NDVI, but the spread of individual points (black lines) suggests variation remains unaccounted for in the landscape. A ten-class unsupervised classification (Figure 4), calculated on the four time steps stacked together as a single dataset, identifies similar PC-NDVI trajectories over time and groups those areas on the landscape together. Classes that do not vary for the four years (eg. Classes 4) indicate minimal change in PC-NDVI. Ecologically, the classes (groups of similar pixel trajectories) that increase and/or decrease in PC-NDVI over time represent shifts in total GPP, as measured by NDVI. These classes that exhibit change in PC-NDVI (ex. Class 1 or Class 6) suggests factors other than seasonal precipitation influence shifts in vegetation cover. The ridge and dune system, natural to the region, is noticeable in the

clustering of PC-NDVI. This pattern identifies with the natural variation of more woody vegetation on top of the ridges (ex. Class 5) and grassier areas more prevalent in the troughs (ex. Class 3). Additionally, there seems to be more change in PC-NDVI, both positive and negative, that occurs through time in areas closer to the river (ex. Class 1, 6 or 10).

PC-NDVI Change

Figure 5 highlights areas on the landscape that showed incremental increase or decrease in PC-NDVI from 1984 to 2007. Areas with increasing PC-NDVI (1984 < 1990 < 2000 < 2007) make up 2.4% of the KCA. Continual increase in PC-NDVI is more prevalent in the northwest region and along parts of the eastern side of the protected area. In contrast, continually decreasing PC-NDVI (1984 > 1990 > 2000 > 2007) is concentrated in the southern half of the protected area with smaller areas scattered through the KCA and makes up 3.3% of the total area in the KCA.

The areas of directional change (continually increasing or decreasing) make up a relatively small percentage of the landscape (~ 5.7%). To identify patterns of PC-NDVI that do not exhibit a unidirectional change in PC-NDVI, a change trajectory of differenced PC-NDVI across the three differenced time steps (1990 - 1984, 2000 - 1990, and 2007 - 2000) provides a more detailed view of a single pixel's trajectory (Figure 6). A ±2 standard deviation threshold applied to the differenced images highlights areas on the landscape of extreme change in PC-NDVI not accountable by prior wet season rainfall.

The majority of the landscape remains stable (88.1%). The largest area of change occurs in the NE portion of the protected area. A decrease in PC-NDVI occurs from 2000-2007 and covers 2.1% of the landscape. The second largest percent of change

occurs from 1990 - 2000 with an increase of PC-NDVI covering 1.9% of the KCA also concentrated in the NE section of the protected area. Together the two trajectories make up the largest change observed in the NE. The northeastern increase from 1990-2000 corresponds in general to Class 1 and 6 in Figure 4 although the Class 6 cluster also corresponds to pixels that decreased from 2000-2007.

For other parts of the KCA, the recent decrease (2000-2007) is prevalent in the lower SE part of the park and along the *omirambas* and corresponds generally to Classes 8 and 10, along with Class 6 from Figure 4. In contrast, over the same time period (2000 – 2007), an increase (1.4%) of PC-NDVI occurs largely in the NW portion of the KCA corresponding to the increase in pixel values for Classes 2 and 4 in Figure 4. The other shifts of extreme PC-NDVI that is >1% of the landscape occurs from 1984 - 1990 with a 1.6% decrease mostly in the SW area and a 1.5% increase scattered across the KCA. Pictures *a* and *b* in Figure 6 show photographs of areas corresponding to pixel values that exhibit a + 2 standard unit change in PC-NDVI from 2000 to 20007 (Figure 6a) and a -2 standard deviation of change in PC-NDVI from 1984 to 1990 (Figure 6b).

Discussion

Results show minimal change over time in PC-NDVI (residuals) since 1984 in the KCA, which is expected as the KCA is a protected area with no human inhabitants. This indicates that the regional GWR model, parameterized for a savanna land cover, provides a robust approach to control for prior wet season precipitation on BDS GPP, as measured by NDVI. The strong seasonal influence emphasizes the importance of using precipitation-corrected NDVI when examining biomass trends for regions with high inter-annual precipitation variation (Evans & Geerken, 2004). No widespread shift towards

an increase or decrease in GPP since 1984 is detected due to the minimal human presence over the past couple decades but also because there is not demonstrable climatic trend detectable during the time period (Gaughan and Waylen, *in prep*). Figure 6 shows no extreme change in NDVI for the majority of the protected area after controlling for prior wet season rainfall. However, a continual increase in PC-NDVI is prevalent in the upper NW of the KCA and there is an apparent decrease in PC-NDVI in the lower SW portion of the study area (Figure 5). These areas represent trends in different parts of the KCA in which pixel values move in a continual direction away from the overall mean NDVI for each time step. The decreasing trend of PC-NDVI concentrated in the lower SW and a continual increase in PC-NDVI in the NW indicate decreased and increased vegetative cover on the landscape since 1984, respectively. The increase concentrated in the NW corresponds to personal communication with park management of increased woody vegetation in recent decades.

PC-NDVI changes in other areas of the KCA are more spatially and temporally variable. The temporal clustering of PC-NDVI (Figure 4) and the change trajectory of PC-NDVI image differences (Figure 6) identifies these distinct patterns of increased and decreased regions of PC-NDVI for different time steps. These changes identify the pattern of GPP shifts not due to seasonal effects but to some other factor(s) operating on the landscape. These other factors most likely correspond to a variety of different policy and land-use decisions implemented over the past few decades. Throughout the 1980s, conflict continued in the Caprivi Strip due to the border war with Angola (Stanley, 2002). A decline in wildlife populations is attributable to the presence of the South African Defense Force (SADF) in the Caprivi Strip (Bruchmann, 2007). Additionally,

local communities along the Kwando River had access to grazing areas and natural resources on both sides of the river. Since Namibian independence in 1990 (Rodwell *et al.*, 1995) much of the area in Caprivi previously occupied by SADF has not been as heavily used (Rodwell *et al.*, 1995) and with the implementation of Community Based Natural Resource Management initiatives in Caprivi (mid-1990s), local communities have had restricted access to the west side of the Kwando River (Stuart-Hill *et al.*, 2005). The northeastern portion of the KCA was one area that has undergone multiple changes since Namibian independence. The high variability observed in vegetation shifts within the northeastern portion of the KCA (Figure 6) probably relates to the exit of the SADF in 1989 and policy implementation prohibiting grazing rights along the river inside the park (Mayes, 2008). Known locally as the 'Golden Triangle,' this small triangle of land extends southward along the Kwando River, narrowing towards the Botswana border (Mayes, 2008). While this area was not originally part of the protected area, people and their cattle have been excluded from this area since the mid-1990s due to the heightened focus on Caprivi as a wildlife conservation area (Rodwell *et al.*, 1995).

While this study does not explicitly identify the other potential drivers (ex. fire, herbivory, frost) that affect BDS GPP, anecdotal information from game guards and park wardens suggest that the timing of fire may play a significant role in dictating vegetation patterns on the landscape. Fuel moisture depends on how much relative humidity exists throughout various parts of the dry season while the fuel load depends on multiple factors such as tree cover, rainfall, soil type, and grazing pressure (Archibald *et al.*, 2009, Higgins *et al.*, 2000). The interaction of these different factors can have both a positive and negative effect on fuel load. While rainfall and soil

nutrients contribute to increased fuel load on the one hand, they also provide tree canopy cover and optimal grazing conditions which has a negative effect on fuel load (Archibald *et al.*, 2009). The frequency and extent of fire will also be influenced by soil moisture availability (Rodriguez-Iturbe *et al.*, 1999). Figure 6 identifies a more recent decrease in extreme PC-NDVI along the edge of the ridges of the *omirambas* which may be a result of soil moisture dynamics negatively influencing the strength of BDS vegetation productivity from 2000 to 2007. Underlying the effects of these physical system drivers are management and land-use decisions that have changed over recent decades. Until recently, a fire suppression policy was strongly supported for the entire Caprivi Region. Starting in 2006 an early burning regime was implemented on a yearly basis with the management intent to prevent the hotter, more intense late season fires (pers. comm. Robin Beatty, IRDNC). Future research will focus on areas within the KCA that respond to other potential drivers of long-term change such as the influence of fire, herbivory and changes in soil moisture.

Our study builds on previous studies *(*Archer, 2004, Evans & Geerken, 2004, Wessels et al., 2007*)* that apply a correction factor for the influence of climate on NDVI by applying a model with a more spatially detailed examination of the NDVI-precipitation relationship within the KCA. The use of the GWR model allows detection of more subtle shifts in PC-NDVI that may be obscured with a global regression model (ex. ordinary least squares) (Bini *et al.*, 2009). In addition, the GWR model is a more robust regression technique to separate the inter-annual seasonal signal from other factors controlling BDS GPP over time. The use of GWR minimizes the effects of unmeasured, spatially-varying factors and the negative impacts of autocorrelation (Fotheringham,

2002). In addition, unlike global regression models, a GWR model weights observation points that are closer to the estimation point more heavily than those far away. This provides a spatially-explicit estimate of NDVI specific to a certain location on the landscape which minimizes spatial autocorrelation and provides a more representative relationship between wet season rainfall and vegetation across space.

The use of the down-scaled GWR model to calculate the PC-NDVI for the KCA was specifically developed to control for the effects of seasonal precipitation. The GWR model incorporates the prior months of wet season rainfall and can be adjusted to include shorter or longer-term rainfall periods as needed. The down-scaled GWR model correction for seasonal precipitation will decrease NDVI for years with higher than normal rainfall and increase NDVI for years of less than normal rainfall. The detection of subtle changes on the landscape is important for such heterogeneous areas such as savanna drylands where a shift within the mix tree-shrub-grass composition has implication for local livelihood land-use decisions (Shackleton *et al.*, 2007) and global environmental policies (Rotenberg & Yakir, 2010). In this study, areas in the protected area with the most change were those that had the strongest human presence over the past few decades. Prior to Namibian independence and the implementation of more rigorously applied conservation policies, the northeast corner of the KCA was accessible to communities and was also a base location for the SADF. The more dynamic vegetation change identified for this area emphasizes the importance land-use and policy decisions have on landscape changes.

The use of GWR to characterize the regional relationship of precipitation to savanna vegetation and apply it at a local scale provides an important first step to

disentangling the complex interactions of various drivers of land-cover change. Controlling for seasonal precipitation effects on vegetation productivity is a critical component necessary in order to detect other factors driving long-term land-cover change. These other competing drivers may be human-induced or related to longer-term climate patterns (Dube & Pickup, 2001, Wessels *et al.*, 2007). PC-NDVI accounts for wet season months of rainfall on BDS GPP but does not account for potential longer-term lags in the system. Response of GPP to antecedent rainfall effects of previous years is not captured in the seasonal model and thus the response of certain vegetation types that are influenced by longer-term rainfall will not be captured in the model (Richard *et al.*, 2008, Wiegand *et al.*, 2004). However, the purpose of the method is to account for the effects of inter-annual variability in seasonal rainfall to then detect these longer-term trends in vegetation cover. The down-scaled GWR model corrects for inter-annual variability in seasonal rainfall and is a useful first step in determining long-term change in a savanna landscape.

Summary

This study suggest a new approach to scale down a regional relationship between precipitation and vegetation to identify change in long-term vegetation patterns after controlling for inter-annual precipitation variation in seasonal rainfall. The use of GWR as a statistical technique provides a spatially explicit estimation of the precipitation-vegetation relationship across the regional catchment. Local model estimations provide a precipitation-vegetation relationship specific for certain areas in the study region. The structure of the model weights the importance of each wet season month accordingly rather than using a total value to represent the entire seven month period. This is important for determining the strength of association for different months of wet season

rainfall on BDS GPP for savanna vegetation (Gaughan et al., *in prep*). By controlling for prior wet season monthly rainfall, we are then able to identify longer term changes in vegetation cover.

The residual trends analysis provides a valuable technique to identify and remove precipitation effects on NDVI. Used in conjunction with other means of monitoring land cover changes, this approach helps identify changes in vegetation productivity due to factors other than prior wet season rainfall. This study shows that no large-scale changes were detected in the protected area although spatial and temporal variation exists in certain parts of the KCA. These areas experienced change in vegetation productivity most likely due to factors operating on the landscape such as herbivory and fire. Their respective influences were dictated by changes in policy and land-use decisions over the past few decades. More intensive investigation is needed to for areas that experienced extreme change in PC-NDVI in order to determine other drivers that contribute to observed vegetation change. The GWR method to account for prior wet season rainfall effects on NDVI can also be applied to a larger management area which includes communal lands. Detecting how land-use decisions affect vegetation productivity without an underlying climate signal biasing the detected changes is important for semi-arid savanna regions in which management of wildlife, livestock and fire is critical to conservation and development initiatives.

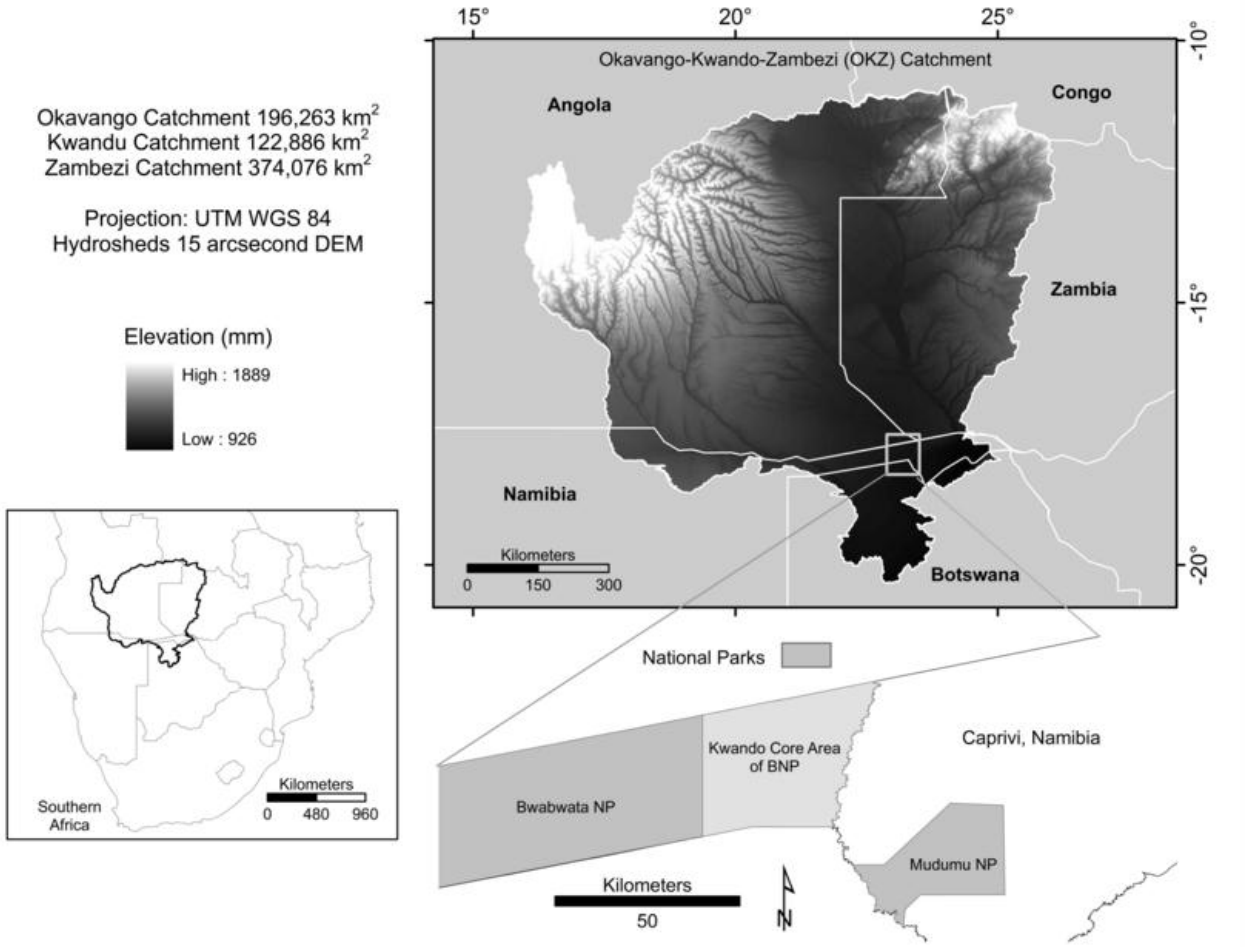


Figure 4-1. Study region in southern Africa outlining the larger Okavango-Kwando-Zambezi catchment and the local protected area of interest – Kwando Core Area in Bwabwata NP, Caprivi, Namibia.

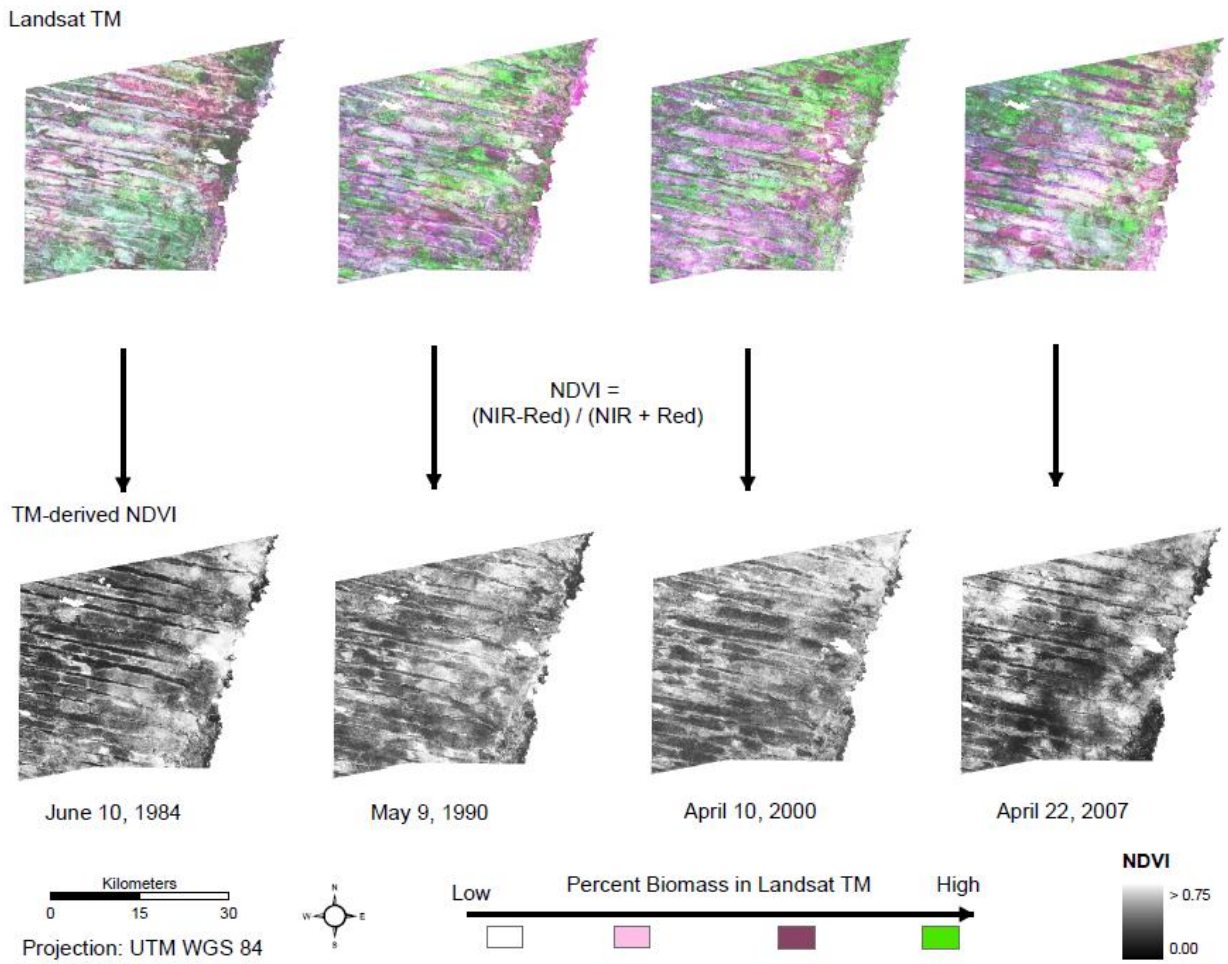
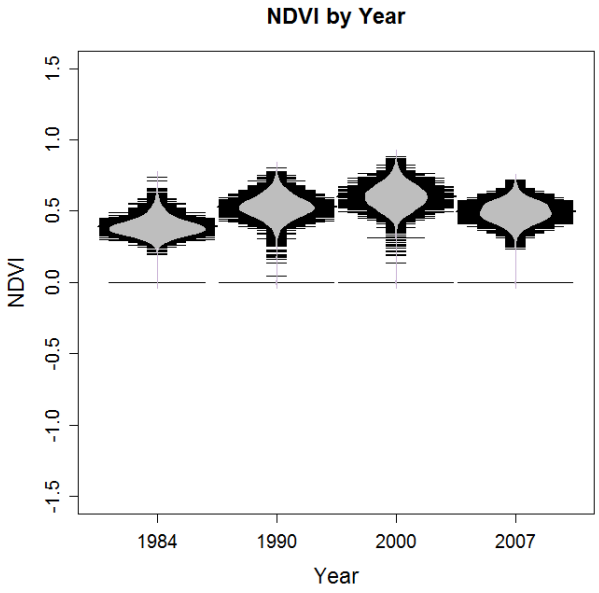


Figure 4-2. Landsat TM RGB: 5,4,3 composite images and observed TM-NDVI for each acquisition year in the study. The “striping” prevalent on the landscape is a natural vegetated linear system of dune ridges constructed from sediments mostly likely transported by fluvial processes during the Quaternary period (Thomas et al., 2000). Fire scars and aquatic vegetation are masked from images.

a.



b.

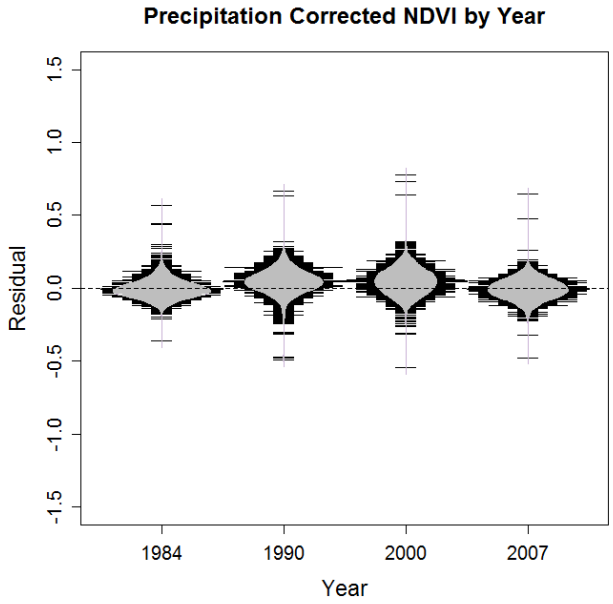


Figure 4-3. Shows a) Landsat TM overall NDVI values for the Kwando Core Area (KCA) plotted across four years showing a declining trend for 1984-1990-2000 and then an increase of overall NDVI in 2007 and b) precipitation-corrected NDVI values for the KCA in the form of residuals ($NDVI_{obs}$ – $NDVI_{pred}$).

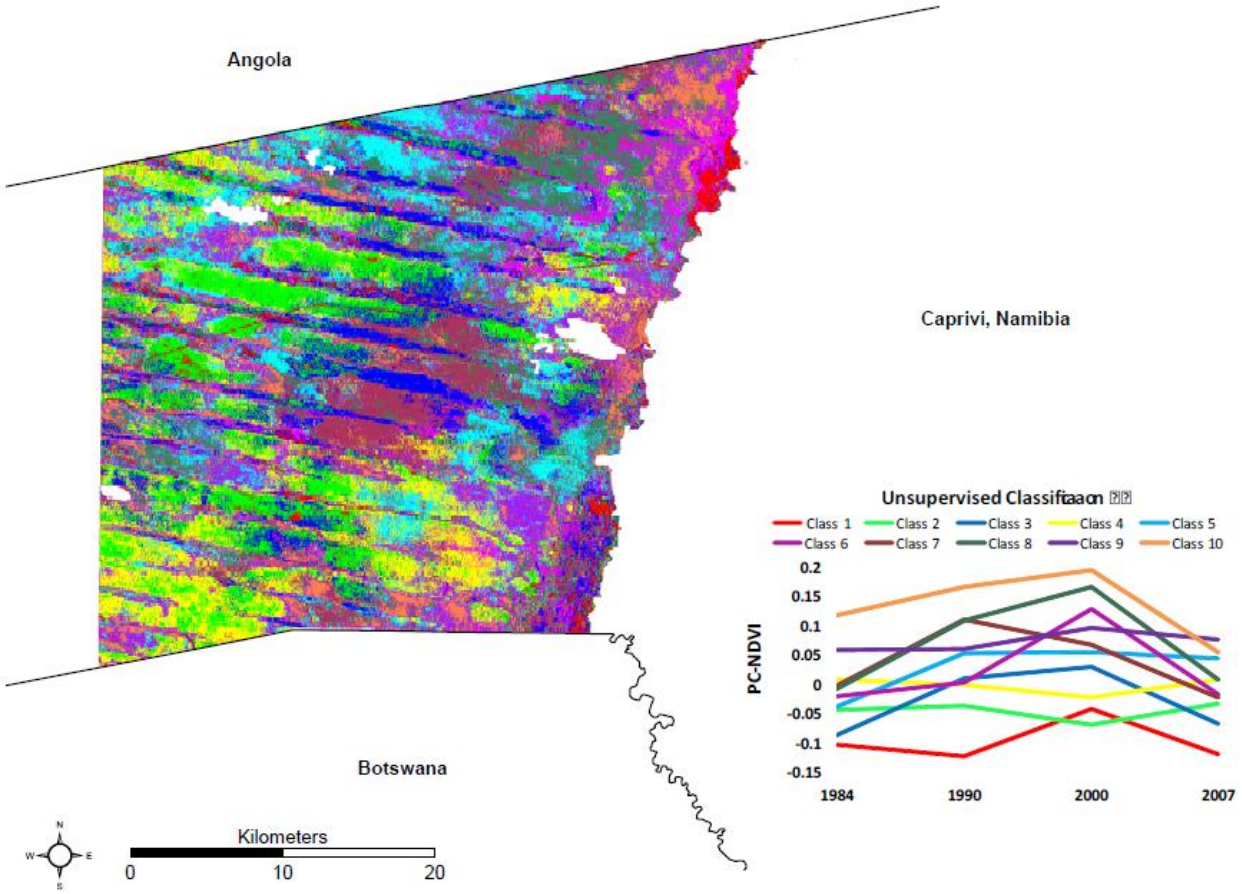


Figure 4-4. Shows a K-means 10-class unsupervised classification of the Kwando Core Area based on four discrete time steps of PC-NDVI (1984-1990-2000-2007). Each class represents similar PC-NDVI values over time.

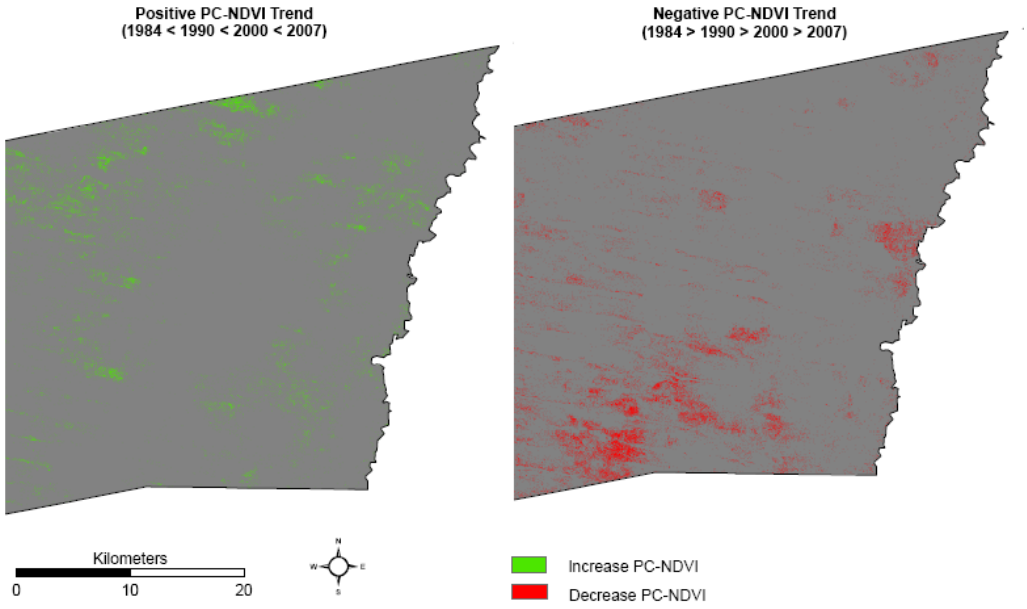


Figure 4-5. Trends PC-NDVI over the four discrete time steps (1984-1990-2000-2007), defined as subsequent increase or decrease in PC_NDVI, is highlighted for a) positive change and b) negative change in the KCA.

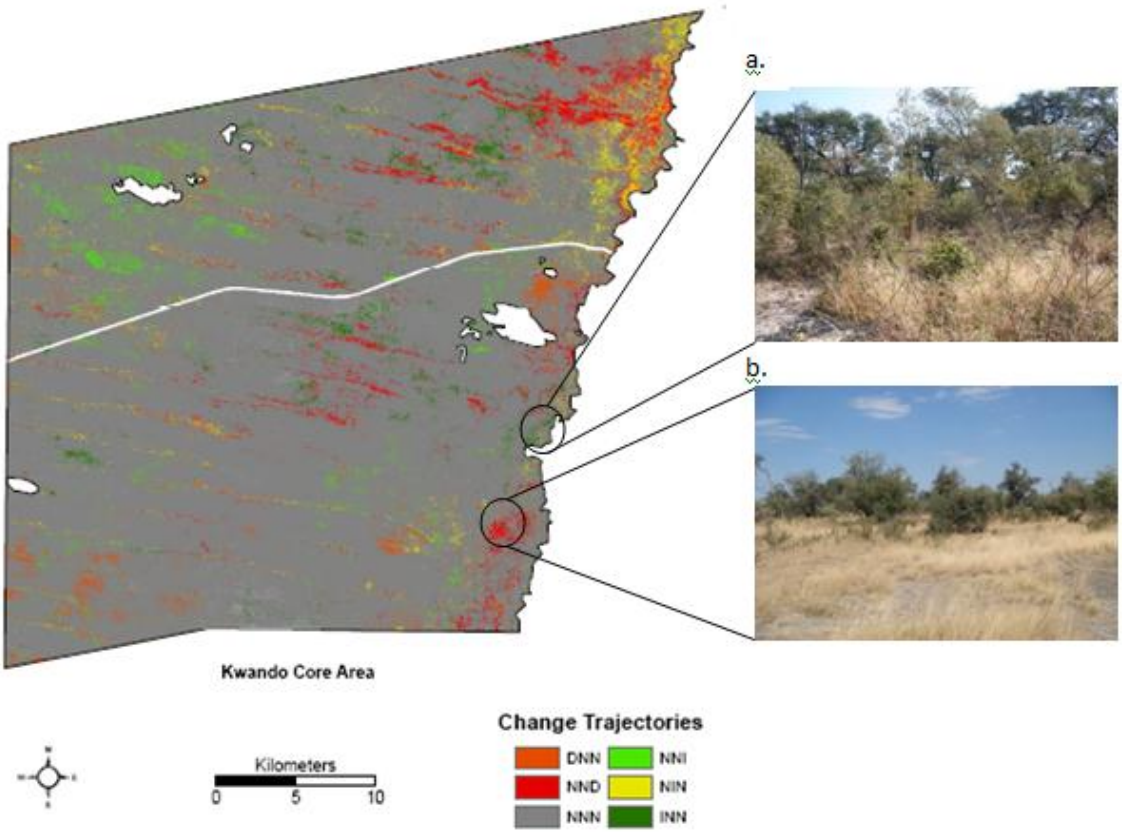


Figure 4-6. Change trajectory for the three differenced PC-NDVI images (1990-1984, 2000-1990, and 2007-2000) with a threshold of ± 1.96 standard deviations. D = Decrease -1.96 SD, I = Increase +1.96 SD, and N = No Change. Percentages > 1% of the KCA region shown. Picture a shows an area of +2 SD Increase (1984 – 1990) and picture b shows an area of -2 SD Decrease (2000 – 2007).

CHAPTER 5
CONCLUSION

Overall Findings

Climate change and climate variability will continue to influence the rate and timing of biological and ecological processes in savanna ecosystems (IPCC 2007). This research specifically focused on the precipitation aspect of climate to answer the question of how precipitation variation, over different spatial and temporal scales, influences vegetation response for a dryland catchment in southern Africa. The study incorporated multiple scales across time and space to identify the climate-land interaction specific to precipitation patterns and savanna vegetation at both a regional catchment level (~693,000 km^2) and within a local protected area (1,300 km^2). The first chapter of this dissertation outlined the rationale for detecting and monitoring savanna landscape dynamics and identifies the importance of directional trends of timing, frequency, and distribution of precipitation on different savanna vegetation covers. To answer the overarching research problem set forth in Chapter 1, subsequent chapters are made up of individual papers with separate research questions, hypotheses, tests, and methods (Chapters 2, 3, and 4).

The first paper showed that mean annual precipitation (MAP) patterns have changed before and after a late 1970s global climate shift within the Okavango-Kwando-Zambezi catchment. More recent years (1980-2005) have seen a decrease in MAP across all three catchments. In addition, the number of dry years and frequency of dry years concurrent with warm phase ENSO events has increased. These precipitation patterns suggest short term changes in the functioning and response of the OKZ catchment to hydro-meteorological patterns from 1950-2005. The findings complement

existing studies which identify changes in southern African rainfall and teleconnections patterns post the late 1970s (Mason 2001; Fauchereau et al. 2003). And while the state of local and regional inputs to each sub-catchment remains relatively strong across the study period (1950-2005), the historical shift from above median conditions in Period 1 (1950-1975) to below median conditions in Period 2 (1980-2005) is important for land-use and conservation management decisions.

The second paper identified the strength of association between wet season (Oct-Apr) precipitation on beginning of dry season (April) vegetation productivity as estimated by NDVI. A large proportion of April NDVI is explained by seasonal rainfall. However, the relationship of beginning of dry season NDVI response to timing of rainfall during the wet season differs across savanna land covers. A stronger association exists for end of the wet season monthly rainfall (February-April) and savanna land covers such as grasslands and open woodlands compared to rainfall at the outset of the rainy season (October - November). In addition, some woodland systems, such as Miombo woodland or evergreen forest, do not show a significant association between beginning of dry season NDVI and the prior seasonal rainfall.

The approach used in paper 2 created an empirical model of the precipitation-vegetation relationship parameterized for savanna vegetation. The third paper applied this model at a local scale to identify the effects of seasonality on remotely sensed imagery and, in turn, isolated areas on the landscape that have changed due to other potential forcing factors (ex. fire, herbivory, people). The model corrects for seasonality on the remotely-sensed data and creates a new, precipitation-corrected estimate of vegetation productivity. The model showed overall seasonality accounts for a large

percent of variation in vegetation productivity, as estimated by NDVI. There was no widespread change in vegetation cover detected from 1984-2007. However, after controlling for seasonal precipitation effects, finer spatial and temporal patterns suggest distinct patterns of increased and decreased precipitation-corrected NDVI exist within the local protected area. These areas will be further investigated in future research as other potential drivers of savanna vegetation change, such as fire or herbivory, may contribute to the changes observed.

Significance of Findings

The conclusions drawn from this study emphasize the variable nature of climate especially common in southern African dryland regions. Land-use decisions and adaptive management of natural resources and development initiatives must incorporate the knowledge of how patterns of precipitation change and variability will affect savanna vegetation dynamics. The Okavango-Kwando-Zambezi catchment encompasses the future Kavango-Zambezi Transfrontier Conservation area (KAZA) that is projected to become the largest transboundary conservation area in Africa. The timing, frequency, and amount of precipitation input across these three basins will play an important and critical role to the distribution of wildlife across wet and dry seasons, agricultural land-use decisions, effects and influence of fire, and transboundary decisions regarding flows of water to balance between ecosystem processes and sustainable livelihood needs. This dissertation identifies that precipitation has shifted across the OKZ basin over the latter half of the twentieth century. The shift may be short term but the nature of the oscillating pattern may not be and an understanding of such patterns is necessary to making conservation and development decisions in such a variable environment.

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BIOGRAPHICAL SKETCH

Andrea E. Gaughan was born in Dallas, TX, and grew up in Texas, Southern California, and Tennessee. In May of 2003, she received a Bachelor of Arts in English and a concentration in environmental studies from Furman University. During her time at Furman, Andrea also spent a term in Chile studying environmental and community health and another term in Hawaii researching effects of engine noise on behaviors of humpback whales. In the year between undergrad and graduate school, Andrea worked at the Newfound Marine Harbor Institute teaching coastal and near-shore ecology and also traveled in the South Pacific. Andrea began the M.S. in geography at the University of Florida in August of 2004 and completed the degree in December of 2006. She focused on land-use and land-cover change in a tropical watershed in Siem Reap, Cambodia. In January 2007 she began the doctorate program in geography at the University of Florida. Her dissertation was on climate-land interactions in a southern African catchment, specifically the response of savanna vegetation to spatial and temporal precipitation patterns. She also participated in a NSF Integrative Graduate Education and Research Traineeship (IGERT) focused on Adaptive Management, Water, Watersheds, and Wetlands (AM:W3).