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SPATIO–TEMPORAL TRENDS IN VEGETATION DYNAMICS ACROSS A SAVANNA–DOMINATED NATIONAL PARK

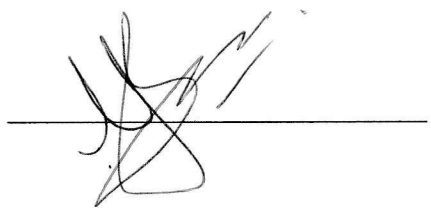
Yolandi-Mari Ernst

A thesis submitted to the Faculty of Science, University of the Witwatersrand, Johannesburg, in fulfilment of the requirements for the degree of Doctor of Philosophy

Johannesburg, October 2018

DECLARATION

I declare that this Thesis is my own, unaided work. It is being submitted for the Degree of Doctor of Philosophy at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination at any other University.



15th day of October 2018 in Johannesburg

In a gentle way, you can shake the world…

- Mahatma Gandhi -

ABSTRACT

The Kruger National Park (KNP) is a savanna-dominated landscape upon which complex processes interact to result in dynamic patterns. Evidently, climate change is already impacting the KNP landscape. A major objective in the KNP's Strategic Adaptive Management approach (SAM) is therefore to maintain ecological integrity through an informed, objective-driven decision-making process that involves Thresholds of Potential Concern. Continuous and informative monitoring at the landscape-scale is therefore essential, but challenging to do for such dynamic savanna environments, over large spatial extents. To address this concerning issue, I aimed to develop and evaluate a remote sensing-based methodological approach for the assessment and monitoring of landscape-scale spatio-temporal trends in vegetation greenness dynamics in relation to the influence of precipitation, fire and elephants across the Kruger National Park. My approach is novel in its combination of methods to monitor dynamic landscapes over large extents. Chapter 2 comprises of a comparison of different NDVI data products within the framework of mean-variance and spatial persistence analyses, thereby building the foundation upon which I based data analyses in the following chapters. Comparison of NDVI data derived from different satellite sensors revealed that the overall mean-variance trajectories and spatial persistence were relatively similar, but some large variations were evident due to differences in sensor characteristics. In Chapter 3, I exploited the fact that the relationship between phenology and vegetation greenness are confounded by the effect of other drivers. Through subjecting NDVI, phenology metrics and precipitation to spatial persistence analyses and then quantifying the converging and diverging change trends, I was able to show that precipitation is the primary driver of the general spatial greenness trends across the park but that persistent changes in vegetation greenness at finer spatial scales were more likely caused by other factors, such as fire and herbivory during the period of observation. Following this, I evaluated the role of fire and elephants as drivers of vegetation change trends with the use of pheno-season (defined by phenology metrics) vegetation greenness in correlation analyses. Here, the results seemed to suggest a combined association of elephants and fire frequency with vegetation greenness change trends, although the results showed much variability. Elephant bull and herd densities

also seem to play different roles in their effects on vegetation greenness Through further development and adjustment of data input the proposed monitoring approach could be optimised for the broad-scale monitoring of vegetation pattern and processes within the SAM framework.

To my blue-eyed boy…may the force (of my love) be with you…

ACKNOWLEDGEMENTS

So ask myself; What was my PHD degree about??
It is definitely not just about science and gaining knowledge… it is perseverance, it is picking yourself up time after time, it is joy and then it is sadness, it is about managing people, managing yourself and managing time, it is believing and then not believing, it is about courage, it is knowing your limits and then exceeding them, it is humbling, it is painful, it is exhilarating, it is doubting yourself, it is doubting the world, it is feeling proud and feeling stupid and then proud again, it is insane and it is finally done!!! Most of all it is being thankful to the people that enabled me to do it;

I thank my supervisor, Prof. Barend Erasmus, for guiding me, believing in me and always having my back. Thank you for letting me own my work and giving me the opportunity to learn and grow as a scientist and as a person. Your continuous patience, enthusiasm, understanding, motivation and inspiration will always be remembered. You gave me back my confidence and my love for science.

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DISCLAIMER

This thesis consists of a sequence of content chapters (Chapters 2-4) that have been prepared for publication in a range of scientific journals. This has meant that there is some degree of overlap to ensure publishable papers. Author contributions and specific Journals have been specified in Chapter 1.

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LIST OF ABBREVIATIONS

APNR	Associated Private Nature Reserves
BCS	Band Collection Statistics
BMP	Biodiversity Monitoring Programme
BMS	Biodiversity Monitoring Strategy
D	Directional persistence metric
DZB	Decrease zone buffer
ENSO	El Niño–Southern Oscillation
EROS	Earth Resources Observation and Science
EVI	Enhanced Vegetation Index
fAPAR	Fraction of Absorbed Photosynthetically Active Radiation
IZB	Increase zone buffer
KNP	Kruger National Park
LAI	Leaf Area Index
LANDSAT TM	LANDSAT Thematic mapper
LANDSAT ETM+	LANDSAT Enhanced thematic mapper
LIDAR	Light Detection and Ranging
LOS	Length of Season
LP DAAC	Land Processes Distributed Active Archive Center
MISR	Multiangle Imaging Spectro-Radiometer
MODIS	Moderate-resolution imaging spectroradiometer
NDVI	Normalised difference vegetation index
PDZ	Persistent decrease zone
PIZ	Persistent increase zone
SAM	Strategic Adaptive Management
SANParks	South African National Parks
SAVI	Soil-adjusted vegetation index
SD zone	Standard Deviation zone
SLC	Scan Line Corrector
SOS	Start of Season
SPOT-VEGETATION	Satellite Pour l'Observation de la Terre Vegetation
SRE	Satellite-derived Precipitation Estimate

TAMSAT	Tropical Applications of Meteorology using Satellite data and ground-based observations
TNDVI	Transformed Normalised Difference Vegetation Index
TPC	Threshold of Potential Concern
USGS	United States Geological Survey
UTM	Universal Transverse Mercator
VI	Vegetation Index
VITO	Vlaamse Instelling voor Technologisch Onderzock
WGS	World Geodetic System
WSA	Weighted Sum of the Local and Total Average

CHAPTER 1

GENERAL INTRODUCTION

1. GENERAL INTRODUCTION

1.1. Rationale

The savanna-dominated Kruger National Park (KNP) in South Africa is an ecosystem that is inherently heterogeneous and dynamic due to cycles of change that arise from a combination of internal and external mechanisms. Some levels of change in the ecosystem may be beneficial as it serves to maintain landscape heterogeneity, ecosystem resilience and biodiversity (Briske *et al.* 2010; Pringle *et al.* 2010; Mori 2011). However, the rate and direction at which the landscape is changing may be amplified through the effect of climate change (Hannah *et al.* 2002; Meadows 2006; Heller & Zavaleta 2009; Buitenwerf *et al*. 2012). Research is already suggesting that precipitation patterns (MacFadyen *et al.* 2018) and temperatures (van Wilgen *et al.* 2015) in the KNP are subject to seasonal shifts and increases, respectively.

The Kruger National Park (KNP) hosts a wide diversity of plants settled in different patterns of vegetation composition, structure and spatial distribution. As a fundamentally crucial element in the landscape, vegetation responds to an abiotic template (e.g. soil, geology, topography) and reacts to disturbance factors such as rainfall, fire and herbivory (Du Toit *et al.* 2003). In turn, the spatio-temporal configuration of vegetation provides the resource template for animals to survive and reproduce. Despite the decades of research studies addressing the dynamic interaction between vegetation, climatic factors, fire and herbivory (e.g. Trollope *et al.* 1998; Midgley *et al*. 2010; Scholtz *et al.* 2014; MacFadyen *et al.* 2016; Pellegrini *et al*. 2017), the subject remains one of the most complicated and pressing issues, especially in the face of climate change (Midgley *et al*. 2010; van Wilgen *et al.* 2015; MacFadyen *et al*. 2018). It is therefore more important than ever for conservation managers to be able to identify and monitor the spatio-temporal trends imposed on the landscape so that they can respond accordingly (Heller & Zavaleta 2009; Ferreira *et al.* 2011; McGeoch *et al*. 2011).

Management of the South African National Parks (SANParks) is primarily based on the Strategic Adaptive Management (SAM) approach that incorporates the concept of "Thresholds of Potential Concern" (TPCs) (Biggs & Rogers 2003). These TPCs are fundamentally a collection of hypothesised limits of tolerable change in ecosystem structure and function that can be adaptively modified as new information is gathered (Biggs & Rogers 2003). More recently, management advanced the strategy to make an important shift towards identification of the "rates of threshold approach" as the objective (Grant *et al*. 2011). Through a focus on maintaining the functional processes that sustain heterogeneity (Biggs & Rogers 2003) the SAM enables management for ecosystem resilience (Allen *et al*. 2011). This strategy is an on-going process that depends on the continuous availability of new and relevant information through focused research and monitoring (McGeoch *et al*. 2011). The KNP hosts many research and monitoring projects but recognised the need for a strategic plan, such as the SANParks' Biodiversity Monitoring System (BMS) framework, to facilitate more focused monitoring (McGeoch *et al.* 2011). To meet some of the monitoring and management objectives, the KNP largely relies on quantitative data collection obtained from in-field measurements (SANParks 2017). However, although field data collection is key to ecological monitoring, it is costly and time-consuming (McGeoch *et al*. 2011). Additionally, it would be impossible to monitor the entire landscape on a regular basis. Despite the benefits that remote sensing data holds for monitoring, its use is still largely underrepresented within the KNP (SANParks 2017).

The KNP management may therefore benefit from a baseline cost-effective landscape-scale monitoring approach that is complimentary to the current monitoring protocols, meets the objectives of the BMS (McGeoch *et al*. 2011) and offers;

i. a synoptic view over the entire landscape extent.
ii. identification of critical areas of concern within the landscape that would allow for future prioritisation of management resources and intervention.
iii. continuous, long-term trend detection through the use of historical and future data sets.
iv. the expression of temporal change trends in a spatially-explicit manner.

v. ecologically relevant trend detection that can be linked to functional processes and influences from global (climate change) and local drivers (e.g. fire, herbivores).

The overall aim of this thesis is therefore to develop and evaluate a remote sensing-based methodological approach for the assessment and monitoring of landscape-scale spatio-temporal trends in vegetation greenness dynamics in relation to the influence of precipitation, fire and elephants across the Kruger National Park.

1.2. Literature Review

1.2.1. The savanna landscape

(a) Balance of nature…or not?

Equilibrium theory dominated ecological thought through most of the 20th century and is based on the premise that complex systems self-regulate through balancing interactions (e.g. competition) and internal feedback mechanisms (Pickett *et al.* 1994). Upon disturbance events, a system in equilibrium is therefore expected to return to a predictable pre-disturbance state (homeostasis) or to its pre-disturbance trajectory (homeorhesis) (O'Neill *et al.* 1986; Wu & Loucks 1995). However, complex systems, such as savanna landscapes, rarely display such predictable behaviour (Jeltsch *et al.* 2000). A wide array of empirical studies was therefore unable to accumulate sufficient evidence in support of equilibrium in complex systems (see review by DeAngelis & Waterhouse 1987). The reason for the lack of support stems from the inability to account for the continuous fluctuation of ecological systems, and the inference that past disturbance events have negligible consequences for ecosystem dynamics (O'Neill *et al.* 1986, Wu & Loucks 1995).

In the 1970s, the foundation for non-equilibrium theory was developed when several studies advocated for the existence of multiple alternative or equilibrium states (Holling 1973; May 1977) and the notion that ecosystems demonstrate a limited ability for internal regulation (Wu & Loucks 1995). Non-equilibrium complex systems are

therefore considered to be more dynamic and less predictable than equilibrium systems (Pickett & Ostfeld 1995). In savanna landscapes, non-equilibrium models typically include the influence of variability in climate and soil on vegetation, with much focus directed at the fluctuations presented by tree-grass dynamics resulting from biotic and abiotic interactions (e.g. Belsky 1990, Scholes & Archer 1997, Illius & O'Connor 1999). Non-equilibrium theory therefore emphasises processes through which spatial and temporal heterogeneity is generated (DeAngelis & Waterhouse 1987; Wu & Loucks 1995).

Several studies further explored conditions under which both equilibrium and non-equilibrium dynamics may drive ecosystem behaviour at different spatial and temporal scales (DeAngelis & Waterhouse 1987; Briske *et al.* 2003; Oba *et al*. 2003). For instance, with their study on the spatio-temporal dynamics of ungulate population dynamics, Illius & O'Connor (1999) concluded that temporary equilibrium dynamics between ungulates and key resource areas may be induced within systems under certain conditions. They demonstrated that during the dry season, when food and water resources become limited, dependence on key resource areas may result in density-dependent population regulation. However, when resources become more available during the wet season, non-equilibrium conditions continue to dominate the system (Illius & O'Connor 1999).

Issues of scale complicate the concepts of equilibrium and non-equilibrium (Turner *et al.* 2001). Ecosystems are structured by processes that involve biotic and abiotic interactions which operate at different spatial and temporal scales. Within discrete scales, different processes reinforce one another and consequently result in persistent scale-specific patterns (Allen & Holling 2010). The concept of discontinuity in patterns and processes across scales also relates to ecological resilience. Ecological resilience broadly refers to the ability of a system to endure change while maintaining the same controls on function and structure (Holling 1973). Assuming multiple stable states or equilibrium points, ecological resilience may therefore be explained as the rate and extent of ecosystem change that is required before the system begins to restructure around a different state with its associated set of reinforcing processes (Peterson *et al.*

1998; Gunderson 2000; Washington-Allen *et al.* 2008; Garmestani *et al.* 2009). Additionally, the definition of spatial resilience should acknowledge large-scale external influences that result from beyond a system's boundaries (Cumming 2011). Thus, spatial resilience of a system is a function of its multi-scale spatial, compositional and structural properties and interactions within and beyond its borders (Cumming 2011).

Within the resilience framework, systems operate well in a fluctuating manner until threshold conditions are approached due to external and internal elements. Thresholds therefore indicate boundaries in time and space at which a system shifts from one state to another (Mayer & Rietkerk 2004; Walker & Meyers 2004; Washington-Allen *et al.* 2006). The existence and potential consequences of thresholds have been the subject of many studies (e.g. Elmqvist *et al.* 2003; Folke *et al.* 2004; Druce *et al.* 2008; Brock & Carpenter 2010). Although research on thresholds is multifaceted and still in the early stages of development (Groffman *et al*. 2006), a reliable monitoring protocol provides the first step towards understanding system changes and potentially identifying thresholds (e.g. Druce *et al*. 2008).

(b) Spatial and temporal savanna vegetation dynamics

The savanna landscape, typical of a number of South Africa's national parks and the focus of this project, provides a classic example of a complex ecological system that is generally characterised by its structure (pattern), function (process) and dynamics of change across different spatial and temporal scales (Turner 1989). Savannas, distinguished by the co-existence of trees and grass at varying densities, continually experience a number of local patch-specific changes due to internal and external mechanisms (see Figure 1.1). Such changes across space create variability, and by quantifying the variability over time, the state of flux of the system can be assessed and long-term trends can be identified. As a whole, these landscapes may therefore experience no mean change or it can change directionally in response to fluctuating processes.

Spatial variation in savanna vegetation is often continuous with patches rarely having distinct boundaries (Pearson 2002). Vegetation pattern may therefore be characterised

by different aspects of vegetation variability. For instance, variability in vegetation patch characteristics, such as patch size and configuration may provide insight into the structural pattern of the landscape mosaic (Li & Reynolds 1994; McGarigal & Marks 1995). On the other hand, spatial and temporal variability of vegetation cover, productivity and biomass presents an entirely different set of aspects that portrays vegetation heterogeneity. The spatial dynamics of vegetation are therefore the direct result of many interacting processes that occur over various temporal scales.

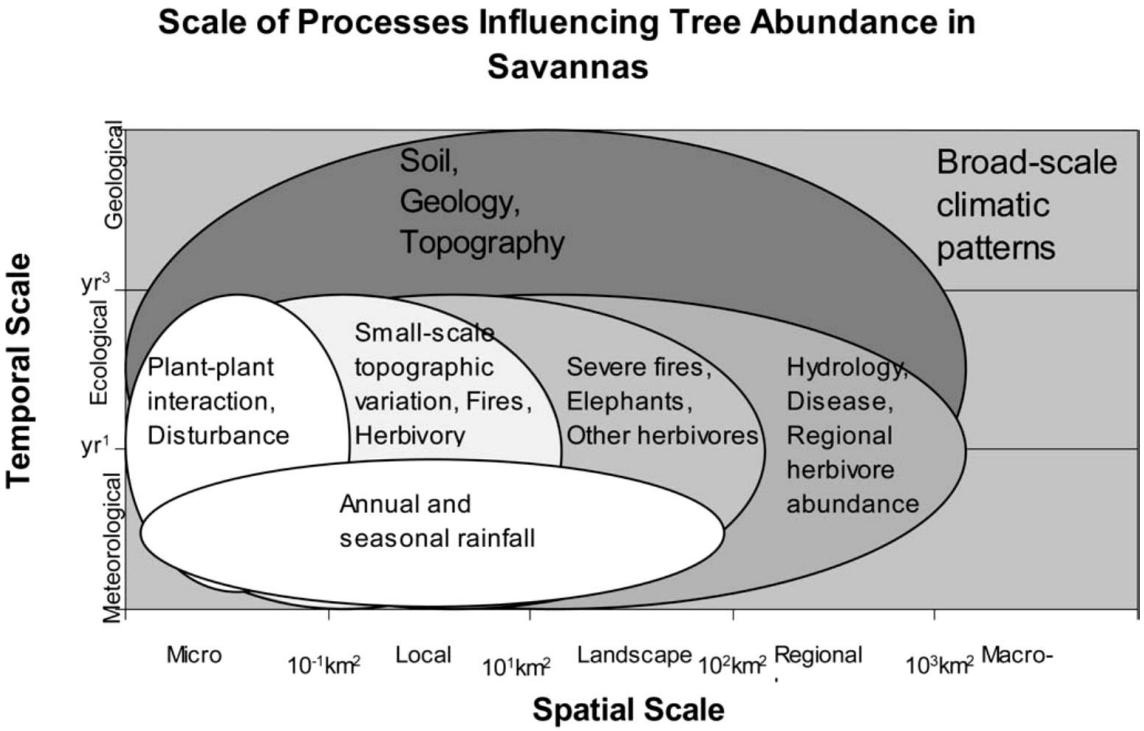


Figure 1.1. A spatio-temporal framework representing the drivers of savanna vegetation pattern (extracted from Gillson 2004).

(c) Drivers and responders of vegetation pattern changes

The spatially and temporally dynamic nature of the pattern of vegetation cover (Wiens *et al.* 1993) is mainly the consequence of several key drivers (Du Toit *et al.* 2003). Reciprocally, vegetation may influence the interactions between the landscape elements.

i. Climate

Climate plays an imperative role in shaping the structure, composition and distribution of vegetation across savanna landscapes (see Figure 1.1). Climate-induced changes may be gradual or more dramatic, but either way, significant (Godfree *et al.* 2011). Precipitation and temperature influences the physiological characteristics of plants directly, but also indirectly shapes vegetation characteristics through the influence it has on the substrate and fires (Venter *et al.* 2003). In the semi-arid savannas of South Africa, precipitation is erratic and typically occurs during the warm summer months. The result is therefore inter-annual variability in vegetation through the effect of precipitation on germination and growth (Venter *et al*. 2003).

Vegetation phenology (intra-annual cycles of vegetation growth and senescence) is strongly dependent on precipitation and day length, which initiates the appearance of green leaves and regulates the duration of vegetation growth (Spano *et al*. 1999; Cook & Heerdegen 2001; Archibald & Scholes 2007). This implies that global climate change may have a significant influence on vegetation cover and variability in this region through the alteration of precipitation seasonality, the incidence of extreme weather events (floods and droughts), and the intensification of precipitation variability (Tyson 1991; Fauchereau *et al*. 2003; MacFadyen *et al*. 2018). Moreover, it is expected that increases in the intensity of precipitation may further stimulate woody plant encroachment by enhancing soil water depth that may favour woody plant water uptake at the expense of grasses with shallower roots (Kulmatiski & Beard 2013; Berry & Kulmatiski 2017).

Through the effect of precipitation on vegetation, the persistence of large herbivore species may also be under threat (Ogutu & Owen-Smith 2003). Temporal variation in primary production due to climatic variability causes fluctuations in population numbers and underlies the seasonal ranging behaviour of large herbivores. The effect of climatic variability on vegetation dynamics therefore indirectly shapes the population and spatial dynamics of large herbivores, which subsequently affects vegetation patterns in a feedback response (Illius & O'Connor 2000).

Heterogeneous landscapes, characterised by a higher diversity of species are more likely to sustain ecosystem processes and stability when presented with disturbances (Tilman 1999; Yachi & Loreau 1999; Loreau *et al*. 2003). For instance, the response of different species to environmental fluctuation may vary in such a way that while the functional contribution of some species may decrease, other species may fulfil that role thus stabilising the ecosystem processes and enhancing persistence (Yachi & Loreau 1999; Loreau *et al*. 2003). Indeed, in a ten-year experiment, Tilman *et al*. (2006) showed that higher grass species diversity resulted in an increased temporal stability of annual aboveground plant production within a grassland ecosystem. Increased vegetation heterogeneity within an ecosystem may therefore enhance the resilience of that system to changes in climate (Holling 1973; Gunderson 2000; Thuiller *et al*. 2005; Virah-Sawmy *et al*. 2009).

Global human-induced climate change (e.g. altered temperature and precipitation patterns) are already causing species extinctions (Thomas *et al.* 2004; Pimm 2008) and geographical range contractions and expansions of species (Thomas *et al.* 2006; Wiens *et al.* 2009). Conservation and management strategies that have resulted from climate change studies therefore mostly focused on planning reserves to incorporate the expected range shifts of species or to enhance landscape connectivity to allow for migration of species (Heller & Zavaleta 2009). Although plans for the expansion of parks in South Africa are in the pipeline (Department of Environmental Affairs, South Africa 2009), maintaining vegetation heterogeneity within existing protected areas may play an imperative role in preserving biodiversity under climate change conditions in the future (Du Toit *et al.* 2003). Park managers should therefore adopt strategies for enhancing resilience through the management and maintenance of vegetation heterogeneity.

ii. Soil

The substrate (soil) is a primary determinant of vegetation pattern (Figure 1.1) and includes several interacting variables such as the topography, geology, geomorphology and the dynamics of water in the soil (Venter *et al*. 2003). Within the savanna landscape, soil characteristics vary greatly and affect the species composition,

physiognomy, structure and function of vegetation (Scholes *et al.* 2003; Venter *et al*. 2003). Soil heterogeneity may be enhanced through the functional role of vegetation (Belsky *et al*. 1989; Pärtel *et al*. 2008), insects (Jouquet *et al*. 2004; Gosling *et al*. 2012) and herbivores (van der Waal *et al.* 2011), while fire can further influence soil characteristics through nutrient mediation (Bond & Keeley 2005). For example, soil-dwelling termites shape vegetation assemblages by altering the soil porosity, texture, nutrient content and infiltration rates (Fox-Dobbs *et al.* 2010; Pringle *et al.* 2010). Additionally, vegetation influences the soil through obstructing surface flow and enhancing infiltration of rain due to the presence of plant debris (e.g. dead leaves) (Belsky *et al.* 1989; Venter *et al*. 2003).

iii. Fire

Fire is a frequent and widespread disturbance in savannas with significant impact on vegetation dynamics. Through the removal of biomass, fire elicits varied outcomes from the interactions with other components in the landscape due to the variation in fire frequency, timing and intensity (van Wilgen *et al.* 2003). For example, increased levels of biomass in the absence of herbivory promote high-intensity fires that can affect tree height distribution. Fire intensity therefore has important consequences for the dynamics of the woody plant layer through its effect on tree mortality and recruitment into larger size classes (Govender *et al*. 2006). Fire intensity is largely determined by the seasonal differences in fuel moisture and fuel load making it a useful parameter that can be manipulated for specific management objectives (Govender *et al.* 2006; Smit *et al*. 2016). High fire frequency, on the other hand, may have alternative effects on vegetation, including the prevention of tree establishment (Trollope *et al.* 1998; Higgins *et al.* 2000) and decreased woody plant basal area, biomass, density, height, and mean stem circumference (Schackleton & Scholes 2000).

The relative importance of fire as an ecological process that maintains the structure of savannas differs for arid (mean annual precipitation <650 mm) and moist savannas (mean annual precipitation >650 mm) (van Wilgen 2009). In arid conditions, low precipitation limits tree density and prevents the woody vegetation from forming closed canopies, even in the absence of fires (van Wilgen 2009). Grass fuel loads are further

limited by precipitation variability and herbivory, thus fire frequency is often more sporadic than in the moist savannas (Holdo *et al.* 2009; van Wilgen 2009). Alternatively, in moist savanna regions, higher precipitation and absence of fire promote woodland canopy closure, while the occurrence of frequent fires and herbivore foraging pressure prevent woodland-dominated state shifts. The effect of fire is therefore expected to be much more dominant in moist savannas (van Wilgen 2009).

iv. Herbivory

The population and spatial dynamics of large herbivores are a function of the availability and distribution of water and food resources (Johnson *et al.* 1992; Gough & Rushton 2000) as well as the distribution of predation pressure (Burkepile *et al*. 2013; Courbin *et al*. 2015). In return, large herbivores can exert considerable changes on vegetation patterns that may even result in state changes (e.g. from woodland to grassland). For example, through removal of the biomass (McNaughton 1979; McNaughton & Chapin III 1985), grazers can modify the water relations between the woody plants and grasses (Sinclair 2003) and further prevent fire from affecting the woody component by limiting fuel loads and subsequently induce a landscape that favours trees and shrubs (Holdo *et al*. 2007). Moreover, by increasing grass quality and productivity, fire may facilitate "grazing lawn" patches, which is then subsequently maintained by the feeding of herbivores (Donaldson *et al*. 2018). In the KNP, the interaction between both fire and herbivores therefore presents another important driver of vegetation dynamics.

Browsers and mixed feeders substantially alter the structure and composition of woody plants. For instance, elephants are often responsible for the loss of trees as they are notoriously known to uproot them in search of food (Jacobs & Biggs 2002) and at large densities may even convert woodlands to a grass-dominated state (Caughley 1976; Owen-Smith 1988; O'Connor *et al*. 2007; Kerley *et al*. 2008), especially when the exacerbating effect of factors such as fire (Shannon *et al.* 2011) and water augmentation (Smit *et al*. 2007) complicates the dynamics. In another example, a substantial decrease in the impala population of Lake Manyara in Tanzania due to anthrax outbreaks, lead to substantial seedling recruitment that transformed the open grassland into thicket (Prins

& van der Jeugd 1993). Tree populations may therefore be negatively affected by meso- and megaherbivores through their contribution to tree mortality and/or the prevention of regeneration.

Large herbivores affect nutrient cycling rates in addition to modifying the physical vegetation structure, thereby altering plant growth rates, distribution, quantity, and quality of vegetation (McNaughton 1984; Sinclair 2003). High soil nutrient content may lead to high net primary productivity that may then result in high herbivore densities. Consequently large herbivore densities may be responsible for rapid vegetation consumption and high faecal deposition, ultimately returning nutrients to the soil which can then be used by the vegetation (McNaughton *et al*. 1997). Thus, in principle, large herbivores maintain their own food resources, and in this manner, create a positive feedback.

Across the KNP landscape, vegetation patterns are characterised by the variation in species composition, spatial distribution and the vertical structure of the plants. Within this vast variability, differences in the quality and the quantity of resources will present herbivores with the template from which they can select favourable resources in order to increase their chances for survival and reproduction. Keystone structures within the landscape may therefore play a distinctive role in large herbivore ecology and in the maintenance of ecological processes (Manning *et al.* 2006). Some of the most important keystone structures include scattered trees (isolated tree and tree-dominated patches) (Parker & Muller 1982; Vetaas 1992; Belsky & Canham 1994), termite mounds (Moe *et al.* 2009; Fox-Dobbs *et al.* 2010; Levick *et al*. 2010), grazing lawns (Archibald 2008; Cromsigt & Olff 2008; Bonnet *et al.* 2010) and sodic patches (Grant & Scholes 2006). Although these keystone structures are fundamentally different in the processes that give rise to them, all are associated with increased vegetation productivity and resource quality, thereby exhibiting important benefits to large herbivores in the form of high energy availability (Duffy & Pettorelli 2012). The functional role of the different keystone structures may therefore vary at finer spatial scales, but at the landscape scale, the functional role may simply translate to the distribution of productive patches among

lower quality patches that create a heterogeneous pattern of vegetation productivity at a coarser spatial resolution.

1.2.2. Vegetation monitoring and change detection

Measuring and monitoring vegetation dynamics at the landscape scale is challenging (Lawley *et al.* 2009), especially if one needs to make inferences about the relative influences of different drivers on vegetation pattern over time. Savanna landscapes are changing constantly. Changes in vegetation can be abrupt (e.g. fire and floods) or it can manifest as gradual trends (e.g. resulting from climate change). The ability to detect change is dependent on the identification of an initial state from which a follow-up altered state may be quantified (Coppin *et al.* 2004). This implies that changes in the spatial distribution of vegetation variables across the landscape are directly related to specific temporal scales (Coppin *et al.* 2004).

Remote sensing, which is a process through which the measurement of an object's reflected and emitted radiation from a distance provides information on its physical characteristics, generates a unique source of data that can be used to identify and quantify spatio-temporal changes in aspects of vegetation at large spatial scales (Xie *et al*. 2008). Vegetation index differencing is a relatively straightforward technique that takes advantage of the unique contrast between the absorption and the reflectance of electromagnetic radiation from the sun by chlorophyll-containing plants. Vegetation indices are defined as "dimensionless, radiometric measures that function as indicators of relative abundance and activity of green vegetation" that are often associated with percentage green cover, chlorophyll content, green biomass, primary productivity and absorbed photosynthetically active radiation (Jensen 2000; Glenn *et al*. 2008). Many vegetation indices have been developed over the years for various applications. Of the more than twenty vegetation indices that exist, the most frequently used include the Normalised Difference Vegetation Index (NDVI) (Lyon *et al.* 1998; Kerr & Ostrovsky 2003; Pettorelli *et al.* 2005), the Enhanced Vegetation Index (EVI) (Huete *et al.* 2002; Hüttich *et al.* 2009) and for sparsely vegetated areas, the Soil-Adjusted Vegetation Index (SAVI) (Glenn *et al*. 2008; Jiang *et al.* 2006). Alternatively, the Leaf Area Index

(LAI) and Fraction of Photosynthetically Active Radiation (fAPAR) are indices with much potential to yield important ecological information (Asner *et al*. 2003; Fensholt *et al*. 2004).

Green, chlorophyll-containing plants display high reflectivity in the near-infrared wavelengths of the radiation spectrum and absorb red wavelengths for photosynthesis. Given this ability of green vegetation to reflect and absorb, NDVI is calculated by the following equation:

$$NDVI = (NIR–VIS) / (NIR + VIS) \qquad \text{(Equation 1.1)}$$

In the equation, NIR is the reflectance of the Earth's surface in the near-infrared channel and VIS is the reflectance in the visible portion of the spectrum or the red channel (Tucker & Sellers 1986). High values of NDVI are indicative of well-developed green vegetation such as closed canopy woodlands or stretches of continuous green grass, whereas low NDVI values are mostly associated with a non-contiguous vegetation cover or a non-green cover like exposed bare soil, water or plant senescence (van Bommel *et al.* 2006).

At large spatial resolutions, NDVI measures are susceptible to inaccuracies through soil surface reflectance and high vegetation densities (Pettorelli *et al.* 2005). Often, the Soil-Adjusted Vegetation Index (SAVI) and more recently, the Enhanced Vegetation Index (EVI) are considered better alternative indices to NDVI for sparsely vegetated areas (Jiang *et al.* 2006; Glenn *et al*. 2008). The EVI is an optimized combination of blue, red, and near-infrared bands, designed to represent canopy greenness without interference from the underlying soil background and atmospheric aerosol variations (Huete 1988; Kaufman & Tanré 1992). EVI is calculated by the following equation:

$$EVI = G\,[(NIR - RED) / (NIR + C1 \times RED – C2 \times BLUE + L)] \qquad \text{(Equation 1.2)}$$

where G is the gain factor; NIR, RED, BLUE are reflectances in the near-infrared, red, and blue bands, respectively; L is the canopy background adjustment factor and C1 and

C2 are the aerosol resistance weights (Liu & Huete 1995). In comparison the EVI is more responsive to canopy structural variations, including leaf area index (LAI), canopy type, plant physiognomy, and canopy structure than the NDVI, which is chlorophyll sensitive (Gao *et al*. 2000).

Another alternative to minimise the inaccuracies from NDVI measures is the Transformed Normalized Difference Vegetation Index (TNDVI), which has been advocated to have a better signal-to-noise ratio in drylands (Perry & Lautenschlager 1984; Washington-Allen *et al*. 2008). The TNDVI is calculated as:

$$TNDVI = 50\ (NDVI + 1) \qquad \text{(Equation 1.3)}$$

For some vegetation index data products (e.g. MODIS and SPOT), the coarse spatial resolution of the data is often pointed out as a disadvantage as it limits the researcher to a specific scale at which finer-scale patterns may not be detected (Bro-Jørgensen *et al.* 2008). However, the disadvantages of the coarse spatial resolution of some vegetation index data products may be outweighed by the advantages of the fine temporal resolution at which such data are available. Additionally, NDVI data do not provide for accurate distinction between woodland and grassland vegetation cover due to subpixel variability (Guerschman *et al*. 2009). Landscape variables such as the fractional cover of woodlands and grasslands may therefore be incorporated into data analyses to compromise for the disadvantages of the vegetation index data.

Vegetation index data sets from various satellite instruments (e.g. MODIS, Landsat, AVHRR, SPOT-VEGETATION) are available at different spatial and temporal resolutions, and different temporal coverage. As a result of certain trade-offs in data volume and satellite instrument design, high-resolution sensors tend to emphasise one of the four main characteristics (spatial, spectral, temporal, or radiometric) at the expense of the other properties [see Figure 1.2 for a schematic illustration extracted from Key *et al*. (2001)]. Selecting the most appropriate image data therefore requires careful consideration of the advantages and disadvantages of the image data from different sensors in order to meet specific project objectives (Key *et al*. 2001; Kerr &

Ostrovsky 2003; Cushman & McGarigal 2004). Selection of one or more vegetation index for a specific study should therefore account for the spatial and temporal resolution and coverage of the data, the sensitivity of the vegetation index to atmospheric and background noise and the compatibility of vegetation index data from different instruments.

Remote sensing techniques for the quantification of vegetation pattern changes mostly involve two main approaches (see review by Sirami 2016). The first and also most frequently applied is a categorical map analysis which is based on the categorisation of vegetation using a patch-mosaic approach (McGarigal & Marks 1995; Turner *et al*. 2001). This form of landscape pattern analysis subdivides satellite images of a landscape into homogeneous patches and classes (Gustafson 1998). Typically, landscape metrics are then applied to quantify vegetation heterogeneity characteristics pertaining to the composition (e.g. number of patch types, proportions of patch type) and the configuration (spatial arrangement of patches, patch shape) of the patch mosaic (Li & Reynolds 1994; McGarigal & Marks 1995; Turner *et al*. 2001). If one should be interested in assessing changes associated with vegetation heterogeneity, landscape metrics applied to categorical maps at different times can then be evaluated comparatively to provide coarse-scale ecological indicators of change (McGarigal & Marks 1995).

Categorical map analysis provides a useful simplification of the landscape that is relatively straightforward to interpret (Li & Reynolds 1994; McGarigal *et al*. 2009). The patch-mosaic approach is well-advanced with a vast number of landscape metrics available for patch characterisation (McGarigal & Cushman 2002). However, categorical map analysis assumes a collection of discrete patches of which the definition is greatly biased by the subjectivity of the researcher who ultimately decides on the basis for defining boundaries (Turner 1989; McGarigal & Cushman 2002). As mentioned previously, patches in savanna landscapes are seldom characterised by distinct boundaries and within-patch variation are unaccounted for by this method (McGarigal & Cushman 2002). Categorical map analysis may therefore not be an appropriate method for continuous vegetation monitoring.

Changes in vegetation characteristics across the savanna landscape may be best quantified using methods that do not assume distinct boundaries and which do not limit quantitative variation through classification processes (see Gustafson 1998). As an alternative to the patch-mosaic approach, spatial changes in vegetation heterogeneity can be quantified on a continuum by which ecologists increasingly take advantage of a landscape-gradient approach (McGarigal & Cushman 2002). In this model, heterogeneity does not exist in discrete patches, but rather exists as a continuously varying property of the local environment and landscape (McGarigal & Cushman 2002). This enables the researcher to preserve some independence of variables in the analysis rather than limiting the set of variables through categorisation based on one or more characteristics. The subjective delineation of boundaries is therefore eliminated, while many computational errors involving scale and boundary sensitivity is also reduced (McGarigal *et al*. 2009). Overall, the landscape-gradient approach based on vegetation index data offers a more robust measure of vegetation pattern that incorporates gradients of certain vegetation characteristics rather than arbitrarily categorising the landscape into discrete patches of similar vegetation cover (Murwira & Skidmore 2005).

(a) The mean-variance time-series analysis

To examine vegetation trends in response to shifts in climate or other variables, continuous vegetation indices (e.g. NDVI, TNDVI and EVI) can be employed to provide an estimation of the amount of variation and the spatial heterogeneity in green vegetation cover across the landscape in question (Washington-Allen *et al*. 2008; Southworth *et al*. 2011; Tsai 2012; Cui *et al*. 2013). Using a mean-variance time-series analysis, vegetation dynamics can be quantified and vegetation response to climate and other variables can be characterised.

The mean-variance time-series analysis was developed by Pickup & Foran (1987) as a specific variant of graphical dynamical systems analysis to characterise the spatio-temporal behaviour of a vegetation index. In this form of graphical analysis, the variance of the vegetation index is plotted as a function of the mean of the vegetation index to produce phase diagrams that describe the shift or trajectory of states through

time (Washington-Allen *et al.* 2008). Specifically, the method may be used to describe and quantify dynamic regimes of vegetation index response to disturbance for a given area using properties of ecological resilience (Zimmermann *et al.* 2007; Washington-Allen *et al.* 2008).

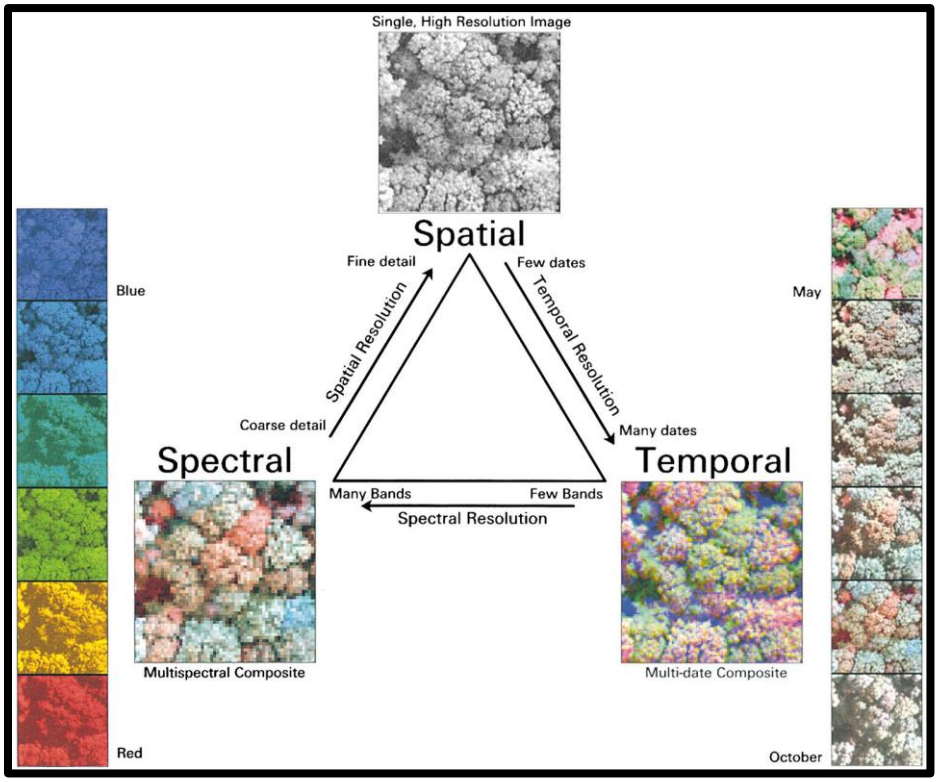


Figure 1.2. Trade-offs has to be made between spectral, temporal, and spatial properties of satellite imagery. For example, users requiring finer temporal resolution data may need to sacrifice spectral or spatial detail due to the limitations imposed by the design of the instrument from which the imagery originated (extracted from Key *et al.* 2001).

Figure 1.3 illustrates a phase diagram of the inter-annual mean-variance dynamics of an agricultural landscape's vegetation index (extracted from Washington-Allen *et al.* 2008). This particular phase diagram consists of four sectors that are delineated by the overall mean and mean variance of the landscape's NDVI time series (Washington-Allen *et al.* 2008). The mean NDVI reflects on the amount of green vegetation (cover) and the variance gives an indication of the degree of heterogeneity in the spatial distribution of green vegetation biomass (Washington-Allen *et al.* 2008). Vegetation

dynamics are therefore quantified as the trajectory of the states of green vegetation cover and variability across the landscape as represented by the sequence of time steps (e.g. annual) over the period of interest.

Each sector in the phase diagram represents the condition of the landscape's trajectory (Figure 1.3). Specifically, sector 1 signifies a relatively degraded condition of the landscape with lower green vegetation cover and lower variability as measured by a predefined reference state. Sector 2 indicates higher heterogeneity but in this case a higher proportion of the landscape tends toward bare ground (low vegetation cover) and thus, may be more prone to degradation. Sector 3 represents a state where a higher proportion of the landscape has green vegetation cover with high variability, and sector 4 indicates relatively stable conditions where the green vegetation cover is high and relatively homogenous (Figure 1.3).

Within the phase diagram, the mean and variance of each point in the time-series can settle within any of the sectors as determined by the time-specific vegetation greenness and might not follow a specific sequence over the time series. However, for a heterogeneous savanna landscape, it is expected that points in Sector 1 would characterise years of very low precipitation, while points for years with exceptionally high precipitation would show up in Sector 4. The points representing years with more variable precipitation is expected to settle in Sectors 2 and 3 where vegetation greenness heterogeneity will be highest.

The significance of change implies thresholds where the normal range of change is exceeded (Washington-Allen *et al.* 2008). For instance, a reference state may be defined by a minimum value of the vegetation index or the calculation of a cover line, indicating the amount of vegetation cover at which soil background noise may dominate the vegetation signal of the index (Huete *et al.* 2002). This line therefore allows for the interpretation of the condition and trajectory of vegetation cover with regard to a pre-defined undesirable state or condition (Washington-Allen *et al.* 2008).

Measuring and monitoring vegetation change across diverse landscapes has most frequently been the subject of localised field surveys and evaluations of discrete data satellite imagery. Field surveys are limited by their cost and logistical requirements for observing changes across spacious landscapes, while analyses based on sporadic temporal satellite observations of the landscape are inadequate for characterising the historical context of change within a region. The mean-variance time-series analysis provides a method through which the dynamics of change in vegetation greenness and productivity can be detected across large areas on a more continuous basis. The method may therefore hold much promise as a baseline, coarse-scale monitoring method, which is cost- and time-effective and relatively easy to apply.

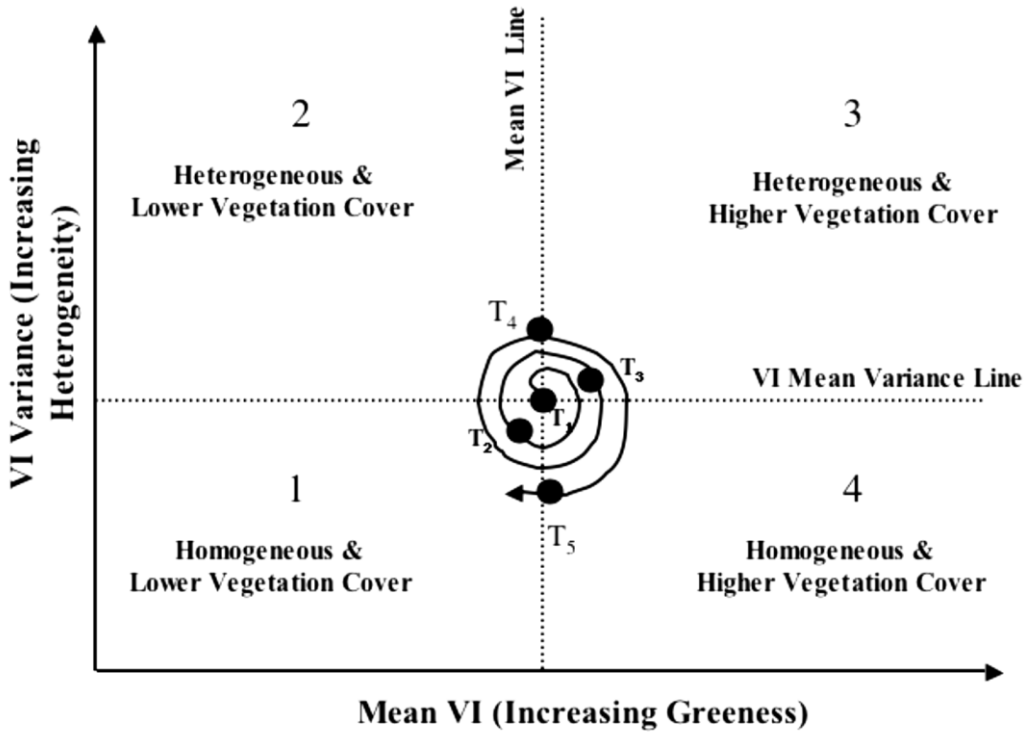


Figure 1.3. Hypothetical phase diagram of the inter-annual mean-variance dynamics of an agricultural landscape's vegetation index (VI). T = time (extracted from Washington-Allen *et al.* 2008).

(b) Spatial persistence analysis

Application of the mean-variance time-series analysis is often paired with a persistence analysis to assess vegetation changes in a spatially explicit manner (Gibbes 2006; Tsai

2012; Tsai *et al.* 2014). Based on statistical image differencing, the persistence analysis is employed as the quantification (e.g. percentage pixels) and visualisation of the spatial accumulation of disturbance impacts at the landscape scale (Gibbes 2006). More recently, Waylen *et al*. (2014) developed the concept of persistence metrics. Directional and Relative directional persistence metrics encapsulate the direction of change, while Massive persistence captures both magnitude and direction of NDVI change over time. Statistical significance levels of all three metrics can be established in order to emphasise the spatial extent of areas that experienced unusual change (Gibbes *et al.* 2014; Waylen *et al.* 2014). These persistence metrics (Waylen *et al*. 2014) are calculated by the following equations:

Directional persistence: A measure, D, of the cumulative direction of change over time relative to a fixed reference observation of NDVI (e.g. disturbance event such as El Niño), during successional annual observations of NDVI values is derived as:

$$D = \sum_{i=1}^{n-1} t_i \qquad \text{(Equation 1.4.1)}$$

$$V_{ref} < V_i : t_i = +1 \qquad \text{(Equation 1.4.2)}$$

$$V_{ref} > V_i : t_i = -1 \qquad \text{(Equation 1.4.3)}$$

where V*ref* is the observed NDVI values at the time of the reference state and V_i is the annual NDVI at time *i*. For example, V*ref* is the reference state NDVI values for the year 2000. A value of +1 is assigned to t_i when the pixels for that year record a value of NDVI greater than the reference state, and -1 for values less than the reference state. In this study, the consistency of persistence across the different NDVI products was of special interest and we defined the threshold reference state by the initial NDVI observations made in the time series.

Relative directional persistence: A measure, R, of the cumulative direction of change in NDVI values over time relative to the preceding year's observations of NDVI, during successional annual observations is derived as:

$$R = \sum_{i=1}^{n-1} t_i \qquad \text{(Equation 1.5.1)}$$

$$V_i < V_{i+1} : t_{i+1} = +1 \qquad \text{(Equation 1.5.2)}$$

$$V_i > V_{i+1} : t_{i+1} = -1 \qquad \text{(Equation 1.5.3)}$$

Directional and Relative directional persistence metrics provide valuable, complimentary landscape measures of the direction of change. However, to account for the magnitude of the changes in a series, a third metric is calculated.

Massive persistence: A measure, M, of the cumulative direction and magnitude of change over time relative to the preceding year's actual observations of NDVI, during successional annual observations is derived as:

$$M = \sum_{i=1}^{n-1} (V_{i+1} - V_i) \qquad \text{(Equation 1.6)}$$

The greatest advantage of the use of the persistence metrics is that it enables interpretation of the changes of vegetation greenness relative to a predefined benchmark or reference condition (Washington-Allen et al. 2008; Waylen et al. 2014). Benchmark conditions could include the initial condition (start of the time series), deviation from some measure of central tendency (e.g. mean), calculation of a critical boundary condition (e.g. minimum or percentile) as well as the condition set by a point in the time series when the conditions were under pressure from a disturbance (e.g. drought). Given that the time series is assessed relative to a benchmark, it provides a comparative basis for the description of the time series behaviour (e.g. increasing, decreasing or no change). For instance, if the benchmark condition is defined as a year that was

characterised by drought conditions, the persistence metrics may therefore provide insight into the recovery and resilience of the system. As Directional and Relative directional persistence only account for the direction of change, these metrics are not influenced by years characterised by extreme increases or decreases. Massive persistence however do take the magnitude of change into account and although extreme values may seem to affect the metric disproportionately, such extreme years are expected to have ecological significance that may carry over to subsequent years. Given the sensitive nature of the persistence metrics, defining benchmark conditions (reference state) should be considered carefully with regard to the objectives of the study questions and interpreted accordingly.

(c) Phenology

Phenology depicts the seasonal cycle of leaf functioning and provides fundamental information for understanding the interactions between the biosphere, climate and biogeochemical cycles (Reed *et al.* 1994; Myneni *et al*. 1997; Schwartz & Reed 1999; Menzel 2000; Nemani *et al*. 2003). Vegetation phenology is primarily linked to climatic conditions as precipitation and temperature plays a major role in the greening characteristics of plants. The timing and development of vegetation may therefore provide invaluable information to help researchers make inferences about vegetation condition and the biophysical environment (Reed *et al*. 1994).

Phenological analyses involve the use of vegetation index time series data to derive key phenology metrics (seasonality parameter) that describe aspects of the phenological growing season. Examples include parameters such as the time of the start and end of the season, the length of the season, and the amplitude of the season. Figure 1.4 illustrates an example of the phenological parameters that can be derived from a fitted curve as described in the Timesat 3.1 software manual by Eklundh & Jönsson (2012). Year-to-year changes in these parameters may therefore signal important changes in climate and land cover which is essential for understanding vegetation dynamics.

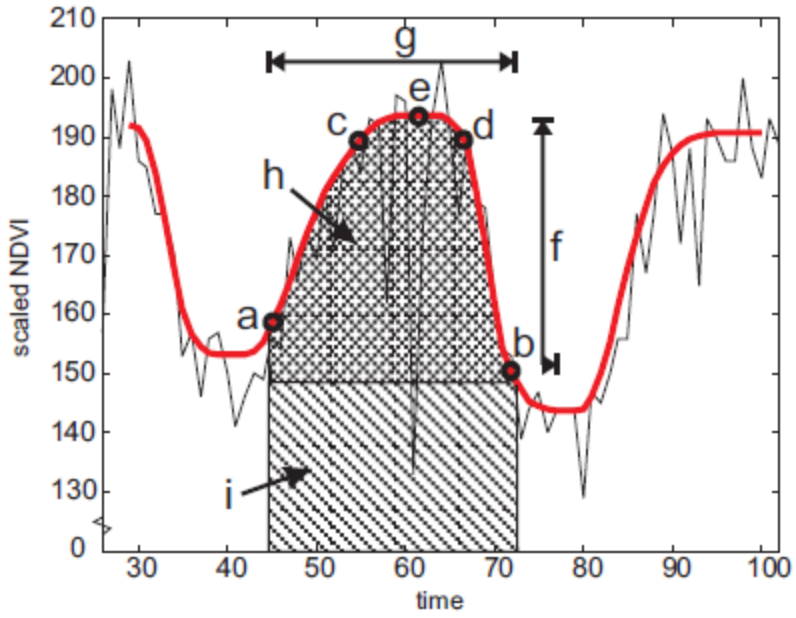


Figure 1.4: An example of the phenological parameters that can be derived from a fitted curve as described in the Timesat 3.1 software manual by Eklundh & Jönsson (2012). Here, (a) and (b) indicate the start and end of the growing season, respectively. Points (c) and (d) represent the 80% levels. The point marked (e) is the point with the highest value. The distances indicated by (f) and (g) depict the seasonal amplitude and seasonal length, respectively. Finally, (h) and (i) are integrals showing the cumulative effect of vegetation during the season.

(d) Using NDVI to monitor vegetation dynamics

Based on its long-term availability (more than 20 years), NDVI (or variants thereof) has been the vegetation index of choice in applications of the mean-variance time-series analysis (Washington-Allen *et al*. 2008; Tsai 2012; Cui *et al*. 2013). NDVI, as an index of vegetation greenness, is commonly used as a proxy for vegetation quality or productivity (Myneni *et al*. 1995; Groom & Harris 2009).

Studies that applied the mean-variance time-series analysis to quantify spatio-temporal trends in vegetation dynamics mostly relied on NDVI data derived from Landsat imagery (e.g. Washington-Allen *et al*. 2008; Cui *et al*. 2013). Typically, these studies used one Landsat scene representative of the dry season for each of the years over the period of interest to avoid excessive cloud cover (E.g. < 10% - Washington-Allen *et al*.

2008). Landsat-based assessments are limited by a temporal resolution of 16 days, image availability and infrequent image acquisition dates (Ju & Roy 2008), which makes the use of Landsat data difficult for assessments of vegetation dynamics across different seasons, especially in landscapes with a pronounced annual phenological cycle such as savannas. In this study, I am interested in the inter-annual trajectories of vegetation greenness across the phenological cycle represented by a wet season, a dry season and two inter-peak seasons. This makes it necessary to consider the NDVI data from other satellite sensors that represents higher frequency multi-temporal data. The high temporal resolution of NDVI data sets derived from AVHRR, MODIS and SPOT-VEGETATION allows for a more dynamic representation of vegetation changes. However, the assessment of trends from coarse resolution data (250 m – 8 km) may be confounded by problems related to spectral mixtures and the pre-processing of remote sensing data sets (Yin *et al*. 2012). It is therefore important to acquire an understanding of the possible differences in trends that may result from different data sets in order to interpret the trajectories of change correctly.

1.3. Aim and objectives

In this thesis, I aim to develop and evaluate combinations of mean-variance, spatial persistence and phenology analyses as a methodological approach for the assessment and monitoring of landscape-scale spatio-temporal trends in vegetation greenness dynamics in relation to precipitation, fire and elephants across the Kruger National Park. Ultimately, the intention is to provide the first step towards the development and implementation of a broad-scale monitoring approach that can detect spatially-explicit vegetation change trends along with the associated driver effects in order to guide future prioritisation of limited resources and management efforts.

The objectives of this research project together with their associated research questions are listed below:

1.3.1. Objective 1 (addressed in Chapter 2)

To compare and evaluate remotely sensed NDVI data from different satellite sensors using mean-variance and spatial persistence analyses to characterise inter-annual vegetation trends across the Kruger National Park landscape.

> ***Question 1:*** How do the behaviour of NDVI data from different satellite sensors compare within the application of mean-variance and spatial persistence analyses?
>
> ***Question 2:*** How effective is the combined application of mean-variance and spatial persistence analyses in tracking broad-scale vegetation changes in a protected area landscape?

1.3.2. Objective 2 (addressed in Chapter 3)

To characterise and compare spatial vegetation greenness trends in response to two phenometrics (start of season and length of season) and precipitation between 2002 and 2015 in order to provide unique insight into the relative role of precipitation as a driver of vegetation change patterns in the KNP.

> ***Question 1:*** How did the overall vegetation greenness trends vary spatially across the KNP in response to trends in mean growing season precipitation, mean season onset and mean season length?
>
> ***Question 2:*** What were the cumulative persistence trends in vegetation greenness, season onset, season length and growing season precipitation and how were these spatially related?

Question 3: What was the spatial extent of significant persistence in vegetation greenness and how did it spatially overlap with significant changes in season onset, season length and growing season precipitation?

1.3.3. Objective 3 (addressed in Chapter 4)

To evaluate a methodological approach for the broad-scale identification and monitoring of the role of fire and elephants as drivers of change trends in pheno-season vegetation greenness.

Question 1: How do (a) elephant bull density, (b) elephant herd density and (c) fire frequency differ for NDVI trend zones?

Question 2: What are the relationships between the pheno-season NDVI and (a) elephant bull density, (b) elephant herd density and (c) fire frequency for the different NDVI trend zones?

Question 3: How do the relationship between annual pheno-season NDVI and (a) elephant bull density and (b) elephant herd density differ for burn areas and non-burn areas?

Question 4: How effective was our methodology for the broad-scale monitoring and evaluation of the effects of elephants and fire on vegetation greenness trends?

1.4. Structure of the thesis

The thesis has been prepared as a series of three content chapters (Chapter 2-4) formatted as papers for submission to appropriate scientific journals. It includes an introductory chapter (Chapter 1) outlining the issues addressed in the research, and a concluding chapter highlighting and synthesising the main findings of the thesis (Chapter 5). Some repetition of the methodology occurs in the chapters due to the

content chapters (Chapter 2-4) having been prepared as research articles for submission to scientific journals.

1.4.1. Publication details

The following journals have been selected for the first submission of the content chapters:

Chapter 2 – *Remote Sensing of Environment* (reviewed, ready for resubmission)
Chapter 3 – *Landscape Ecology* (in preparation)
Chapter 4 – *Journal of Arid Environments* (in preparation)

1.4.2. Author contributions

The paper versions of Chapters 2-4 include my PhD supervisor as co-author. The list below provides a description of the contributions of each author:

- **Y. Ernst:** PhD candidate and primary author
  (will be publishing as "Y. Ernst-de Beer")
- Conducted all data extraction, preparation and analyses
- Responsible for paper concepts, result interpretation and write-up

- **B.F.N. Erasmus:** PhD Supervisor
- Provided guidance with regard to theoretical approach
- Commented on various drafts of all chapters as well as the paper versions

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CHAPTER 2

COMPARISON OF NDVI PRODUCTS IN THE EVALUATION OF SPATIO-TEMPORAL VEGETATION DYNAMICS IN A SAVANNA

2. COMPARISON OF NDVI PRODUCTS IN THE EVALUATION OF SPATIO-TEMPORAL VEGETATION DYNAMICS IN A SAVANNA

2.1. Abstract

Effective vegetation monitoring is an elementary requirement for protected area conservation. In this study, we evaluate the application of mean-variance analyses in combination with spatial persistence analyses for the monitoring of savanna vegetation dynamics. Previous applications of the methods focused on describing regional vegetation dynamics across different land use categories with various NDVI data products. Our assessment of the methods therefore focused on comparing the behaviour of different NDVI data products over a 10-year period for the smaller scale savanna-dominated Kruger National Park landscape. Results indicate that the combined application of a mean-variance analysis with a spatial persistence analysis can successfully describe savanna vegetation dynamics at the smaller landscape scale. Our study further showed that spatial and temporal vegetation cover trends are relatively consistent for Landsat, MODIS and SPOT-VEGETATION data products although expected differences occur due to inherent dissimilarities in sensor characteristics. Careful interpretation is needed when using a specific product and combining products into one analysis may require normalisation of the NDVI data. As a baseline monitoring approach, the methodology holds much potential for the identification of rainfall-driven vegetation trends. By using data with finer temporal resolution, intra-annual vegetation dynamics may also provide valuable information regarding local drivers, such as fire and herbivores.

Keywords: Mean-variance analysis, persistence metrics, Landsat, MODIS, SPOT-VEGETATION

2.2. Introduction

An understanding of the patterns and processes of the key environmental resources of a protected area is a baseline requirement for effective management. Vegetation

monitoring is therefore one of the most important aspects for protected area conservation, especially in the light of a global threat such as climate change (Hannah *et al.* 2002; Meadows 2006; Heller & Zavaleta 2009).

Maintaining and enhancing ecosystem integrity is a fundamental objective in the conservation of South Africa's wildlife in national parks (Ferreira *et al.* 2011). Ecosystem function is dependent on ecological processes that can sustain a dynamic state that fluctuates upon disturbances of varying frequencies (Hobbs & Huenneke 1992). Such disturbance frequencies may reach upper and lower extremes that may compromise ecosystem integrity and ultimately result in biodiversity loss of plants and animals (Hobbs & Huenneke 1992; Holdo *et al.* 2009; Briske *et al.* 2010). The ability of an ecosystem to either recover from change or to withstand change are therefore very important concepts to consider when such ecosystems need to be managed for influences such as climate change (Heller & Zavaleta 2009; Mori 2011).

SANParks (South African National Parks) recognises the importance of change detection and recently adopted an adaptive management strategy that involves Thresholds of Potential Concern (TPCs) (Biggs & Rogers 2003). These TPCs, mostly developed for the larger Kruger National Park, are essentially a set of hypothesised limits of tolerable change in ecosystem composition and function that can be adaptively modified as knowledge is gained (Biggs & Rogers 2003). The development of this strategy is a continuing process with many aspects still in need of improvement (Biggs *et al.* 2011; Ferreira *et al.* 2011; Gaylard & Ferreira 2011), especially for the smaller national parks (Gaylard & Ferreira 2011). This highlights the need for a baseline cost-effective landscape-scale monitoring approach through which SANParks may be able to identify vegetation trends of concern that may be prioritised for possible management intervention.

Measuring and monitoring vegetation change across protected areas with differing management and diverse vegetation has most frequently been addressed at local scales with field survey techniques and analyses of discrete date satellite imagery. Field surveys are costly, time consuming and logistically challenging for monitoring changes

across landscapes (Xie *et al.* 2008), while studies based on remotely sensed data of only a few temporal snapshots of the landscape are limited in their ability to generate a historical context of change within a region (White *et al.* 2003).

The application of remotely sensed vegetation indices in a mean-variance time-series analysis, which is essentially a graphical depiction of the temporal dynamics of a system (Pickup & Foran 1987; Washington-Allen *et al.* 2008), offers a method with much potential to describe and quantify dynamic regimes of vegetation response within a resilience framework (Washington-Allen *et al.* 2008; Cui *et al.* 2013). Hereby, the method allows for the detection of the states of vegetation cover over time relative to disturbance events (Pickup & Foran 1987). The mean-variance time-series analysis is further often paired with a persistence analysis through which changes in vegetation can be expressed spatially (Tsai 2012; Gibbes *et al.* 2014; Tsai *et al.* 2014). Based on statistical image differencing, the persistence analysis is employed as a spatial aggregation approach whereby the collective impacts of a disturbance at the landscape scale can be expressed as a percentage of affected pixels at various time periods (Waylen *et al.* 2014). Image differencing is therefore a form of change detection that allows spatial quantification and visualisation of the direction and magnitude of change across a landscape.

The mean-variance analysis therefore enables the evaluation of the relative states of vegetation on a temporal scale while the persistence analysis addresses the spatial aspect of vegetation change. For example, Washington-Allen *et al.* (2008) effectively applied the methodology to show an agropastoral dryland landscape located in the Northern Altiplano of Bolivia had decreased vegetation cover and increased variance in response to the intense 1982–1984 El Niño-induced drought. They further identified the wet meadow vegetation cover class as a key resource being the most resilient and the least susceptible to soil erosion compared to other cover classes (Washington-Allen *et al.* 2008). In another study with the mean-variance and spatial persistence analyses combined, Gibbes *et al.* (2014) indicated that changes in climatic patterns across the Kavango-Kwando-Zambezi catchment area of southern Africa resulted in varied vegetation responses and resilience characteristics across differing ecosystems.

Specifically, their study suggested a general increase of biomass in drier savannas, despite a decrease in mean annual precipitation after the late 1970's. However, the wetter savanna areas, characterised by miombo woodlands, showed more vulnerability in response to increasing variability in rainfall and may therefore be more prone to state shifts (Gibbes *et al.* 2014).

With the use of NDVI (Normalised Difference Vegetation Index) as long-term representation of green vegetation (Rouse *et al.* 1973; Sellers 1985), the approach may provide a baseline, cost-effective long-term monitoring method for protected areas. Due to its long-term availability, NDVI (or variants thereof) has been the vegetation index of choice in applications of the mean-variance time-series analysis (Washington-Allen *et al.* 2008; Tsai 2012; Cui *et al.* 2013; Tsai *et al.* 2014). Although NDVI saturates for large biomass values (Hobbs 1995) and soil reflectance at very low biomass values influence smaller NDVI values (Pettorelli *et al.* 2005), there remains a strong positive relationship between NDVI and vegetation biomass (Hobbs 1995; Wessels *et al.* 2006).

Previous applications of the mean-variance and spatial persistence analysis approach mainly focused on characterising regional vegetation trends across different land use categories (Cui *et al.* 2013; Tsai *et al.* 2014). In these cases, protected areas were considered a relatively homogenous class within the study areas and the more subtle differences in vegetation cover within the protected areas have not been specifically subjected to the proposed methods. Moreover, studies that applied the mean-variance time-series analysis using NDVI data derived from Landsat TM/ETM+ imagery (e.g. Washington-Allen *et al.* 2008; Cui *et al.* 2013) typically used one Landsat scene representative of the dry season for each of the years over the period of interest to avoid excessive cloud cover (E.g. < 10% - Washington-Allen *et al.* 2008). Landsat-based assessments are limited by image availability and infrequent image acquisition dates (Ju & Roy 2008), which makes the use of historical Landsat data difficult for assessments of intra-annual vegetation dynamics, especially in landscapes with a pronounced annual phenological cycle such as savannas (Coppin *et al.* 2004). More recently, this limitation imposed by Landsat data (Ju & Roy 2008) motivated the use of NDVI data products with more consistent temporal feedback (Tsai *et al.* 2014; Southworth *et al.* 2016).

In order to explore long-term intra-annual dynamics of change, it may be worth sacrificing some spatial resolution to benefit from the more temporally continuous and consistent SPOT-VEGETATION and MODIS NDVI data products. We expected the trajectories of change for MODIS and SPOT-VEGETATION data to be relatively similar to that obtained for the Landsat data despite inherent differences related to sensor characteristics and the processing of the data products (Théau *et al.* 2010; Yin *et al.* 2012). It is therefore important to acquire an understanding of the possible differences in trends that may result from different data products in order to interpret the trajectories of change correctly. The aim of the study was therefore to evaluate the use of mean-variance analyses in combination with spatial persistence analyses for the monitoring of savanna vegetation dynamics across a protected area while comparing different NDVI products over a 10-year period. We provide an example of the application of the methods using MODIS NDVI data. Hereby we describe the spatio-temporal trend of vegetation greenness between 2002 and 2015 across the Kruger National Park to illustrate how the methods can be informative to the management of the park.

2.3. Materials and Methods

2.3.1. Study area

The Kruger National Park (KNP) (24° S, 31.5° E) together with the Associated Private Nature Reserves, (APNR), cover an approximate area of 23 000 km^2 in the north-eastern region of South Africa (Figure 2.1). The APNR is an association of privately owned nature reserves bordering the west of the Kruger National Park spanning 1800 km^2 of land dedicated to conservation. In June 1993 the fences between KNP and the APNR were removed and the combined area can therefore be regarded as a unit. For the purpose of the study, referral to KNP or "the park" also includes the APNR. Classified as semi-arid savanna, the climate of the park is subtropical with hot, wet summers and dry winters. Rainfall mostly occurs from November to April following a gradient that ranges from ~300-500 mm per year in the north to ~500-700 mm per year in the south.

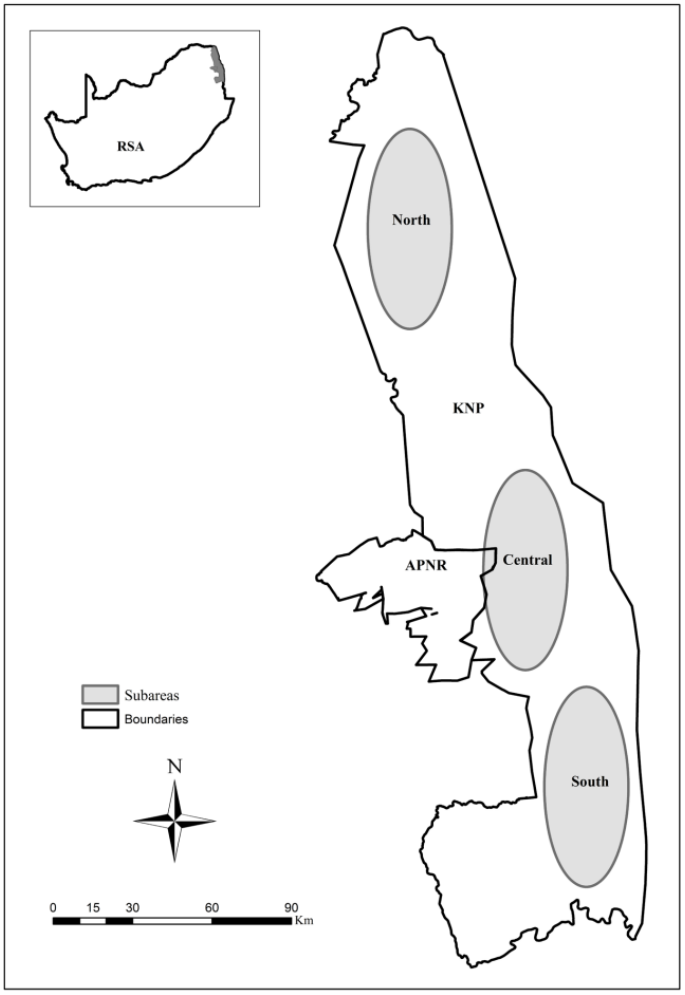


Figure 2.1. The location and extent of the study area represented by the north, central and south subareas across the Kruger National Park (KNP) and Associated Private Nature Reserves (APNR).

KNP is divided into sandy, nutrient-poor soils originating from granite substrates in the west while clay-rich soils weathered from basalts dominate the east (Venter *et al.* 2003). In the north, the granite areas are characterised by mopane (*Colophospermum mopane*) and red bush willow (*Combretum apiculatum* subsp. *apiculatum*) with low grass cover, while basalts to the east mostly support mopane shrubs (Van Wilgen *et al.* 1998). Centrally, on the basalts and gabbros, savanna grassland is interspersed with tree species such as knobthorn (*Senegalia nigrescens*), umbrella acacia (*Vachellia tortilis*) and marula (*Sclerocarya birrea*), while the central granites carry denser woody cover dominated by *Combretum* and *Terminalia* species and less grass. Towards the south-east, stretches of broadleaf mixed woodland amongst a less palatable grass layer are

found on granite substrate, while thorn thickets become more prominent on the basalts to the west. Apart from the large-scale general patterns, a variety of geological formations, soil types and climatic conditions underlie heterogeneous vegetation varying from open bushveld savanna to closed woodland (Du Toit *et al.* 2003).

Previous studies that applied the mean-variance and spatial persistence analyses reported varied responses for differing ecosystems (Gibbes *et al.* 2014). Therefore, in order to account for the broad-scale differences in vegetation and climatic conditions described above, comparisons between NDVI data products were repeated for three similarly-sized subareas (1880.4 km^2) that were representative of the north (mopane-dominated veld), central (open savanna) and south (woodland) of the Kruger National Park (Figure 2.1) with KNP central overlapping the eastern boundary area of the APNR.

2.3.2. NDVI data products

We used NDVI imagery from three different satellite instruments: Landsat, MODIS and SPOT. Landsat TM/ETM+ scenes (30 m spatial resolution) were obtained from the United States Geological Survey (USGS) Land Processes Distributed Active Archive Center (DAAC) at the Earth Resources Observation and Science (EROS) Data Center (URL: http://earthexplorer.usgs.gov). Landsat scenes were selected to represent an annual time-series with minimal (<15%) cloud cover from 2000 to 2011 for the KNP north subarea and from 2000 to 2010 for the KNP central and south subareas. Given the failure of the Landsat ETM+ Scan Line Corrector (SLC) in 2003 and excessive cloud cover for scenes available from Landsat TM archives, suitable scenes for 2003 could not be obtained. As this study focuses on a methodological comparison of NDVI data products, the changes in NDVI values from 2002 to 2004 were treated as a single annual time step. Landsat images were standardised and projected to the Universal Transverse Mercator (UTM) projection system (zone: 36S; reference datum: WGS 1984) and converted to NDVI images using the standard NDVI tool in ERDAS software (ERDAS IMAGINE® 2015). The KNP north subarea were represented by the 169/76 path-row images while the KNP central and KNP south subareas overlapped with the 168/77 path-row images.

The MOD13Q1 version 5 product consisting of 16-day composites, is available at a 250 m spatial resolution through the MODIS Reprojection Tool Web Interface from the USGS DAAC at EROS (URL: http://mrtweb.cr.usgs.gov/). The SPOT-VEGETATION S10 products were downloaded from the Vlaamse Instelling voor Technologisch Onderzock (VITO) Image Processing Center (www.vgt.vito.be). The SPOT-VEGETATION S10 products (from here on referred to as SPOT) comprise 10-day maximum value composites at 1 km spatial resolution. MODIS and SPOT composite images were selected to coincide with the acquisition dates of the Landsat images and were also projected to the WGS 1984 UTM 36S.

Landsat, MODIS and SPOT NDVI images were clipped to the extent of the KNP north, central and south subareas. Annual (based on calendar-year) NDVI means and variances were then calculated separately for each subarea using the Spatial Analyst extension of ArcGIS 10.2 (ESRI, Inc. 1999-2010). Statistical analyses for each of the subareas were done with Prism 6 software (© 1992-2014 Graphpad Software, Inc.).

2.3.3. Mean-variance analysis

A mean-variance phase diagram is essentially a graph of the NDVI variance as a function of the NDVI mean where the mean NDVI is a proxy of green vegetation cover and the variance gives an indication of the degree of heterogeneity in the spatial distribution of green vegetation (Washington-Allen *et al.* 2008; Gibbes *et al.* 2014). The phase diagram typically consists of four sectors delineated by a reference state (Figure 2.2). The significance of change implies thresholds where the normal range of change is exceeded (Washington-Allen *et al.* 2008). For instance, a reference state may be defined by the grand mean and average variance of the landscape's NDVI time series. Alternatively, a minimum value of the vegetation index or the calculation of a cover line, indicating the amount of vegetation cover at which soil background noise may dominate the vegetation signal of the index (Huete *et al.* 2002) may be used. This line enables interpretation of the condition and trajectory of a location with regard to vegetation cover and, by extension, bare ground as a proxy for soil erosion or degradation (Washington-Allen *et al.* 2008). Careful consideration should therefore be

given to the way the reference states are defined in order to keep it relevant to the study questions.

As described by Washington-Allen *et al.* (2008), each sector in the phase diagram represents the condition of the landscape's trajectory (Figure 2.2) as a relative measure of green vegetation cover (NDVI mean) and green vegetation heterogeneity (NDVI variance). Specifically, sector 1 signifies a landscape with less green vegetation cover and less heterogeneity compared to a predefined reference state. Sector 2 indicates greater heterogeneity but less vegetation cover and thus, may be more prone to degradation. Sector 3 represents a state of relatively greater green vegetation cover and heterogeneity, while sector 4 indicates relatively stable conditions where the green vegetation cover is more substantial and comparatively homogenous (Figure 2.2). The shaded area on the phase diagram in Figure 2.2 indicated as the SD zone is derived from the standard deviation of the grand mean and average variance. The SD zone, defined for comparative purposes, gives an indication of the magnitude of the deviation of individual mean-variance points from the reference state. It should be emphasised that the calculation of a reference state is dependent on the question asked and the standard deviation is only one method by which to define it.

We constructed mean-variance phase diagrams for each of the subareas using the Landsat, MODIS and SPOT NDVI data products. We therefore produced graphical representations of the long-term trajectories in vegetation dynamics of KNP north, central and south on an annual (based on calendar-year) time-step. For each of the subareas, the means, variances, and overall trajectories obtained for each of the data products were then statistically compared and analysed for the series of time that the data sets overlapped. In order to establish the similarity of the mean-variance trajectories between the different NDVI data products for KNP north, central and south, respectively, we first evaluated the magnitude of change in NDVI mean and variance on the phase diagrams. For each NDVI data set, we multiplied the variance values by 10 in order to standardise the order of magnitude for the means and the variances so that the variances do not disproportionally influence the distance calculation. We then

calculated the Euclidean distances between each pair of consecutive years following the equation:

$$d(_{t,t+1}) = \sqrt[2]{(M_{t+1} - M_t) + (V_{t+1} - V_t)} \qquad \text{(Equation 2.1)}$$

where, d is the distance between the mean (M) and variance (V) measured at time (*t*) and the following year (time *t+1*), thus for each NDVI data set, the distance between mean-variance points on the phase diagram was calculated on an annual time step. We assessed the consistency of the magnitudes of change as measured by the Euclidean distance for the different data products and subareas with a Pearson rank correlation test.

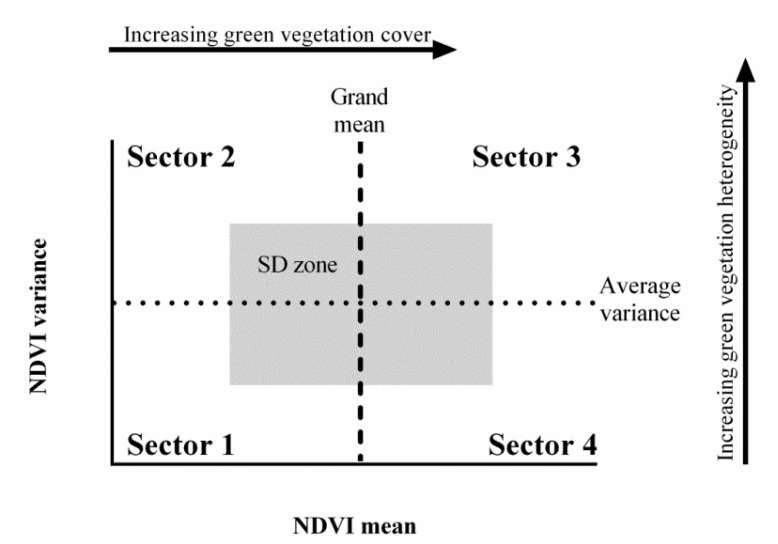


Figure 2.2. Hypothetical mean-variance relationship and associated vegetation status of each sector in the phase diagram delineated by the grand mean and average variance (based on illustration from Washington-Allen *et al.* 2008).

The annual change between points on the phase diagram further required a test of the direction of change. For each NDVI data set, we recorded the direction of change for each of the annual time steps. In this case, we specified the direction as the sector towards which the change occurred with respect to the previous year. Time steps for the MODIS and SPOT data (observed data) were then categorised as "similar" (direction of change towards the same sector) or "different" (direction of change towards any of the three other sectors) compared to Landsat directions (expected data). We then used a χ^2-

test to assess the null hypothesis that there is no significant difference between the expected and observed directions of change.

2.3.4. Spatial persistence analysis

The spatial persistence analysis involved the use of three persistence metrics developed by Waylen *et al.* (2014) and applied by Gibbes *et al.* (2014). Directional and Relative directional persistence encapsulate the direction of change, while Massive persistence captures both magnitude and direction of NDVI change over time. To highlight areas that have likely experienced pronounced cumulative changes, statistical significance levels can be established for all three metrics (Gibbes *et al.* 2014; Waylen *et al.* 2014).

Directional persistence

A measure, D, of the cumulative direction of change over the time relative to a fixed benchmark observation of NDVI (e.g. disturbance event such as El Niño), during a series of annual observations of NDVI values is derived as:

$$D = \sum_{i=1}^{n-1} t_i \qquad \text{Equation 2.2.1}$$

$$V_{ref} < V_i : t_i = +1 \qquad \text{Equation 2.2.2}$$

$$V_{ref} > V_i : t_i = -1 \qquad \text{Equation 2.2.3}$$

where V*ref* is the observed NDVI values at the time of the reference state and V*i* is the annual NDVI at time *i*. For example, V*ref* is the reference state NDVI values for the year 2000. A value of +1 is assigned to t*i* when the pixels for that year record a value of NDVI greater than the reference state, and -1 for values less than the reference state. In this part of the study, the consistency of persistence across the different NDVI products was of special interest and we defined the threshold reference state by the initial NDVI observations (the year 2000) made in the time series for all three persistence metrics.

Relative directional persistence

A measure, R, of the cumulative direction of change in NDVI values over time relative to the preceding year's observations of NDVI, during a series of annual observations is derived as:

$$R = \sum_{i=1}^{n-1} t_i \qquad \text{Equation 2.3.1}$$

$$V_i < V_{i+1} : t_{i+1} = +1 \qquad \text{Equation 2.3.2}$$

$$V_i > V_{i+1} : t_{i+1} = -1 \qquad \text{Equation 2.3.3}$$

Directional and Relative directional persistence metrics are only measures of the direction of change. However, to account for the magnitude of change, the Massive persistence metrics can be calculated to encapsualte sudden large changes within the time series.

Massive persistence

A measure, M, of the cumulative direction and magnitude of change over time relative to the preceding year's observed value of NDVI, during a series of annual observations is derived as:

$$M = \sum_{i=1}^{n-1} (V_{i+1} - V_i) \qquad \text{(Equation 2.4)}$$

Directional persistence and Relative directional persistence metrics are useful measures in any location where NDVI values are approximately normally distributed (Waylen *et al.* 2014; Tsai *et al.* 2014). For the latter two metrics, statistical significance was derived from predetermined critical significance levels as developed in detail by Waylen *et al.* 2014). For KNP north with a time series of 12 years (2000 – 2011) the critical value of D ($\alpha = 0.05$) is ± 7 and of R ($\alpha = 0.05$) is ± 5. For KNP central and south with an 11-year time-series (2000 – 2010), the critical value of D ($\alpha = 0.05$) is ± 8 and of R ($\alpha =$

0.05) is ± 6. However, establishing statistical significance for Massive persistence requires consideration of the variance of NDVI calculated with auxiliary data drawn from "control pixels" that have remained unchanged with regard to time of year, climatic zone and land cover (Waylen *et al.* 2014). In this study, however, we only required a comparison of the change pixels between the data products. Instead, we calculated a threshold value as the ΔNDVI layer digital number mean ± (1×standard deviation) (Singh 1989; Coppin *et al.* 2004). The threshold therefore identified a left and right tail of the near-normal distribution, which represented pixels with significant NDVI changes.

2.3.5. Application of methods

To illustrate the usefulness of the methods described above, we used the MODIS NDVI data for the entire extent of the Kruger National Park. The year 2002 was an especially dry year due to the effect of El Niño and we therefore used it as the benchmark date for analyses. We summed the NDVI composites on an annual basis, standardised the data to range between the normal NDVI values and then applied the zonal statistics tool from the Spatial Analyst extension of ArcGIS 10.2 to retrieve mean and variance values.

Subsequently we constructed a mean-variance phase diagram depicting the dynamics of vegetation greenness on an annual basis and interpreted the location of years within specific sectors of the phase diagram in relation to the annual precipitation deviation from the average calculated from 2000 to 2015. We further also generated persistence maps based on annual time-steps using the methods described previously.

2.4. Results

2.4.1. Mean-Variance analysis

Figure 2.3 illustrates the mean-variance phase diagrams constructed from Landsat, MODIS and SPOT NDVI data. For KNP north (Figure 2.3a-c), most points settled in the SD zone (shaded area) around the reference state as defined by the average NDVI mean and variance values calculated over the time series. Outside the SD zone, 2005 and 2008 consistently settled in sector 1 (Figure 2.2 - small mean-small variance sector) for all three NDVI data products. The 2010 mean-variance points for Landsat, MODIS and SPOT show consistently larger means although a greater variance value for the Landsat NDVI data puts it in a different sector (Figure 2.3a). For the Landsat data, 2000 shows less variance than 2002 (Figure 2.3a), while for MODIS and SPOT the opposite is apparent (Figure 2.3b and c). However, 2000 and 2002 remains within the same sector across all three data products.

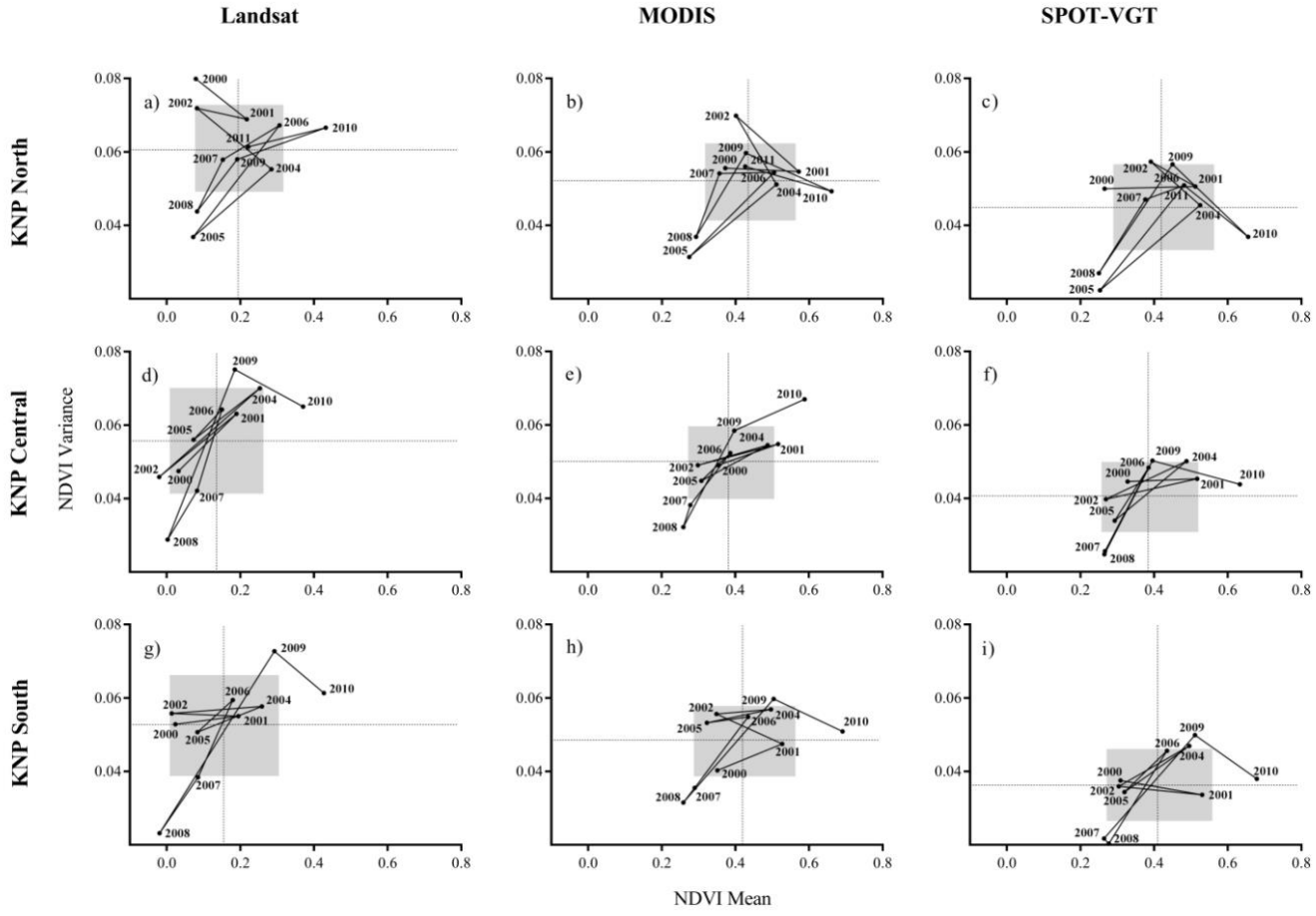


Figure 2.3. Mean-variance phase diagrams constructed from Landsat, MODIS and SPOT-VEGETATION NDVI data from 2000 to 2011 for KNP north, and from 2000 to 2010 for KNP central and south, respectively.

For KNP central (Figure 2.3d-f) and KNP south (Figure 2.3g-i), most points settled within the SD zone of sectors 1 and 3. Outside the SD zone, the appearance of 2007 and 2008 in sector 1 is consistent across all data products for KNP central (Figure 2.3d-f) and KNP south (Figure 2.3g-i). Similar trends are also observed for 2009 and 2010 in sector 3, although the 2009 MODIS (Figure 2.3e) and SPOT (Figure 2.3f) mean-variance points for KNP central are within the SD zone.

Exploratory analyses of the magnitude of change sequences for each of the NDVI products as derived from the Euclidean distances (d) between successive years indicated normal distributions of the data. Correlation analyses consistently indicated statistically significant positive associations ($p<0.05$) between Landsat and MODIS for KNP north ($R^2=0.546$; Figure 2.4a), central ($R^2=0.685$; Figure 2.4d) and south ($R^2=0.640$; Figure 2.4g), between MODIS and SPOT for KNP north ($R^2=0.674$; Figure 2.4c), central ($R^2=0.780$; Figure 2.4f) and south ($R^2=0.886$; Figure 2.4i) and between Landsat and SPOT for KNP south ($R^2=0.448$; Figure 2.4h). The associations between Landsat and SPOT were not statistically significant for KNP north ($p=0.08$, $R^2=0.331$; Figure 2.4b) and central ($p=0.098$, $R^2=0.343$; Figure 2.4e). Results of the χ^2-test for differences in the direction of change from one year to the following indicated statistically similar trajectories of change across all data products for KNP north ($\chi^2 = 3.360$, df = 2, p = 0.1864), KNP central ($\chi^2 = 0.5690$, df = 2, p = 0.7524) and KNP south ($\chi^2 = 4.320$, df = 2, p = 0.1153), respectively.

2.4.2. Spatial persistence analysis

For the KNP north subarea, the Directional persistence metric displays a relatively consistent spatial pattern of NDVI increase in the lower third area of the subarea for Landsat (Figure 2.5a), MODIS (Figure 2.5b) and SPOT (Figure 2.5c) data. Overall, the area of NDVI increase across KNP north was much larger for Landsat (29.2%) and SPOT (33.4%) than for MODIS (6.6%). Spatial signals of NDVI decreases were only minimally (0.1%) evident in the Landsat data (Figure 2.5a) and the remaining areas therefore indicated no significant changes. Relatively consistent spatial patterns of persistent NDVI increase were detected in the southern area (Appendix 1) of the KNP

central subarea. Here, the total area exhibiting NDVI increase was however much larger for Landsat data (21.1%) than for MODIS (2.6%) and SPOT (1.7%). For KNP south, the spatial pattern and amount of persistent NDVI increase was also larger for Landsat (40.5%) than for MODIS (4.8%) and SPOT (11.4%). NDVI decrease was not detected for any of the NDVI data products across KNP central or KNP south (Appendix 1).

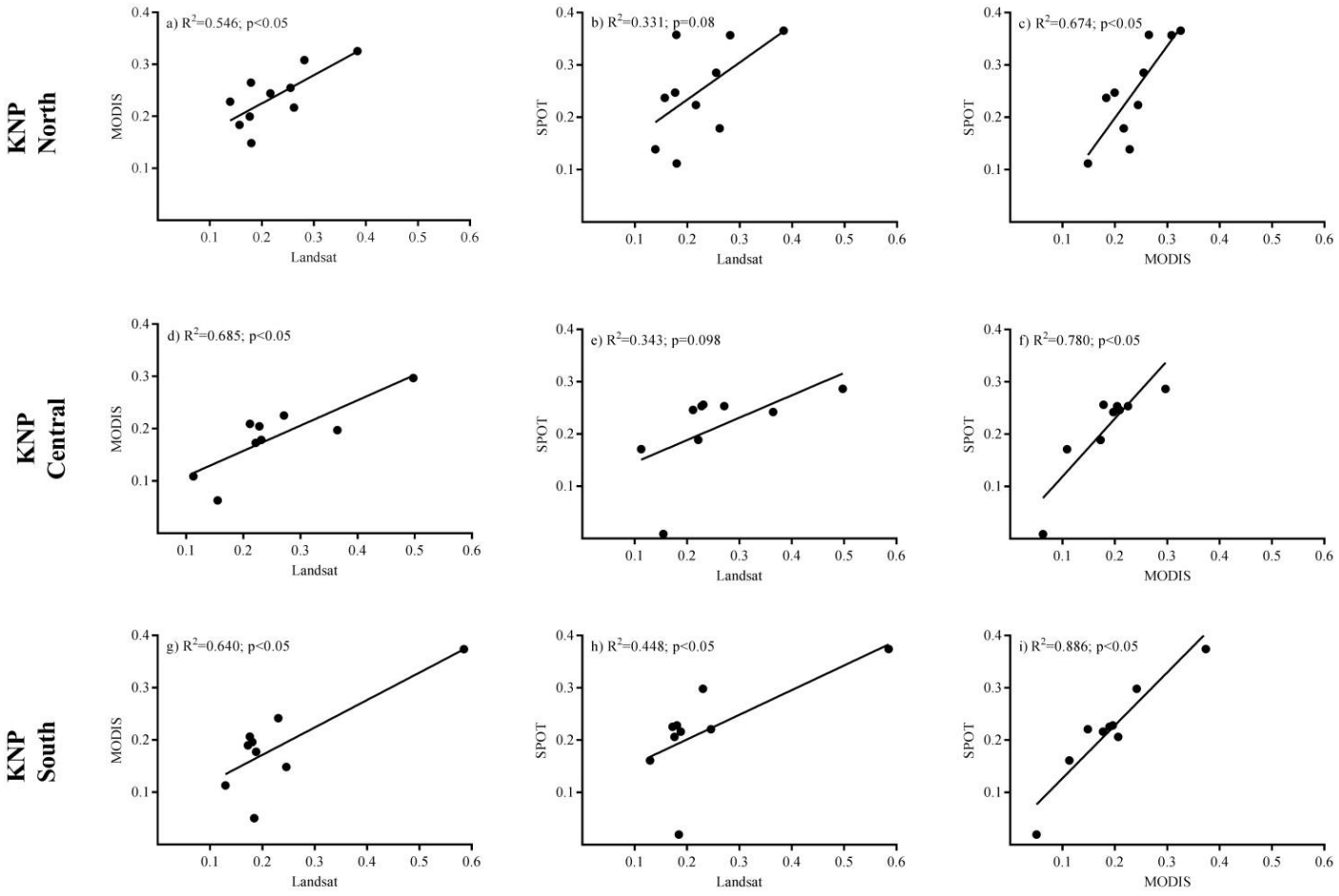


Figure 2.4. Correlation graphs of the Euclidean distance (d) between successive years compared for different NDVI products for the KNP north, central and south subareas.

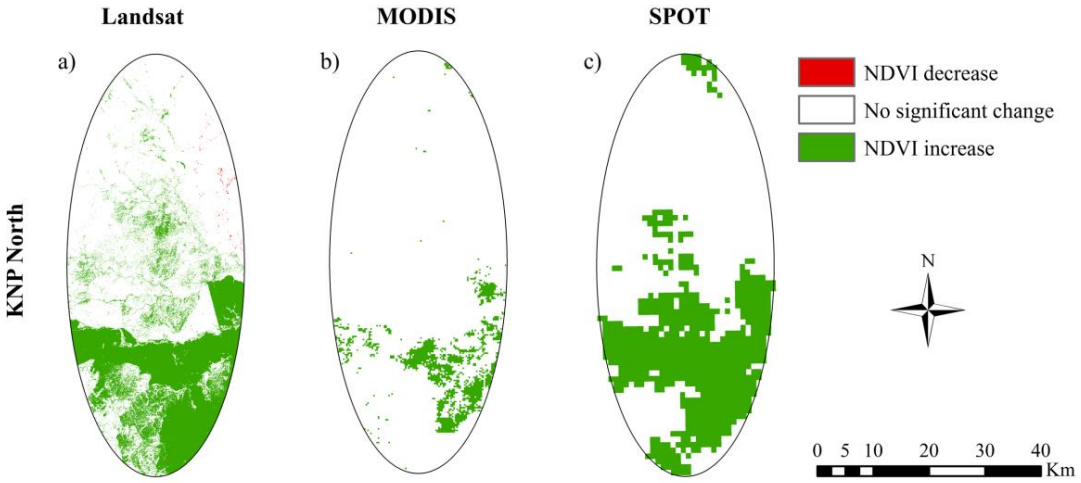


Figure 2.5. Statistically significant persistence of vegetation greenness at 0.05 level as measured by the Directional persistence metric, D, for a) Landsat, b) MODIS and c) SPOT NDVI from 2000 to 2011 for the KNP north subarea.

Relative directional persistence for KNP north, central and south consistently signalled less than 1% of the area with NDVI increase for the Landsat, MODIS and SPOT data with no significant changes being apparent across the three subareas. The spatial distribution and percentages of persistent NDVI increases and decreases as measured by the Massive persistence metric corresponded well across all data products for KNP north (Figure 2.6), central and south (Appendix 2). Specifically, NDVI decreases for Landsat (north: 14.5%; central: 14.7% and south:16.5%), MODIS (north: 16.1%; central: 17.5% and south:13.9%) and SPOT (north: 16.8%; central: 18.5% and south:10.6%) were mostly clustered in the southern area of the subareas, while NDVI increases typically showed up in the northern part of the subareas (Landsat: 17.0%, 15.2% and 16.4% for north, central and south, respectively; MODIS: 16.4%, 16.3% and 14.1% for north, central and south, respectively; SPOT: 16.8%, 13.6% and 14.4% for north, central and south, respectively).

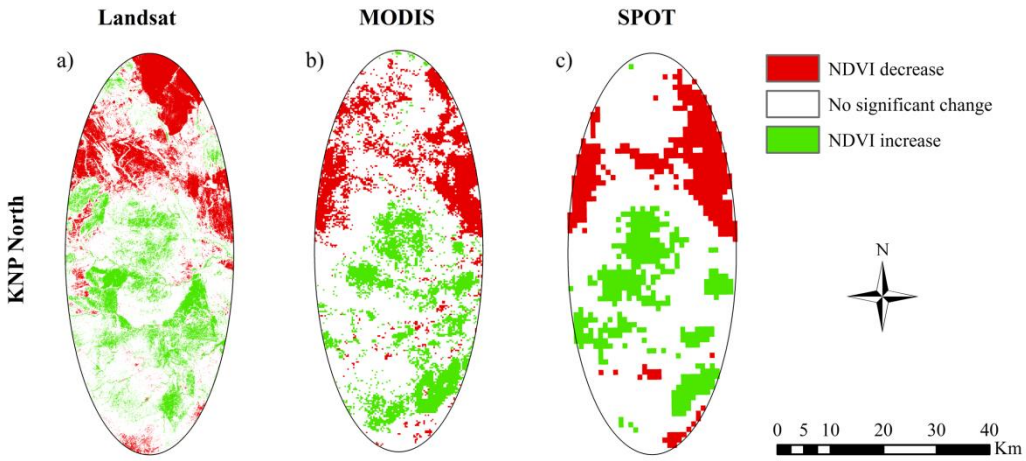


Figure 2.6. Statistically significant persistence of vegetation greenness at (1 × standard deviation) measured by the Massive persistence metric, M, for a) Landsat, b) MODIS and c) SPOT NDVI from 2000 to 2011 for the KNP north subarea.

2.4.3. Application of methods

From the mean-variance phase diagram (Figure 2.7), shifting between different states as represented by the four sectors from year to year is apparent. Specifically, the mean-variance analysis of the KNP (Figure 2.7a) indicates that the system has a clear tendency to shift between sector 2 with less green vegetation cover and greater variance and sector 4 with greater green vegetation cover and less variance. Years during which precipitation was well below the average (Figure 2.7b) consistently shows up in sector 2 except for 2015 that was found in sector 1. The latter year was also an exceptionally dry year for the KNP. For years with above-average precipitation, NDVI means were greater and variances less as these years showed up in sector 4.

Annual spatial persistence analyses for the KNP (Figure 2.8) shows that vegetation greenness as measured by Directional persistence largely increased when measured against the benchmark of the 2002 drought. However, the cumulative effect of year to year changes in vegetation greenness from 2002 to 2015 shows very subtle localised negative and positive persistence when only direction of change is considered through the Relative directional persistence analysis. When the magnitude of change is considered through the Massive persistence analysis, persistent year to year decline in

vegetation greenness becomes more pronounced in the southern and central areas of the park.

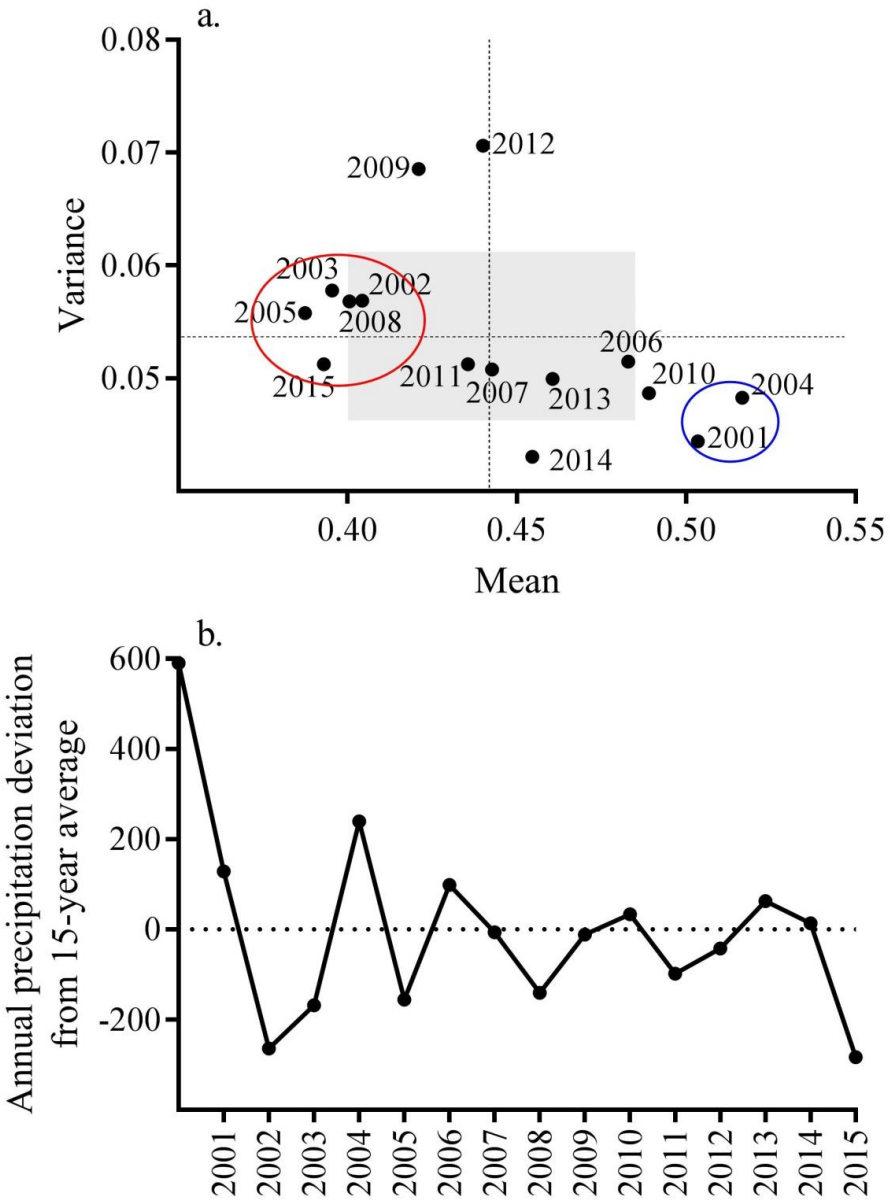


Figure 2.7. (a) Mean-variance phase diagram of the annual MODIS NDVI from 2001 to 2015 for KNP. The red circle indicates years that received precipitation well below the average as is illustrated in (b). The blue circle indicates years that received precipitation well above the average.

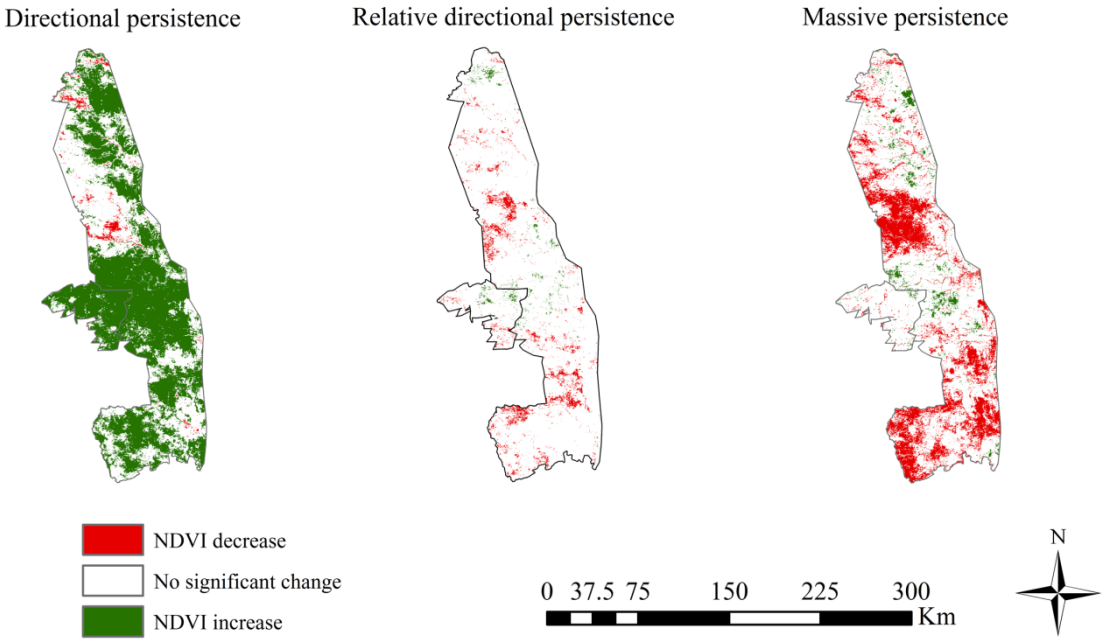


Figure 2.8. Statistically significant persistence of vegetation greenness as measured by the three spatial persistence metrics for the Kruger National Park area between 2002 and 2015.

2.5. Discussion

This study demonstrated the use of mean-variance analyses in combination with spatial persistence analyses for the monitoring of savanna vegetation dynamics across a protected area while evaluating the behaviour of different NDVI products over a 10-year period. Whereas previous applications of this monitoring approach aimed at describing vegetation dynamics at the regional scale (Cui *et al.* 2013; Gibbes *et al.* 2014; Pricope *et al.* 2015; Southworth *et al.* 2016), our results indicated that its application is also informative at the relatively smaller landscape scale as represented by a savanna-dominated protected area.

A comparison of NDVI data derived from Landsat, MODIS and SPOT NDVI products within a mean-variance analysis indicated that the method is robust despite the inherent differences of the data. Mean-variance phase diagrams for Landsat, MODIS and SPOT NDVI data showed some similarity with regard to the position of annual mean-variance

points across the four sectors when visually compared. Evaluations of the magnitude and direction of change on the phase diagrams further established general consistency in trends among NDVI data products in mean-variance analyses. The magnitude of change between the different data sets indicated overall positive correlations although some of the correlations were relatively weak. Of interest is the lack of correlation between Landsat (30 m spatial resolution) and SPOT data (1 km spatial resolution), while MODIS (250 m spatial resolution) correlated with both Landsat and SPOT. It therefore appears that correlations between NDVI data products may break down at some scale and that data products with a more similar spatial resolution tend to be better correlated.

Several factors related to sensor characteristics, including spatial and temporal resolution (Jelinski & Wu 1996), may also have contributed to weaker correlations in the magnitude of change for the different NDVI products. In their evaluation of the effect of change in spatial resolution (through pixel aggregation) on NDVI values of semi-arid land-cover types, Munyati & Mboweni (2013) showed significantly smaller NDVI values for the coarser resolution images (larger pixel size) than for the finer resolution images (smaller pixel size). They explained their results by an aggregation effect where the combined NIR reflectance from green vegetation patches within a non-productive matrix (intra-pixel variation) resulted in reduced maximum NDVI values (Munyati & Mboweni 2013). Such differences in the mean and variance values of the different data products likely influenced the strength of the correlations. However, assessment of direction of change on the phase diagrams suggested relatively strong similarity between Landsat and MODIS NDVI data and to a somewhat lesser extent Landsat and SPOT NDVI data.

The spatial distribution of inter-annual changes in NDVI as measured by persistence metrics was less consistent. All persistence metrics showed some similarity in the spatial distributions of the increasing NDVI but the total area representing persistent NDVI increase for Directional persistence was much less for the MODIS and SPOT data. The spatial resolution of the data therefore appears to have a noticeable effect on the Directional persistence metric most likely due to the aggregation effect (Jelinski & Wu 1996; Munyati & Mboweni 2013). Overall, the data sets behave somewhat similarly

within the spatial persistence analysis, although the MODIS and SPOT data appear to greatly underestimate critical areas of change relative to the Landsat data, especially for the Directional persistence metric. Compositing of the MODIS and SPOT data may also cause a number of pixels to have larger values than the real-time snapshot data of Landsat scenes and may further have contributed to such differences (Huete *et al.* 2002). One should therefore interpret results with caution, particularly if more than one data product is combined for analysis. In the latter situation, normalisation of the NDVI data may be required (e.g. Yao *et al.* 2013; Gan *et al*. 2014)

Irrespective of the broad-scale differences in vegetation of the three KNP subareas, results indicated some uniformity in trends. Vegetation greenness changes in the KNP savanna landscape appear to be captured rather well by the mean-variance and spatial persistence analysis approach. Moreover, our findings indicated that the mean-variance analysis provides valuable insight into climatological disturbance events at the landscape scale. For instance, for all data sets, the year 2015 settled in the small mean - small variance sector (sector 1) on the phase diagram, where the system is within its least productive state. This specific year was also characterised by very low precipitation linked to El Niño events (Johnson 2013).

Indeed, application of the methods for the whole of KNP using annual MODIS NDVI between 2002 and 2015 clearly illustrates the response of vegetation greenness to precipitation. Importantly, the mean-variance analysis indicated green vegetation cover to recover after the drought years suggesting that the KNP system is resilient. When we consider the Directional persistence metric over the same time period, it further indicates that the vegetation recovered with significant increases of vegetation greenness over most of the KNP. Relative directional persistence and Massive persistence on the other hand show that the year to year changes in green vegetation cover may be decreasing in localised areas.

An important consideration would be to identify the scale at which changes in vegetation are ecologically meaningful. Our study methods indicated that precipitation is a strong driver of vegetation dynamics across the KNP as we observed with remotely

sensed NDVI at spatial resolutions that range from 30m to 250m. Disaggregating the effects of climate and local drivers (e.g. fire and herbivores) from each other may however present a further challenge. We propose that the evaluation of long-term intra-annual vegetation cover dynamics through the use of NDVI data with finer temporal resolution (such as MODIS) may enable us to separate the relative effects of local disturbances from climatological induced changes (e.g. Alexandridis *et al.* 2008). For instance, defining seasons based on phenology metrics could remove the intra-annual seasonal influence of climate on vegetation, making it possible to identify local disturbance effects.

The methodological approach combining a mean-variance and spatial persistence analysis provides a cost-effective monitoring application which is readily available to conservation managers. Specifically, for KNP, this approach provides a means by which the vegetation across the entire extent of the park can be monitored continuously for changes related to climate and other disturbances. This will enable better management through the ability of the method to identify areas of concern that may be prone to degradation. Finally, the approach may enable SANParks to identify TPCs that will guide the management of the park within a resilience framework. Given the limited funding and resources available to conservation managers, application of the methods described in this study could direct and justify more costly finer scale research. Moreover, with the increasing availability of remote sensing data that captures structural features of the landscape (e.g. LIDAR and MISR), the methodology have much potential to expand the scope of vegetation monitoring for protected areas.

2.6. Conclusion

Our study established that the combined application of a mean-variance analysis with a spatial persistence analysis holds much potential for the monitoring of green vegetation cover across protected areas. As a baseline monitoring approach, the methodology enables the tracking of temporal vegetation changes as well as the identification of critical areas of persistent change across a savanna landscape. We also determined that the behaviour of NDVI data from Landsat, MODIS and SPOT within the application of

mean-variance and spatial persistence analyses tend to be similar although obvious variation in the behaviour of the NDVI products exist due to inherent differences in the data products. The use of a specific data product for analysis should therefore be interpreted very carefully, while combining data sets may present some further challenges. Our findings set the foundation for further assessment of the effect of different drivers on the long-term intra-annual vegetation dynamics of savanna protected areas as well as the potential value of remote sensing data that provide structural vegetation information.

2.7. Acknowledgements

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CHAPTER 3

PRECIPITATION AND PHENOLOGY AS DRIVERS OF VEGETATION GREENNESS TRENDS IN THE KRUGER NATIONAL PARK, SOUTH AFRICA

3. PRECIPITATION AND PHENOLOGY AS DRIVERS OF VEGETATION GREENNESS TRENDS IN THE KRUGER NATIONAL PARK, SOUTH AFRICA

3.1. Abstract

Climate change is expected to alter the structure and function of savanna ecosystems in South Africa. Especially for conservation areas, such as the Kruger National Park, vegetation monitoring is imperative to inform management decisions. In this paper we aimed to assess the relative role of precipitation as a driver of vegetation patterns. We evaluated the relationship of overall spatial vegetation greenness patterns to the spatial patterns of precipitation and the phenometrics, start of season and length of season, between 2002 and 2015. We further used spatial persistence analyses to identify and assess the spatial correlation of the cumulative change trends in vegetation greenness, precipitation and the phenometrics. Large spatial correlation between the mean vegetation greenness to both precipitation patterns and phenometrics indicated that precipitation was the primary driver of the inter-annual vegetation greenness patterns in the Kruger National Park landscape during our study period. Persistent vegetation greenness changes amounted to about 30% of the park area. However, apart from localised converging trends, vegetation greenness change trends showed little association with changes in precipitation, season onset and season length, indicating that top-down drivers, such as fire and herbivores, were most likely the predominant causal factor underlying the observed changes in vegetation greenness that persisted in the landscape. Understanding the spatio-temporal change patterns of vegetation greenness and how it relates to precipitation and phenological characteristics could therefore be instrumental in separating the precipitation signal from impacts of local drivers such as fire and herbivores. Our methods provide a useful approach through which vegetation changes can be monitored continuously at the landscape scale. Future work should focus on intra-annual change dynamics and optimising our current methodology.

3.2. Introduction

Future climate change scenarios for South African savannas predict decreased or similar precipitation and increased temperatures, along with changes in carbon sequestration patterns and potential evapotranspiration rates (IPCC 2007; Buitenwerf *et al*. 2012). Such changing weather patterns are further expected to be exacerbated by the increase in the frequency and intensity of El Niño/La Niña – Southern Oscillation (ENSO) cycles (Power *et al*. 2013; Cai *et al.* 2014). Subsequently, increased precipitation variability has been identified as one of the most important and primary drivers that will impact these savannas (Fauchereau *et al*. 2003; Tews & Jeltsch 2004). Coupled with co-dynamic modifications in fire regimes (Archibald *et al*. 2013) and large herbivore distributions (Smit *et al*. 2007; Purdon & van Aarde 2017), changes in vegetation cover and productivity (Bunting *et al.* 2016), plant species composition (Thuiller *et al*. 2006) and tree/grass ratios (February *et al*. 2013) are inevitable (Eamus & Palmer 2007; Buitenwerf *et al*. 2012; Parr *et al*. 2012). Savanna ecosystems such as the Kruger National Park (KNP) are already experiencing shifts in precipitation patterns (MacFadyen *et al*. 2018), increased temperatures (van Wilgen *et al*. 2015) and climate-linked localised increases in woody biomass (Moyo *et al.* 2015; Berry & Kulmatiski 2017) which could ultimately change the dynamics of the mechanisms through which fire and herbivores regulate vegetation (Scheiter & Higgins 2009; Smit & Prins 2015; Bunting *et al*. 2016). Facing such evidence, it is imperative to have vegetation monitoring programs in place that can serve to identify trends of concern that may threaten the integrity (i.e. the quality of an ecosystem in which the natural ecological processes sustain the function, composition and structure of the system) of savanna ecosystems. Moreover, it is essential to understand the significance of climatic factors, such as precipitation, as drivers of vegetation trends.

Vegetation greenness (actively growing vegetation) and vegetation phenology (seasonal characteristics of green vegetation cover) are critical aspects of ecological change that are especially sensitive to climatic variations (Wang & Fensholt 2017). Phenology is directly linked to functional ecosystem processes (Forrest & Miller-Rushing 2010; Polgar & Primack 2011). Leaf flushing and senescence are related to plant growth, and

as such play a vital role in our understanding of plant–water relations, primary productivity, interspecific relationships, gas exchange rates, biogeochemical cycling, and the dynamics of carbon sequestration (Morisette *et al*. 2009; Forrest & Miller-Rushing 2010; Polgar & Primack 2011). The onset and length of a growing season is therefore expected to govern changes in the overall growth of vegetation (Chang *et al*. 2013). For instance, a longer growing season increases the photosynthetically active period, which could potentially favour woody plant densities due to increased carbon accumulation (Moyo *et al.* 2015). However, at the landscape-scale, the relationship between phenology metrics and vegetation greenness may be confounded by the impact of local drivers such as fire and large herbivores (Shannon *et al*. 2011; Munyati & Sinthumule 2016). For example, fire intensity and frequency is dependent on the available grass fuel load (van Wilgen *et al*. 2000). Longer growing seasons, associated with higher biomass, are therefore expected to increase the probability of re-occurring fires (van Wilgen *et al.* 2000), which may then result in vegetation structural changes (Gandiwa & Kativu 2009). Alternatively, the response of herbivores, such as elephants, to changes in the timing of the greening characteristics of a growing season through migration and alteration of their home range size (Loarie *et al*. 2009; Bohrer *et al*. 2014) is expected to lead to increased localised pressure on vegetation that may result in several ecological problems (Loarie *et al*. 2009). Understanding the spatio-temporal change trends of vegetation greenness and how it relates to precipitation and phenological characteristics could therefore be instrumental in separating the precipitation signal from impacts of local drivers such as fire and herbivores.

For the KNP, general phenological patterns are known but have not yet been documented extensively in a spatially explicit manner (Scholes *et al*. 2003). Moreover, although some studies of changes in phenology and vegetation greenness in relation to precipitation have been conducted separately, research into the relationship between phenology metrics and vegetation greenness is still lacking for the KNP. The aim of our study was therefore to characterise and compare spatial vegetation greenness trends in response to two phenometrics (start of season and length of season) and precipitation between 2002 and 2015 in order to provide unique insight into the relative role of precipitation as a driver of vegetation change patterns in the KNP. Our application of

remotely sensed vegetation indices in phenology analyses, in conjunction with spatial persistence analyses (Tsai 2012; Cui *et al*. 2013; Tsai *et al*. 2014), also offer a unique approach through which the change patterns of phenology parameters can be expressed spatially. Through identifying and comparing the spatial extent and overlap of persistent changes in vegetation greenness, precipitation and phenometrics, we should be able to distinguish the effect of precipitation from other contributing factors (Wang & Fensholt 2017).

Given the above, our study was designed to answer the following questions:

1. How did the overall vegetation greenness patterns vary spatially across the KNP in response to trends in mean growing season precipitation, mean season onset and mean season length?
2. What were the cumulative persistence trends in vegetation greenness, season onset, season length and growing season precipitation and how were these spatially related?
3. What was the spatial extent of significant persistence in vegetation greenness and how did it spatially overlap with significant changes in season onset, season length and growing season precipitation?

3.3. Materials and Methods

3.3.1. Study area

The Kruger National Park (KNP) (24° S, 31.5° E) spans approximately 20 000 km^2 in the north-eastern semi-arid savanna region of South Africa (Figure 3.1). Characterised by subtropical climate with hot, wet summers and dry winters, precipitation in the KNP mostly falls from November to April following a gradient that ranges from ~300-500 mm yr^{-1} in the north to ~500-700 mm yr^{-1} in the south (Zambatis & Biggs 1995). The prominent geology of the KNP can generally be divided in sandy, nutrient-poor soils from granitic origin in the west and clay-rich soils weathered from basalts in the east (Venter *et al.* 2003).

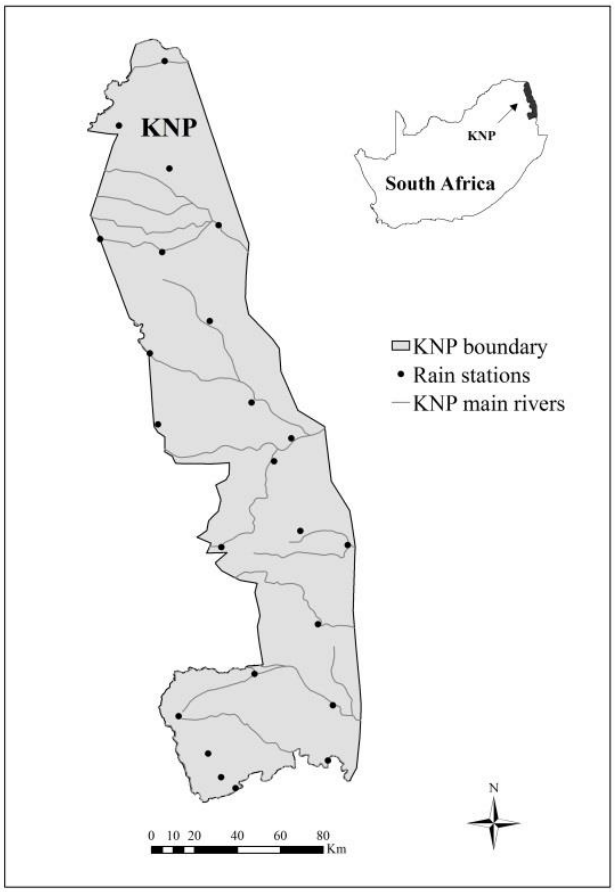


Figure 3.1. Map illustrating the Kruger National Park situated in the north-eastern part of South Africa and the locations of the 23 weather stations used in this study.

The northern granite areas are dominated by mopane *(Colophospermum mopane)* and red bush willow *(Combretum apiculatum* subsp. *apiculatum)* with low grass cover, while the basalts in the north-eastern area of the KNP mostly carry mopane shrubs (Van Wilgen *et al.* 1998). The eastern basalts in the central area of the park is characterised by more open savanna with a dominant grass layer and the scattered occurrence of tree species such as knobthorn (*Senegalia nigrescens*), umbrella acacia (*Vachellia tortilis*) and marula (*Sclerocarya birrea*). The central granites on the other hand are characterised by a more prominent woody component and a lower herbaceous cover. In the southern area of the KNP, *Combretum*-dominated broadleaf mixed woodland and *Acacia* thorn thickets are noticeable features of the landscape.

3.3.2. General overview of methods

Figure 3.2 illustrates a flowchart that highlights the methods and associated analyses that were used in our study.

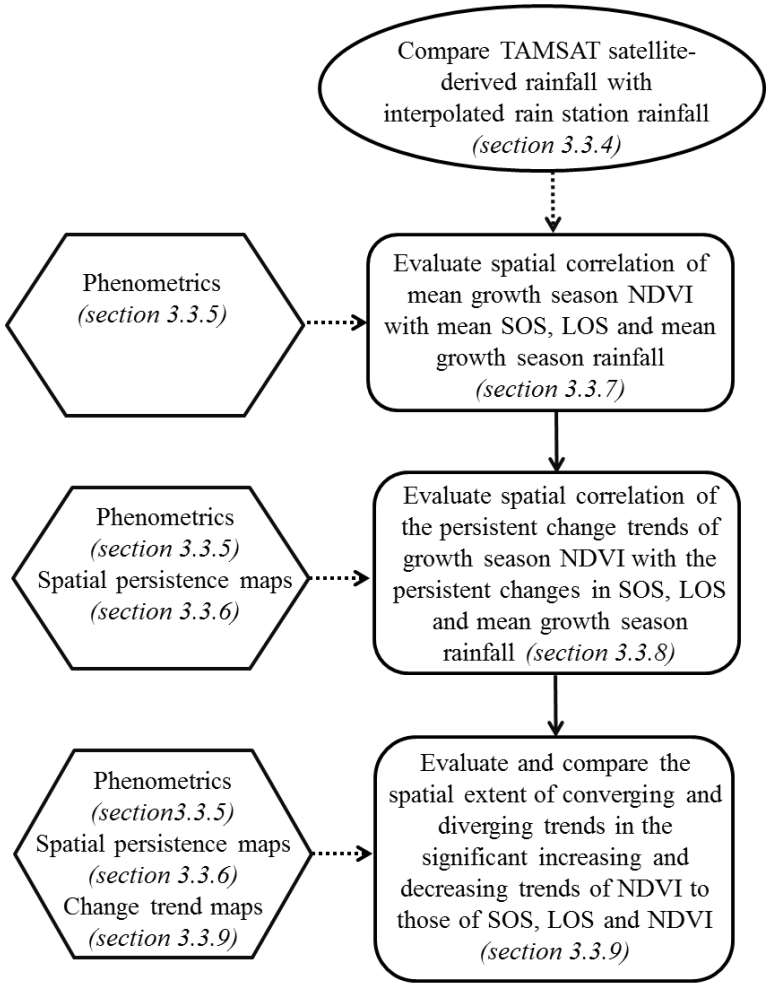


Figure 3.2. Flowchart of the workflow highlighting the main methodology and analyses.

3.3.3. Vegetation index data

We used the Normalised Difference Vegetation Index (NDVI) imagery data from the MODIS satellite instrument on the Terra platform between 2002 and 2015. The MOD13Q1 version 5 product archive consists of 16-day composites and is available at a 250 m spatial resolution through the MODIS Reprojection Tool Web Interface from the

USGS DAAC at EROS (URL: http://mrtweb.cr.usgs.gov). The NDVI combines the spectral measurements of the red (RED) and near-infrared (NIR) reflectance of the Earth's objects [NDVI = (NIR-RED)/ (NIR+RED)] and is an effective measure of absorbed photosynthetically active radiations (Tucker and Sellers 1986). The NDVI has further been shown to be a good proxy of vegetation production and biomass in savannas (Pettorelli *et al*. 2005; Santin-Janin *et al*. 2009); although the NDVI is not a direct measure of NPP (net primary productivity). We chose to work with NDVI because of its long-term availability and easy accessibility at medium spatial resolution (250m) and to make our study comparable to previous phenological studies that were predominantly based on NDVI data (Parrini & Erasmus 2009; Zurita-Milla *et al*. 2013). NDVI imagery were processed and analysed in the WGS 1984 UTM 36S projection framework.

3.3.4. Precipitation data

For our study we required gridded precipitation data. We therefore had the option to use satellite-derived precipitation estimates for which several products are freely available, or we could use interpolation techniques to produce gridded data based on the long-term precipitation record of the KNP. Both options have drawbacks. Satellite-derived precipitation data is only available at relatively coarse spatial resolution, requiring complex methods of downscaling to produce estimates at finer resolution (Zhao *et al*. 2015). Biased precipitation estimates from satellite-derived products in the form of over- and underestimation is also often reported in the literature (Young *et al*. 2014). Conversely, the accuracy of predicted surfaces through the interpolation of ground-based measurements of precipitation may be affected by the high spatial variability of precipitation in the KNP (Parrini & Erasmus 2009). However, very little is known about the behaviour of satellite precipitation products over the KNP area. We therefore decided to do a simple comparative evaluation of the two options in order to decide which data will be more suitable for our study.

The KNP has a long historical climate record of ground-based measurements dating back to 1903 (Zambatis 2003). Today, a total of 23 weather stations (Figure 3.1) give

reliable and continuous precipitation measurements on a daily basis (MacFadyen *et al*. 2018). We obtained the daily records for each of the 23 weather stations in the KNP from SANParks. In a few instances (< 0.1% of all data points), measurement values were missing and we filled the gaps by using the Weighted Sum of the Local and Total Average (WSA) method described by Pappas *et al*. (2014). Although computationally very simplistic, the method of combining a local average of one measurement value before and one after the missing value with the sample mean, provides a quick and easy technique to fill sporadic, single value gaps (Pappas *et al*. 2014). We accumulated daily measurements into the total annual precipitation amounts for each year and then averaged the data over the study period (2002 – 2015) to produce the mean annual precipitation for each weather station. The mean annual precipitation values at the 23 locations of weather stations were then interpolated using ordinary kriging within the Geostatistical Analyst Toolbox in ArcGIS 10.1. Kriging (Krige 1966) is a geostatistical method of predicting unknown values based on point measurements across a geographic area. Kriging parameters were optimised through minimising the model error when selecting the most appropriate semivariogram model for the data set. Finally, we generated an interpolated raster image representative of the mean annual precipitation between 2002 and 2015 across the park.

The TAMSAT rainfall product (Tropical Applications of Meteorology Using Satellite Data and Ground-Based Observations; https://www.tamsat.org.uk) provides precipitation estimates for the African continent and its development was originally aimed at aiding drought monitoring (Maidment *et al.* 2017). Precipitation estimates are derived through a combination of geostationary Meteosat data with gauge observations through a calibration approach that exploits both data sources (Maidment *et al*. 2014; 2017). With algorithms aimed at optimising the detection of precipitation amounts in dry conditions, the product tends to underestimate total precipitation (Tarnavsky *et al.* 2014; Maidment *et al.* 2017). However, the product has been shown to be valuable in applications of drought risk assessment and monitoring of long-term precipitation trends (Maidment *et al*. 2017). For our study, we acquired cumulative estimates of precipitation from TAMSAT for each 10-day period (dekad) at 4-km spatial resolution between 2002 and 2015. These dekadal grids were processed and composited into

annual precipitation estimates after which we averaged the annual data over the study period to give us a comparable satellite-derived precipitation estimate (SRE) grid of mean annual precipitation over the study period.

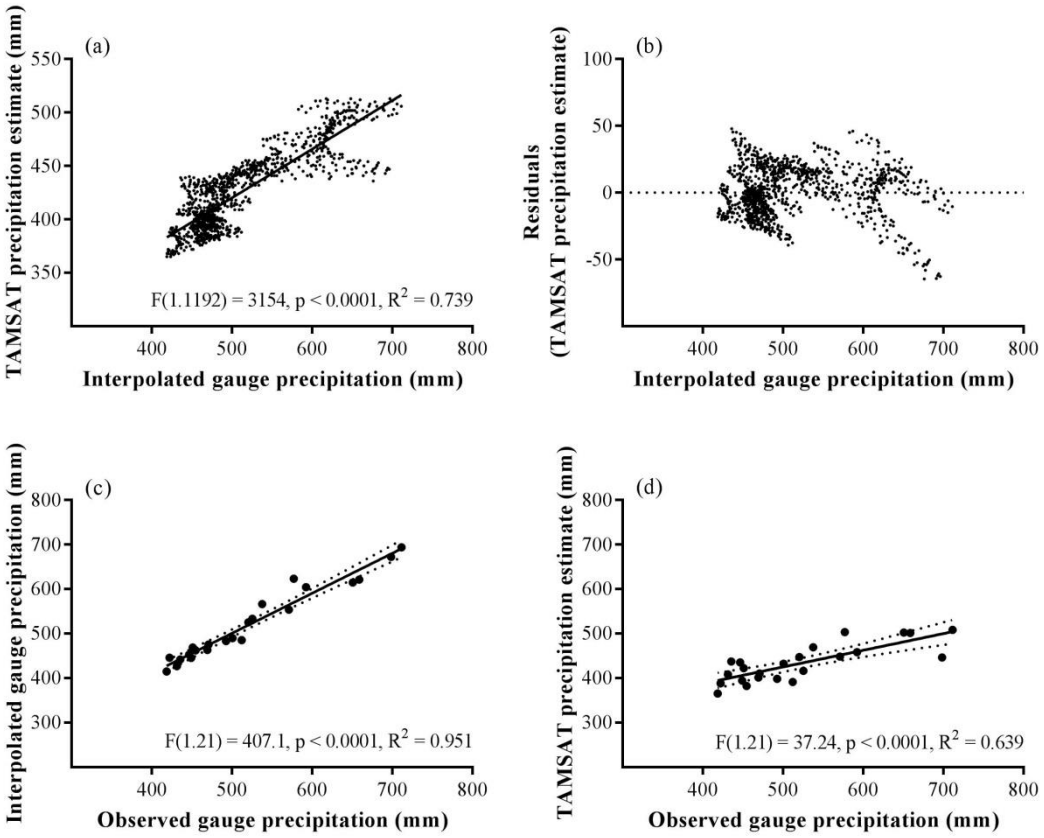


Figure 3.3. Results from linear regression analyses showing the (a) relationship between mean annual precipitation from the TAMSAT satellite-derived estimates and the mean annual precipitation derived from the interpolation of gauge precipitation measurements, (b) distribution of residuals from the linear regression analysis in (a), (c) relationship between mean annual interpolated precipitation and the mean annual observed gauge precipitation data, and (d) relationship between the mean annual TAMSAT precipitation estimates and the mean annual observed gauge precipitation data.

Following the preparation of the data from TAMSAT and the KNP weather stations, we converted the interpolated mean annual precipitation grid into point data. For each of these points we extracted the mean annual SRE values and finally compared the two

data sets with a linear regression analysis. Results indicated a strong relationship (Figure 3.3a) between the SRE and the interpolated data. However, evaluation of the residuals indicated that that there is considerable variability not explained by the linear model (Figure 3.3b). Generally, SRE values for mean annual precipitation were also much lower than for the predicted values obtained from interpolation, in accordance with biases previously reported for the TAMSAT data in other regions (Kimani *et al.* 2017). Due to the inherent spatial autocorrelation of the data, we further validated the resulting trend by analysing the linear relationships for the TAMSAT and interpolated gauge data, respectively, as a function of the observed mean precipitation values at each of the weather stations over the study period. Here, results indicated a much stronger positive linear relationship between the interpolated gauge precipitation and the observed precipitation data (Figure 3.3c) than for the relationship between TAMSAT and the observed precipitation data (Figure 3.3d). Coupled with the added disadvantage of the coarser resolution of the TAMSAT data, we decided to base all further analyses on interpolated precipitation station data. It is also important to note that our methods here are relatively simple and a more in-depth comparison of the SRE and interpolated gauge precipitation (e.g. a jacknifing approach where observed values are compared to the interpolated values when the specific observed values were not used in the interpolation of data) is advisable.

3.3.5. Phenology metrics

The Timesat software package version 3.1 (Eklundh & Jönsson 2012; Jönsson & Eklundh 2002, 2004) is designed primarily for analysing time-series of satellite data. Timesat uses an adaptive Savitzky-Golay filtering method and methods based on upper envelope weighted fits to asymmetric Gaussian and double logistic model functions (Jönsson & Eklundh 2002, 2003, 2004). From the fitted model functions a number of seasonality parameters can be extracted. The user-defined time-series filtering parameters used for this study has been selected based on parameter settings for the Savitzky-Golay filtering method reported by Wessels *et al*. (2010) for their study on the biomes of South Africa and additional trial-and-error runs of the software. The parameters we used in our study include: Spike method – median filter 1; Number of

envelope iterations – 1; Adaptation strength – 2; Savitsky-Golay window size – 3; Start of season method – Amplitude; Season start – 0.8; Season stop – 0.2. We extracted two phenology metrics for each year namely; Start of season (SOS) and Length of season (LOS) for the extent of the KNP area.

3.3.6. Spatial persistence metrics

The spatial persistence analysis involved the use of the Massive persistence metric described by Waylen *et al.* (2014). In this study, persistence was measured relative to the benchmark conditions of the 2002/03 phenological growing season that was characterised by drought conditions as it could provide insight into the resilience of the landscape to recover after disturbance. Massive persistence, M, (changes in magnitude relative to the preceding value) captures both magnitude and direction of the cumulative annual NDVI change over time. The metric, M, of the cumulative direction and magnitude of change over the time series relative to the preceding year's actual observations of NDVI, is derived as:

$$M=\sum_{i=1}^{n-1}(V_{i+1}-V_i) \qquad \text{(Equation 3.1)}$$

where V*i* is the annual NDVI at time *i* (Waylen *et al.* 2014*).* Hereby, the metric accounts for years with extreme NDVI values where the difference between V_{t+1} and V_t will be large. Although it may seem that one extreme year can inflate M disproportionally, the vegetation cover from a very productive year (or a drought year) may have ecological consequences for the following year.

Waylen *et al*. (2014) provides a detailed method for determining statistical significance for M, the application thereof requires the input of values for "control pixels" that remained unchanged over time. At the time of the study, we were unable to identify such control areas that would provide a large enough data set and we proceeded with the standard deviation approach reviewed by Coppin *et al*. (2004). By using the latter, we acknowledge that we did not account for the variance of the observed data under null

conditions (Waylen *et al*. 2014). However, since our study area represents a vegetated area within one climatic region for a series of growing seasons, we based our application of the massive persistence metric on the premise that the variance of the observed data under null conditions would not influence the correlation between the different variables. In our study we therefore calculated critical values of change at (1×standard deviation) of the ΔNDVI layer (Massive persistence map) digital number mean (Coppin *et al.* 2004). These threshold values therefore identified a left and right tail of the near-normal distribution, which represented pixels with statistically significant NDVI changes.

3.3.7. Spatial correlation in mean NDVI, precipitation, SOS and LOS

Mean growing season NDVI was calculated by summing the individual NDVI 16 day composites that fall within the start and end dates of each year's growing season, and then averaged across all years. For precipitation, we accumulated precipitation measurements for each year's growing season and added an additional month's data before the start of the growing season to account for the time-lag effect between precipitation and season onset (Parrini & Erasmus 2009). Precipitation that fell outside the growing season was characteristically periodic events during the dry season that did not contribute considerably to the overall annual precipitation. We then used ordinary kriging to interpolate the precipitation data for each year using the same procedure as explained earlier in section 3.3.3. We further prepared maps of the mean SOS and mean LOS of the 14 growing seasons between 2002 and 2015. These maps representing the mean NDVI, precipitation, SOS and LOS were then evaluated for spatial correlation using the Band Collection Statistics (BCS) Tool in ArcGIS. In this analysis, correlation coefficients are calculated as the ratio of the covariance between two layers divided by the product of their standard deviations. These correlation coefficients are analogous to Pearson's correlation coefficients (r) where values range from −1 to 1, with a positive correlation indicating a direct relationship between two layers, and a negative correlation means that one variable changes inversely to the other. A correlation of zero means that two layers are spatially independent of one another. The BCS tool in ArcGIS, however, do not report p values associated with the correlation coefficients due

to the spatial autocorrelation of individual variables that violates the assumption of independence of values for each of the pair of raster variables.

3.3.8. Spatial correlation of change trends in NDVI, precipitation, SOS and LOS

To identify and assess the spatial relationships between changes in NDVI, precipitation, SOS and LOS over the study period, we calculated the Massive persistence metric, M, for all the variables. Even though the persistence metrics have only been applied to vegetation index data, we argued that if the precipitation and phenology metrics data conform to the requirements of a near-normal data distribution and serial independence, persistence metrics could also be applied to produce persistence maps of precipitation, SOS, and LOS. Massive persistence maps were therefore prepared and evaluated for spatial correlation of the change trends between NDVI, precipitation, SOS and LOS using the ArcGIS BCS tool.

3.3.9. Change trend comparison

Complimentary to the correlation analyses of the persistence maps, we quantified and mapped the spatial extent to which the persistence change trends in NDVI converged (overlap of similar statistically significant trends) with SOS, LOS and precipitation. Firstly, we applied statistical significance to the massive persistence maps (produced in the previous section) at (1×standard deviation). The massive persistence for precipitation did not show any cumulative decreasing trend. To enable comparison of trends between precipitation and the other variables we therefore made an algebraic adjustment to the massive persistence map for precipitation by classifying the lower values beyond (1×standard deviation) as a "negative" trend. Throughout the study period, annual growing season precipitation variably deviated from the study period mean (Figure 3.4) and areas within the landscape that were characterised with cumulatively low persistence values were most likely subjected to precipitation decreases at some points during the study period. The growing seasons with below-average precipitation could therefore have contributed to the decreasing trends in NDVI, SOS and LOS despite the cumulative low increasing trend over the study period.

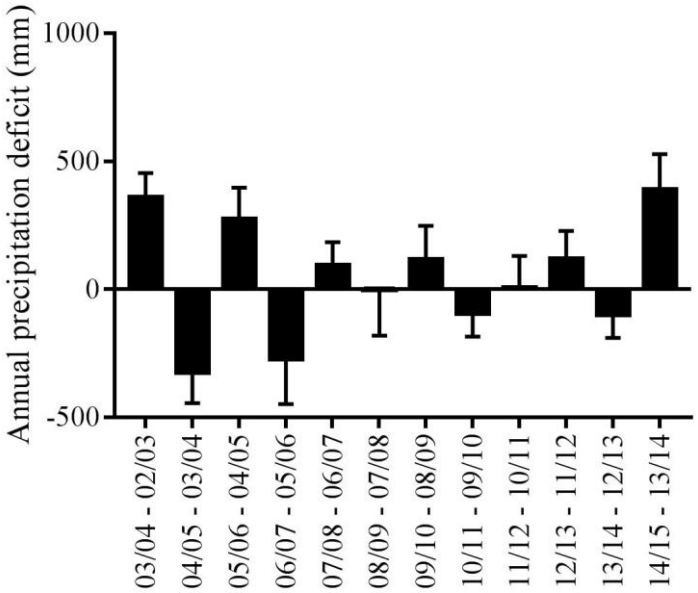


Figure 3.4. Annual deviations of growing season precipitation calculated from the overall mean precipitation of the growing seasons over the study period (2002 – 2015).

Following the method described by Wang & Fensholt (2017), we then reclassified each of the massive persistence maps (NDVI, SOS, LOS and precipitation) by assigning a positive value to pixels depicting significant increases, a negative value to pixels with significant decreases and a zero value to "no change" pixel and summed the reclassified maps to produce change trend maps. Specifically, as illustrated in Figure 3.5, by combining map 1 (e.g. NDVI) with map 2 (e.g. SOS), the trend difference map will essentially show if the overlapping pixels of map 1 and map 2 have similar (converging) or different (diverging) change trends. A change trend difference map will therefore have the following classes; positive convergence (both increased), negative convergence (both decreased), divergence (only one of the overlapping pixels showed significant change) and no change (none of the two overlapping pixels showed significant changes) (Wang & Fensholt 2017). In certain instances, the value of a positive (+1) value in map 1 combines with a negative (-1) value in map 2, resulting in a zero value. To compensate for this, we assigned a (+/-2) value to map 1 (e.g. NDVI) so that convergence values in the change trend map accumulated to (+/-3) and diverging values to either (+/-1) or (+/-2). In this specific analysis, we inverted the negative and positive values for the start of season so that positive values indicated earlier seasonal onset and

negative values represented later onset of the season. Finally, we produced three change trend maps showing the extent of the overlap between significant changes in NDVI relative to significant changes in SOS, LOS and precipitation, respectively.

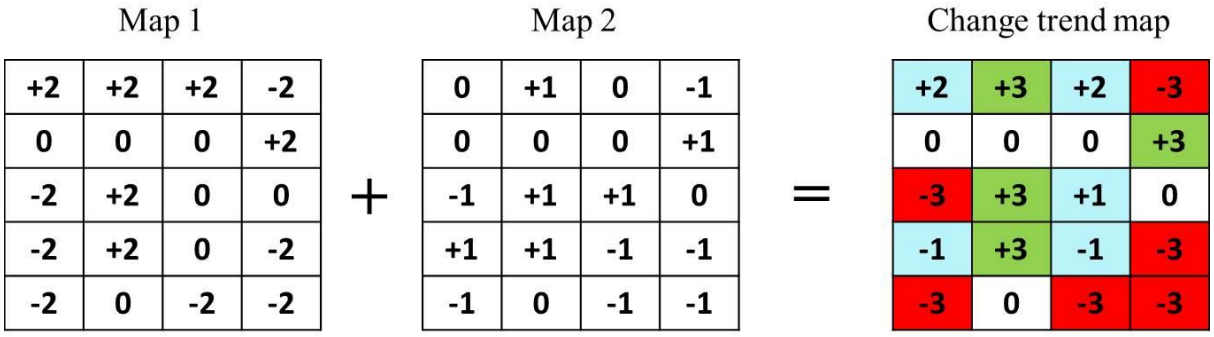


Figure 3.5. A simplified illustration that explains the procedure followed for creating a change trend difference map. Significant changes in map 1 are reclassified to (+2) for increases, (0) for no changes and (-2) for decreases, while for map 2; (+1) for increases, (0) for no change and (-1) for decreases. Summation of the two maps results in the "change trend map" where (+/-3) indicates converging trends, (+/-1) and (+/-2) indicates diverging trends and (0) indicates overlap of no significant change trends.

3.4. Results

3.4.1. Spatial trends and correlations in mean NDVI, SOS, LOS and precipitation

Figure 3.6 shows the mean growing season NDVI (a), SOS (b), LOS (c) and precipitation (d) for the KNP between 2002 and 2015. Correlation coefficients (Table 3.1) indicate a strong positive spatial correlation between the mean NDVI and the mean LOS, showing larger mean NDVI and mean LOS values in the southern region of the park and in some localised areas in the far north and central regions. Similarly, the mean NDVI was positively correlated with mean precipitation (Table 3.1). The correlation coefficient for the mean NDVI and mean SOS indicated that these two variables were inversely correlated, with mean SOS generally occurring earlier in the southern region and gradually transpiring later on towards the northern region of the park.

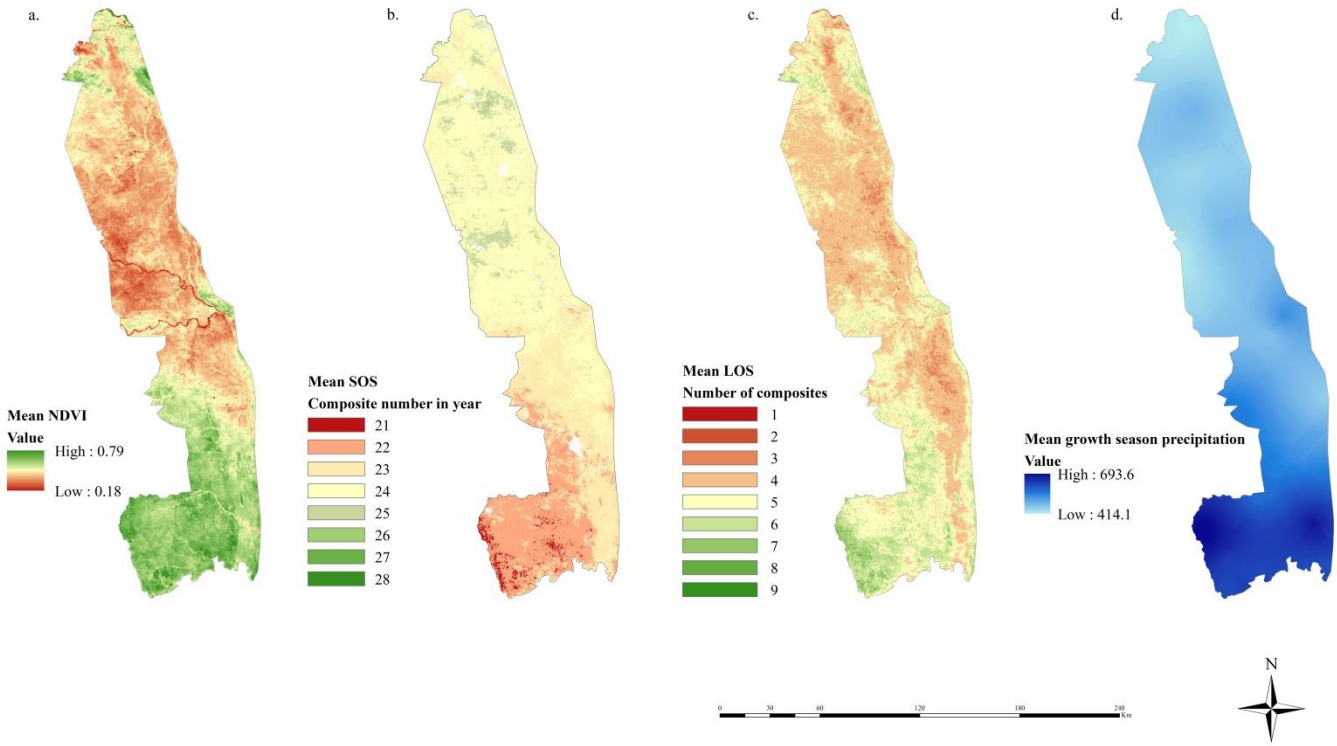


Figure 3.6. Maps illustrating the spatial distribution of the a) mean NDVI, b) mean SOS, c) mean LOS and d) mean precipitation (TAMSAT) across the KNP calculated from 14 growing seasons between 2002 and 2015. For mean SOS, the composite (16-day) numbers represent the period between November and February of the following year.

Table 3.1. Correlation coefficients (r) depicting the spatial relationships between the mean growing season NDVI and the mean growing season variables; SOS (start of season), LOS (length of season) and precipitation.

	NDVI (mean)
SOS (mean)	-0.764
LOS (mean)	0.667
Precipitation (mean)	0.777

3.4.2. Massive persistence change trends: NDVI, SOS, LOS and precipitation

Persistence analyses of the cumulative sum of year to year differences in NDVI, SOS, LOS and precipitation over 13 growing seasons (Figure 3.7) showed a widespread pattern of localised increases and decreases across the park relative to the 2002/03 drought year as the starting condition. Mean growing season NDVI showed noticeable patterns of persistent increases in the far south and central areas of the park while persistent decreases in NDVI were evident in the northeast and central areas of the KNP (Figure 3.7a). A significantly earlier SOS trend were noted for the south-western corner of the park while localised areas of persistently later onset of the growing season were noted in the north of the park (Figure 3.7b). LOS showed localised areas of persistent decrease in the southern region of the KNP and increase in the central area of KNP (Figure 3.7c). Considering precipitation persistence with respect to the 2002/03 El Niño-induced drought conditions, our map indicated persistently higher precipitation in the southern region of the park while increases in the northern region were less and more variable (Figure 3.7d).

Results from the BCS tool analysis of the persistence maps showed a moderately weak inverse correlation between NDVI persistence and SOS persistence while no relationship was found between NDVI persistence and LOS persistence (Table 3.2). A very weak correlation between NDVI persistence and precipitation persistence were indicated by the correlation coefficient (Table 3.2).

Table 3.2. Correlation coefficients (r) depicting the spatial relationships between the NDVI massive persistence and the massive persistence of the variables; SOS, LOS and precipitation.

	NDVI (massive persistence)
SOS (massive persistence)	-0.315
LOS (massive persistence)	-0.012
Precipitation (massive persistence)	0.105

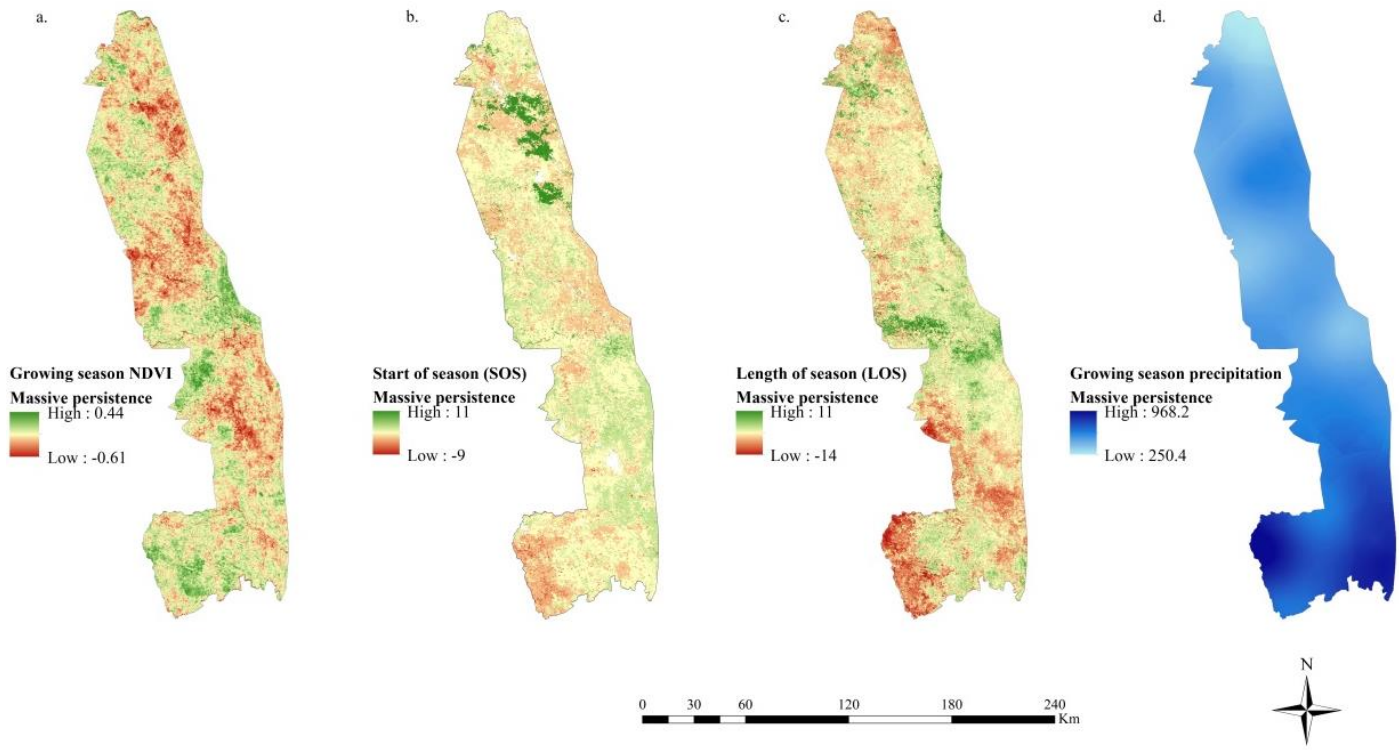


Figure 3.7. Spatial persistence of growing season a) NDVI, b) SOS, c) LOS and d) precipitation calculated by the massive persistence metric (M) as the cumulative sum of year to year differences of the 13 growing seasons between 2002 and 2015.

3.4.3. Converging and diverging trends in NDVI, SOS, LOS and precipitation

The percentages of the KNP landscape area with statistically significant positive (increasing) and negative (decreasing) changes for NDVI, SOS, LOS and precipitation are summarised in Table 3.3. For NDVI, LOS and precipitation persistent changes covered about 30% of the KNP landscape, while for SOS the area affected was less than 10%.

Of the KNP area that showed statistically significant persistent changes in NDVI (Table 3.4), less than 5% of these changes spatially converged with LOS (Figure 3.8b) and precipitation (Figure 3.8c) and almost none with SOS (Figure 3.8a; Table 3.4) for increasing and decreasing trends, respectively. The percentage area that was affected by divergence of spatial increases and decreases in NDVI was above 10% for SOS, LOS and precipitation, while the percentage area of "no change" overlap with NDVI was

large for all three variables (Table 3.4). Negative convergence with NDVI appeared clustered in the far north, on the western and eastern borders of the central region, and more scattered and isolated in the southern region (Figure 3.8). Positive convergence trends were most noticeable in the south and to a lesser extent in the central region. Diverging trends of NDVI increases and decreases were distributed throughout the park landscape with some areas appearing more clustered than others (Figure 3.8). These include an area of NDVI decrease in the north-eastern region and towards the south-central region.

Table 3.3. Percentage of the KNP area affected by significant persistent increases and decreases between 2002 and 2015 for NDVI, SOS, LOS and precipitation calculated at (1× Standard deviation) of the massive persistence maps.

	NDVI	SOS	LOS	Precipitation
Significant decrease (1SD)	15.32	3.13	18.93	12.02
No significant change	69.33	91.45	68.29	69.32
Significant increase (1SD)	15.35	5.42	12.78	18.66

Table 3.4. The spatial convergence and divergence change trends of statistically significant persistence in NDVI with respect to significant persistence of SOS, LOS and precipitation calculated as a percentage of the KNP landscape area.

	Percentage area of the KNP landscape affected by overlap of significant change trends.		
Change trend	NDVI - SOS	NDVI - LOS	NDVI - Precipitation
Converging positive	0.16	2.39	3.88
Converging negative	0.10	2.07	2.54
Diverging NDVI positive	15.89	11.26	10.95
Diverging NDVI negative	14.21	14.74	10.95
No significant change trend	65.06	47.37	47.74

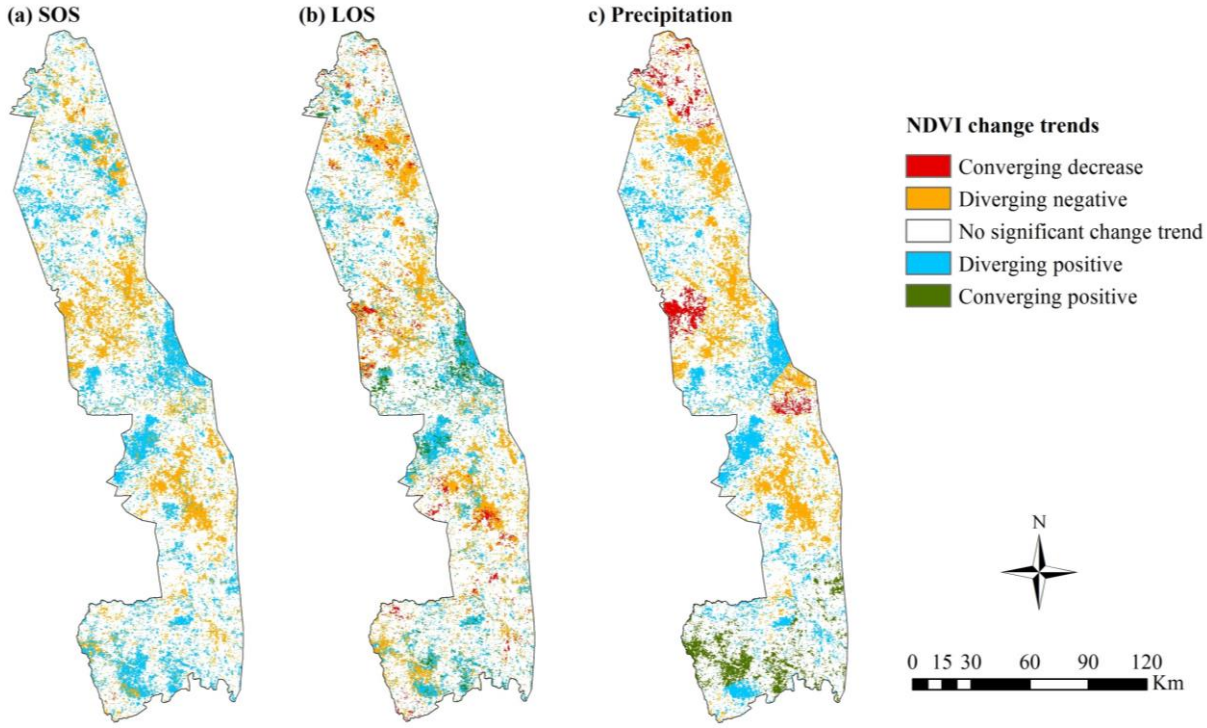


Figure 3.8. Spatial distribution of the converging (similar) and diverging (different) change trends of the statistically significant persistent increases and decreases of (a) NDVI and SOS, (b) NDVI and LOS and (c) NDVI and precipitation across the Kruger National Park.

3.5. Discussion

Savanna ecosystems are expected to be substantially influenced by changes in climate with state shifts from open grassland with scattered trees to landscapes dominated by woody cover at the forefront of predictions (Kulmatiski & Beard 2013; Bunting *et al*. 2016). Monitoring of vegetation in relation to climatic factors, such as precipitation, is therefore essential for informed decision-making and management actions. In this study we aimed to characterise and evaluate spatio-temporal vegetation greenness trends in relation to the relative role of precipitation as a driver of vegetation change patterns in the KNP. In addition to precipitation as a variable, we employed phenology metrics in our analyses to attempt to separate the direct effects of precipitation from those confounded by local disturbances from top-down drivers such as fire and herbivores (Wang & Fensholt 2017).

Across the KNP landscape, vegetation greenness patterns were strongly correlated with mean growing season precipitation as well as the mean start (SOS) and duration (LOS) of the growing season despite the presence of disturbance factors such as fire and herbivores. When considering the means of the vegetation greenness and phenometric patterns between 2002 and 2015, our results suggested that precipitation is the primary driver of the overall inter-annual vegetation greenness in the KNP, albeit not the only factor in play. Indeed, previous studies in the park also established a strong association between precipitation and vegetation phenology patterns (Parrini & Erasmus 2009) and between precipitation and vegetation biomass (Wessels *et al*. 2006; Wessels & Dwyer 2011). However, studies also reported that factors such as soil moisture and tree/grass ratios may complicate the relationships (Archibald & Scholes 2007; Parrini & Erasmus 2009). For instance, the onset of greening for trees has been shown to be strongly affected by day length while grass greening were influenced by soil moisture as well (Archibald & Scholes 2007). Parrini & Erasmus (2009) further found that the start of the season was affected by dry season precipitation, while the length of the season was strongly influenced by precipitation from the previous wet season. Nevertheless, from our correlation analyses between NDVI and precipitation and between NDVI and SOS, it appears that the onset of the season, which is also dependent on precipitation, has a strong control on the general flux of vegetation greenness across the KNP landscape. From this we were then able to deduce that if changes in vegetation greenness do not spatially correlate with changes in precipitation, SOS or LOS, it is most likely that vegetation greenness changes are a result of other factors.

In the second part of our study we focused on the cumulative spatial changes in growing season NDVI in relation to spatial changes in SOS, LOS and precipitation. Overall, our findings indicated that about 30% of the KNP landscape was characterised by increases and decreases of vegetation greenness. Of these, convergence with significant changes in precipitation, SOS and LOS accounted for very small percentages of the total KNP area and apart from some locally clustered areas, explained little of the vegetation greenness change trends across most of the landscape. The clustered spatial distribution of converging change trends between NDVI and precipitation suggest that changes in vegetation greenness in these areas (far north, far south and localised areas in the central

regions – Figure 3.8) may be a direct consequence of changes in precipitation. Indeed, in a recent study, it was shown that areas in the far north and far south of the park experienced greater precipitation seasonality changes (MacFadyen *et al*. 2018). Converging change trends between vegetation greenness and the change trends in the start and duration of the growing season change trends accounted for less than 5% of the total KNP area and were more dispersedly distributed across the park. In this case, the effect of precipitation through its relationship with vegetation seasonality may not have been ecologically meaningful.

Diverging change trends in vegetation greenness were more widespread across the extent of the park. The observation that these changes were not associated with changes in precipitation or changes in phenological characteristics lead us to conclude that the "top-down" effect of local disturbances, such as fire and herbivory, may have been overriding the "bottom-up" effect of precipitation in these areas. Indeed, the KNP vegetation dynamics is dictated by complex interactions of different drivers (Du Toit *et al*. 2003) and any changes beyond the threshold of the "normal" inherent flux of the ecosystem may result in process changes that may threaten the integrity of the ecosystem.

Despite the indication that changes in vegetation greenness could be predominantly driven by local disturbances of fire and herbivory, we should keep in mind that we did not account for factors such as soil moisture and temperature, while the differential seasonal response of trees and grasses to environmental cues may also have influenced our findings. Although the spatial extent of converging change trends in SOS, LOS and precipitation seem to be rather small in the larger landscape, the scattered distribution of these observed trends throughout the park rationalises the need for continued monitoring and further exploration of the spatio-temporal trends and changes in vegetation characteristics in relation to precipitation. Given that we observed not only changes in vegetation greenness, but also in the seasonal characteristics of vegetation greenness patterns, our results may have several ecological consequences and management implications. For example, longer growing seasons may promote increased fire frequency and intensity (van Wilgen *et al.* 2000), which could subsequently

influence the vegetation composition and structure (Shackleton & Scholes 2000; Smit *et al*. 2010). Additionally, the combination of increased fire frequency and seasonal availability of green vegetation could change herbivore distribution and movement behaviour (Birkett *et al*. 2012; Chamane 2012) which in turn could exacerbate impact on vegetation through the combined effect of fire and herbivores (Munyati & Sinthumule 2016). Moreover, if precipitation patterns continue to change as predicted (IPCC 2007; Buitenwerf *et al*. 2012; Cai *et al*. 2014; MacFadyen *et al*. 2018), the response of vegetation may be more pronounced and consequently affect the dynamic nature of the relationship between different drivers that may cause the system to exceed thresholds of tolerable change (Druce *et al*. 2008; Grant *et al*. 2011).

Our methods provide a means through which the spatial extent of changes in vegetation greenness and the relative influence of precipitation can be tracked continuously across the entire landscape. With careful consideration of the benchmark conditions for interpretation our methods could serve as a baseline, cost-effective monitoring approach. Additional field validation of what would be considered ecologically significant changes instead of arbitrarily using (1 × Standard deviation) may further optimise the spatial persistence analysis. Evaluating the intra-annual characteristics of vegetation trends in relation to fire and herbivores in the framework of our study may further improve our understanding of the co-dynamic relationship between the drivers of vegetation change.

3.6. Conclusion

Our unique combination of phenology and spatial persistence analyses allowed for a complimentary approach through which we were able to identify different patterns of change that are underpinned by different drivers that are dynamic over space and time. Through our evaluation of the relationships between vegetation greenness, SOS, LOS and precipitation, we were able to separate the effect of precipitation on vegetation changes from the changes that were likely the consequence of top-down drivers. The observed spatial correlation between the mean vegetation greenness to both precipitation patterns and phenometrics indicated that precipitation was the primary

driver of the overall inter-annual vegetation greenness patterns in the KNP landscape during our study period. More importantly, change trends of vegetation greenness showed little association with changes in precipitation, season onset and season length, indicating that for the current study period, other drivers, such as fire and herbivores, were most likely responsible for the observed changes in vegetation greenness that persisted in the landscape. Future research should focus on the intra-annual dynamics of vegetation changes in relation to the various drivers. With some improvements, the approach we used has much potential to benefit management through continued long-term monitoring that is relatively straightforward and informative.

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CHAPTER 4

PHENO-SEASON EFFECTS OF ELEPHANTS AND FIRE ON SPATIO-TEMPORAL CUMULATIVE CHANGES IN VEGETATION GREENNESS

4. PHENO-SEASON EFFECTS OF ELEPHANTS AND FIRE ON SPATIO-TEMPORAL CUMULATIVE CHANGES IN VEGETATION GREENNESS

4.1. Abstract

Continued monitoring of vegetation change and its associated causes is essential for conservation managers who need to be pro-active in a world where climate change is already affecting ecosystems. To address this important issue, we evaluated a methodological approach for the broad-scale identification and monitoring of the role of fire and elephants as drivers of persistent spatial change trends in vegetation greenness between 2002 and 2015. We defined four different NDVI trend zones that included increase and decrease zones with the associated buffers as controls. For these NDVI trend zones we compared the mean fire frequency as well as mean elephant densities (bulls and herds separate). We further defined ecologically relevant seasons based on phenology metrics (pheno-seasons) and used the vegetation greenness values calculated for the pheno-seasons (pheno-season NDVI) as the response variables in correlation analyses with fire frequency and elephant densities for each of the NDVI trend zones. Similarly, we delineated burn and non-burn areas for which we compared the relationships between elephant densities and pheno-season NDVI. Our results seemed to suggest that cumulative vegetation greenness change trends could be linked to the combined effect of elephant bull densities and fire frequency although the observed correlations were relatively weak. The relationships between elephant densities and pheno-season NDVI for burn and non-burn areas showed much variability and stress the importance of other variables, such as rainfall, that may influence these dynamics. By addressing the limitations of this study, the approach could be optimised for the continuous monitoring of the spatio-temporal change dynamics of vegetation in relation to driver dynamics.

4.2. Introduction

The nature of the complex and variable interactions of fire and elephants as drivers of vegetation patterns in the KNP remains one of the most important subjects of interest to conservation managers. Our understanding of the impact of elephants and fire as drivers of vegetation dynamics at localised spatial and temporal scales are relatively well established (van Wilgen *et al.* 2007; Guldemond & van Aarde 2008). However, how the finer scale impacts of this co-dynamic relationship between elephants and fire translate to the landscape scale, is less clear.

In the Kruger National Park (KNP), South Africa, fire is an important disturbance that influences vegetation patterns through its variability in the removal of biomass (van Wilgen *et al.* 2003). Depending on the intensity, frequency and season, fire dynamics elicit much varied responses from the interactions with other components in the ecological framework (van Wilgen *et al.* 2003). For example, high-intensity fires resulting from high biomass due to low herbivore pressure can affect tree height distribution (Trollope *et al.* 1998; Higgins *et al.* 2000). Fire frequency and intensity has also been shown to modify woody vegetation structure, while species composition does not seem to be much affected by fire (Govender *et al*. 2006). On the other hand, frequently re-occurring fires can prevent tree establishment (van Wilgen *et al*. 2000) and alter the spatial distribution of animals (Chamane 2012).

In arid savanna landscapes, the density of trees is prevented from forming closed canopies through the limitation imposed by low and variable rainfall (van Wilgen 2009). The exclusion of fire is therefore unlikely to shift an arid savanna system to a closed woodland state. Rainfall variability and herbivory in these arid landscapes often limit the grass fuel load, thereby creating a more irregular frequency of fire incidence than in the moist savannas (Holdo *et al.* 2009; van Wilgen 2009). In moist conditions, high rainfall promotes woodland closure (Sankaran *et al*. 2005). However, trees are prevented from forming closed canopies in the occurrence of frequent fires and herbivore foraging pressure. The exclusion of fire may then shift the system into a woodland-dominated state (van Wilgen *et al*. 2000). Fire is often considered to increase

grass quality over short periods of time by removing the dead biomass and has even been shown to have positive effects on the nutritional quality of grasses that outweigh those of grazing (Mbatha & Ward 2010). However, decreasing grass quality has also been reported for frequently burned grasses as it negatively influences stored reserves (Trollope 1987; 1999). Fire therefore exerts considerable impact on the primary productivity of vegetation across the KNP landscape, thereby affecting short- and long-term vegetation dynamics.

The spatial use and temporal resource selection behaviour of the African elephant (*Loxodonta africana*) may dominate the consequences for landscape-scale vegetation patterns through their ability to transform vegetation (Lock 1972; Waldram *et al.* 2007; Guldemond & van Aarde 2008). Elephants alter the structure of vegetation directly through consumption and indirectly through processes such as nutrient mediation (Holdo *et al.* 2007). Grazing may further prevent fire from affecting the woody component by the removal of fuel and therefore a landscape that favours woody species may result (Holdo *et al.* 2007). Accordingly, woody plant encroachment has been ascribed to grazing-induced reductions in fire frequency (Scholes & Archer 1997; Roques *et al.* 2001; Smit 2004). Browsing by elephants also induce considerable modifications in the structure of the woody component. The vegetation impact of elephants through bark removal and toppling of trees has for instance been linked to tree reductions (Asner & Levick 2012), conversion of woodland to open savanna as well as the local extirpation of plant species (Caughley 1976; Owen-Smith 1988; O'Connor *et al*. 2007; Kerley *et al*. 2008).

At the landscape scale, it has been shown that elephants favour greener vegetation (Young *et al.* 2009; Murwira & Skidmore 2010) throughout the phenological cycle (Loarie *et al*. 2009). Elephants further show pronounced differences in their seasonal behaviour and spatial movement response to water availability (Grainger *et al*. 2006; Purdon & van Aarde 2017). During the dry season, elephants tend to concentrate their spatial movements around water sources, while during the wet season they disperse more freely (Smit *et al*. 2007; Purdon & van Aarde 2017). Consequently, we assume that their impact on the vegetation would be differential across various seasons, with the

dry season most likely the time when severe reductions in vegetation (especially woody vegetation) would take place. Based on previous observations that elephants select for greener vegetation in the landscape we investigate the possible role that elephants and fire may have had in cumulative vegetation greenness changes across the KNP landscape.

Understanding the seasonality of vegetation greenness and how cumulative vegetation greenness change trends are differently influenced by the interaction of elephants and fire may enable us to gain some insight into this problem. The aim of the present study is therefore to evaluate a methodological approach for the broad-scale identification and monitoring of the role of fire and elephants as drivers of change trends in pheno-season vegetation greenness. Using a spatial persistence map from our previous work (Ernst-de Beer & Erasmus *in prep*. – Chapter 3 of this thesis) representing the cumulative changes in satellite-derived Normalised Difference Vegetation Index (NDVI) between 2002 and 2015, we define NDVI trend zones (locations where all the pixels have the same long term NDVI trends) for which we compare elephant densities and fire frequencies. We further investigate the relationships between pheno-season NDVI and elephant densities and fire frequency, respectively, within the NDVI trend zones. Finally we focus on the pheno-season NDVI-elephant relationships for burn areas and non-burn areas.

Specifically, we considered the following *a priori* hypotheses;

1. Elephant bull density, elephant herd density and fire frequency will be highest in the NDVI decreasing zone and lowest in the NDVI increasing zone when compared to control areas.
2. There is a positive correlation between pheno-season NDVI and elephant bull and herd densities while there is a negative correlation between pheno-season NDVI and fire frequency for the NDVI decrease zone.
3. Pheno-season NDVI is positively correlated with elephant bull and herd densities within the burn areas while there is no correlation within the non-burn areas.

4.3. Materials and Methods

4.3.1. Study area

Stretching across almost 20 000 km^2 of the lowveld in the north-eastern region of South Africa, the semi-arid Kruger National Park (KNP) (24° S, 31.5° E) is a world-renowned conservation area (Figure 4.1). The heterogeneity and diversity of the KNP landscape can be ascribed to various abiotic and biotic factors.

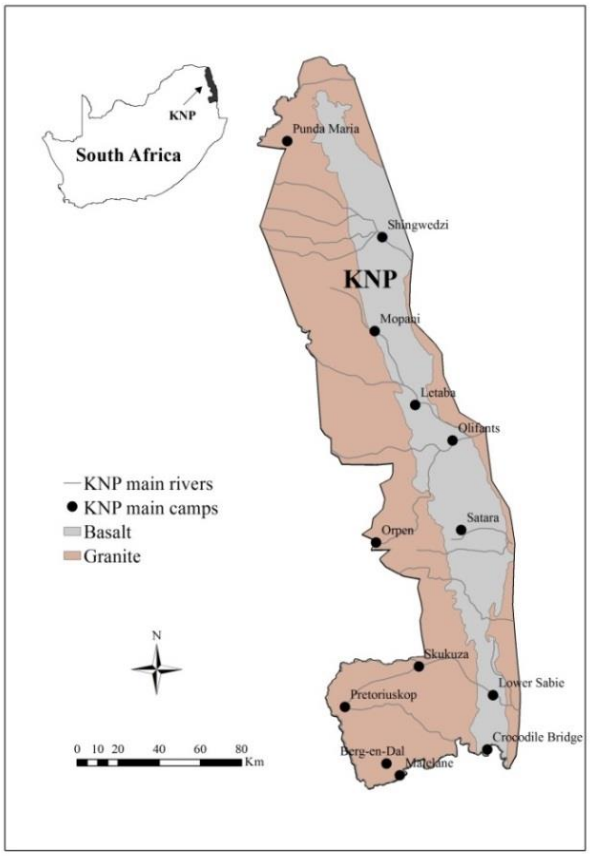


Figure 4.1. Map illustrating the Kruger National Park situated in the north-eastern part of South Africa. Basic geology roughly divides the park into the western granites and eastern basalts.

Obvious precipitation patterns include a gradient that ranges from ~300-500 mm yr^{-1} in the north to ~500-700 mm yr^{-1} in the south, mostly occurring during the hot, summer

months (November to April). Another important feature of the KNP is the east-west division between clay-rich basaltic soils and sandy, nutrient-poor granite with the latter generally supporting denser woody vegetation (Venter *et al.* 2003). Broadly, mopane *(Colophospermum mopane)* and red bush willow *(Combretum apiculatum* subsp. *apiculatum)* with low grass cover commonly occur on the granite substrates in the north, while basalts to the east carry mopane shrubs (Van Wilgen *et al.* 1998). Centrally, the park supports open savanna bushveld on the basalts where the dominant grass layer is interspersed with low density tree species such as knobthorn (*Senegalia nigrescens*), umbrella acacia (*Vachellia tortilis*) and marula (*Sclerocarya birrea*) while *Combretum/ Terminalia* tree savanna are characteristic of the western granites. Towards the south, broadleaf mixed woodland on granites and thorn thickets on the basalts are more prominent.

4.3.2. General overview of methods

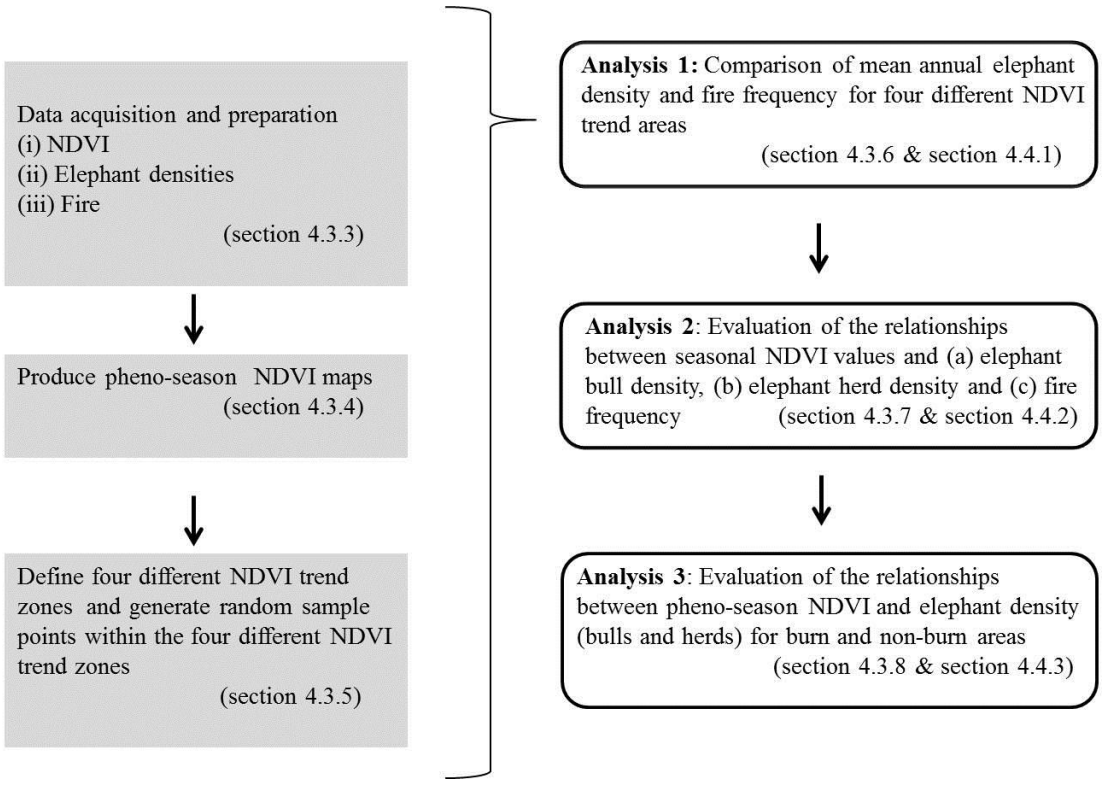


Figure 4.2. Diagram showing a general overview of the workflow followed. Pheno-seasons are derived from phenology and are based on the 20% and 80% levels of NDVI throughout the phenological cycle.

4.3.3. Data acquisition and preparation

(i) NDVI

Calculated as the ratio between the difference and the sum of the near-infrared and the red reflectance of the earth's objects, the NDVI is a measure of photosynthetically active vegetation (Tuckers & Sellers 1986) and a reliable representation of green vegetation production in savannas which is often associated with vegetation health (Pettorelli *et al*. 2005). We downloaded the 16-day composite images of MODIS Normalised Difference Vegetation Index time-series imagery (MOD13Q1 version 5, BRDF-corrected product) for the time period between 2001 and 2015 at a spatial resolution of 250 m from the MODIS Reprojection Tool Web Interface from the USGS DAAC at EROS (URL: http://mrtweb.cr.usgs.gov). The WGS 1984 UTM 36S projection was used for all our analyses.

(ii) Elephant densities

SANPARKS' Scientific Services provided us with the aerial elephant census data record that dates back to 1967. The KNP elephant census protocol involves total counts during the dry season (usually August or September) when visibility is greatest. For each of the years between 2002 and 2015, we separated the bull and the herd counts and then calculated elephant bull and herd densities at 250m spatial resolution using the Kernel density tool in the Spatial Analyst extension of ArcGIS. This tool utilises a quadratic kernel function with a bandwidth algorithm (default search radius) (Silverman 1986). Census data for 2013 and 2014 was not available and we therefore could not include these years in our analyses. The annual elephant density maps were then further averaged to give us a mean elephant density map for the study period.

(iii) Fire

Fire data were provided by SANParks as the spatial extent of satellite-derived burn scars (see Govender *et al*. 2012 for detailed description of fire mapping) across the park for each year between 2002 and 2015. Firstly we added the fire occurrence for each year together to provide us with a fire frequency map indicating the number of years of fire occurrence between 2002 and 2015. Secondly we separated the fires that occurred

according the pheno-seasons as derived by the methods in section 4.3.4 in order to produce maps with the spatial extent of fires specific to each pheno-season.

4.3.4. Defining seasons with phenology metrics (pheno-seasons)

In order to capture ecologically relevant intra-annual greenness of vegetation, we defined four different seasons for the KNP with the use of phenology metrics. We analysed the NDVI time-series data in the Timesat software package version 3.1 (Eklundh & Jönsson 2012; Jönsson & Eklundh 2002, 2004) to identify season start and end dates at 20% and 80% NDVI levels (Eklundh & Jönsson 2012). These points in time were then used to define the seasons for the KNP as follows; a green-up season during which greening of the vegetation initiates and increases; a wet season where green vegetation typically reaches its maximum; a brown-up season during which plant senescence sets in; and a dry season characterised by minimum levels of vegetation greenness (Figure 4.3). Timesat parameters used for this study include: Spike method – median filter 1; Number of envelope iterations – 1; Adaptation strength – 2; Savitsky-Golay window size – 3; Start of season method – Amplitude; Season start – 0.8; Season stop – 0.2.

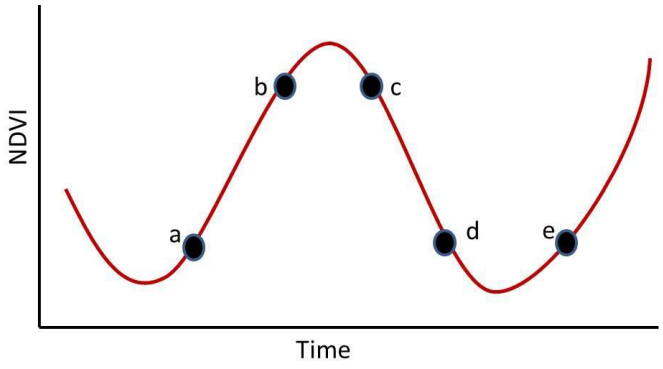


Figure 4.3. A hypothetical curve to illustrate how pheno-seasons were defined for the study. (a), (d) and (e) indicate the times when 20% levels of NDVI are reached while (b) and (c) mark the 80% levels. The time between (a) and (b) defines the "green-up" inter-peak season, time between (b) and (c) defines the wet season, time between (c) and (d)

defines the "brown-up" inter-peak season and time between (d) and (e) defines the dry season.

4.3.5. NDVI trend zones

As the basis for our analyses that investigate the influence of fire and elephants on vegetation greenness trends, we used the spatial persistence map of NDVI between 2002 and 2015 (Figure 4.4a) that formed part of a study that used spatial persistence analyses (Waylen *et al.* 2014) and phenology to evaluate the relative role of precipitation variability as a causal factor of vegetation greenness changes (Ernst-de Beer & Erasmus *in prep.* – Chapter 3 of this thesis). In summary, the spatial persistence map represents the cumulative changes in vegetation greenness calculated from the annual phenological cycles that were derived from phenology parameters. Details of the methods used for the creation of the cumulative change map can be found in Ernst-de Beer & Erasmus (*in prep.* – Chapter 3).

Defining NDVI trend zones and random samples

For the purpose of this paper, we distinguished between the zones (total pixel area) in the spatial persistence map where NDVI showed significant cumulative increases (Figure 4.4a) and cumulative decreases (Figure 4.4b). To enable comparative assessment of the possible influence of elephants and fire we created "control areas" for the persistent increasing and decreasing areas, respectively, by generating surrounding buffer areas at a 1 km distance (Figure 4.4). We decided on a 1km distance (~ 4 pixels) to minimise the inevitable overlap between the control trend zones. We therefore defined four different NDVI trend zones representing cumulative NDVI increases (persistent increase zone – PIZ), the buffer zone surrounding the NDVI increases (increase zone buffer – IZB), cumulative NDVI decreases (persistent decrease zone – PDZ) and the buffer zone surrounding the NDVI decreases (decrease zone buffer – DZB).

Given the large differences in the total pixel area sizes of the four NDVI trend zones (Table 4.1), we generated a random point sample that was initially specified at 500

points at least 150m apart. This was done to equalise the sample sizes and avoid violation of the "homogeneity of variance" assumption. Due to the latter specifications and some points in the buffer zones that had to be removed as they were located outside the park boundary, the final random point sample sizes varied as specified in Table 4.1.

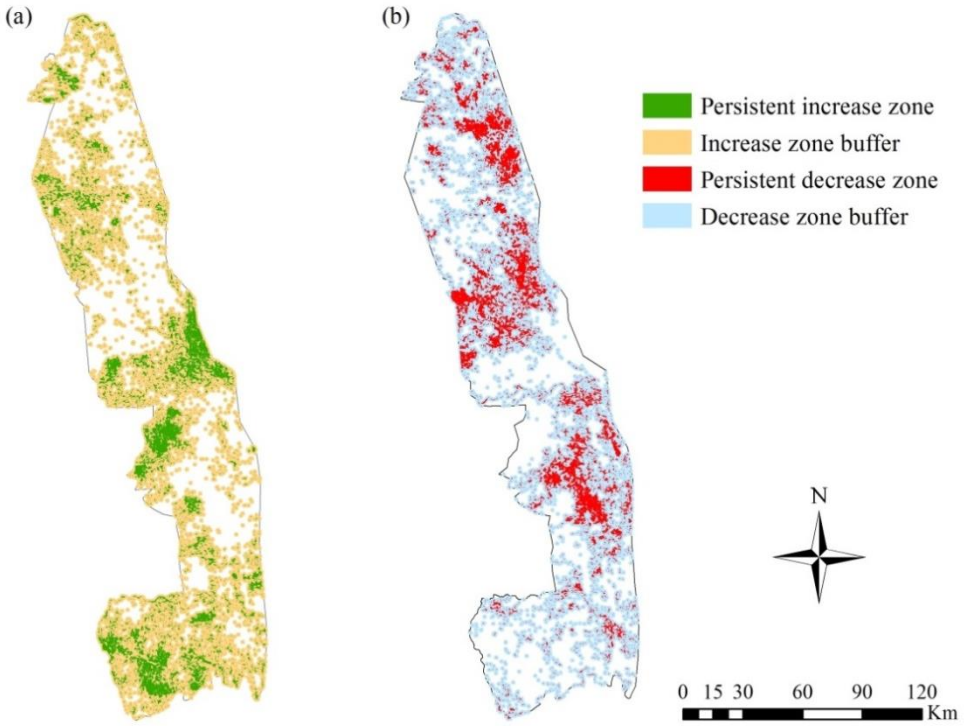


Figure 4.4. Maps illustrating the spatial distribution of the (a) persistent NDVI increase zone with the associated increase zone buffer and the (b) persistent NDVI decrease zone with associated decrease buffer zone.

Table 4.1. The total pixel area and number of random sample points for each of the four NDVI trend zones that were defined for analyses.

	Total pixel area (km^2)	Number of random sample points (n)
Persistent increase zone (PIZ)	2 695	465
Increase zone buffer (IZB)	10 413	439
Persistent decrease zone (PDZ)	2 741	495
Decrease zone buffer (DZB)	9 954	460

4.3.6. Analysis 1: Comparison of mean annual elephant densities and fire frequency between NDVI trend zones

For each of the random point samples that were generated for the four NDVI trend zones we extracted values of the elephant bull density and elephant herd density from the mean elephant density maps for the time period between 2002 and 2015 (section 4.3.3). We also extracted fire frequency values for the random points. We then compared the mean elephant densities and fire frequencies between each of the NDVI trend zones using the Kruskal-Wallis analysis of variance for non-parametric data and the Dunn's multiple comparison post-hoc test.

4.3.7. Analysis 2: Relationships between seasonal NDVI and (i) elephant bull density, (ii) elephant herd density and (iii) fire frequency

To evaluate the relationships between seasonal NDVI and elephant densities and between seasonal NDVI and fire frequency we used the same extracted values for the random point samples as in the previous section (section 4.3.6). Additionally, we extracted the NDVI values from the mean NDVI maps that we created for the brown-up, dry, green-up and wet seasons. For each pheno-season we used the non-parametric Spearman r correlation analysis to assess the correlations between NDVI and elephant bull density, between NDVI and elephant herd density and between NDVI and fire frequency. We then graphed the Spearman r correlation coefficients as a function of time (pheno-seasons).

4.3.8. Analysis 3: Relationship between elephant density and seasonal NDVI for burn areas and non-burned areas

For this analysis we used the seasonal fire maps (section 4.3.3). For each year we delineated non-burn areas by creating 1 km buffers around the burn areas. We then generated random point samples for the burn and the non-burn areas for each season on an annual basis. We initially specified the random point sample at 150 points at least 150 m apart but due to the smaller size of some burn areas and the location of some

points outside the park boundary in the non-burn areas, the number of points per sample varied between 100 and 150. Using these random points we extracted the corresponding seasonal NDVI values as well as elephant bull and herd densities. We then applied the non-parametric Spearman r correlation analysis to evaluate the relationship between elephant densities (bulls and herds) and the pheno-season NDVI values for burn and non-burn areas. We finally plotted the Spearman r correlation coefficient over time (years) for each season and for bulls and herds separately.

4.4. Results

4.4.1. Analysis 1: Comparison of mean annual elephant densities and fire frequency between NDVI trend zones

The mean and standard deviations of the elephant bull densities, elephant herd densities and fire frequencies for the four different NDVI trend zones are illustrated in Figure 4.5. Results from the Kruskal-Wallis test show that the distributions of elephant bull densities (Figure 4.5a) differed significantly among the NDVI trend zones ($X^2 = 47.25$, $p < 0.0001$). Post-hoc multiple comparison tests indicate that the PDZ had significantly larger elephant densities than PIZ ($p < 0.0001$), IZB ($p < 0.0001$) and DZB ($p < 0.001$). For elephant herd densities (Figure 4.5b), there was no detectable differences in the distributions between any of the NDVI trend zones ($X^2 = 6.969$, $p=0.0729$). Fire frequencies (Figure 4.5c) differed significantly between the NDVI trend zones ($X^2 = 20.90$, $p < 0.0001$) with PDZ showing greater fire frequency than PIZ ($p < 0.0001$), IZB ($p < 0.01$) and DZB ($p< 0.05$). However, even though statistically significant differences were found in the distribution of elephant densities and fire frequency between the four trend zones, the standard deviations were rather large (Figure 4.5).

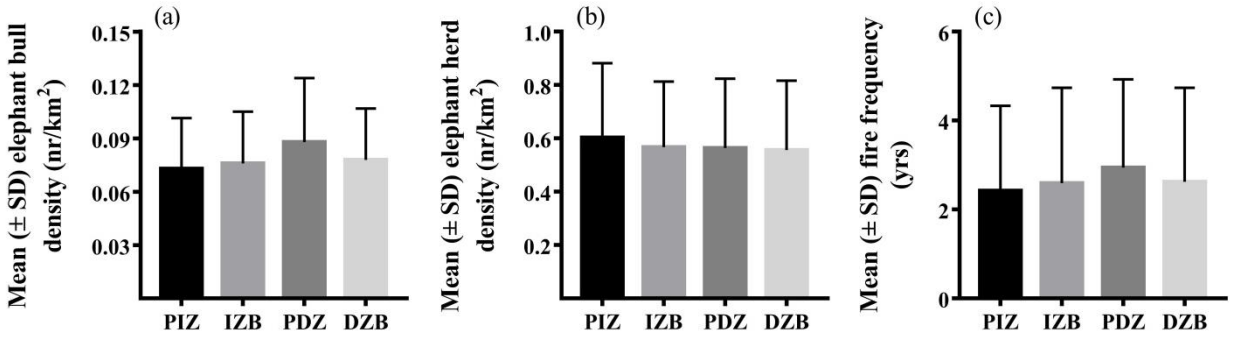


Figure 4.5. Graphs illustrating the (a) mean (±SD) elephant bull densities, (b) elephant herd densities and (c) fire frequencies for the different NDVI trend zones where PIZ is the persistent increase zone, IZB is the increase zone buffer, PDZ is the persistent decrease zone and DZB is the decrease zone buffer.

4.4.2. Analysis 2: Relationships between seasonal NDVI and (i) elephant bull density, (ii) elephant herd density and (iii) fire frequency

The Spearman r correlation coefficients indicating the relationship between the pheno-season NDVI and elephant densities (bulls and herds) as well as fire frequency for four different NDVI trend zones are illustrated in Figure 4.6. Elephant bull densities showed negative correlations across all seasons for all four NDVI trend zones (Figure 4.6a). The strongest negative correlation was observed for the PDZ during the dry season and the green-up season as well as for DZB during the green-up season. For the PIZ, elephant bull densities showed the weakest relationships although these were all also statistically significant (Table 4.2) except for the wet season. Correlations between pheno-season NDVI and elephant bull densities were very similar for the two buffer zones and their strength intermediate to the increase and decrease zones.

Correlations between pheno-season NDVI and elephant herd densities were mostly positive with NDVI increases being associated with higher elephant herd densities (Figure 4.6b, Table 4.2). For the PDZ and DZB, the correlation trends were very similar. The strongest positive correlation was noted for the PIZ during the green-up and wet seasons, while during the wet season, the PIZ was the only trend zone with a

positive correlation. Some negative correlations were also observed for the IZB during the brown-up and wet seasons while no correlations were evident during dry and the green-up seasons.

The relationship between fire frequency and pheno-season NDVI was negative for the PDZ and the DZB during the brown-up, dry and green-up seasons although the negative correlations were much stronger for the PDZ (Figure 4.6c, Table 4.2). For both of these NDVI trend zones the dry season showed the strongest correlation. In contrast, the PIZ and the IZB had mostly positive correlations, except for the dry season when no correlation was evident. In this case, the strongest positive correlations were observed for the wet season in both the PIZ and the IZB.

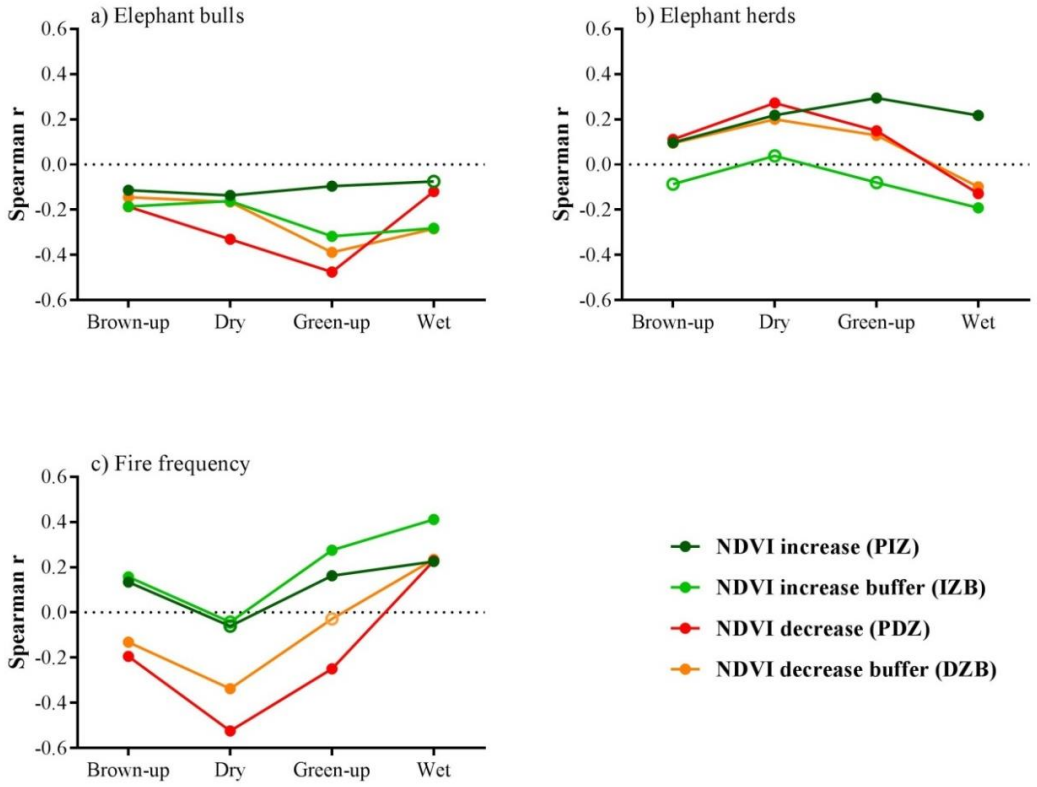


Figure 4.6. Graphs depicting the spearman r correlation coefficients for the relationships between (a) the pheno-season NDVI and elephant bull densities, (b) the pheno-season NDVI and herd densities and (c) the pheno-season NDVI and fire frequencies. Filled symbols indicate correlations that were statistically significant while open symbols indicate no statistical significance.

Table 4.2. Spearman r correlation analysis statistics for the relationships between (a) the pheno-season NDVI and elephant bull densities, (b) the pheno-season NDVI and herd densities and (c) the pheno-season NDVI and fire frequencies.

	Brown-up season	Dry season	Green-up season	Wet season
(a) Elephant bull density				
PIZ	r = -0.114, p < 0.05	r = -0.136, p < 0.01	r = -0.095, p < 0.05	r = -0.075, p = 0.11
IZB	r = -0.185, p < 0.0001	r = -0.161, p < 0.001	r = -0.318, p < 0.0001	r = -0.281, p < 0.0001
PDZ	r = -0.187, p < 0.0001	r = -0.330, p < 0.0001	r = -0.476, p < 0.0001	r = -0.120, p < 0.01
DZB	r = -0.144, p < 0.01	r = -0.166, p < 0.0001	r = -0.389, p < 0.0001	r = -0.285, p < 0.0001
(b) Elephant herd density				
PIZ	r = 0.098, p < 0.05	r = 0.219, p < 0.0001	r = 0.294, p < 0.0001	r = 0.217, p < 0.0001
IZB	r = -0.087, p = 0.066	r = 0.039, p = 0.419	r = -0.079, p = 0.095	r = -0.191, p < 0.0001
PDZ	r = 0.111, p = 0.013	r = 0.273, p < 0.0001	r = 0.149, p < 0.001	r = -0.129, p < 0.01
DZB	r = 0.094, p < 0.05	r = 0.200, p < 0.0001	r = 0.129, p < 0.01	r = 0.098, p < 0.05
(c) Fire frequency				
PIZ	r = 0.135, p < 0.01	r = -0.060, p = 0.19	r = 0.162, p < 0.001	r = 0.225, p < 0.0001
IZB	r = 0.157, p < 0.001	r = -0.042, p = 0.377	r = 0.275, p < 0.0001	r = 0.411, p < 0.0001
PDZ	r = -0.194, p < 0.0001	r = -0.524, p < 0.0001	r = -0.250, p < 0.0001	r = 0.228, p < 0.0001
DZB	r = -0.132, p < 0.01	r = -0.337, p < 0.0001	r = -0.029, p = 0.540	r = 0.235, p < 0.0001

4.4.3. Analysis 3: Relationship between elephant density and seasonal NDVI for burn areas and non-burned areas

During the brown-up season we did not observe any clear trends with regard to the correlations between NDVI and elephant herd densities (Figure 4.7a), except for some years when positive correlations were stronger for the burn areas. Similarly, the

correlation coefficients for NDVI and elephant bull densities (Figure 4.7b) showed mostly no correlation but 2007 to 2009, positive correlations were observed within the burn areas.

Dry season results showed that elephant herds (Figure 4.7c) had mostly positive correlations with NDVI in the burn areas. In the non-burn areas, correlation coefficients were mostly non-significant with the exception of some significant positive correlations for 2004, 2005, 2006 and 2008. For elephant bulls (Figure 4.7d), negative correlations were predominant in the burn areas while for the most part there were no correlations in the non-burn areas.

For the green-up season, positive correlations between NDVI and elephant herd densities were observed for the non-burn areas in all years (Figure 4.7e), while for most of the years there were no correlations in the burn areas. Elephant bull densities showed no specific trend in the correlations with green-up season NDVI (Figure 4.7f), with burn areas showing some positive and negative correlations and non-burn areas showing either negative or no correlation.

Wet season NDVI correlations for elephant herd densities (Figure 4.7g) were positive within the burn areas for the three years of observation while there was either negative or no correlation for the non-burn areas. No patterns of correlation were evident for the relationship between NDVI and elephant bull densities (Figure 4.7h).

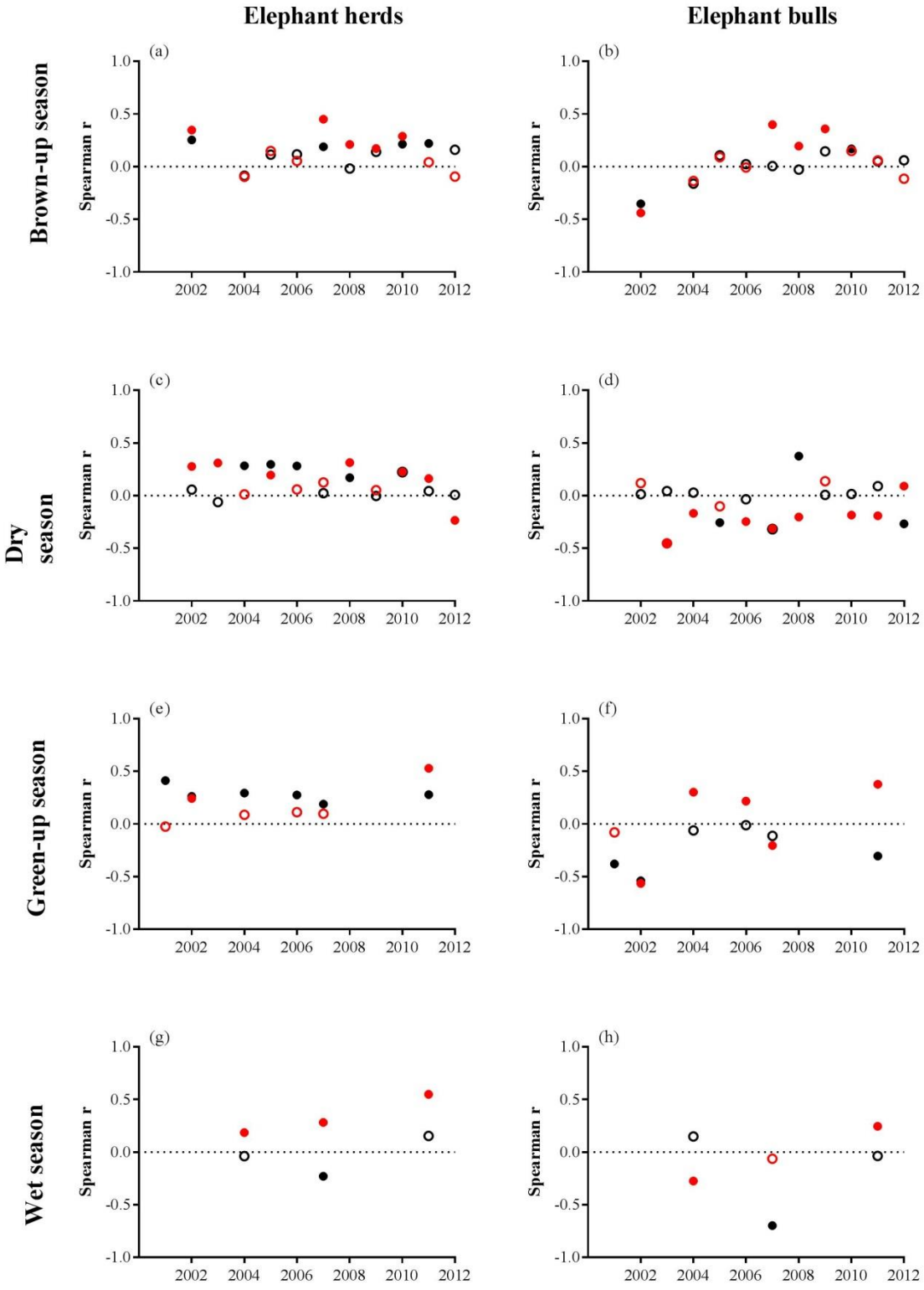


Figure 4.7. Graphs illustrating the Spearman r correlation coefficients over time for the relationships between the pheno-season NDVI and elephant herd and bull densities, respectively, for burn areas (indicated by red symbols) and non-burn areas (indicated by black symbols). Filled symbols represent statistically significant correlations and open symbols represent no significance of correlations.

4.5. Discussion

Managing and conserving a large protected area, such as the KNP, requires comprehensive knowledge of the complexity and dynamics of the ecosystem patterns and processes. Broad-scale monitoring through remote sensing has the potential to provide a synoptic view of the spatial changes in the landscape that may be reaching critical thresholds of change. Following our previous work (Ernst-de Beer & Erasmus *in prep*. – Chapter 3) which concluded that landscape-scale cumulative change trends in vegetation greenness between 2002 and 2015 were for the most part not a result of changes in precipitation, we aimed to investigate the effect of fire and elephants on such changes within a similar methodological framework.

From our first analysis, results seem to suggest that persistent decreases in vegetation greenness may be a consequence of the combined effect of larger elephant bull densities and more frequent fires. Elephant bulls are infamously known for causing excessive damage to woody vegetation through bark-stripping, toppling, uprooting and snapping of trees (Duffy *et al*. 2002). Although this behaviour is not exclusive to elephant bulls, researchers hypothesise that elephant bulls may be more prone to such behaviour than cows due to several reasons that include; their superior size and strength that enables bulls to reach higher into canopies, their preference for coarser browse and their social and sexual dominance displays, among others (Midgley *et al*. 2005). Indeed, it has been shown that the rate of tree toppling by bulls is up to five times higher than for family units (Stokke & du Toit 2000). Moreover, as a consequence of elephant damage, the woody component may be more susceptible to structural losses due to fires and by opening up the canopy, elephants may induce higher intensity fires and thereby exacerbate biomass removal (van Wilgen 2009). On the other hand, fires may be facilitating the preferential feeding within burn areas through the increased nutritional quality and weakened defence mechanisms of the post-fire flush (Skidmore *et al*. 2010), thus reinforcing the cycle of vegetation damage and loss.

Contrary to our expectation that elephant bull densities would increase with increasing pheno-season NDVI, we observed negative correlations during all four pheno-seasons

and within all four trend zones. For bull elephants, this negative correlation was the strongest for the dry and green-up seasons where vegetation greenness showed persistent decreasing trends (PDZ) and the weakest where vegetation greenness cumulatively increased within the landscape. This is an interesting observation that contradicts records of the opposite trend for elephants in savanna landscapes (Chammaille-Jammes *et al*. 2007; Young *et al*. 2009). The finding could simply be a reflection on the preferential utilisation of more open savanna (Smit *et al*. 2007) or that elephant bulls are less selective of vegetation greenness, especially when restricted by the availability of water during the dry season and early green-up seasons. Moreover, the result seem to suggest that higher densities of bull elephants may be associated with a decline in vegetation greenness on a seasonal time scale, but due to the high variability and marginal differences in elephant bull densities, further studies with more seasonally specific elephant data may be needed to confirm this.

Elephant herds did seem to preferentially seek out greener vegetation within most of the NDVI trend zones with the exception of the buffer surrounding the zone where pheno-season greenness increased (IZB). For the dry season, the positive correlation between elephant herd density and dry season NDVI was stronger than for the remaining seasons, most likely due to a shift in the diet towards woody plants (Codron *et al*. 2006). The observation by Smit *et al*. (2007) that elephant herds prefer denser tree cover while elephant bulls utilise more open areas within the landscape also provides a possible explanation for why we may have found this relationship for elephant herds, and not elephant bulls. During the wet season, elephant herd densities decreased with increasing NDVI for most of the trend zones. This is not completely unexpected as food resources during the wet season are abundant and elephant herds are not restricted by the availability of water. Subsequently the lack of a positive correlation may be due to the more uniform availability of green vegetation and a possible difference in the scale of selection (Marshal *et al.* 2010). However, as for the correlation trends observed for bull densities, it may indicate a decrease in vegetation greenness as a result of higher densities. In general, elephant herds do not appear to be a primary driving force of cumulative vegetation greenness trends in the NDVI trend zones. Conversely, one could argue that due their presence in relatively high densities, elephant herds are probably

exerting additional pressure onto the combined effect of fire and elephant bull densities that may have resulted in vegetation greenness decreases over the study period.

Within the persistent increase zone (PIZ) and the increase zone buffer (IZB), higher fire frequencies were associated with larger pheno-season NDVI values during all seasons except during the dry season. Conversely, within the persistent decrease zone (PDZ) and the decrease zone buffer (DZB), NDVI decreased with increasing fire frequency. The effects of fire frequency can be diverse and depending on factors such as precipitation, soil, tree/grass ratios, among others, may include reduced height of woody vegetation, changes in woody vegetation structure (Govender *et al*. 2006) as well as increased coppicing and plant density (Schackleton & Scholes 2000). Additionally, increased fire frequency may enhance plant development by stimulating growth and improving the nutritional content (Skidmore *et al.* 2010). Our results therefore seemed to suggest that for different areas and different seasons, fire frequency elicited varied responses from pheno-season vegetation greenness and may have played a role in cumulative vegetation greenness trends over the study period.

The final analysis of the interaction between elephant densities and pheno-season NDVI for burn and non-burn areas indicated much variability across seasons and between bulls and herds. We did not find any clear trends except for the dry season when elephant herd densities showed more consistent positive correlations with the dry season NDVI in the burn areas, while elephant bull densities showed consistent negative correlations with the dry season NDVI in the burn areas. We postulate that the inconsistent relationships between elephant densities and pheno-season NDVI for burn and non-burn areas may have been influenced by the elephant census data that only provided an annual snap-shot of the elephant distribution. Further studies that utilise data from which seasonal distributions can be calculated may provide a better understanding of the fire-elephant dynamic in relation to vegetation greenness.

With our methods, we were to some extent able to infer that fire frequency and elephant densities combined to induce vegetation greenness changes at the landscape scale. From our results, elephant bulls and elephant herds influence the vegetation differently. We

further showed that differentiating between seasons that are based on ecologically meaningful parameters (i.e. phenology) could be insightful of the effects of fire and elephants on vegetation changes. For instance, as we expected, the effect of fire and elephants were most pronounced during the dry season. Furthermore, our study provides a first step towards the development of a remote sensing-based monitoring approach that evaluates spatial vegetation dynamics in relation to drivers of change. However, our methods could be improved in several aspects, including the use of elephant location data in order to incorporate the differences in elephant seasonal preferences more accurately and the inclusion of water availability as an additional factor that influence elephant spatial use. Importantly, we need to account for precipitation as a "bottom-up" driver that underlies the co-dynamic relationship between vegetation, fire and elephants.

4.6. Conclusion

At the landscape scale, our results suggested that cumulative vegetation greenness trends may be a function of the combined effect of elephants and fire frequency. Elephant bull densities were possibly more influential in observed cumulative decreases of vegetation greenness over the study period. Elephant herds, on the other hand, showed preferential selection of greener vegetation across the majority of the trend zones. Given the variability in the relationships between elephant densities and pheno-season NDVI for burn and non-burn areas, our remote sensing-based methods need to be improved by the inclusion of season-specific elephant location data and accounting for the effects of other variables, such as rainfall and water provisioning.

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CHAPTER 5

DISCUSSION AND SYNTHESIS

5. DISCUSSION AND SYNTHESIS

5.1. Introduction

A major objective in the KNP's Strategic Adaptive Management framework (SAM) is the maintenance of heterogeneity in the structure and function of the landscape (Du Toit *et al*. 2003). The KNP is a savanna ecosystem that is characterised by the inherent natural flux of its structure and function that serves to maintain heterogeneity under non-equilibrium conditions (Du Toit *et al*. 2003). However, with evidence that climate change may already be starting to affect the system (e.g. van Wilgen *et al*. 2015; MacFadyen *et al*. 2018), concern is raised over the ecological resilience of the system (ability to recover from or adapt to disturbances). Changes in the structure and function of the ecosystem are inevitable due to the strong relationship between precipitation and vegetation patterns (Wessels *et al*. 2006). Vegetation is the key element with which local disturbances, such as fire and herbivores, interact to sustain the heterogeneity of the system (Grant *et al*. 2011). However, with increasingly variable precipitation patterns, the influence of fire and herbivory, may be exacerbated by the effects of climate change through increasing the rates at which concerning thresholds are approached (Grant *et al*. 2011). Continuous and informative vegetation monitoring at the landscape-scale is therefore essential for evidence-based decision-making and effective conservation.

Despite the benefits of remote sensing as a data source and research tool, very little attention have been given to take advantage of the potential that remote sensing holds for broad-scale monitoring in the KNP (SANParks 2017). Within SANParks' SAM, vegetation monitoring is an essential and elementary requirement (McGeoch *et al*. 2011). However, with much of the focus currently directed at field-based monitoring (McGeoch *et al*. 2011), there is a need for a comprehensive landscape-scale approach that can provide ecologically relevant temporal trend and change detection in a spatially explicit way. More significantly so if the monitoring approach does not only focus on ecosystem patterns, but incorporates the dynamics of the processes that govern the

patterns (Kupschus *et al*. 2016). I therefore set out to evaluate and develop a methodological approach that would;

i. enable the identification of the spatio-temporal vegetation change trends across the entire landscape
ii. enable the assessment of the role of precipitation as a causal factor in spatio-temporal vegetation change trends
iii. enable the evaluation of the influence of fire and elephants on spatio-temporal vegetation trends.

5.2. Development and evaluation of the proposed monitoring approach

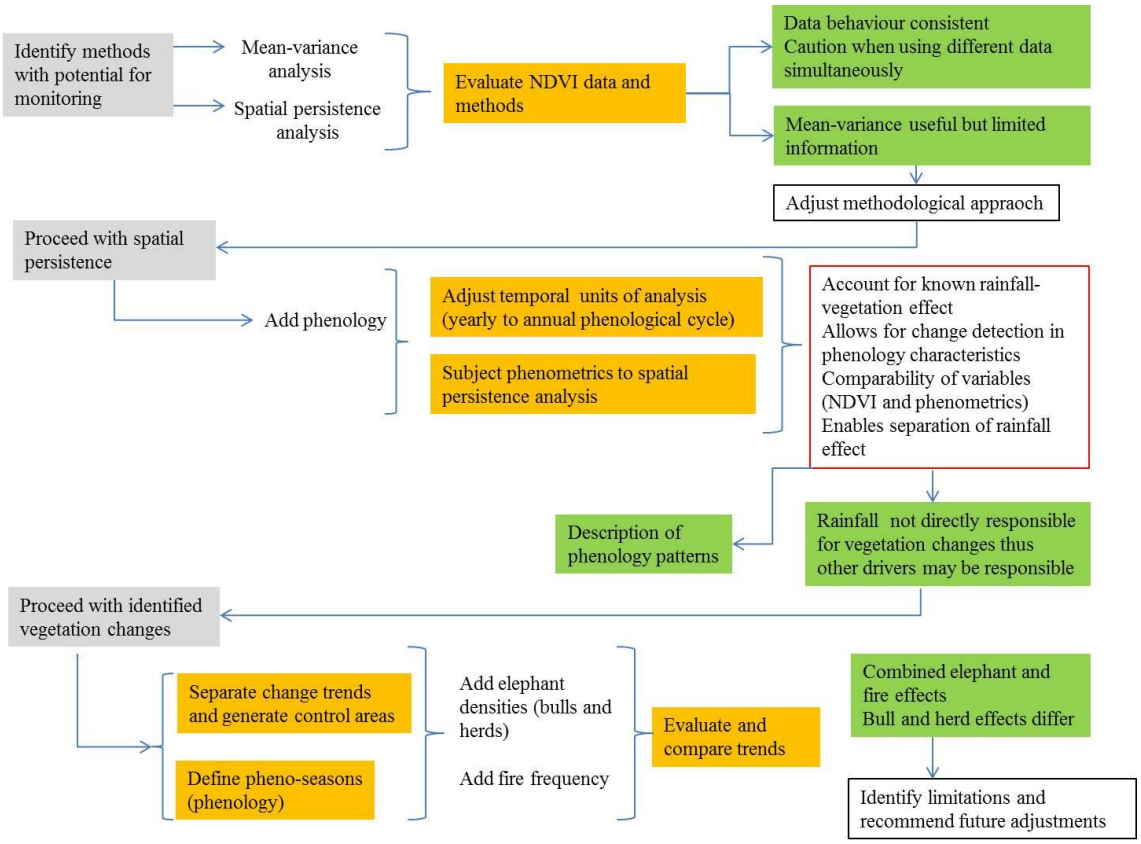


Figure 5.1. A flowchart of the workflow followed for Chapters 2-4 in the thesis. The orange blocks highlight the analyses while the green blocks highlight the most important findings. Grey blocks indicate the start of the respective chapters in chronological order.

Figure 5.1 presents a flowchart of the general workflow followed throughout the thesis (Chapters 2-4) with the overall aim to develop and evaluate combinations of mean-variance, spatial persistence and phenology analyses as a methodological approach for the assessment and monitoring of landscape-scale spatio-temporal trends in vegetation greenness dynamics in relation to precipitation, fire and elephants across the KNP. In the following paragraphs I briefly discuss the findings of Chapters 2-4 in terms of the development of the proposed monitoring approach throughout the thesis.

The mean-variance analysis for vegetation monitoring has its roots in rangeland degradation monitoring (Pickup & Foran 1987). Ever since, this analysis received little attention in the field of ecology until more recently when it was applied by several authors to asses land use change at a regional scale (e.g. Washington-Allen *et al*. 2008; Cui *et al*. 2013). Important, is the use of spatial persistence analyses as a form of image differencing that are often used complimentary to mean-variance analyses in order to add a spatial dimension to the identification of vegetation changes. This also led to the development of spatial persistence metrics (Waylen *et al*. 2014). For this thesis, I saw the potential of this combination of analyses and hence took the opportunity to evaluate and adjust its use as a vegetation monitoring approach for the KNP savanna-dominated protected area landscape.

However, given my relatively smaller study area in relation to previous studies (e.g. Cui *et al*. 2013; Southworth *et al*. 2016) and the necessity for satellite imagery, such as MODIS NDVI, with more consistent finer temporal resolution than Landsat, I had to assess the influence of the inherent differences in sensor characteristics between the datasets on the outcome of these methods. My findings in Chapter 2 confirmed that the spatial and temporal vegetation greenness change trends are relatively consistent for the Landsat, MODIS and SPOT-VEGETATION data products. However, the interchangeable use of different NDVI data sets should take the dissimilarities in sensor characteristics into account. This is especially important since my results indicated that the correlation between the different NDVI products may break down at larger differences between the spatial resolutions of the data.

Overall, the mean-variance analysis provides a landscape-scale evaluation of the state of vegetation within a resilience framework (Washington-Allen *et al*. 2008). The benefit of the mean-variance analysis stems from the ability to set reference points or thresholds from which departures in the change trajectory can be evaluated against (Washington-Allen *et al.* 2008). For instance, if a threshold for the KNP is defined as the lowest point of vegetation greenness mean and variance from which it previously recovered (e.g. El Niño-induced drought period), the flux of the vegetation greenness trajectory may be acceptable until it reaches the specified threshold again. If the overall recovery or the rate of recovery decreases after reaching the threshold, it may signal that the system may be less resilient and therefore rationalise further research and possible intervention by management. The mean-variance analysis may therefore be a good starting point for setting a broad-scale TPC of overall landscape vegetation greenness. Nevertheless, although this analysis provides important information about the temporal trajectories of change, it is limited by its inability to shed light on localised change dynamics across the spatial extent of a landscape.

My focus therefore remained on spatial persistence analysis that provides a spatial dimension to vegetation change detection across the landscape (Tsai 2012; Cui *et al*. 2013; Gibbes *et al*. 2014; Tsai *et al*. 2014). With this method it is possible to observe cumulative vegetation change trends in a spatially explicit manner. However, I recognised that by adjusting the temporal unit of analysis (annual) to be ecologically more meaningful than arbitrarily analysing data on a yearly basis (e.g. January to December) I could ensure that I capture the full extent of the effect of precipitation on observed changes in vegetation greenness and thereby separate the role of precipitation as a driver of change from the role of other drivers. I therefore uniquely combined spatial persistence analyses with phenology.

The outcome of this analysis was two-fold. First, the description of the general phenology patterns contributed to the overall understanding of the variability in the time of onset and length of the growing season across the KNP. Despite the established importance of phenology patterns, a limited amount of work on this subject has been directed at the KNP. Secondly, I explored the effects of changes in phenometrics on the

changes in vegetation greenness, thus providing a different perspective on the relationship between precipitation and NDVI. The results of Chapter 3 indicated that precipitation is a very important driver of the overall patterns of vegetation greenness but played only a small part (in some localised areas) in the observed cumulative changes in NDVI that amounted to about 30% of the KNP landscape area. The effect of precipitation through its role in phenology patterns however, did not show any noticeable effect on the persistence of vegetation greenness. The differential response of trees and grasses to environmental cues most likely complicated the relationships and would require some adjustment to the methods.

In Chapter 4, I proceeded to investigate the role of fire and elephants as drivers of the changes in vegetation greenness observed in Chapter 3. In this case, I took into account that the effects of both fire and elephants may vary throughout the phenological cycle. I therefore uniquely defined pheno-seasons using phenology metrics. By categorising the cumulative increasing and decreasing NDVI trends from the previous chapter (Chapter 3) and through generation of "control" areas, I was able to evaluate and compare the trends of the relationship between pheno-season NDVI and elephant densities and between pheno-season NDVI and fire frequency. My findings suggested that there is definitely scope for detecting noticeable trends of elephants and fire as drivers of change at the landscape scale. However, it also revealed that monitoring of these drivers of vegetation change at the landscape scale may be confounded by the effect of other variables, such as precipitation and water availability (e.g. Loarie *et al*. 2009), and that the analysis would require different and/or additional data input.

5.3. The proposed monitoring approach within the framework of SAM

Inherent to the success of monitoring, is the ability to frequently detect and quantify change. As mentioned in Chapter 1, thresholds indicate the points in time and space at which a system may shift between different states (e.g. grassland to woodland) (Washington-Allen *et al*. 2008). Within the SAM framework, TPCs present the upper and lower limits within which a system is allowed to undergo fluctuation (Biggs & Rogers 2003). When the system reaches any one of these limits, managers should be

alerted that the system may be approaching an undesirable state (Biggs & Rogers 2003). Within the SAM framework, this implies that a monitoring approach should embrace continuity and frequent output of ecologically relevant information that can be used to adaptively manage the system. Frequent and continuous monitoring would therefore also allow for the identification of the rates at which TPCs are approached. This is fundamental to SAM as it would allow for pro-active management intervention and adaptation.

The proposed monitoring approach addresses frequency and continuity of observation on a spatial and temporal scale through the use of remote sensing data as the fundamental input. Essentially, the minimum frequency of observation is dictated by the temporal resolution of the data (e.g. MODIS 16-day composites, available near-real time every 16 days), while the maximum frequency of observation will be dependent on the functional response time of the variable in question. The key is to identify the temporal interval and frequency at which the observations will be ecologically relevant. For instance, in Chapter 3, the temporal resolution of the analysis was dictated by the fact that precipitation has a strong control on vegetation growth (Wang & Fensholt 2017). Ecologically it therefore made sense to adjust the temporal resolution to that of the phenological cycle which represents the functional response of vegetation to precipitation. Hereby, I was able to account for the seasonal dynamics of vegetation growth. On the other hand, in Chapter 4, the use of pheno-seasons was intended to compensate for the seasonal differences in the use of resources and space by elephants as well as fire characteristics. In this case, the variability of the seasonal interaction between vegetation greenness and elephants and fire may have been more pronounced if I had used season-specific elephant data instead of the once-a-year snapshot nature of the census data.

Added to the advantage of continuity and frequency on a temporal scale, remote sensing-based monitoring further provides continuity and frequency on a spatial scale. Being able to identify changes at a frequency set by the spatial resolution of the data (e.g. 250 m for MODIS NDVI) and at the extent of the entire landscape, provides a birds' eye view of specific areas in the landscape where vegetation changes may be of

concern to management. In Chapter 3, I was able to show that vegetation greenness increases and decreases are dispersed across the entire park while there were localised areas where the changes seemed more pronounced (Figures 3.7 & 3.8). This presents several advantages that include; the information on the locality of changes and the identification of changes in areas that are difficult to access from the ground. Moreover, with regard to TPCs, the proposed monitoring approach enables the quantification of the extent of changes across the park. For example, a TPC could take the form of; "the percentage of area that are affected by decreases should not exceed a certain predefined percentage of the landscape". If the limit of this predefined percentage of the landscape is approached or reached, it may require some intervention by park managers.

A further advantage of the proposed monitoring approach within the SAM framework is that it incorporates a benchmark condition from which change is quantified within the spatial persistence analysis (Waylen *et al.* 2014). In Chapter 3, the benchmark condition was the 2002/2003 phenological cycle that were characterised by El Niño-induced drought conditions. In itself, this benchmark may therefore represent a TPC from which cumulative decreases may raise concern if precipitation conditions showed improvement for the time period of analysis. For SAM, this could be a particularly useful advantage as the setting of the TPC is inherent to the methodology. Moreover, due to the ability to change the timing of the benchmark condition, it may serve to answer different questions of interest. For example, monitoring the success of rehabilitation projects or possible management interventions in areas within the landscape would require the benchmark condition to be set at the start of the project or management interference. In this thesis, I focused on the Massive persistence metric (Waylen *et al.* 2014) which incorporates the cumulative summation of year-to-year differences of the actual observed values of NDVI. There is however scope for the additional use of the Directional persistence metric or the Relative directional persistence metric (Waylen *et al.* 2014) as shown in Chapter 2, which would ultimately provide answers to different questions. This would however require some adjustments to the proposed monitoring approach (discussed in next section).

SAM not only relies on information that can be used to make decisions about when and where to intervene but also on how to do it. Of essence to the latter question is the ability to understand the reasons why changes occurred. In order to address the question of why certain changes occurred, it is necessary to incorporate the underlying causes of changes in the observed patterns into a monitoring protocol (Kupschus *et al*. 2016). Mostly, in an information-rich environment like the KNP, it is intuitive to assume what the underlying cause of observed changes may be. However, processes are complex and by the nature of the interaction of different drivers of change it may prompt different management strategies. In the proposed monitoring approach, the evaluation of precipitation, fire and elephants as the driving forces of vegetation greenness change patterns addresses this issue. For instance, precipitation evidently underpins the dynamics of vegetation greenness through its effect on the seasonal cycles of growth and senescence, while its role in persistent changes was found to be minimal (Chapter 3). However, elephant bull densities and fire appeared to have a combined role in causing persistent greenness decreases (Chapter 4). This finding suggests that potential management intervention may be more effective if the differential effects of elephant bulls and herds are taken into account. Similarly, the complimentary assessment of the correlation between changes in phenometrics and changes in vegetation greenness (Chapter 3) added a different dimension to the perceived effects of precipitation on vegetation greenness changes by pointing out that in certain areas the changes may be due to changes in the length of the season that are ultimately a function of precipitation. The distinction between the different ways in which precipitation effects on vegetation greenness may present themselves could therefore also guide the decision-making process within SAM.

Overall, the proposed monitoring approach was effective in;

i. providing a detailed landscape-scale view of the dynamics of vegetation greenness change trends.
ii. the identification of areas within the landscape that may justify prioritisation of management resources and intervention

iii. the capacity for long-term monitoring that would frequently and continuously provide valuable new information, complimentary to existing monitoring programmes.
iv. providing spatially-explicit information on the location and extent of the areas in the landscape that were subjected to changes
v. incorporating the monitoring of functional processes that underlies the observed vegetation greenness change patterns (e.g. climate change, fire, herbivores).

5.4. Limitations and future recommendations

The proposed monitoring approach as set out and evaluated in this thesis provides a sound framework for further development and improvement. Throughout the process, several points for improvement have been identified. The obvious next step would be to validate the accuracy of the results. This would require some ground-truthing through field surveys to establish the current state of the areas of vegetation greenness increases and decreases and comparing it to historical field data records. This might be challenging since the frequency and continuity of field monitoring is poor and might require the combining of different sources of data to achieve the goal. Fortunately, data in the form of aerial photos, fixed-point photos and fine-scale 3-dimensional remote sensing data (e.g. LIDAR - Light Detection and Ranging) could be of significant value in validating the observed patterns. Similarly, in order to establish specific TPCs, these sources of data can be used to "calibrate" the observations from the coarser-resolution data against the finer-resolution observations.

Another avenue of improvement includes the remote sensing data upon which the monitoring approach is based. In this thesis, MODIS NDVI was the obvious first choice for the evaluation of the effectiveness of the approach because of its use in previous applications of the methods. However, many vegetation indices on various satellite platforms provide an array of potential data sets that may be superior in their ability to produce ecologically relevant information. For instance, LAI (Leaf Area Index) and fAPAR (Fraction of Absorbed Photosynthetically Active Radiation) could provide information regarding the fractional cover of trees and grasses (Kahiu & Hanan 2018),

while vegetation index data from the MISR (Multiangle Imaging Spectro-Radiometer) satellite instrument may provide a structural dimension to landscape-scale observation through its multi-angle observations (van Leeuwen *et al.* 2006). Evaluating different types of data in the proposed monitoring approach may therefore add additional variables to the process that could increase the overall effectiveness and accuracy of the approach. Additionally, by finding a means through which NDVI data from different sources can be made more compatible (see Chapter 2), it could substantially lengthen the time period of observation within the monitoring approach. Indeed, increasing the temporal extent of monitoring could be very informative. For instance, the current TPC set for woody vegetation cover in the KNP is at 80% of the highest recorded cover (Biggs & Rogers 2003). The problem is that what is perceived to be the highest cover value may be totally different from what the cover was at some point in history.

Additionally the data input for the driver variables could be improved and expanded. In Chapter 3, I had to decide between the use of satellite derived precipitation data and the use of interpolated ground-measured data. From a simple comparison, the interpolated precipitation map was chosen. However, further evaluation of the accuracy of satellite precipitation estimates may justify the use thereof and thereby it may improve the temporal extent of monitoring precipitation. Alternatively, future research should also focus on deriving accurate, GIS friendly data maps from the KNPs exceptional weather station record. Within the proposed monitoring approach, precipitation, as a climate-change response variable could provide an additional monitoring focus with different objectives to that proposed in this thesis. In Chapter 4, I calculated elephant densities from the annual census data. This provided a snapshot record of the annual distribution of elephants across the KNP landscape. Therefore, by utilising GPS location data within the analysis in Chapter 4, the results may be more accurate and relevant. Most importantly, the combination of all explanatory variables into one analysis may be beneficial to the approach as this may ultimately provide the most insight into the relative roles that each variable plays in the vegetation greenness dynamics.

5.5. Ecological contributions to KNP

Information generation is fundamental within the monitoring framework. The effectiveness of the proposed monitoring approach is therefore dependent on its ability to yield useful information that can inform management actions in order to maintain the ecological integrity of the KNP. In Chapter 2, a mean-variance analysis of the annual vegetation greenness (Figure 2.7) showed the trajectory of mean vegetation greenness changes between 2001 and 2015. An important observation from this analysis is that years that were characterised by low precipitation, had smaller mean NDVI but greater variability, while for other years, the trend was of greater mean greenness and smaller variability. This finding suggests that the system retains some heterogeneity even when stressed and that the landscape as a whole recovers from low precipitation years to conditions where the vegetation greenness cover is greater. This suggests that the KNP landscape was resilient towards periods of lower precipitation as represented by the time period. Continued monitoring of the trajectory may therefore enable management to identify times when the system is under pressure and to realise when the system is not recovering from such pressure.

In Chapter 3 we confirmed a strong relationship between the mean trends of NDVI, LOS, SOS and precipitation. Although this finding was to be expected, it provides confirmation of the known patterns that has until now not been explicitly documented (Scholes *et al*. 2003). Moreover, the analyses showed much spatial variability in the spatial extent of changes in the start and onset of vegetation growth over the study period. In this case, SOS showed trends of persistently later onset in the northern area of the park and persistently earlier onset in the south-western area where the LOS showed a surprising decreasing trend. Being able to observe how these trends coincide therefore gives some indication of the underlying cause. For instance, from the latter observation one can deduce that the trends are likely a result of the effect of fire as you would expect LOS to increase where SOS is earlier if precipitation was responsible. Precipitation did however show strong signals of persistent increase in the south and very low increases in the north of the park which supports some of the findings of MacFadyen *et al*. (2018) that showed that precipitation variability increased in the

north-western regions of the park while precipitation seasonality changes were evident in the far north and south of the park. Evidently, the areas where precipitation was identified as the driver of vegetation greenness changes coincided with the areas identified by MacFadyen *et al*. (2018) as having been affected by climate change. The vegetation greenness change trends (30%) were more widespread than the changes in SOS and LOS and also showed little overlap with these phenometrics. However, if I had only used precipitation as a variable, the possible effect of precipitation through its control on phenology could have been missed. Phenology therefore contributed essential information to the proposed monitoring approach, but future use of the methodology should make an effort to account for the differential response of trees and grasses to environmental cues.

Subsequently the findings in Chapter 3 implied that "top-down" drivers such as elephants and fire may be responsible for the majority of the observed changes in vegetation greenness. In Chapter 4, results were indicative of some effect of fire and elephants that may have been overriding the "bottom-up" effect of precipitation in these areas. Although the analyses of elephant densities were limited by the snapshot nature of the census data, it was possible to deduct that for elephant densities, at least during the dry season, there was a differential effect of elephant bulls and elephant herds and that these were likely in combination (or additive) to the effects of fire. High elephant densities in the park may also have contributed to a weakened relationship between densities and pheno-season vegetation greenness.

5.6. Conclusion

In this thesis, I developed and evaluated a monitoring approach that uses different combinations of mean-variance, spatial persistence and phenology analyses for the evaluation of landscape-scale spatio-temporal trends in vegetation greenness in relation to precipitation, fire and elephants across the Kruger National Park. With reference to specific monitoring objectives, I showed that the monitoring approach was effective in its practicality as well as the information that was generated for biodiversity and conservation management. Within the SAM framework, the proposed monitoring

approach may be of great value due to its ability to provide frequent and continuous information with regard to patterns of change as well as the processes that may be responsible for change. Its potential with regard to the identification of TPCs is also of significant value. Ultimately, the work in this thesis provide the first step towards the development and implementation of a broad-scale monitoring approach that can detect spatially-explicit vegetation change trends along with the associated driver effects in order to guide future prioritisation of limited resources and management efforts of savanna-dominated protected areas landscapes.

5.7. References

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APPENDICES

Appendix 1.

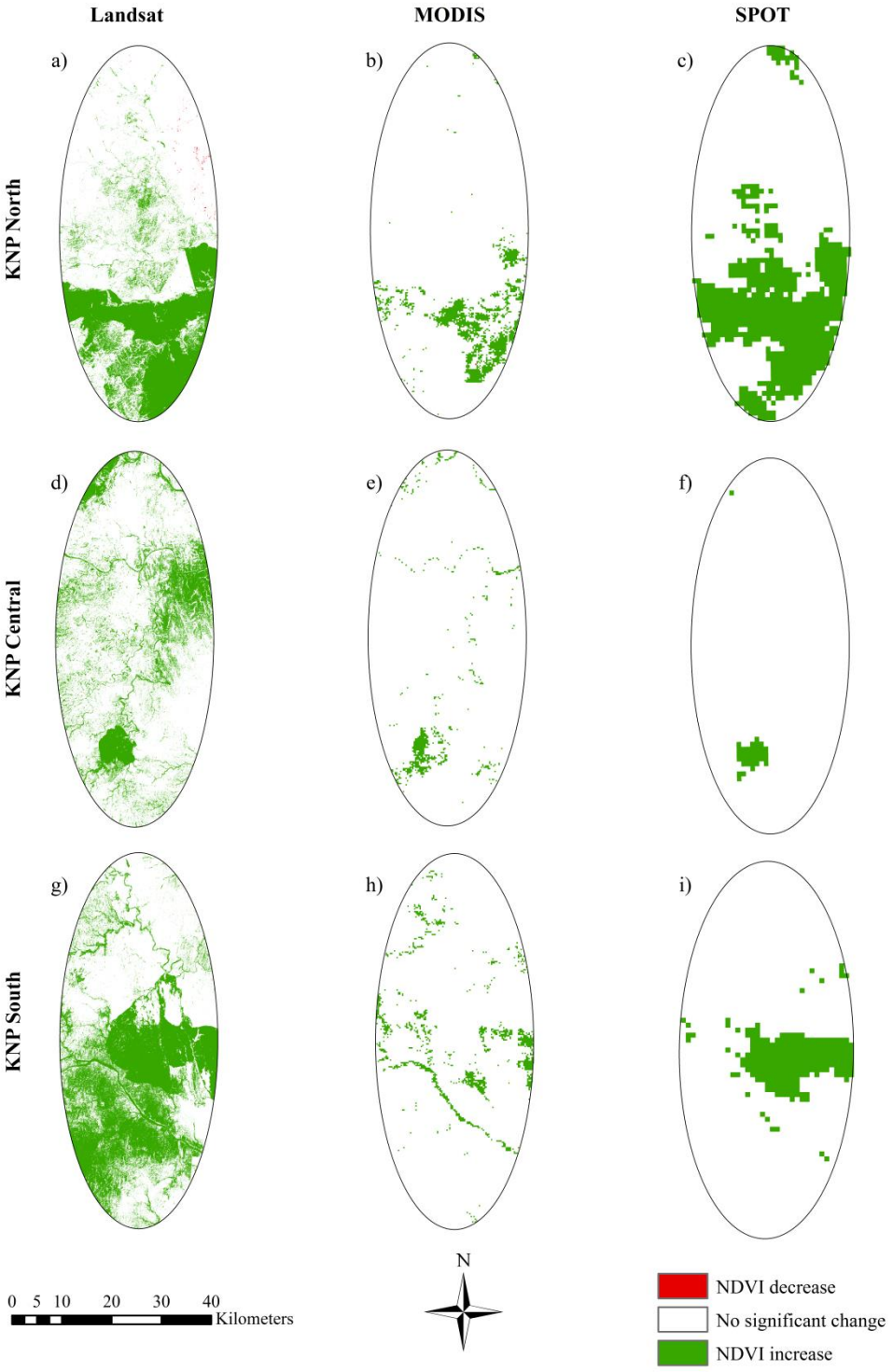


Figure 6.1. Statistically significant pixels at 0.05 level for the Directional persistence metric, D, of different NDVI products from 2000 to 2011 for KNP north and from 2000 to 2010 for KNP central and south.

Appendix 2

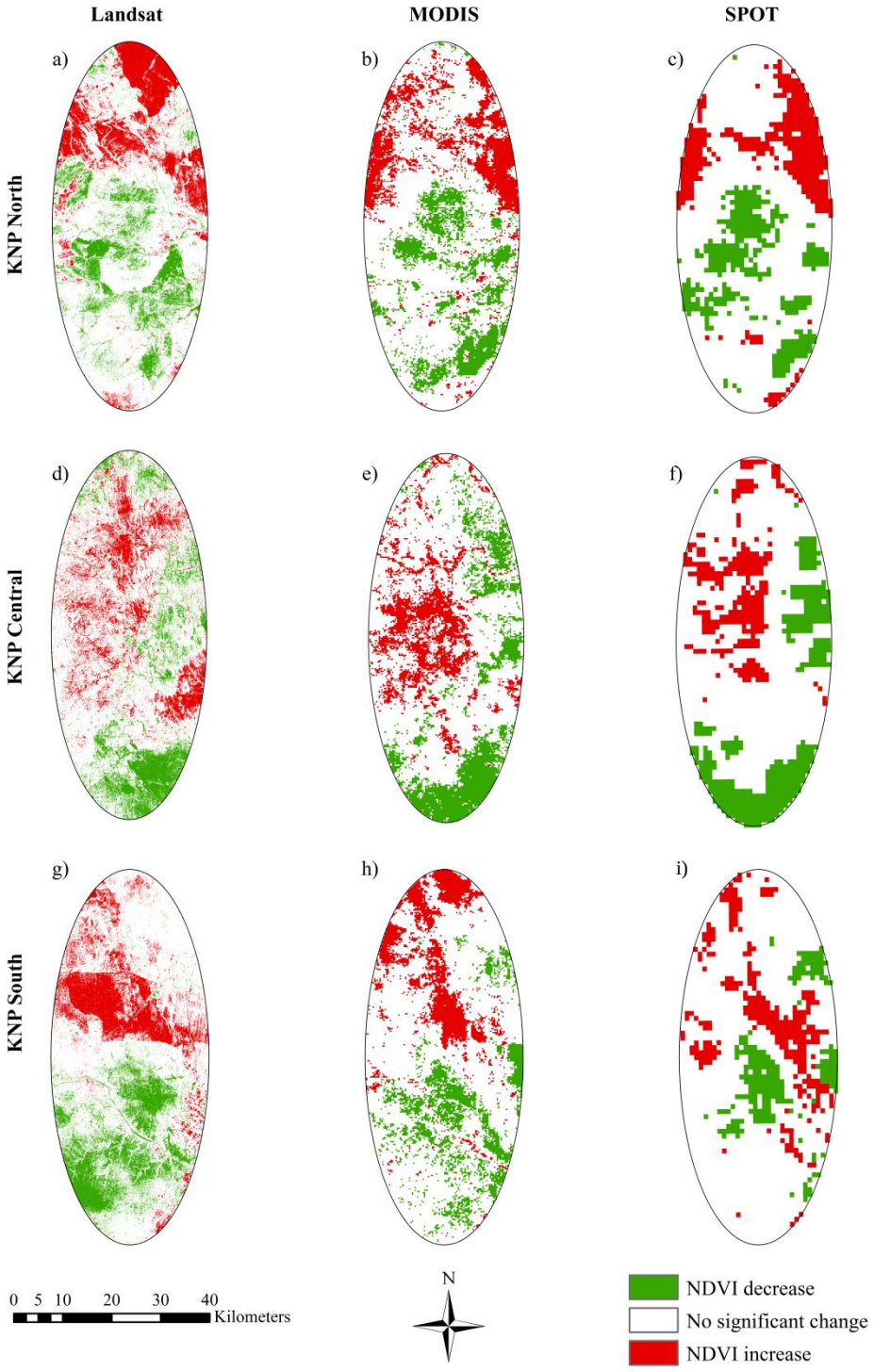


Figure 6.2. Statistically significant change pixels at 1*standard deviation for the Massive persistence metric, M, of different NDVI products from 2000 to 2011 for KNP north and from 2000 to 2010 for KNP central and south.