Remote sensing environmental change in southern African savannahs:

A case study of Namibia

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Abstract

Savannah biomes cover a fifth of Earth's surface, harbour many of the world's most iconic species and most of its livestock and rangeland, while sustaining the livelihoods of an important proportion of its human population. They provide essential ecosystem services and functions, ranging from forest, grazing and water resources, to global climate regulation and carbon sequestration. However, savannahs are highly sensitive to human activities and climate change. Across sub-Saharan Africa, climatic shifts, destructive wars and increasing anthropogenic disturbances in the form of agricultural intensification and urbanization, have resulted in widespread land degradation and loss of ecosystem services. Yet, these threatened ecosystems are some of the least studied or protected, and hence should be given high conservation priority. Importantly, the scale of land degradation has not been fully explored, thereby comprising an important knowledge gap in our understanding of ecosystem services and processes, and effectively impeding conservation and management of these biodiversity hotspots.

The primary drivers of land degradation include deforestation, triggered by the increasing need for urban and arable land, and concurrently, shrub encroachment, a process in which the herbaceous layer, a defining characteristic of savannahs, is replaced with hardy shrubs. These processes have significant repercussions on ecosystem service provision, both locally and globally, although the extents, drivers and impacts of either remain poorly quantified and understood. Additionally, regional aridification anticipated under climate change, will lead to important shifts in vegetation composition, amplified warming and reduced carbon sequestration. Together with a growing human population, these processes are expected to compound the risk of land degradation, thus further impacting key ecosystem services.

Namibia is undergoing significant environmental and socio-economic changes. The most pervasive change processes affecting its savannahs are deforestation, degradation and shrub encroachment. Yet, the extent and drivers of such change processes are not comprehensively quantified, nor are the implications for rural livelihoods, sustainable land management, the carbon cycle, climate and conservation fully explored. This is partly due to the complexities of mapping vegetation changes with satellite data in savannahs. They are naturally spatially and temporally variable owing to erratic rainfall, divergent plant functional type phenologies and extensive anthropogenic impacts such as fire and grazing. Accordingly, this thesis aims to (i) quantify distinct vegetation change processes across Namibia, and (ii) develop

methodologies to overcome limitations inherent in savannah mapping. Multi-sensor satellite data spanning a range of spatial, temporal and spectral resolutions are integrated with field datasets to achieve these aims, which are addressed in four journal articles.

Chapters 1 and 2 are introductory. Chapter 3 exploits the Landsat archive to track changes in land cover classes over five decades throughout the Namibian Kalahari woodlands. The approach addresses issues implicit in change detection of savannahs by capturing the distinct phenological phases of woody vegetation and integrating multi-sensor, multi-source data. Vegetation extent was found to have decreased due to urbanization and small-scale arable farming. An assessment of the limitations leads to Chapter 4, which elaborates on the previous chapter by quantifying aboveground biomass changes associated with deforestation and shrub encroachment. The approach centres on fusing multiple satellite datasets, each acting as a proxy for distinct vegetation properties, with calibration/validation data consisting of concurrent field and LiDAR measurements. Biomass losses predominate, demonstrating the contribution of land management to ecosystem carbon changes.

To identify whether biomass is declining across the country, Chapter 5 focuses on regional, moderate spatial resolution time-series analyses. Phenological metrics extracted from MODIS data are used to model observed fractional woody vegetation cover, a proxy for biomass. Trends in modelled fractional woody cover are then evaluated in relation to the predominant land-uses and precipitation. Negative trends slightly outweighed positive trends, with decreases arising largely in protected, urban and communal areas. Since precipitation is a fundamental control on vegetation, Chapter 6 investigates its relation to NDVI, by assessing to what extent observed trends in vegetation cover are driven by rainfall. NDVI is modelled as a function of precipitation, with residuals assumed to describe the fraction of NDVI not explained by rainfall. Mean annual rainfall and rainfall amplitude show a positive trend, although extensive “greening” is unrelated to rainfall. NDVI amplitude, used as a proxy for vegetation density, indicates a widespread shift to a denser condition.

In Chapter 7, trend analysis is applied to a Landsat time-series to overcome spatial and temporal limitations characteristic of the previous approaches. Results, together with those of the previous chapters, are synthesized and a synopsis of the main findings is presented. Vegetation loss is predominantly caused by demand for urban and arable land. Greening trends are attributed to shrub encroachment and to a lesser extent conservation laws, agro-forestry and rangeland management, with precipitation presenting little influence. Despite prevalent greening, degradation processes associated with shrub encroachment, including soil

erosion, are likely to be widespread. Deforestation occurs locally while shrub encroachment occurs regionally. This thesis successfully integrates multi-source data to map, measure and monitor distinct change processes across scales.

Declaration by author

This thesis is composed of my original work, and contains no material previously published or written by another person except where due reference has been made in the text. I have clearly stated the contribution by others to jointly-authored works that I have included in my thesis.

I have clearly stated the contribution of others to my thesis as a whole, including statistical assistance, survey design, data analysis, significant technical procedures, professional editorial advice, and any other original research work used or reported in my thesis. The content of my thesis is the result of work I have carried out since the commencement of my research higher degree candidature and does not include a substantial part of work that has been submitted to qualify for the award of any other degree or diploma in any university or other tertiary institution.

List of publications during candidature

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Publications under review

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List of conference presentations

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June 2017 4th Oxford Interdisciplinary Desert Conference, Oxford. Poster: Estimating aboveground woody biomass change in Kalahari woodland: combining field, radar and optical datasets

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September 2014 2nd Namibia Research Day 2015, Basel. Presentation: Satellite data to map vegetation in the Kalahari woodlands of Namibia.

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Chapter 3

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Key words

Land-use, land cover change, Landsat, MODIS, ALOS PALSAR, LiDAR, ICESat, Sentinel-2, Corona, aboveground biomass, savannah, tropical dry forests, time-series, trend, deforestation, shrub encroachment, land degradation, drylands, Africa, Namibia, woodland, phenology, land surface phenology, precipitation.

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Acronyms

AGB	Aboveground woody biomass
AIC	Akaike information criterion
ALOS	Advanced Land Observing Satellite's
AMP	Amplitude value
AVHRR	Advanced Very High Resolution Radiometer
BA	Basal area
CART	Classification and Regression Trees
CMORPH	CPC MORPHing technique
CO^2	Carbon dioxide
CV	Coefficient of variation
DBH	Diameter at breast height
DMSP	Version 4 of the Defence Meteorological Program
DSI	Dry season index
DSINT	Dry season integral
DOY	Day of the year
ENSO	El Niño southern oscillation
EO	Earth observation
EOS	End of season
ETM+	Landsat 7 Enhanced Thematic Mapper Plus
EVI	Enhanced Vegetation Index
FAO	Food and Agriculture Organization

GEOV1	Geoland2 version 1
GIMMS3g	Global Inventory Monitoring and Modelling System Third generation
GIS	Geographical Information Systems
GPS	Global Positioning Systems
HH	Horizontal send and horizontal receive
HV	Horizontal send vertical receive
ICESat	Geoscience Laser Altimeter System
JAXA	Japan Aerospace Exploration Agency
L1T	Level 1 terrain corrected products
LAI	Leaf Area Index
LiDAR	Light Detection and Ranging
LOS	Length of season
LTDR	Land Long Term Data Record
LULCC	Land-use and land cover change
MAU	Mean autumn value
MGS	Mean growing season values
MODIS	Moderate Resolution Imaging Spectroradiometer
MSE	Mean standard error
MSS	Multispectral Scanner System
MSP	Mean spring value
NDVI	Normalised Difference Vegetation Index
NE	North East
NIR	Near infra-red

NP	Node purity
NPP	Net primary productivity
OOB	Out of bag estimation
OLI	Landsat 8 Operational Land Imager
OLS	Operational Line scan System Night time Lights Time Series
OLS	Ordinary least squares
PALSAR	Phased Array-type L-Band Synthetic Aperture Radar
RAU	Rate of autumn senescence
RF	Random Forest
RMSE	Root Mean Squared Error
RSP	Rate of spring green-up
SAR	Synthetic Aperture Radar
SLC	Scan Line Corrector
SOS	Start of season
SPOT	Satellite Pour L'Observation de la Terre
SST	Sea surface temperature
STA	Seasonal Trend Analysis
STM	Seasonal trend model
SWIR	Short wave infra-red
TAMSAT	Tropical Applications of Meteorology using Satellite
TOA	Top of the Atmosphere
TM	Landsat 5 Thematic Mapper
TS	Theil-Sen

UMD	University of Maryland
USGS	United States Geological Survey
VIS	Visible
VI	Vegetation indice
POP	Position of peak value
POT	Position of trough value

Chapter 1

Introduction and background

1 Introduction and background

1.1 Global land cover change

Land cover and land-use change are major drivers of global declines in fundamental ecosystem services, functions and biodiversity (Foley 2005; Pettorelli et al. 2017; Hansen et al. 2013). The area impacted by humans has increased manifold, drastically affecting the provision of key ecosystem services and functions (Foley 2005; E. C. Ellis and Ramankutty 2008; Vitousek 1997; Ramankutty et al. 2006). Globally, the conversion of landscapes to anthropogenic land-uses, including intensive conventional agriculture, urban and grazing land, presents one of the most urgent contemporary challenges faced by society (Assessment 2005). As urbanization and agriculture continue to expand and intensify, so will pressures on biodiversity and ecosystem services and functions (Leadley 2010). This is particularly the case for developing countries in the tropics, which encompass most of the Earth's biodiversity and a significant amount of undeveloped arable land (Lambin et al. 2013).

1.2 Global drylands and the carbon cycle

Over 41% of the Earth's surface comprises dryland biomes (Bastin et al. 2017). They encompass some of the most neglected and threatened ecosystems and biodiversity hotspots while simultaneously being under immense human and climatic pressures (Janzen 1988; Durant et al. 2012; Myers et al. 2000; Miles et al. 2006; Intergovernmental Panel On Climate Change 2007). Dryland vegetation provides numerous essential ecosystem services critical for livelihoods, from local (1,000 km^2) to continental scales (1,000,000 km^2), including forest resources, water provision, biodiversity conservation and global ecosystem service markets (Y. Y. Liu et al. 2015; Hansen et al. 2005). These sustain over 38% of the world's population of 6.5 billion, yet currently dryland vegetation degradation affects 250 million people, and this figure will be greatly exacerbated by climate change and population growth (Adeel et al. 2005; Zafar et al. 2005; Huang et al. 2016).

Quantitative estimates of change in dryland vegetation, which include savannahs and tropical dry forests, are key to our understanding of the global carbon cycle (Adeel et al. 2005). In fact, recent studies have demonstrated that dryland vegetation is the predominant driver of the carbon cycles inter-annual variability. Savannahs in the southern hemisphere are an important carbon sink (Adeel et al. 2005; Poulter et al. 2014; Y. Y. Liu et al. 2015; Scheffer et al. 2001), and contribute significantly to the carbon cycle (Poulter et al. 2014; Ahlström et al. 2015; Y.

Y. Liu et al. 2015). In recent decades anthropogenic pressures and climatic fluctuations have caused their widespread structural, functional change and degradation (Adeel et al. 2005; Zafar et al. 2005; Hoekstra et al. 2005). As a result of its significant impact on global biogeochemical cycles their role in climate regulation and their widespread change, the monitoring of vegetation spatial and temporal trends across drylands is increasingly important (Poulter et al. 2014; Ahlström et al. 2015).

1.3 Land degradation in drylands

Research in recent decades has demonstrated the extensive occurrence of land degradation processes and associated declining vegetation productivity throughout drylands (Adeel et al. 2005; Zafar et al. 2005), although the magnitude, severity and drivers are frequently debated (Bai et al. 2008). Land degradation is usually characterized by a reduction in ecosystem productivity, services and functions, triggered by disturbances, especially anthropogenic, from which the land does not recover. It is generally measured as deviations from normal net primary productivity (NPP). However, the issues of land degradation in drylands are fraught with complexities. For instance, a decreasing NPP trend may not signify land degradation, nor may a positive trend imply an improvement. Indeed, dryland vegetation growth is dependent on numerous environmental factors, primarily climatic variability, land-use and the co-occurrence of disturbance processes such as fire.

Some of the main issues identified which highlight the extensive and varied nature of dryland land degradation include, i) its heterogeneous spatial and temporal patterns of gains and losses in vegetation productivity at continental scales, ii) the inconsistent trends captured between different satellite sensors when measuring NPP, iii) complex greening trends identified in drylands including the Sahel. Here, the greening trend was found to occur simultaneously with a loss of tree and shrub species richness, a reduction in the number of old trees and a shift in vegetation functional types toward more drought-tolerant and shrub land state. Therefore, careful interpretation of results is required when interpreting satellite data to monitor land degradation (Herrmann and Tappan 2013; Bai et al. 2008; Anyamba and Tucker 2005; Hickler et al. 2005; Olsson, Eklundh, and Ardö 2005; Wessels et al. 2007; Fensholt et al. 2013). Moreover, since the greening phenomenon is observed throughout much of Australia, America, Africa (Archer, Schimel, and Holland 1995; Hudak and Wessman 1998; Fensham, Fairfax, and Archer 2005; D Ward 2005; Edward T. A. Mitchard and Flintrop 2013; O'Connor, Puttick, and Hoffman 2014), northern latitudes (Jia, Epstein, and Walker 2003) and at altitude (Caviezel et al. 2014), its interpretation in terms of recovery from land degradation is likely to be an oversimplification.

1.4 Global and African savannahs

Savannah biomes cover over a fifth of the globe and support a significant proportion of the world's mega fauna, livestock and human population. A characteristic and defining feature of these biomes is the co-occurrence and coexistence of woody (trees and shrubs) and herbaceous (grasses) vegetation, in effect, they encompass much of the world's tropical dry forests (Scholes and Archer 1997). The equilibrium state between these two plant functional types significantly influences numerous key ecosystem functions and services, including livestock production, nutrient and biogeochemical cycles, hydrology and in carbon sequestration potential (House et al. 2003; Jackson et al. 2002). Nevertheless, the exact processes which facilitate the co-occurrence of woody and herbaceous vegetation in savannahs dictates the proportions of each, and how these respond to anthropogenic and climatic change drivers, remains an active area of research (Scholes and Archer 1997; House et al. 2003; Scholes and Archer 1997; Jeltsch, Weber, and Grimm 2000).

1.5 Tropical dry forests across the globe and Africa

Tropical humid forests have received high conservation priority throughout the tropics and Africa. In fact, recent research suggests the world's tropical forests are a net carbon source, with releases mainly resulting from deforestation and degradation (Harris et al. 2012). This has often not been the case for tropical dry forests, which as an integral component of savannah biomes, have received relatively little consideration (Parr et al. 2014; Gasparri et al. 2016; Lehmann 2010). However, savannahs and tropical dry forests harbour very high levels of biodiversity, endemic and large charismatic species, as well as vast tracks of wilderness land (Parr et al. 2014; Shumba et al. 2010). Tropical dry forests around the globe are severely threatened by anthropogenic change processes including land degradation and deforestation; hence they should urgently be awarded high conservation priority (Hansen et al. 2013; Miles et al. 2006; Hoekstra et al. 2005). Above all, they are also among the least researched biomes and this deficiency seriously impacts the development of sustainable management and policy actions (Blackie et al. 2014). The principle threats to tropical dry forests in Africa are the ever expanding human populations, consequent urbanization, combined with changing and intensifying land-use practices and associated shifts in fire regimes and land cover change (Miles et al. 2006; Leadley 2010; Sloan and Sayer 2015). Importantly, since tropical dry forest biomes are expected to respond strongly to anthropogenic pressures and predicted climate change, a rigorous understanding, not only of the factors which control savannah vegetation community structure, composition and function, but also of how they are changing, is urgently required to guide the sustainable management of these biomes (Pereira et al. 2010; W. J. Bond, Midgley, and Woodward 2003; Sankaran et al. 2005; Ahlström et al. 2015; Poulter et al. 2014).

1.6 The effect of climate change on African savannahs

To date, the role that global climate change will have on Africa's tropical dry forests and savannahs remains unclear, since global climate model predictions vary at regional scales (10,000 km^2) (Hansen et al. 2005; Leadley 2010; H. Liu and Yin 2013; Y. Y. Liu et al. 2015; Lucht et al. 2006). For instance, Hély et al. (2016) find that African deciduous and semi-deciduous forests are likely to be highly responsive to expected declines in amount and changes in the seasonality of rainfall (Hély et al. 2006). The most pronounced impacts on vegetation from the predicted changing rainfall regimes are anticipated to occur in the more unstable or transitioning ecoregions of savannah biomes, such as ecotones or boundary regions which merge from woodlands and forest into shrub and grasslands (Sankaran et al. 2005; Sankaran, Ratnam, and Hanan 2008). Expected increases in drought and fire frequency, in combination with the rising environmental pressures posed by industrial and agricultural expansion, will likely exacerbate changes in vegetation functional types, thereby further impacting species diversity and rural communities which depend on forest resources for their livelihoods (N. G. Pricope and Binford 2012; N. Pricope et al. 2015).

1.7 Importance of woody vegetation in African savannahs

Woody vegetation is an integral component of savannah biomes and a major indicator of the overall degradation status of an ecosystem since, unlike herbaceous vegetation, it does not vary substantially inter-annually in response to rainfall (Herrmann and Tappan 2013; De Cauwer et al. 2016; Burke 2006). Moreover, woody vegetation in savannahs plays a pivotal role in ecosystem functioning owing to its important influences on numerous soil properties, including erosion potential, stability, nutrient cycling and chemical composition, but also evapotranspiration and water storage (Sankaran et al. 2005). In addition to being a key wildlife habitat, it also furnishes ecosystem services to rural communities which depend on these for their livelihoods, in an environment which is typically harsh and frequently drought prone. For instance, throughout the prolonged dry season, which is a distinguishing feature of savannahs, as the herbaceous layer and crops residues become depleted, woody vegetation acts as a crucial source of livestock forage. Many tree and shrub species can be coppiced for use as both livestock browse, fuel and construction material, while numerous species also provide fruit and leaves which complement the diets of rural communities especially in times of resource scarceness, as well as providing important medicines. Hence, tree species and woody vegetation generally are highly valued for their diverse services, functions and resources (John Mendelsohn and el Obeid 2005; Sankaran et al. 2005; Lykke, Kristensen, and Ganaba 2004; Schnegg, Rieprich, and Pröpper 2014).

1.8 Determinants of African savannah vegetation

Africa harbours by far most of the world's tropical savannah biomes, together with transition biomes spanning rainforests to hyper-arid deserts (Bastin et al. 2017). Together with wild browsers, the continual impact of fire has determined vegetation structure, composition and function across the continent, often ensuring the predominance of grasslands. Fire is a pervasive force shaping ecosystem change and has been used extensively throughout history at least since the Holocene period, and is still commonly used by rural communities to manage rangeland (Bird and Cali 1998). In the absence of such controls as fire and browsers, it is widely expected that a substantial proportion of these biomes would revert to a state dominated by forests and woodlands; indeed the process is already believed to be widespread (Edward T. A. Mitchard and Flintrop 2013; E. T. A. Mitchard et al. 2009; E.T.A. Mitchard et al. 2011). Africa's forests, woodlands and savannahs are influenced by numerous additional factors, in particular, the frequency and quantity of precipitation, drought periods, domestic herbivores such as goats and cattle, as well as human change pressures including urbanization, deforestation, forest resource extraction and stocking densities. Several studies find that key determinants of vegetation composition and structure in African savannahs are rainfall, fire and browsing (Sally Archibald et al. 2009; Burke 2006). Nevertheless, the extent to which fire impacts vegetation structure and composition is a controversial topic, since it interacts with numerous other environmental variables, including rainfall, soil, livestock and browsers. Moreover, a certain frequency of fire is believed to be required, in order for the ecosystem to remain in a“disturbed” state, which is beneficial for a range of ecosystem serviced functions, including forage resource and species habitat (Sankaran, Ratnam, and Hanan 2008; W. J. Bond, Midgley, and Woodward 2003; W. Bond et al. 2003). In summary, the continent's natural vegetation cover is subject to a continual range of influences which contribute to its continual modification, with these processes are especially pronounced in savannahs (William J Bond and Keeley 2005; Sankaran et al. 2005).

1.9 Africa's population and agriculture

Africa's population is growing rapidly and this growth is expected to lead to a heightened need for land and natural resources. This need often translates into the clearing and loss of the continent's forests, woodlands and savannahs for conversion to urban, arable land and cattle and livestock ranching (Adeel et al. 2005). Although the greater part of the continent's land surface is not converted to direct anthropogenic land-uses, for instance, ploughed and urban land, most of the land surface is impacted by low intensity anthropogenic activities in some form or other, essentially rendering them anthropogenic biomes (Mayaux et al. 2004; E. C. Ellis and Ramankutty 2008). Nevertheless, the indispensable ecosystem services and functions which these ecosystems provide to rural communities are increasingly under pressure (Shackleton et al. 2007; Chidumayo and Gumbo 2010). Since most of the population relies on agricultural production, large areas of natural vegetation are continually and increasingly being converted to arable land. Across most African countries, however, small-scale (1-10 ha) arable farming which relies on little or no technical and material inputs, continues to be the most widespread form of agriculture (Mendelsohn 2006; E. C. Ellis and Ramankutty 2008). Importantly however, the growth of large-scale, fenced, industrial, conventional agriculture and especially cattle ranching in the drier regions, is predicted to result in widespread habitat loss. In particular, such large-scale operations are expected to further impinge on biodiversity conservation through the alteration of key dispersal and migration routes (Beale et al. 2013).

1.9.1 Rangeland and livestock in Africa

Africa is a dry continent, receiving on average less than 800 mm of rainfall per year, and this can be highly variable both in space and time (Middleton and Thomas 1992; J Mendelsohn et al. 2002a). In this context, livestock are a key asset for rural farmers, both economically and culturally, but also in terms of agriculture and ecology (Blench 2001; A. Verlinden and Kruger 2007a). It has long been recognized that major drivers of environmental and vegetation changes in savannah biomes are the numbers, range and management practices associated with livestock (Scoones 1995). In fact, mainly because of the susceptibility of annual vegetation to overgrazing, together with the light, friable nature of the dryland soils which are heavily impacted by trampling, the seasonal cycles of grazing intensity acts as a major control on land degradation (Turner and Hiernaux 2002; Reynolds et al. 2007). Data on the spatial and temporal distributions, movements and densities of livestock and other large herbivores are essential to understanding their impact across the landscape soil and vegetation, as well as fundamental for assessing the sustainability of land management practices. However, this information is often scarce throughout much Africa (Turner and Hiernaux 2002; A. Verlinden, Seely, and Hillyer 2006; A. Verlinden and Dayot 2005a; A. Verlinden and Kruger 2007a; Scoones 1995). Numerous authors hold that sustainable rangeland management in drylands relies on the ability of pastoralists to graze their herds over large areas and seasonally migrate to new areas so as to halt any negative effects on soil quality and herbaceous plant development (Sinclair and Fryxell 1985; J. E. Ellis and Swift 1988).

1.10 Southern African tropical dry forests and savannahs

The tropical dry forests and savannahs of southern Africa, also known as Miombo woodlands, stretch from the eastern to the western coasts, encompassing an area over of 2.7 million km^2. They play a pivotal part in the regulation of precipitation both for the northern humid forests and the arid savannahs and shrub lands in the south. At the same time, they are a significant carbon sink and source. Their important role in the global carbon cycle and climate system, as well as the integral part they play in sustaining rural livelihoods and conserving biodiversity, together with the magnitude and multiplicity of threats they face, all contribute to potentially placing this biome on the brink of major environmental and socio-economic tipping points (Leadley 2010; Pereira et al. 2010; Timberlake, Chidumayo, and Sawadogo 2010). For instance, agricultural intensification is predicted to greatly increase throughout the African continent and especially southern Africa. This is due to much of the region's suitability for intensive soybean production and the rise in industrial, conventional agriculture; concurrently, the growing rural population is primarily dependent on subsistence agriculture. In addition, the expansion of cattle ranching has resulted in unrestricted large-scale fencing of tracts of commonage land throughout southern Africa, the Kalahari biome in particular (Perkins 1996). Both processes contribute to the increased risk of conflicts over land and resource allocation (Gasparri et al. 2016; Röder et al. 2015).

1.11 Major vegetation change process in southern African savannahs

Two major vegetation change processes occur across southern African savannahs. The first is the pervasive disappearance of all vegetation strata, also known as regressive vegetation dynamics, which manifest as either deforestation or desertification. The process is often triggered by the need for new arable land, urbanization, land-use intensification and salinization and can result in the loss of fundamental ecosystem services and functions, including, for example, forest and forage resources (Adeel et al. 2005; Bai et al. 2008; Dregne 1986). The second constitutes a shift towards a denser, woodier condition with the replacement or encroachment of herbaceous vegetation strata with hardy, often unpalatable shrub species, also known as progressive dynamics or shrub encroachment. The herbaceous or forage layer is of vital importance to the livelihoods of a significant proportion of the population, as they depend upon it for livestock raising. Ultimately, both these changes affect ecosystem processes, biodiversity and the way the land is used economically (Hudak and Wessman 1998; D Ward 2005; David Ward et al. 2000; Archer, Schimel, and Holland 1995; Fensham, Fairfax, and Archer 2005; Edward T. A. Mitchard and Flintrop 2013; O'Connor, Puttick, and Hoffman 2014; Scholes and Archer 1997; Briggs et al. 2005). Various hypothetical drivers have been identified for shrub encroachment. The rising atmospheric concentration of carbon dioxide (CO^2), for instance, is thought to be an important driver of increasing woody cover, especially in tropical grasslands (William J Bond and Midgley 2000; Donohue et al. 2013). However, a number of many other important factors have been shown to contribute to the process, they include, shifts in fire activity (William J Bond and Midgley 2000; Bowman, Murphy, and Banfai 2010), over-stocking (Asner et al. 2004; D Ward 2005), long-term rainfall changes (Fensham, Fairfax, and Archer 2005) and the synergy and interaction of these (D Ward 2005). Notably, the modifications in vegetation structure and composition which are inherently associated with shrub encroachment have been shown to result in soil erosion, loss of land productivity and economically important forage species as well as overall plant species impoverishment (D Ward 2005; De Klerk 2004a). Moreover, once woody encroachment and associated herbaceous decline has developed, it is extremely difficult to reverse the process (Schlesinger et al. 1990; Scheffer et al. 2001). Over 13 million hectares are known to be affected by shrub encroachment across southern Africa (Trollope et al. 1989; Buitenwerf et al. 2012), which alongside the pervasive loss of vegetation are thought to impact over two billion people (Adeel et al. 2005). Importantly, the broad-scale rate at which this process is occurring has impacted the net ecosystem carbon balance and has triggered major changes in global biogeochemical cycles (Poulter et al. 2014; Ahlström et al. 2015; Y. Y. Liu et al. 2015; Scheffer et al. 2001). Thus, fully discerning the causes, extent and consequences of shrub encroachment and associated land degradation is critical for long-term land management.

1.12 Namibia

1.12.1 Land degradation in Namibia

Both deforestation and woody encroachment are widespread throughout Namibia and are thought to be the primary land degradation processes affecting farming sectors (Ben J Strohbach 2000a, 2000c, 2000c, 2000d). However, only limited data are available for analysing the extent and intensity of these processes (B. Strohbach 2001; De Klerk 2004a). Namibia encompasses three principal land-uses, including commercial farming which occupies 45% of the land area, communal farming which occupies 40% of the land area, while the remaining 15% are managed as nature reserves (J Mendelsohn et al. 2002a). A long standing debate remains as to the sustainability of these land-uses. It is widely believed that commercial farming better manages resources while communal farming results in a "tragedy of the commons" (Hardin 1968; B. Strohbach 2001). However, the validity of these claims has not been confired and both deforestation and shrub encroachment are thought to be widespread, regardless of farming practice or conservation stuats (De Klerk 2004b; Erkkilä 2001; John Mendelsohn and el Obeid 2005; Tian, Brandt, Liu, Rasmussen, et al. 2016).

1.12.2 Deforestation in Namibia

Several studies have demonstrated the widespread loss of forests and woodlands in Namibia, especially in the northern regions (Erkkilä 2001; Erkkilä and Löfman 1999; Kreike 2010; John Mendelsohn and el Obeid 2005). They have also highlighted the complexities of mapping deforestation and the dynamics associated with fallowing, forest regrowth and shrub encroachment in savannahs. There remains a lack of research addressing the extent and rate of deforestation, with available research on the process in Namibia often being highly localized (Rohde and Hoffman 2012; M Pröpper et al. 2010; Michael Pröpper and Vollan 2013; Röder et al. 2015; Gessner et al. 2013). The Kalahari woodlands of northern Namibia, which comprise the principle forested ecoregion of Namibia, are drier than the Miombo woodlands of neighbouring countries and have a lower population pressure. They contribute importantly to the national economy through the provision of forage, timber, fuel and habitat for large mammal conservation (Barnes et al. 2010; De Cauwer et al. 2016). Numerous detailed studies are available on the composition of Namibia's forests and woodlands, as well as the Kalahari biome in general, although few focus specifically on long-term changes using satellite remote sensing (B.J. Strohbach and Petersen 2007; Ben J Strohbach 2013; de Cauwer 2013a; S. L. Childes 1988; S. Childes and Walker 1987; Aarrestad et al. 2011).

1.12.3 Contemporary trends in Namibian rangelands

Throughout Namibia, and especially in the communally held regions, a great deal of research has been undertaken to understand the agro-pastoral system and its impact on land degradation. Specifically, these have focused on translating rural farmers' knowledge into metrics usable for resource managers and in understanding contemporary livestock movements. In addition, they have provided a historical perspective to better understand long-term environmental changes (A. Verlinden and Dayot 2005a; A. Verlinden, Seely, and Hillyer 2006; A. Verlinden and Kruger 2007a; M. Seely and Klintenberg 2011a; Patrik Klintenberg and Seely 2004; M. K. Seely 1998; P. Klintenberg, Seely, and Christiansson 2007; B.J. Strohbach and Petersen 2007; Antje Burke and Ben J. Strohbach, n.d.; John Mendelsohn 2006). These investigations have centred on how changing transhumance patterns, growth of new homesteads and villages, expansion of fences and enclosures, as well as the establishment of piped water and boreholes, are collectively impacting Namibia's forests, woodlands and grasslands (A. Verlinden and Dayot 2005b; Mendelsohn JM, el Obeid S, and Roberst CS 2000; M. Seely and Klintenberg 2011b; Ben J Strohbach 2000a, 2000b, 2000d).

1.12.4 Large-scale enclosures, water availability and over-exploitation

A leading cause of contemporary changes in land-use and grazing intensity has been the privatisation of vast tracks of land for large-scale livestock farming, principally through the enclosure of commonage land. The expansion of intensive livestock farming throughout much of the Namibian Kalahari biome is a relatively contemporary development, since before the 1970s, settlement was mostly limited by the availability of water, which was only available through the active management of rare, seasonal, shallow wells and water holes. Within this context, in their recordings of oral history undertaken a large area of the northern communal regions, Verlinden and Dayot (2005) find that substantial changes in tree and grass cover have transpired in recent decades. In fact, the intensity of grazing throughout much of the north of the country in the 1990s was found to be so serious that in the early 2000s it was deemed critical, even in remote regions, thus further preventing the transhumance of cattle to new grazing areas to allow for rangeland recovery (B. Strohbach 2001).

1.12.5 Historical and contemporary processes affecting Namibia's woodlands

A number influences must be considered with respect to the impact of grazing on vegetation, especially in the northern Kalahari ecoregion. Historically, the landscape was used and maintained by hunter-gathers with vegetation structure, composition and function being for the most part controlled and characterized by low-intensity fire together with cattle and wildlife grazing. The spread of present-day cattle grazing into previously unsettled land occurred in recent decades as a response to population growth and the associated scarcity of arable farm land in the already settled, fertile regions. The process was greatly facilitated by the installation of water infrastructure, including pipelines and boreholes since the 1970s, which permitted the settlement of new fertile grazing and cropping regions in a sequence which is repeated today. At present, most if not all the land is utilized for grazing, resulting in widespread land shortages. Over-stocking has impacted the quality of the land, mainly through reductions in herbaceous cover, especially perennial grasses, which are thought to have brought about increases in unpalatable woody species (shrub encroachment). Concurrently, these processes are accompanied by land clearing or deforestation, for the creation of settlements, farmsteads and crop fields. New roads, both formal and informal, are often used for timber extraction and thereby aggravating deforestation and degradation (Erkkilä 2001; Erkkilä and Löfman 1999; Erkkilä and Siiskonen 1992).

Transhumance and fencing are two additional factors influencing vegetation structure and composition. Patterns of transhumance have greatly altered in recent decades, with most livestock now remaining at fixed water points throughout the year. This further increases the pressure on the land by reducing the amount of time available for herbaceous vegetation to recover from grazing and often results in the loss of perennial forage species. Moreover, the interruption of the seasonal cycle of transhumance between cattle posts and arable crop fields has resulted in the removal of a major input of fertility, thereby causing a pronounced deterioration of arable crop land (A. Verlinden and Dayot 2005b; A. Verlinden and Kruger 2007b).

The fencing of large tracts of land (often informally) has mainly been carried out by a small fraction of the population with access to the necessary capital. It is thought to heighten the problem of grazing land shortage for commonage pastoralists. Furthermore, it restricts seasonal transhumance, leading to over grazing and land shortages, leaving many communal pastoralists increasingly dependent on seasonal rainfall for grazing, thereby making their livelihoods from pastoralism more vulnerable to drought. Lastly, the impact of browsers and especially elephants (*Loxodonta africana*) on the Kalahari woodlands and surrounding ecoregions, has been extensively studied. Browsers are essentially scarce outside of protected areas and livestock constitute the most important pressure on forage resources across the country (Aarrestad et al. 2011; de Beer et al. 2006).

To conclude, population growth has resulted in some complex and interrelated trade-offs between arable cropping, grazing and stocking densities, new enclosures, fixed water points, and changing transhumance patterns. These are engendering widespread and significant vegetation change processes and associated land degradation. Grazing is a key driver of vegetation change processes throughout the country, consequently, studies endeavouring to explore the drivers and implications of vegetation change based on satellite remote sensing need to take this factor into account (David Ward et al. 2000).

1.12.6 Expected impacts of climate change on Namibian savannahs

Certain climate change scenarios predict important decreases in precipitation for much of the African savannah transition regions. These encompass considerable parts of northern Namibia but also neighbouring countries, including Angola, Botswana and South Africa, and are expected to profoundly impact savannahs of these regions (Rogelj, Meinshausen, and Knutti 2012; Edenhofer et al. 2014; Thuiller et al. 2006). Thuiller et al. (2006), in their first comprehensive assessment of the possible effects of anthropogenic driven climate change on the vegetation of Namibia, find that important changes in ecosystem function, vegetation structure and composition, species distributions and diversity are highly likely to occur before the end of the century, in light of expected climate change (Thuiller et al. 2006).

1.13 Remote sensing for monitoring environmental change

1.13.1 Satellite remote sensing for environmental change monitoring

Satellite remote sensing contributes a wealth of quantitative data ideal for monitoring environmental change (i.e. deforestation) and quantifying biophysical parameters (i.e. vegetation biomass) at continental scales (Röder and Hill 2010). These data span a range of spatial, temporal and spectral resolutions while consistently yielding synoptic measurements at appropriate scales (Coppin et al. 2004; Brink and Eva 2009a; Bodart et al. 2013).

Satellite-based land cover products characterize the Earth's surface by providing biophysical data which are closely linked to landscape environment and ecology. Land cover change is one the of the most pressing environmental issues due to its multiple impacts on fundamental ecosystem processes, hence monitoring its development is imperative (Foley 2005; Lubchenco 1998).

Vegetation is a good indicator of diverse ecosystem processes, and changes in vegetation density or "greenness" can be measured using a range of satellite derived vegetation indices (VIs) which act as proxies (Pettorelli et al. 2005). They include, among many others, the Normalised Difference Vegetation Index (NDVI), which can be derived from passive optical sensors such as Landsat and Moderate Resolution Imaging Spectroradiometer (MODIS) (Higginbottom and Symeonakis 2014). Likewise, active space-born radar and Light Detection and Ranging (LiDAR) sensors have also proved highly effective at retrieving biophysical parameters related to vegetation canopies. Numerous studies have demonstrated the effectiveness of active and passive (i.e. optical) satellite data for quantifying vegetation change processes such as deforestation (Ahl et al. 2006; Zhang et al. 2003; Fensholt et al. 2012; Tucker et al. 2005).

1.13.2 Monitoring trends and cycles in biophysical variables and land surface phenology

Biophysical phenomena often show marked inter- and intra-annual cycles, for instance, precipitation, land surface temperature and vegetation or land surface phenology, which are generally driven by the annual flux of solar energy. A major area of contemporary scientific research focuses on monitoring these seasonal cycles and trends, since they provide key indicators used in quantifying the Earth's response to global climate change. For example, the study of plant phenology and trends in the timing of events such as earlier flowering, often reflect a response to increasing temperatures. Importantly, satellite remote sensing yields fundamental data and methods to study these processes (Sparks and Menzel 2002; Eastman 2009).

Land surface phenology, which describes the cycles of vegetation intra- and inter-annual fluctuations in response to climate and anthropogenic forcing, as captured by satellite remote sensing, is a fundamental feature of vegetation change monitoring (M. Friedl et al. 2006). It characterizes the seasonal timing of vegetation or plant development, for instance, the timing of leafing and senescence. Importantly, land surface phenology is a fundamental control and feedback mechanism of the climate system and serves as a key indicator of climate change. It is also an indicator of ecosystem processes and productivity, since it describes such biophysical attributes as energy balance and albedo (Barr, Black, and McCaughey 2009; Rechid, Raddatz, and Jacob 2009; Richardson et al. 2010; Song 1999).

Changes in land surface phenological metrics, such as the start of the growing season, act as proxies for vegetation change and shifts in functional type, for example, deforestation and changes from herbaceous to woody vegetation, respectively (Gallinat, Primack, and Wagner 2015; Morisette et al. 2009). By analysing trends in satellite-derived phenological metrics, these processes can effectively be quantified (Reed, White, and Brown 2003; X. Zhang et al. 2003).

1.13.3 The need for satellite remote sensing products

The quantitative mapping of land surface phenology and biophysical parameters such as biomass and cover, are essential to numerous applications (Broich et al. 2014). These range from agricultural land management and payment for ecosystem services studies, which measure forage production and carbon sequestration, respectively, to conservation, environmental change monitoring and climatology research, to inform ecosystem processes, land surface dynamics and climate modelling studies (Helman et al. 2015). The Earth's surface properties have a direct impact on the way the atmosphere and biosphere interact. Therefore, accurate biophysical data on Earth's surface properties is a fundamental requirement for calibrating and parameterizing land surface process models across scales. Moreover, quantitative biophysical map products are a fundamental component of global climate change prediction models which account for feedbacks between the climate and land surface (Bonan et al. 2002).

1.13.4 Field observations and multi-scale, multi-data approaches

Satellite-based studies monitoring vegetation changes often suffer from a shortage of local field data to validate results, identify how change manifests on the ground and determine drivers of change. The importance of using field and satellite data in conjunction to explain ground-level change processes has been widely demonstrated. It is especially relevant in savannah landscapes, where complex and often contrasting change processes occur over decadal time-scales (Herrmann and Tappan 2013; Brandt et al. 2015). Moreover, coarse (>500m) and moderate (30 – 500 m) spatial resolution imagery may conceal or mask local, fine-scale spatial and temporal heterogeneity of change processes. Therefore, it is crucial to employ multi-sensor data spanning spatial, temporal and spectral resolutions. Integrating information from the ecological and social sciences, is also valuable for achieving a rigorous understanding of actual change processes. To conclude, detailed regional studies employing a range of available multi-sensor, multi-resolution satellite remote sensing imagery, together with qualitative and quantitative field data from across disciplines, for the calibration and validation of map products, are more likely to accurately identify and measure complex environmental change processes (Kuenzer, Dech, and Wagner 2015; de Jong et al. 2011).

1.14 Challenges and limitations of remote sensing savannah vegetation change

Numerous limitations are apparent when attempting to quantitatively characterize vegetation change African savannah biomes using satellite data. The landscape is highly heterogeneous and dynamic, both spatially and temporally. Savannah vegetation is composed of different vegetation functional types, namely grasses, shrubs and trees. The landscape is usually a patchwork of different vegetation communities, ranging from shrub land and grassland, to woodland and forest. Vegetation functional types have contrasting phenologies and respond differently to environmental and climatic conditions. For example, rainfall is considered the main driver of photosynthetic activity, yet it is often highly irregular intra- and inter-annually, thus contributing to fluctuating photosynthetic activity.

Herbaceous vegetation has a short life span and is primarily dependent on rainfall for photosynthesis. Growth is generally highly variable seasonally, due to changeable precipitation patterns. In addition, herbaceous vegetation is very sensitive to disturbances, including fire and grazing. Together, these factors contribute to creating exceedingly irregular land surface phenological cycles, with individual years and seasons differing markedly across time and often not being representative of normal, steady conditions (Brandt et al. 2017). Woody vegetation, in contrast, is long-lived (i.e. decades) and less restricted by water availability. For instance, photosynthesis can take place even in times of drought; in fact, many tree species exhibit pre-rainfall leaf flushing. Lastly, woody vegetation is more resilient to the effects of fire and grazing (Tian, Brandt, Liu, Verger, et al. 2016).

Collectively, these factors contribute to making the extent of vegetation, and in particular vegetation change processes, especially difficult to define, characterize and quantify in savannah biomes. Although numerous map products exist for the African continent, the development of methods which accurately quantify environmental change across such dynamic biomes, while exploiting the ever-increasing collection of satellite remote sensing data, is a fundamental challenge in environmental change research and an active area of research (Ganzin et al. 2005; Espach, Lubbe, and Ganzin 2009; Hüttich et al. 2009, 2011; De Cauwer et al. 2016).

1.15 Knowledge gap and problem statement

At present, only limited information exists on the extent and rate of deforestation and shrub encroachment in Namibia (Burke and Strohbach 2000; Hüttich et al. 2009; Gessner et al. 2013). However, several studies have identified both widespread greening throughout the country, and concurrently, extensive small-scale deforestation, although the sptail and temporal scales of these analyses are limited (Erkkilä 2001; Erkkilä and Löfman 1999; Tian, Brandt, Liu, Rasmussen, et al. 2016). Importantly, this paucity of quantitative monitoring data on land cover impinges on (a) the development of rigorous adaptation strategies to climate change, (b) effective long-term management policies for conservation and rangeland management. These issues are especially pertinent since far-reaching changes in vegetation structure and composition are predicted to take place across the country as a result of anthropogenic and climatic drivers (Thuiller et al. 2006). Hence, there is a requirement for accessible science and management information. Thus, several research questions present themselves:

(i) How can either deforestation or shrub encroachment be measured?
(ii) How widespread are both vegetation change processes?
(iii) What is the contribution of either vegetation change process to the carbon cycle?
(iv) What is driving the observed vegetation change processes?
(v) Are shifts in precipitation causing the observed changes in vegetation or are they primarily the results of anthropogenic drivers?

These questions need to be addressed in the context of rural livelihoods, the carbon cycle, climate, conservation and environmental monitoring.

1.16 Aims and objectives

The primary aims of this thesis are to provide quantitative local to region-scale estimates of vegetation change in Namibia and identify what is driving these changes. This is done by developing methods which address these limitations implicit on savannah vegetation change mapping. These methods are based on the use of multi-sensor, multi-resolution and multi-temporal satellite remote sensing datasets, in conjunction with field calibration and validation datasets.

In order to address these research problems and questions, the thesis is comprised of several objectives:

(i) To track the degree of change experienced by the main thematic land cover classes across the Namibian Kalahari woodland ecoregion using the Landsat satellite archive data.
(ii) To estimate aboveground woody biomass change in the Namibian Kalahari woodland ecoregion by combining field, radar, and optical data sets.
(iii) To map trends in fractional woody cover across Namibia using seasonal phenological metrics and field inventory data, and investigate how these are related to anthropogenic and climatic drivers.
(iv) To monitor contemporary trends in NDVI and precipitation, and quantitatively map their spatial patterns and identify how their temporal dynamic relate.

These objectives serve to build on the current understanding of environmental change in the country, contribute to the science of vegetation change monitoring of drylands, and address some of the many challenges pertaining to the retrieval of biophysical information from satellite remote sensing in tropical savannah biomes.

1.17 Thesis hypotheses

In the context of contemporary scientific understanding concerning vegetation changes and their drivers in southern Africa, the research questions, aims and objectives prompted three hypotheses. These address the extent and drivers of vegetation change as well as the limitations associated with their measurement.

Hypothesis 1: The widespread greening trend observed throughout much of the country is masking small-scale land clearing.

Several studies based on high resolution satellite remote sensing data have demonstrated the occurrence of small-scale deforestation and woodland degradation in northern Namibia, which is presumably the result of small-scale subsistence agriculture. Concurrently, an increase in woody vegetation density throughout much of Namibia has been established using coarse-scale satellite remote sensing analyses. These results suggest the occurrence of contrasting vegetation change processes (i.e. deforestation and shrub encroachment), both of which are associated with land degradation. Therefore, a multi-senor, multi-data approach combining field data from across disciplines is required to identify and quantify the extent of either process (Erkkilä 2001; Erkkilä and Löfman 1999; Röder et al. 2015; Patrik Klintenberg and Seely 2004; De Klerk 2004a; Michael Pröpper and Vollan 2013; M Pröpper et al. 2010;

Tian, Brandt, Liu, Rasmussen, et al. 2016; B.J. Strohbach and Petersen 2007; B. Strohbach 2001).

Hypothesis 2: The greening trends observed throughout much of the country are not completely related to precipitation trends. Instead, they are the result of numerous interacting environmental factors, with anthropogenic land-use being the principle factor. Collectively, they contribute to increasing woody vegetation density in certain areas. Moreover, the greening trend observed at coarse spatial scales may be also concealing land degradation, which manifests as a loss of perennial herbaceous strata, encroachment of hardy shrubs, loss of large trees and an increased susceptibility to soil erosion.

The roles of precipitation, anthropogenic activities (i.e. intensive grazing and fire management) and land-use (i.e. conservation land and urban areas), as drivers of shrub encroachment, are poorly understood and have not been fully assessed across regional scales in Namibia. For instance, the effects of particular management or land-use activities on vegetation dynamics have not been fully explored nor adequately quantified. Observed greening trends may simply be the result of more vegetation (i.e. both herbaceous and woody). Or they may constitute a shift in vegetation functional type, for instance, from predominantly grassland to shrub and woodland. However, the greening trend may also be masking and/or co-occurring with related environmental and ecological change processes, such as reductions in valuable forage species, losses of large tree species, and increases in soil erosion taking place due to a reduced perennial and annual herbaceous cover (De Cauwer et al. 2016).

Hypothesis 3: The capacity for moderate spatial resolution satellite imagery to successfully characterize land cover changes, in particular land clearing, occurring at the scale of individual farmsteads (~2 ha) has not yet been assessed. Yet, it is likely to be highly effective at capturing regional, gradual vegetation changes and shifts in land surface phenology. Contrarily, small-scale local land clearing or abrupt vegetation changes, together with modifications in vegetation biomass, can effectively be captured using high spatial resolution satellite optical and radar multi-temporal imagery and field measurements. Consequently, a multi-sensor multi-scale approach is necessarily best suited to quantitatively mapping contrasting vegetation change processes in highly dynamic savannah biomes.

The high resolution Landsat sensors spanning 1973 to the present have been widely used to monitor vegetation changes (Brink and Eva 2009b). With a spatial scale ranging from 60 to 30 m, it is ideally suited to mapping small-scale land clearing (Hansen et al. 2013). Nevertheless, Landsat is limited by temporal resolution and technical issues, including Scan Line Corrector (SLC) -off (Chander and Markham 2003). Accordingly, its usefulness for capturing gradual shifts in vegetation, including changes in vegetation functional type such as those which occur as a consequence of shrub encroachment, is likely to be restricted but has not been fully explored. The MODIS sensors, although providing data only since 2000 and at a lower resolution (250 m), grant very high temporal and spectral resolution. This may overcome many of the issues associated with Landsat, however, its coarser spatial resolution may conceal localized degradation processes, mainly in the form of small-scale deforestation and pervasive vegetation loss, which tend to occur only at very local scales. In addition, ecological change processes including reductions in valuable forage species, losses of large tree species, and increases in soil erosion taking place due to a reduced perennial and annual herbaceous cover, may not be readily captured.

The capacity to characterize and quantify these processes, their spatial patterns and trends, depends on the type of satellite and field data used, as well as how environmental and climatic variability are integrated into the analysis. Thus, the following thesis endeavours to investigate spatial and temporal change in vegetation at a number of different scales, by integrating a diverse array of multi-sensor satellite and field data to facilitate the interpretation of their origin and to address the hypothesis presented for Namibia. In effect, single scale satellite data only (i.e. high or low resolution), would not adequately capture vegetation change processes.

Chapter 2

Materials and methods

2 Materials and methods

The following chapter introduces the study site, materials and methods used to test the hypotheses. This thesis exploits multi-sensor satellite imagery, at a range of temporal, spatial and spectral scales, including radar and LiDAR, together with field data on land cover types, above ground biomass and fractional vegetation cover, to quantitatively map local to regional patterns of contrasting vegetation change processes, including deforestation and shrub encroachment and identify their contribution to the carbon cycle (research questions 1, 2 and 3). Change in mapped biophysical variables is then assessed in relation to potential drivers of change (research question 4 and 5).

Each thesis chapter endeavours to address specific aspects of vegetation change monitoring in savannahs, and in-depth discussions of the data and methods and how they are interpreted, can be found in the relevant sections of the manuscripts in question. Although the present thesis remains largely a satellite remote sensing-based study, through the development of collaborations with researchers from various disciplines and institutes, the validation and results interpretation processes employs not only ecological field work, but also benefits from the social sciences, which rely on interviews and qualitative methodologies. Specifically, we draw upon a number of Master and PhD theses conducted at the same time.

2.1 Study site

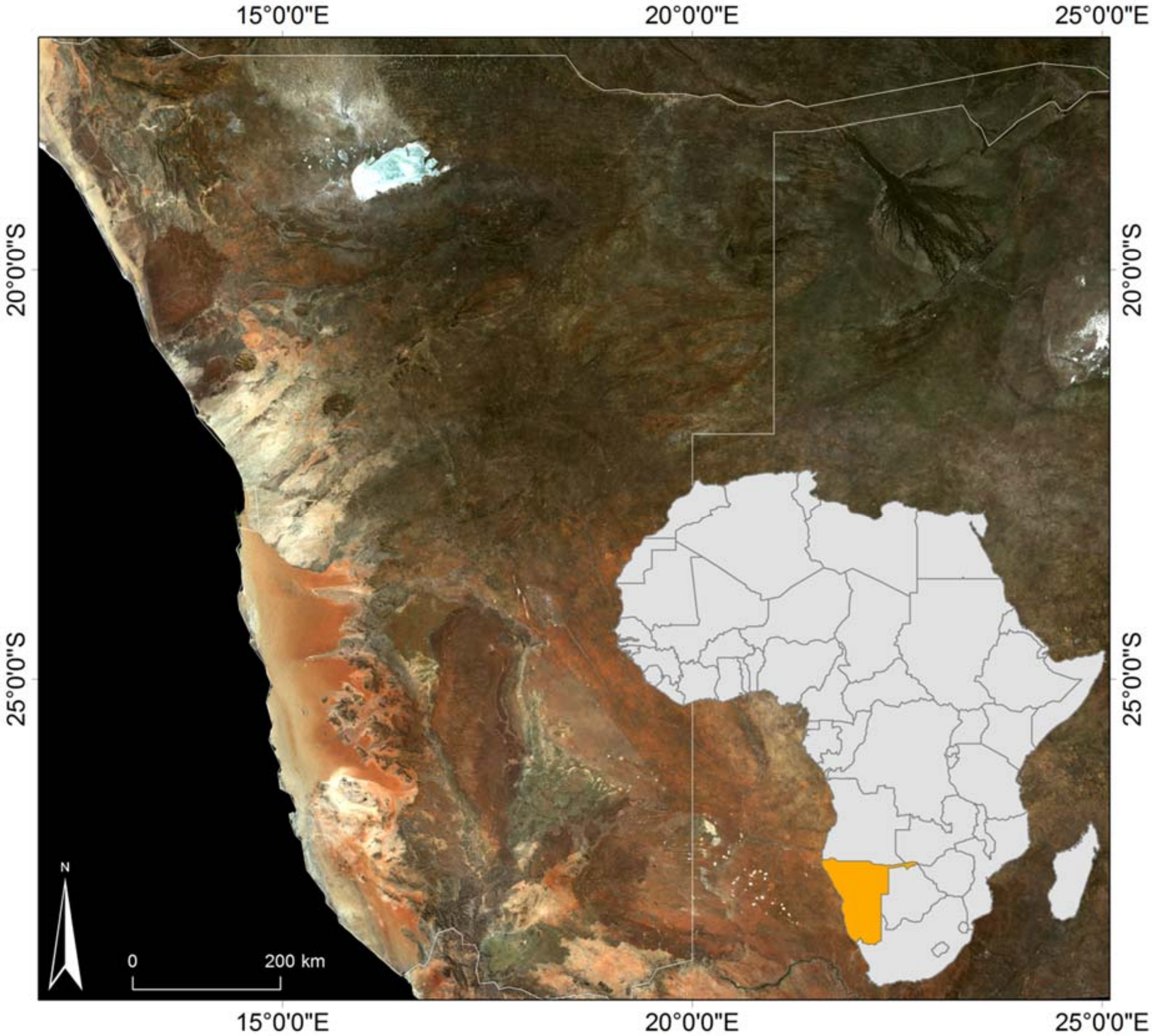

Figure 2.1. Study area superimposed on a Sentinel-2 dry season image composite.

2.1.1 Population growth and environmental change

Namibia has one of the lowest population densities, with less than 2 million people in 2001, and an average of one person per km^2. Nevertheless, the country is experiencing increasing pressures to its land and water resources and hence greater risks of conflicts over land, which is especially pertinent to low income and subsistence farmers. Across the country, there is considerable divergence in regional population density; the highest densities reach up to 100 people per km^2 in the north-central communal regions, in particular, the Cuvelai basin. Ranging out from the basin, the population drops precipitously to less than one person per km^2 for much of the rest of the country, except around large urban areas including the capital Windhoek. In northern Namibia, the human population has increased dramatically over the past five decades, partly as a result of conflicts in neighboring countries which provoked a constant influx of refugees and migrants (John Mendelsohn 2009). Much of the growth of towns, villages and farmsteads has taken place along ephemeral river beds and new roads and has resulted in the clearing of woodland for small-scale agriculture. This is despite of the often poor soil quality found in the Kalahari sand basin, which encompasses the better part of the north and east of the country. Rates of deforestation derived from satellite remote sensing vary for the region, mainly because of the difficulties associated with mapping vegetation change in savannah biomes. They are composed of shrub lands, grasslands, woodlands and forests, all of which have distinct phenological cycles and respond differently to rainfall; additionally, disturbances such as fire and grazing are common. Together, these factors contribute to making the vegetation signal, as measured by satellite remote sensing, highly dynamic both intra- and inter-annually, which complicates any change mapping endeavor (Erkkilä and Löfman 1999; John Mendelsohn and el Obeid 2005).

Rates of woodland clearing and timber harvesting in neighboring Angola are also increasing, since the end of the civil war has allowed people to resume normal agricultural activities (A Schneibel et al. 2013). Throughout the forests and woodlands of Namibia, charcoal is not produced, as opposed to many neighboring countries with similar woodlands (I. Bond et al. 2010). Similarly, shifting agriculture is not practiced as it is in neighboring Angola, instead, farmers rely on fallow periods and manure (M Pröpper et al. 2010). Commercial logging takes place in Namibia, with harvests of large *Baikiaea plurijuga* and *Pterocarpus angolensis* being the main focus. However, it is restricted to community forests (i.e. reserves managed by a number of villages for conservation), although historically timber extraction was much higher. Timber is also regularly harvested for construction, fencing and firewood, with illegal logging also frequently taking place, and harvesting of timber species in Angola is increasing (Michael Pröpper and Vollan 2013; A Schneibel et al. 2013; Anne Schneibel et al. 2017). In much of northern Namibia, shrub encroachment was found to be prevalent in areas containing relatively high numbers of cattle, and this process has also been identified throughout the country (De Cauwer et al. 2016; de Cauwer 2013a).

2.1.2 Climate and vegetation

The country is semi-arid to arid, with precipitation across the country varying from an annual average of 650 mm in the northeast, to 50 mm in the southwest. Rainfall events are variable both within and between years for any given period. In the north and central regions, precipitation is often highly variable but generally concentrated within the five summer months (December to April), while in the southernmost regions, it may occur at any time of year but especially in the austral winter (John Mendelsohn and el Obeid 2005).

Namibia is a biogeographically diverse southern African savannah biome, which accordingly provides the backdrop to an exceptionally biodiverse flora and fauna. The ecoregions of northern Namibia include the Mopane, Kalahari woodland, saline grasslands, Western-Highlands and Western and Central Kalahari Woodland ecoregions. The central regions are used for commercial farming and are part of the Highland shrub lands, Karstveld, Western-Highlands (central) and Thorn-bush shrub lands ecoregions (Giess 1998). The forests and woodlands of the Kalahari woodland ecoregion are classed as open forest by the Food and Agriculture Organization (FAO), with a copy height varying between 10 and 15 m and a mean canopy cover of 25% and a low carbon stock. Common tree and shrub species include *Burkea Africana, Pterocarpus angolensis, Baikiaea plurijuga, Burkea africana* and *Schinziophyton rautanenii* and *Combretum* species, although numerous other characteristic species which are broadly highly deciduous to semi-deciduous are also encountered. This ecoregion extends north and eastwards where it gradually merges into the characteristic southern African Miombo forests which are composed mainly of *Brachystegia bakeriana*, *Julbernardia paniculata* and *B. spiciformis* (de Cauwer 2013b; De Cauwer et al. 2016). Fire is a key determinant of the landscape, with satellite-based studies finding high proportions (i.e. up to 20% and often increasing) of the landscape burning every year (Marion Stellmes 2013). Fires were also found to occur later in the dry season and the resulting higher burning intensity is known to damage tree species in both small and large diameter classes (M Stellmes et al. 2013; de Cauwer 2013b). Southern Namibia encompasses the exceptionally biodiverse Succulent shrub lands, Succulent Karoo and southern Kalahari Woodland ecoregions, while the coastline is broadly hyper-arid Namib desert (Desmet 2007; John Mendelsohn and el Obeid 2005). In these regions, the tree and shrub strata are shorter and more open, with grasslands and tree species from the genus *Vachellia* and *Senegalia* (formally *Acacia*) predominating (Burke 2002, 2006).

2.1.3 Soils

A vast portion of the interior of the country comprises the Kalahari sand basin, where the soils are largely arenosols and dunes, deficient in key nutrients including phosphorus and nitrogen. This is especially the case for the inverted dunes of the eastern Kalahari woodlands. In the north eastern most portion of the country (Zambesi region), fluvisols are present in the seasonal floodplains. An important feature of the north-central part of the country is the

Cuvelai basin, which is composed of numerous drainage channels (*oshanas*) with clay soils and pans, the most extensive of which is the Etosha pan in the Etosha National Park. The soils of this landscape feature vary between saline solonetz soils, cambisols and arenosols, a distinguishing feature of which is a hard pan found at variable depths (Mendelsohn JM, R Trevithick, P Scarth and JB Stewart, and Roberst CS 2000). For the remaining portion of the country along the western and southern portions, soils are predominantly calcisols, cambisols, leptosols and regosols (J Mendelsohn et al. 2002b). The diverse geology of the country and millions of years of erosion has resulted in the highly varied substrates, landscapes and ranges of altitude.

2.1.4 Farming systems and land-use

The livelihoods of the majority of the population are dependent either directly or indirectly on the land's natural resources; in fact most of the land is used for agriculture. Land tenure (referred here to as land-use), can be classified into three inclusive types, in which 15% of the land constitutes government or protected areas, 41% is under communal land and 44% is freehold or commercial farm land. The largest communal area is in the north and encompasses the bulk of the Kalahari and mopane woodland biomes, while most of the freehold land is found in the central highlands and the south. Freehold land mainly comprises large-scale commercial enterprises on private lands, which sell products on international markets, including notably beef and wildlife tourism.

2.1.5 Communal farming sector

The rural communal farming sector is most often subsistence and labour-intensive, with only limited conventional inputs. It comprises chiefly small-scale agro-forestry, pearl millet (*Pennisetum glaucum*) arable cropping and livestock raising on commonages (communally held land) in the northern areas. Access to land for grazing and cropping is governed by user rights as opposed to ownership rights. Only arable land for cropping is leased to individual homesteads, while grazing land is open for use by the community. Increasingly, farmers who create enclosures for their cattle are considered commercial farmers, with their enclosures sometimes classed as informal fences, while those whose livestock is not enclosed are usually considered communal farmers. Livestock forms the basis of the livelihoods of a significant portion of the population, both in the communal and freehold regions. In the communal areas, however, cattle, as opposed to land, comprises the most important economic element, since they can be inherited while land cannot. The contemporary importance of cattle is both economic and cultural, with informal marketing playing an increasingly important role in off-take, together with government incentives to provide markets, however income from livestock is still extremely low compared to the rest of the country (Siiskonen 1992; Erkkilä and Siiskonen 1992; Mendelsohn JM, el Obeid S, and Roberst CS 2000; Thomas, Togarepi, and Simasiku 2014).

2.2 Satellite datasets

2.2.1 MODIS

Chapters 3 and 4 are based on the MODIS MOD13Q1 NDVI time-series gridded level-3 product (version 6), available at 250 m spatial resolution and computed from atmospherically corrected bi-directional surface reflectances for the period from February 18th, 2000 to March 22nd, 2017. Masks for water, clouds, heavy aerosols and cloud shadows are applied and the results merged into 16-day composites (Huete et al. 2002). A number of additional processing steps were applied, including masking pixels flagged as low quality and computing a Savitzky-Golay smoothing filter for each pixel of the time-series, so as to interpolate missing values and smooth outlier values. These steps allow only the best quality values to be used and reduce the effects of noise.

2.2.2 Sentinel-2

Chapters 3 and 4 incorporate the Sentinel-2 senor, which comprises a terrestrial observation constellation of two satellites launched by the European Space Agency. It captures high spatial resolution optical imagery with global coverage of the Earth's terrestrial surface at 5 day intervals, making the data highly valuable for time-series analyses. With 13 spectral bands covering the visible (VIS), near infra-red (NIR) and short wave infra-red (SWIR) at spatial resolutions varying from 10 m to 60 m, it is ideal for high resolution vegetation change monitoring. Notably, it secures continuity for both the Satellite Pour L’Observation de la Terre (SPOT) and Landsat missions, initiated in 1986 and 1972, respectively (Drusch et al. 2012).

2.2.3 Landsat

Chapters 1 through 4 make use of different Landsat archive datasets, distributed by the United States Geological Survey (USGS). These provide high resolution (30 m to 60 m) multi-spectral data from 1972 to the present. They include Landsat 1 to 4 Multispectral Scanner

System (MSS), Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+) and Landsat 8 Operational Land Imager (OLI) scenes, which are level 1 terrain corrected products (L1T). This group of sensors has been extensively used for terrestrial ecosystem monitoring (Chander, Markham, and Helder 2009).

2.2.4 Radar

Chapter 2 employs Advanced Land Observing Satellite's Phased Array-type L-Band Synthetic Aperture Radar (ALOS PALSAR) provided by the Japan Aerospace Exploration Agency (JAXA). It is an L-Band, 23 cm wavelength Synthetic Aperture Radar (SAR) capturing cross-polarized data in horizontal send vertical receive (HV) and horizontal send and horizontal receive (HH). For this study we use the global 25 m resolution PALSAR/PALSAR-2 seamless mosaics for the years 2007 and 2015 with backscatter data in gamma naught (Shimada et al. 2014).

2.2.5 LiDAR

Chapter 2 integrates data from the space-born LiDAR sensor Geoscience Laser Altimeter System (ICESat), which provided continuous observations of the Earth (2003-2009) and is used to measure a range of environmental parameters including vegetation canopy height (Lefsky et al. 2005; Simard et al. 2011). ICESat is a waveform sampling LiDAR sensor with a 70 m footprint spaced at 170 m intervals; due to its limited sampling area it is often used in conjunction with other sensors (Badreldin and Sanchez-Azofeifa 2015; Cartus et al. 2012). It emits short duration (5 ns) laser pulses and records the echoes of those pulses as they reflect from the ground (Zwally et al. 2002). When the surface is vegetated, the return echoes (waveforms) are a function of the vertical distribution of vegetation and ground surfaces. For forests on flat ground, stand height is calculated as the difference between the elevation of the first returned energy minus the mean elevation of the ground return (Harding 2005).

2.2.6 Precipitation data

Two precipitation datasets were used in chapter 3 and 4. The Tropical Applications of Meteorology using SATellite data and ground-based observations Research Group (TAMSAT) produces daily rainfall estimates for all of Africa at a spatial resolution of 0.03758° in latitude and longitude, or approximately 4 km at nadir. The archive spans from 1983 to the delayed present with pan-African coverage (Maidment et al. 2014, 2017). The TAMSAT dataset merges geostationary Meteosat data with ground-based gauge observations using a calibration approach that takes advantage of both information inputs. Secondly, monthly precipitation was computed using the CMORPH (CPC MORPHing technique) dataset, in which precipitation estimates are derived from satellite passive microwaves and infrared data, which spans the study period and is available at a resolution of 0.25° (Joyce et al. 2004). These rainfall datasets were used since they offer relatively high spatial resolution and temporal spans corresponding to the study period.

2.2.7 Vegetation cover

Field measurements of vegetation cover were sampled by Dr Cornelis van der Waal during 2012, 2014, and 2016 using a standardized procedure. Several different parameters were measured, including fractional herbaceous, bare ground and woody vegetation (Herrick et al. 2013).

2.2.8 Vegetation biomass

Aboveground woody biomass (AGB) was measured in Mg ha^{-1}, as it constitutes the main landscape biomass component; estimates for dead trees, litter and grasses were omitted. Field data were collected at two sites, (i) adjacent to the town of Eenhana (Figure 2f) in the perimeter an un-gazetted community forest, and (ii) within the boundaries of Kakekete (Kandjara) village (Figure 2c). Measurements of diameter at breast height (DBH) and species were collected for all trees with a circumference > 10 cm (diameter > 3.2 cm) in geo-located 30 × 30 m plots (900 m^2), and time-averaged Global Positioning Systems (GPS) coordinates with an accuracy of <5 m were taken from the centre of each plot. Tree height was not measured, since the allometric biomass equation selected uses DBH as the main predictor of biomass. The pantropical allometric as described in Chave et al. (2014) (Chave et al. 2014) was used convert DBH measurements to AGB estimates (Pearson, Walker, and Brown 2005).

2.2.9 Field data on land cover

For the calibration and validation of land cover and biomass models, ground reference land cover data was collected during field campaigns in 2013, 2014, and 2015. Qualitative information on the different land covers was sampled using standard photography and GPS. An assessment of possible contemporary land-use changes and impact of fire were also recorded (Röder et al. 2015).

2.2.10 Spatial datasets

The MODIS Land Cover type (2012), University of Maryland (UMD) scheme product, which identifies 17 land cover classes and includes 11 natural vegetation classes, was used to assess change within distinct vegetation communities (Channan, Collins, and Emanuel 2014; M. A. Friedl et al. 2010). Population density data were taken from the Atlas of Namibia for the year 2002 to give an approximate estimation of the number of people per km^2. Land-use data were derived from the Atlas of Namibia. Here, the different land-use types allow the effects of distinct land management practices on vegetation structure and composition to be distinguished in vegetation proxy signals (J Mendelsohn et al. 2002a).

2.2.11 Additional satellite imagery

Corona imagery, part of the first generation of United States photo intelligence satellites which collected more than 860,000 images of the Earth's surface between 1960 and 1972, was used for map products validation. Aerial orthophotos loaned by the University of Namibia and covering parts of northern Namibia were used also for validation. Version 4 of the Defense Meteorological Program (DMSP) Operational Line scan System (OLS) Night time Lights Time Series was used for mapping the extent of urban landscapes.

2.3 Approaches and background to mapping vegetation changes in Namibia

2.3.1 Focus on mapping woody vegetation

The research focuses on mapping vegetation changes across scales, in particular woody vegetation (i.e. trees and shrub), as opposed to herbaceous vegetation (i.e. grasses and forbes). This is primarily because woody vegetation: i) is a good indicator or proxy for long-term environmental change processes, ii) can easily be identified using satellite imagery, which is the underlying approach used in this study, iii) is a fundamental and heavily sought-after resource for a large proportions of the rural population and finally, iv) remains photosynthetic for longer periods than herbaceous vegetation, thus allowing it to be more readily distinguishable and quantifiable using multi-temporal satellite imagery (John Mendelsohn and el Obeid 2005; Alex Verlinden and Laamanen 2006).

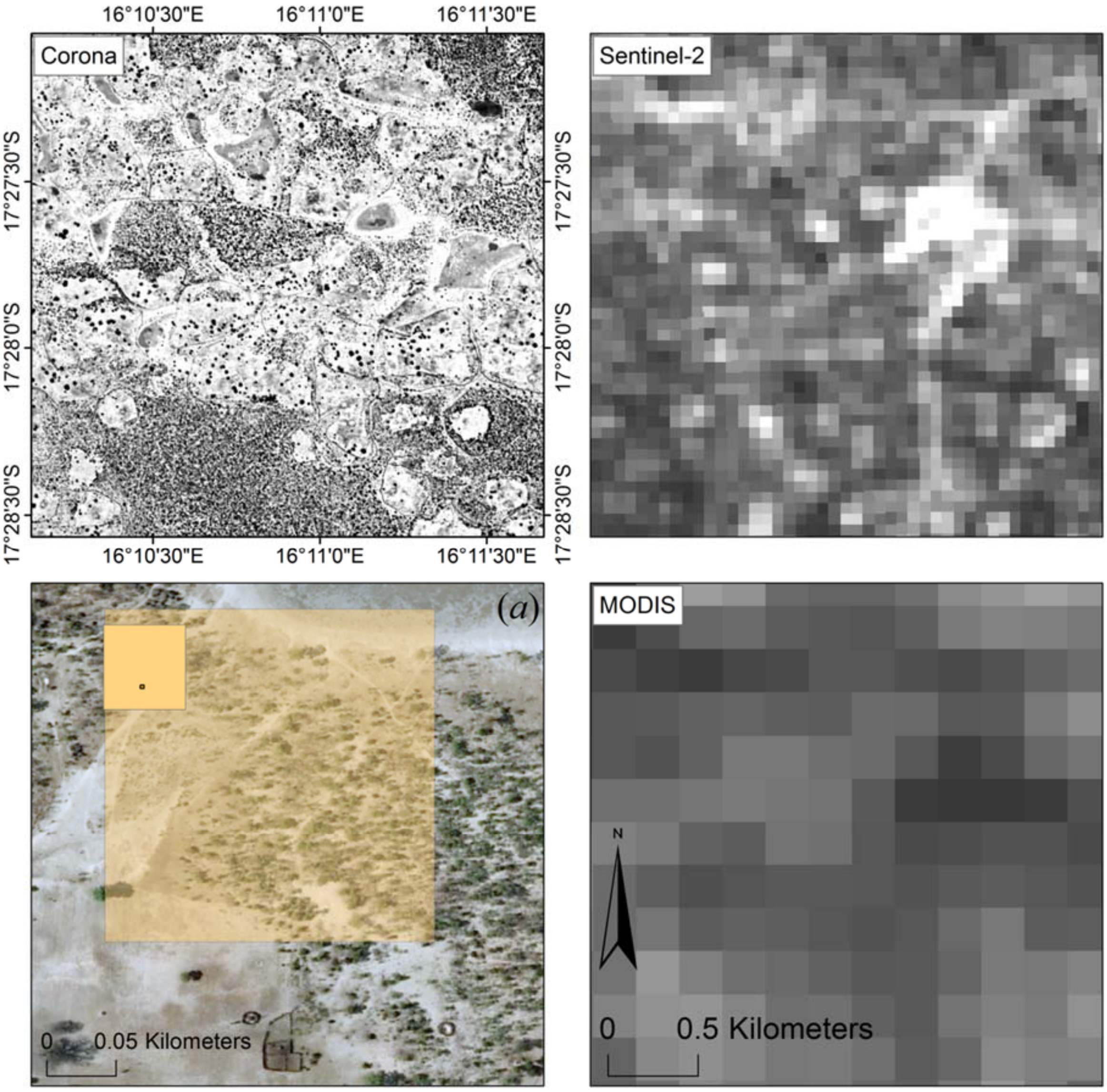

Figure 2.2. Samples of Corona, Sentinel-2 and MODIS imagery illustrating the different spatial scales used for this study. Panel (a) also display the pixel sizes of Corona (6 feet), Sentinel-2 (10 m) and MODIS (250 m). The background is an aerial ortho-photo at (5 cm).

2.3.2 Time-series and trend analyses

Numerous change detection and trend analysis methods can be applied to satellite data to monitor global environmental change (Forkel et al. 2013; Coppin et al. 2004; D. Lu et al. 2004; Mas 1999; Singh 1989). For instance, time-series analysis can be used to detect trends in a given biophysical variable over a given period and area (Brandt et al. 2014). Satellite remote sensing change using time-series analyses is often divided into three main groups, namely, seasonal, abrupt and gradual changes (Verbesselt et al. 2006). Vegetation cover degradation, for instance, is often inferred from a gradual decrease in vegetation activity over time (Reed, White, and Brown 2003). Deforestation, in contrast, is an abrupt change, while the annual shifts of phenological cycles of woody and herbaceous vegetation in response to rainfall in savannah biomes is classified as a seasonal change (Verbesselt et al. 2006). To map long-term trends in vegetation, this thesis processes time-series datasets at annual and monthly temporal scales then applies different trend estimation methods (Forkel et al. 2013; Eastman 2009).

Trend estimation using linear regression analysis is often used in remote sensing studies, despite the fact that it contravenes a number of statistical assumptions, for instance, the independence of observations which results in temporal autocorrelation or homogeneity (deBeurs and Henebry 2004; Eklundh and Olsson 2003). As such, this thesis, in addition to linear regression, employs two non-parametric analyses to bypass these constraints, including the Mann-Kendall and median Theil-Send trends tests, as well as trend analyses developed by Forkel et al. (2013) (Forkel et al. 2013; deBeurs and Henebry 2004; Eastman 2009). For example, the monotonic Mann-Kendall trend test is a non-linear trend indicator which estimates the strength with which a trend is persistently decreasing or increasing. Similarly, the median trend Theil-Sen slope is generally recommended for looking at rates of change in noisy or short time-series and hence is often applied in this thesis (Hoaglin, Mosteller, and Tukey 1983). It is estimated by computing the slope of every pair of values in the time-series and taking the median value.

A number of fundamental points need to be considered when applying trend analyses to satellite remote sensing time-series data. Firstly, the results of a trend analysis are dependent on the time-series length, its temporal resolution, data quality and method of analysis (Sulkava et al. 2007; Badreldin and Sanchez-Azofeifa 2015). Secondly, annually aggregating a time-series diminishes its temporal resolution, which is an essential factor in estimating trend significance. Correspondingly, however, annual aggregation reinforces a trend analysis by removing any seasonal cycles, which can add seasonal correlation structures and thereby increase overall error. Moreover, by aggregating values to average monthly or annual scales, signal (i.e. NDVI) fluctuations due to climate, fire or anthropogenic activity are effectively integrated, permitting the quantification of long-term anomalies, such as deviations from long-term averages (Forkel et al. 2013).

Numerous methods have been developed to fully exploit time-series, either by estimating and/or subtracting the seasonal cycle, including the Seasonal Trend Analysis method which is applied in chapters 5 and 6 (Ronald Eastman et al. 2009; Verbesselt, Hyndman, Newnham, et al. 2010; de Jong et al. 2011; Verbesselt, Hyndman, Zeileis, et al. 2010). However, very often the various approaches used for calculating trends produce comparable results with regard to significant trends, although differences occur for weaker trends (de Jong et al. 2011; Forkel et al. 2013).

2.3.3 Linear regression between satellite imagery time-series

The linear regression between dependent and independent time-series variables has diverse applications in satellite remote sensing (L. Zhu and Southworth 2013; Eastman 2009). They include i) identifying the relationship between vegetation proxies (i.e. NDVI) and precipitation per pixel; here, a low correlation could result from loss of vegetation or a highly dynamic and irregular relationship, ii) allow the dependant variable to be modelled using the independent variable by calculating regression coefficients and residuals, iii) providing a way of checking the coherence of results between different datasets, and iv) calibrating data from different sensors. In this thesis (Chapter 6), we model the dependent variable (NDVI) as a function in the independent variable (precipitation) and map trends in the residuals in order to identify changes in vegetation which are not driven by rainfall, caused by fluctuating rainfall, or triggered by anthropogenic disturbances such as deforestation.

2.3.4 Temporal compositing of satellite imagery

Change detection using satellite imagery and image classification requires data that are temporally and radiometrically consistent, in order to achieve comparable results. For instance, they may include mosaics of calibrated reflectances which represent a particular period (i.e. month or season) for the number of years being assessed for change. In savannah biomes, which are highly variable in terms of the observed spectral signal, this requirement is particularly difficult to achieve. Moreover, it may be hampered by a lack of data due to cloud cover, data gaps and burn scars, for the period of interest. Hence, compositing imagery across time periods is a strategy to achieve consistent imagery, rendering it amenable to accurate image classification and change detection. To address these issues we created seasonal composite imagery using Landsat 5, 7 8, Top of the Atmosphere Reflectance scenes (Roy et al. 2014; Kuenzer, Dech, and Wagner 2015).

The Fmask algorithm was first applied to all scenes to remove cloud and cloud shadows (Z. Zhu and Woodcock 2012; Z. Zhu, Wang, and Woodcock 2015). These were then composited into seasonal images by taking the median pixel value of all available images for the period required, for instance, the dry season. Seasonal composites capture part of the seasonal, phenological cycles of vegetation. Simultaneously it maximises the use of low quality images (i.e. by removing clouds and cloud shadows) and reducing images noise caused by extreme pixel values (i.e. taking the seasonal median value). Where gaps were apparent with single sensors, data sets were merged (i.e. Landsat 5 and 7). Additionally, this approach enables the seasonal differences in phenology between woody and herbaceous vegetation to be captured, thereby allowing their more accurate estimation of the extent of woody vegetation cover.

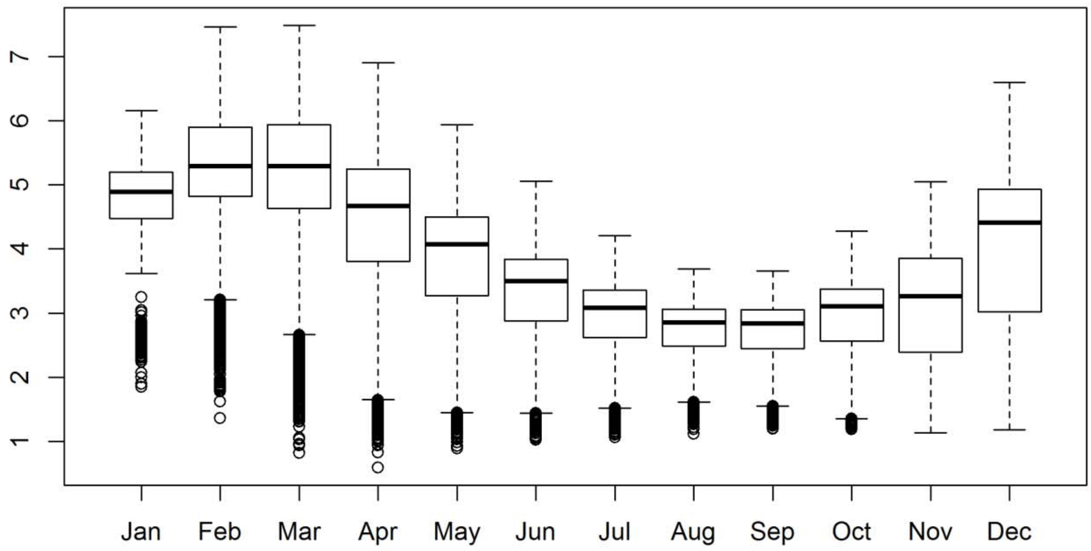

Figure 2.3. Boxplot illustrating high inter-and intra-annual variability in NDVI derived from the MODIS MOD13Q1 product (2000-2017) for a region in Namibia (Ohangwena).

2.3.5 Satellite imagery fusion for empirical modelling with field measurements

Remote sensing data are excellent for monitoring changes in biophysical variables, such as vegetation biomass, over regional scales (Röder and Hill 2010). However, a number of fundamental limitations exist in currently available datasets, including for instance, the problems of persistent cloud cover and saturation of optical sensor vegetation proxies (i.e. NDVI) at moderate to high biomass densities (Ahl et al. 2006; X. Zhang et al. 2003; Fensholt et al. 2012; Jensen 1983; Tucker et al. 2005), while SAR sensors also exhibit this problem (Austin, Mackey, and Van Niel 2003; Myron Craig Dobson et al. 1992; M Craig Dobson et al. 1995; Hoekman and Quiriones 2000; Imhoff 1993; Le Toan et al. 1992; Lucas et al. 2010; Saatchi et al. 2007; Luckman et al. 1998). To overcome these limitations, fusing data from different satellite sensors is an excellent strategy (J. Zhang 2010; Pohl and Van Genderen 1998). It takes advantage of each sensor's relative sensitivities for biophysical modelling, while addressing the particular drawbacks associated with single sensors. For instance, this thesis attempts to quantify biomass changes associated with woody vegetation, by integrating complementary datasets which describe different vegetation parameters, including forest vertical and horizontal structure and "greenness" or density; this was achieved by the fusion of radar and optical sensors, respectively, together with LiDAR-based estimates of canopy height (Montesano et al. 2014; Cartus et al. 2012; Dengsheng Lu et al. 2016; Simard et al. 2011; Baccini and Asner 2013).

2.3.6 Phenology metrics

Land surface and vegetation phenological cycles can be measured from time-series of satellite data (Figure 4a). These are modelled as curves, fitted to a VI time-series for each pixel. Key properties of these curves, known as phenological metrics (i.e. amplitude, peak, start and end of season, etc.) can then be extracted (Figure 4b). These metrics characterizing phenological cycles have successfully been used, together with field vegetation measurements, to quantify a range of climatic and anthropogenic-driven vegetation change processes and elucidate questions pertaining to net primary productivity, carbon sequestration and long-term shifts in savannah vegetation functional types. They exploit seasons when the phenologies of woody and herbaceous vegetation types diverge (i.e. wet and dry seasons). Importantly, these methods provide a novel conceptual model for the quantitative mapping and monitoring of vegetation functional types in heterogeneous biomes, which remains largely unexplored and tested (Broich et al. 2014; Brandt, Hiernaux, Rasmussen, et al. 2016; S Archibald and Scholes 2007; Donohue, McVicar, and Roderick 2009; Andela et al. 2013; Fensholt et al. 2006; Horion et al. 2014; Helman et al. 2015; Brandt, Hiernaux, Tagesson, et al. 2016).

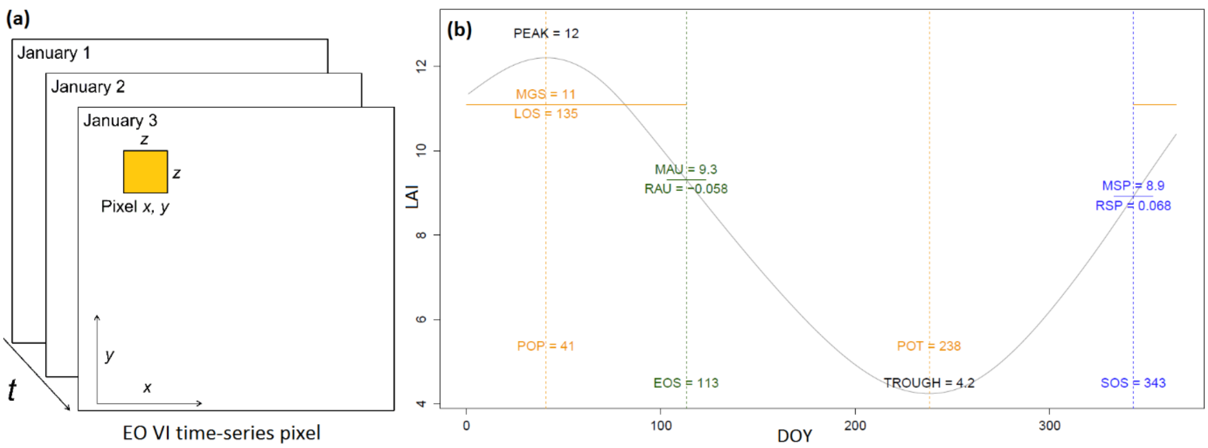

Figure 2.4. (a) Schematic diagram illustrating a vegetation index time-series with pixel values (z) through time. (b) Phenology metrics calculated from an annual cycle of the Moderate Resolution Imaging

Spectroradiometer Leaf Area Index (LAI) product. Metrics include start of season (SOS), among others; day of the year (DOY) is marked on the x-axis and Leaf Area Index (LAI) on the y-axis.

2.3.7 Validation

Field measurements of vegetation cover and biomass constitute a fundamental aspect of this thesis. These were primarily sampled for model calibration but also subsequent model validation (ground-truthing). They comprise multiple datasets, sampled using different methodologies and covering periods before and during the course of this study (2012-2016) and are described exhaustively in the relevant thesis chapters. Together with the analyses of very high spatial resolution imagery, field data were integrated into the analyses for model validation. The subjective image and map product interpretation, supported by field visits, allowed observed trends and measured changes in vegetation to be assessed qualitatively. Specifically, evaluating moderate resolution trend results with very high resolution data allows for the visual analysis and interpretation of hotspots of changes (i.e. areas of deforestation and land cover change).

This thesis also incorporates results from contemporary studies in the social sciences to find explanations for the current environmental conditions and land management practices, while at the same time elucidating drivers of past trends. Satellite remote sensing analyses can identify changes and trends in proxies of vegetation change, however, they cannot directly identify shifts in vegetation functional type changes per se, nor can such results provide an in-depth understanding of anthropogenic drivers of change, or complete explanations for observed local to regional-scale trends in environmental changes. Therefore, these issues were addressed using field-based data and concurrently incorporating results from interdisciplinary studies in the social sciences.

Against this background, the following validation approach was used in this thesis: i) the compilation of extensive field datasets on land cover and above ground woody biomass; iii) qualitative assessment of significant change and trend results using high resolution, multi-temporal satellite imagery (i.e. Sentinel-2, Landsat pan-sharpened, Google Earth, and Corona) and aerial orthophotos; iv) integrating results from contemporary interdisciplinary studies conducted by colleagues throughout the study area, retrospective interviews with stakeholders (i.e. local residents and scientists), to compile information on contemporary and past land use practices, v) correlation and regression of change and trend results as well as temporal profiles from the various datasets created.

2.4 List of software used

Software used for this thesis included several remote sensing and Geographical Information Systems (GIS) programs, as well as cloud computing platforms, including ArcGIS, IDRISI, QGIS, R and Google Earth Engine. All were used to carry satellite image processing, spatial analyses, modelling and map creation.

2.5 Manuscripts and chapters of this thesis

In all four of the papers, the accuracies and limitations of the derived remote sensing products, and how these impact the interpretations of vegetation change processes, are extensively explored in the discussion section.

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Chapter 3

Mapping decadal land cover changes in the woodlands of north eastern Namibia from 1975 to 2014 using the Landsat satellite archived data

3 Mapping decadal land cover changes in the woodlands of north eastern Namibia from 1975 to 2014 using the Landsat satellite archived data

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Abstract

Woodlands and savannahs provide essential ecosystem functions and services to communities. On the African continent, they are widely utilized and converted to subsistence and intensive agriculture or urbanized. This study investigates changes in land cover over four administrative regions of North Eastern Namibia within the Kalahari woodland savannah biome, covering a total of 107,994 km^2. Land cover is mapped using multi-sensor Landsat imagery at decadal intervals from 1975 to 2014, with a post-classification change detection method. The dominant change observed was a reduction in the area of woodland savannah due to the expansion of agriculture, primarily in the form of small-scale cereal and pastoral production. More specifically, woodland savannah area decreased from 90% of the study area in 1975 to 83% in 2004, and then increased to 86% in 2014, while agricultural land increased from 6% to 12% between 1975 and 2014. We assess land cover changes in relation to towns, villages, rivers and roads and find most changes occurred in proximity to these. In addition, we find that most land cover changes occur within land designated as communally held,

followed by state protected land. With widespread changes occurring across the African continent, this study provides important data for understanding drivers of change in the region and their impacts on the distribution of woodland savannahs.

Keywords: deforestation; land degradation; woodland; savannah; Landsat; land cover change; land-use change; Africa; Corona

3.1 Introduction

Human activities are altering the surface of the biosphere in profound ways. Whether by clearing forests, intensifying cropland production or expanding urban areas, anthropogenic activities have altered an increasingly large proportion of the Earth's land surface (Foley 2005). The effects of land surface changes range from alterations to the composition of the atmosphere and climate, to the loss of biodiversity and the disruption of biogeochemical cycles (Tilman 2001; Matson 1997; Vitousek 1997). Due to the significance of such changes on the biosphere, monitoring changes in land cover is a high priority area for research (R. DeFries et al. 2007). In effect, maps and datasets which quantify biophysical variables, including land-use and land cover (LULCC), are essential for understanding and modelling complex interactions and impacts between the natural and human environments, from regional to global scales. These include processes such as deforestation, land degradation and landscape carbon dynamics in the context of global change (R. DeFries et al. 2007; Ellis and Ramankutty 2008; Ruth S. DeFries, Foley, and Asner 2004). Furthermore, multi-temporal analyses of LULC provide important insights into long term trends which serve to identify drivers and determinants of change (Olofsson et al. 2011; R. S. DeFries et al. 2002). Indeed, in regions where there is a lack of sufficiently detailed cartographic information, environmental change detection and monitoring using satellite data can be pivotal in providing a basis for planning, management and conservation initiatives (Schulz et al. 2010). In particular, satellite remote sensing using the Landsat system has been used extensively to quantify the extent of LULCC in numerous environments around the world (Coppin et al. 2004; Lu et al. 2004).

Across the African continent, the overall tendency has been toward the clearing of land, including savannah, for crop farming and grazing (Vittek et al. 2014; Baccini et al. 2012; Bodart et al. 2013; FAO 2010, n.d.). In the communally held regions of North Eastern Namibia, savannahs have declined due to small-scale cropland expansion, increased grazing, fire frequency and land-use pressure (Erkkilä 2001; J. M. Mendelsohn and El Obeid 2003).

However, theses landscapes provide numerous important ecosystem goods and services upon which people depend (Miles et al. 2006; Roger and Archer 2005; A. Verlinden and Kruger 2007; A. Verlinden, Seely, and Hillyer 2006). We use the definition by (Giess 1998) of the study area as falling within the Northern Kalahari woodland savannah and refer to the biome as woodland. Broadly, savannah biomes are characterized by a mixture of herbaceous and woodland plant functional groups, commonly consisting of a woody tree and shrub layer with a grassy or herbaceous understory, and with a forest canopy cover between 10% and 30%. Often arid to semi-arid, they undergo marked spatio-temporal shifts in climate and land-use, resulting in pronounced annual and inter-annual divergence of vegetation characteristics (Scholes and Archer 1997; Asner and Lobell 2000). As a consequence, these ecosystems show some of the lowest satellite based land cover mapping accuracies in comparison to homogenous vegetation types (Jung et al. 2006; Herold et al. 2008). Nevertheless, recent studies (J. M. Mendelsohn and El Obeid 2003; Erkkilä and Löfman 1999; Röder et al. 2015; Pröpper et al. 2010; Hüttich et al. 2009; Strohbach and Petersen 2007) have successfully used remote sensing data to assess changes in woodland and arable land cover in Northern Namibia. However, they have concentrated on mapping vegetation change within spatially restricted areas i.e., either a portion or single Namibian administrative region, and using short time scales, such as two time intervals. Indeed, land cover changes having occurred over the past 40 years have, to our knowledge, not yet been quantified at the landscape scale, and change trajectories among land cover classes explained and evaluated.

To address this gap and to gain an in-depth understanding of the magnitude and trajectory of land cover changes at a regional scale (10^4 km^2), we use Landsat archive satellite imagery, freely available from the United States Geological Survey (USGS). We explore land cover changes in North East (NE) Namibia over the past four decades (1975–2014) at decadal time scale intervals, using a post-classification change detection method. The aim is to map and discuss the changes in the main land cover types with an emphasis on woodland change. We identify increases in area under arable land and losses of woodland by measuring and assessing: (i) the area of change; (ii) the spatial distribution of change; (iii) the trajectories of change between land cover types; (iv) the potential drivers of change; and, finally, (v) the accuracy of the maps. Information resulting from this research can serve as a practical foundation for interpreting the underlying drivers of environmental change, developing strategies for the sustainable development of the region and informing policy and conservation initiatives. For example, these data provide details on the temporal and spatial patterns of land cover change processes, which can be used to assess the consequences of past, present, and future land-use policies, as well as providing a basis for quantifying landscape carbon dynamics.

3.2 Methods

The following section details the: (i) study area; (ii) data acquisition and processing; (iii) change detection work flow; (iv) land cover change analysis; (v) proximal variables of change analysis; and (vi) accuracy assessment.

3.2.1 Study area

The study region is located within the Kalahari woodland savannah of NE Namibia (Giess 1998; Alex Verlinden and Laamanen 2006b) at the southern edge of the African "miombo" ecoregion, and upon the Kalahari sand sheet (Campbell et al. 2007; Wang et al. 2007). It extends over 107,994 km^2 to include the administrative regions of Ohangwena, Oshikoto, Kavango and Zambesi (Caprivi) (Figure 1). The rationale for defining the boundaries of the study region is the overlap between the relatively homogenous eco-floristic and bioclimatic extent of the Kalahari woodland savannah and the common pattern of communal land use within these administrative regions. The communal farming sector is labour-intensive and subsistence-based, with limited mechanical and chemical inputs and user rather than ownership rights defining tenure. They are also characterised by a higher population density relative to other areas of Namibia (A. Verlinden and Kruger 2007; National Planning Commission 2012). The land is owned by the state but administered in trust by the communities and crop land is normally allocated to individual farmsteads while grazing land is shared between community members and is typically not fenced (A. Verlinden and Kruger 2007). Agriculture throughout the region is characterized by agro-silvo-pastoralism centred on small-scale pearl millet (*Pennisetum glaucum*) cultivation, but also includes extensive cattle ranching and conventional irrigated agriculture (Erkkilä 2001) (Figures 9.1-3). Rain-fed crop farming is concentrated on certain soil types found near ephemeral rivers and clay pans which are more fertile than the surrounding deep sandy soils, while extensive grazing takes place in the remaining hinterland areas (Strohbach and Petersen 2007; A. Verlinden and Dayot 2005). Logging in the region has taken place since the early 1900s, but the net cubic meter harvest has declined dramatically. Historically, large areas of woodland were cleared for crop farming, particularly in northern areas where soils and rainfall are better suited (John Mendelsohn and el Obeid 2005). This trend continues and in recent decades new areas of woodland have been cleared for crops and settlements, with much of the deforestation taking place in two core areas, namely along the Okavango River and in western Ohangwena Region (Röder et al. 2015). A rainfall gradient exists within the study area with a mean annual rainfall of 600 mm in the east to 400 mm in the west, and equally from north to south. Rainfall is concentrated from December to March but cumulative amounts vary greatly from year to year. Evapotranspiration rates are elevated and flooding affects a large proportion of the landscape, including primarily the Cuvelai basin and the region of Zambesi, resulting in large, ephemeral water and wetland bodies and pronounced variation in maximum plant growth and production (John Mendelsohn and el Obeid 2002). Woody species are generally semi-deciduous or deciduous, with the western areas being dominated by *Colophospermum mopane* shrub-land and eastern areas by *Burkea africana*, *Baikiaea plurijuga*, *Pterocarpus angolensis* and *Guibourtia coleosperma*, woodland savannah (Strohbach and Petersen 2007; Alex Verlinden and Laamanen 2006b). Fire has a large impact on the landscape, for example, it was found that between 27% and 51% of the regions of Kavango and Zambesi burned annually between 1989 and 2001, resulting in reduced regeneration and tree mortality (Alex Verlinden and Laamanen 2006a).

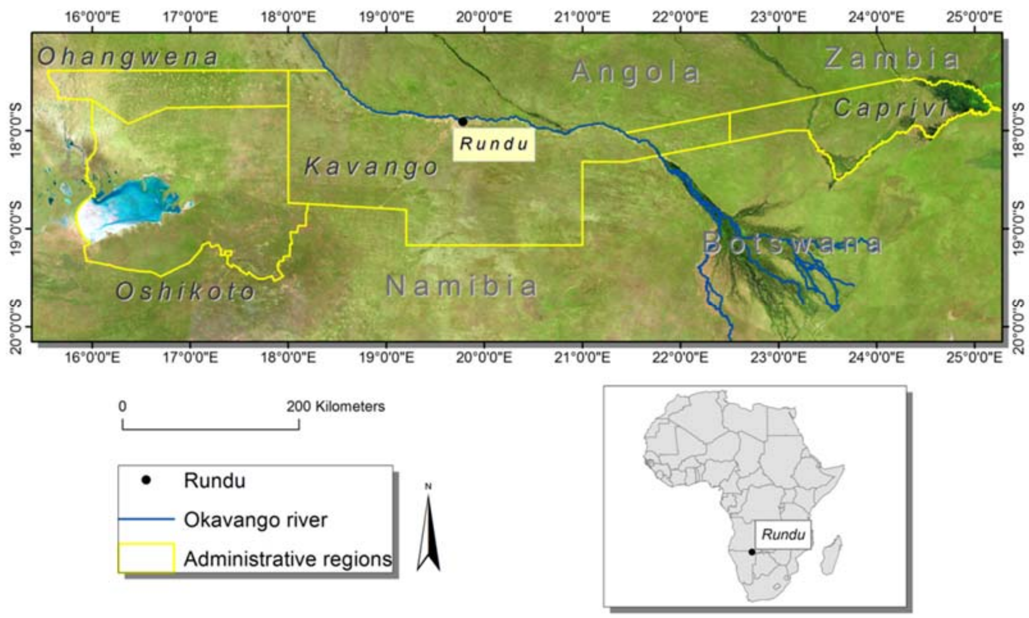

Figure 3.1. Study site, including four administrative regions of Ohangwena, Oshikoto, Kavango and Caprivi (yellow) and the Okavango River (blue) in North East (NE) Namibia. The map background is a Landsat 8 Top of the Atmosphere (TOA) reflectance, median composite, 60 m resolution image mosaic comprised of all scenes available for 2015 using the infrared bands 5, 4 and 3.

3.2.2 Landsat scene acquisition and processing

Landsat Multispectral Scanner System (MSS), Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+) and Landsat 8 Operational Land Imager (OLI) scenes were obtained from the USGS, which are level 1 terrain corrected products (L1T) and offer acceptable levels of spatial accuracy, therefore no geo-rectification was required and image-to-image registration was omitted (United States Geological Survey. Available online: https://www.usgs.gov/ [accessed on 1 June 2014]). Digital numbers were converted to calibrated top of the atmosphere radiances and then corrected for atmospheric effects using the Apparent Reflectance Model, which makes no corrections for atmospheric scattering or absorption (an atmospheric transmittance value of 1, a path radiance due to haze of 0 and a spectral diffuse sky irradiance of 0 were used), resulting in an image of proportional reflectance (Eastman 2009). Cloud free MSS images from the 1975 period were used whenever a suitable image was identified, i.e., one scene was acquired for 1973 and two for 1979, due to their limited availability and quality.

Pre-processed Landsat imagery available through Google's Earth Engine was used to assess LULC change across the study area. Here, Top of the Atmosphere (TOA) composite images were processed using all the available Landsat images for each year (i.e., 1984–1985), for the periods of 1984, 1994, 2004 and 2014. A cloud score was then applied to each pixel using the Simple Landsat Cloud Score algorithm, which selects the lowest possible range of cloud scores at each point and then computes per-band percentile values (i.e., the percentile value to use when compositing each band) from the accepted pixels. This algorithm also uses the Landsat Path Row Limit method to select only the least-cloudy scenes. The median pixel value of the composite image stack was then selected to carry out the analysis, in order to remove the influence of clouds, reduce image noise, cloud and fire scars. This results in multi-band images where each pixel represents the median of all unmasked pixels for each band. Finally, the new images were stacked with a normalized difference vegetation index (NDVI) band generated using the same method (Google Earth Engine. Available online: https://developers.google.com/earth-engine/ [accessed on 1 June 2014]).

3.2.3 Classification and change detection work flow

To obtain a matrix of change between land cover classes, we used the post-classification method at decadal intervals (Singh 1989). A decadal time scale was chosen for several reasons: (i) a lack of cloud free, good quality images for this region, especially at the start of the Landsat archive; and (ii) the necessity to generate a regular time-series for the whole region. Here, we found decadal intervals provided seamless mosaics over the study region because limited imagery for the late 1970s and early 1980s period precluded generating a denser time series. We use the post-classification method to quantify land cover conversions, in which independently generated classifications at two time intervals are compared. The main advantage is to limit issues associated with radiometric calibration (i.e. solar illumination, atmospheric absorption and scattering and sensor properties) in between intervals (Coppin et al. 2004). However, the accuracy of the initial classification will dictate the accuracy of the post-classification comparison. In effect, the end accuracy approximates the compounding of the accuracies of every single classification. The complication thereby rests with producing regular, comparable and accurate results for every comparison (Coppin et al. 2004).

Initially, a preliminary change detection study was carried out over a pilot area (11,240 km^2) on the border between the Ohangwena and Oshikoto administrative regions, known to be experiencing land cover changes. This was done to facilitate: (i) land cover class definition; (ii) the selection of suitable change detection methods; (iii) the identification of applicable image processing; and (iv) an initial accuracy assessment, as field data validation points had been collected in this area (Erkkilä and Löfman 1999). The area was encompassed by a single Landsat footprint and four scenes at decadal intervals between 1984 and 2014. Cloud free images from the early dry season and end of the wet season are considered the best for identifying woody vegetation in NE Namibia (April–May), as they maximize the contrast between the dry herbaceous layer and green canopy layer (Alex Verlinden and Laamanen 2006b). For this pilot study, Landsat TM, ETM+ and OLI scenes as close to the month of June were used due to scene availability. Five initial land cover classes were identified and scenes were classified using a supervised Maximum Likelihood algorithm, with 10 training areas identified per class using Google Earth, aerial images loaned by the University of Namibia and 61 GPS points derived from field visits (Figure 2A).

Machine-learning techniques, including Classification and Regression Trees (CART) and Random Forest (RF) are increasingly used to classify remotely sensed data and RF has been shown to improve classification accuracy (Gislason, Benediktsson, and Sveinsson 2006). Due to spectral differences between MSS scenes, it was not possible to composite all available images for the 1975 period, therefore, selected MSS scenes representing the period between 1973 and 1979 were classified individually using a CART classifier and reference Corona satellite photographs (Breiman 2001). For the remaining periods (1984–2014) the median composite/NDVI image stacks were classified into the major land cover classes, using supervised RF classifiers and up to 8 training areas per class (Gislason, Benediktsson, and Sveinsson 2006; Breiman 2001) (Table 9.1 in the Supplementary Material). Seven land cover classes were selected in an attempt to capture the main landscape variability based on visual interpretation of high resolution satellite imagery and field visits (Table 1).

Table 3.1. Land cover classes used in the final analysis.

Class	Description
Water	Rivers, lakes and standing water bodies
Clay pan	Dry lake bed; layer of clay alternating with water during the wet season
Agriculture	Arable cropland, orchards and pasture, villages and farmsteads
Bare ground	Exposed sands, beaches, riparian sand bars, dunes and roads
Woodland	Predominant land cover class; includes all savannah woodland transitions
Wetland	Seasonally flooded areas found adjacent to rivers and lakes
Urban	Densely populated areas, paved roads, concrete, warehouses, and tarmac (masked)

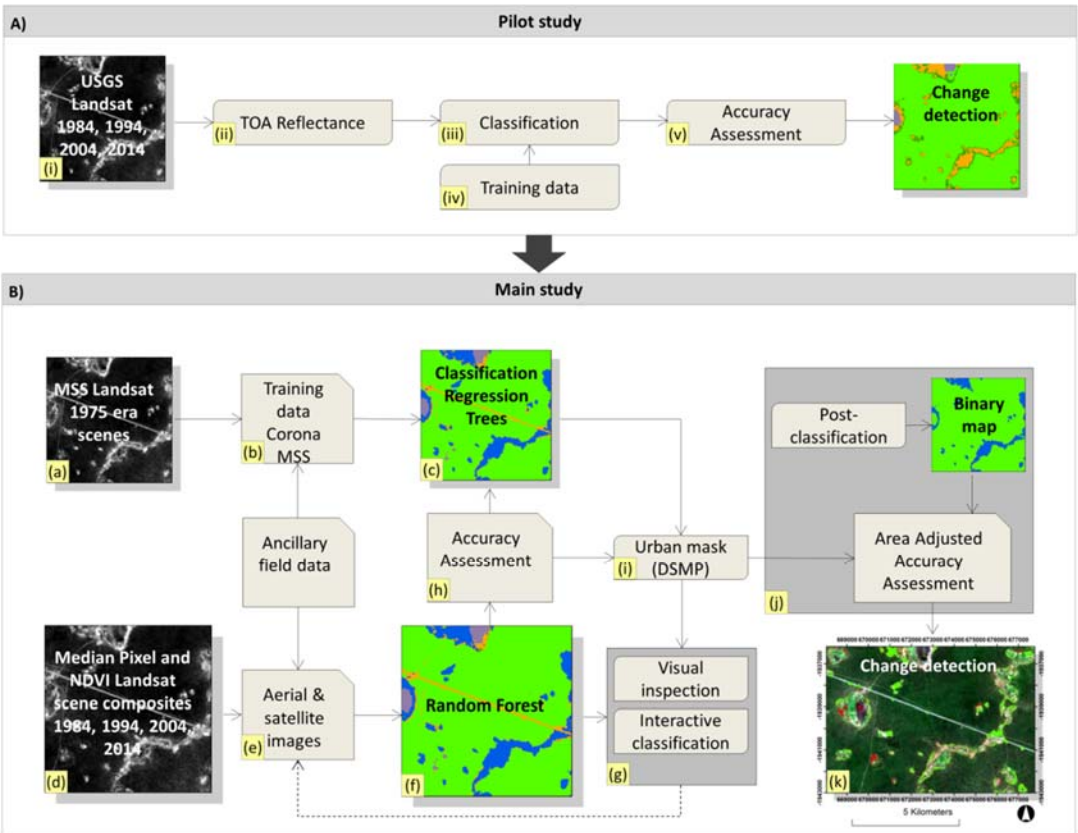

Figure 3.2. Workflow diagram illustrating the steps and methods employed. Pilot study (A): (i) Dry season (June) Landsat images at decadal intervals (1984–2014); (ii) processed to Top of the Atmosphere Reflectance (TOA); (iii) training data from Google Earth, aerial imagery and field Global Position system (GPS) points; (iv) classified with a supervised maximum likelihood classifier; and (v) accuracy assessment: validating 50 random sample points per class using available satellite and aerial imagery. Main study (B): (a) Cloud free (Multispectral Scanner system (MSS) scenes from the 1975 era; (b) training data derived from MSS scenes and Corona imagery; (c) Classification and Regression Tree (CART) classifiers; (d) for periods 1984–2014, all available Landsat scenes for one year (i.e., 1984–1985) were cloud masked and composited into a new image using the median pixel value and an Normalized Difference Vegetation Index (NDVI) band derived using the same method; (e) training data were interactively identified from Landsat scenes, Google Earth and aerial imagery, as well as ancillary knowledge from field visits; (f) Random Forest (RF) classifiers; (g) visual inspection and interactive classification (i.e., selection of training areas, and

subsequent image classification); (h) accuracy assessment; (i) urban mask; (j) area adjusted accuracy assessment on post-classification binary maps; and (k) change area detection.

Classes include" (i) "Water", which represents rivers, lakes and standing water bodies; (ii) "Clay pan", which denotes commonly found dry lake beds associated with drainage channels (often containing water from during the wet season), composed of eutric Arenosols with a high clay content (between 5% and 8%) [48]; (iii) "Agriculture", which designates a mosaic of arable cropland, orchards and pasture; includes, villages and farmsteads; (iv) "Bare ground", attempts to capture areas of sand, beaches, riparian sand bars, dunes and unpaved roads, all of which are spectrally distinct; (v) "Woodland", describes a heterogeneous savannah land cover type, i.e., savannahs, woodlands and transitions at different stages of disturbance and recovery; (vi) "Wetland", signifies permanently or seasonally flooded areas, often found adjacent to rivers and lakes and showing high NDVI values; and (vii) "Urban", attempts to estimate the extent of densely populated areas, which are often characterised by paved roads, warehouses and houses made of concrete brick as well as tarmac, by creating a mask based on Version 4 of the Defence Meteorological Program (DMSP) Operational Line scan System (OLS) Night time Lights Time Series (Elvidge et al. 2007). Spectral separation between classes was not assessed in this study. Training sites were selected interactively, based on Landsat scenes, Google Earth imagery, aerial images and knowledge of land covers gained from previous field visits (Figure 2B).

Urban areas were masked out due to their apparent spectral similarity with urban and agricultural areas, using the DMSP OLS at 1 km resolution. This dataset consists of cloud-free composites made using all the available archived data (Figure 3). We applied a threshold to annual composites from 2012 to 2013, 2002 to 2003 and 1992 to 1993 to mask the 2014, 2004, and 1994 maps, respectively. The 1992–1993 composite was also used to mask out urban areas from the 1984 and 1975 maps, as this dataset is only available from 1992 onwards. However, using this dataset as a pre-1992 mask may have resulted in an overestimation of the urban class extent. Burnt areas were successfully excluded from the analysis by taking the median pixel of the composite images, but extents were quantified using single dry season scenes. Fire is not considered a major land cover change transition, because regularly occurring fires are known to primarily affect the understory of woodland savannahs (as opposed to stand replacing fires) (Röder et al. 2015).

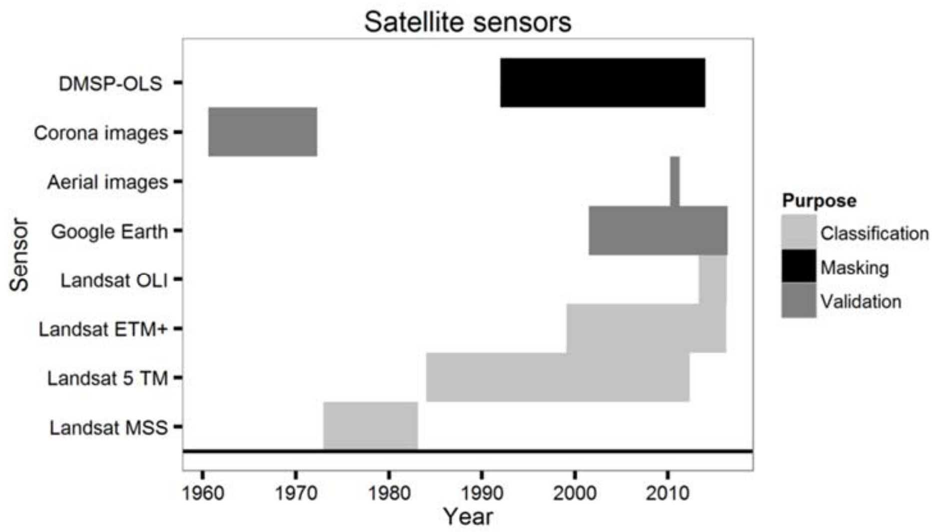

Figure 3.3. Timeline illustrating the satellite sensors used in this study, their purpose (classification, masking and validation) and date range.

3.2.4 Land cover change analysis

For each land cover class, analysis of the spatial extent, changes in area, i.e., gains, losses, persistence, and transitions from one land cover class to another, were calculated as proposed by (Pontius, Shusas, and McEachern 2004) using the IDRISI land change modeller (Eastman 2009). Cross tabulation matrices comparing two different categorical maps between successively mapped periods, allowed transitions among classes to be identified and potential underlying change processes assessed, and were computed as the off-diagonal values of the cross tabulation matrix (Pontius, Shusas, and McEachern 2004). The four administrative regions encompassing the study area have contrasting proportions of land-use categories (i.e., State Protected and Small-scale agriculture on communal land, etc.), population sizes and densities, as well as geographic extents. This is expected to impact on the amount of land converted to the other land-uses. We therefore: (i) map and discuss land cover class changes for each region, and compare these with the results of related satellite-based studies; and (ii) assess the most important land cover class transition in relation to the different land-use categories for each region, with a view to identifying which categories are important in determining change (J Mendelsohn et al. 2002).

Percentage of land cover class changed in relation to the study area was calculated as (Equation (1)):

$$\% \, Area = \left(\frac{Area \; changed \; for \; a \; class}{Total \; area \; of \; land \; cover \; map}\right) \times 100 \qquad (1)$$

3.2.5 Proximal variables of change

To determine which factors were influential in explaining the mapped land cover changes, we quantified the predominant land cover change in relation to the distance from possible drivers of change (proximal variables). They included proximity to: (i) towns; (ii) villages; (iii) roads; and (iv) rivers (including major, minor, perennial and ephemeral). These variables were chosen based on (J Mendelsohn et al. 2002); major towns included the regional centres of Rundu, Katima Mulilo, Divundu, Oshikango and Eenhana, while minor town constituted all remaining settlements. Euclidian distance from each feature was computed, and the output was then divided into 5 km buffers in order to accurately capture the expected small-scale land cover changes. The amount of the land converted is calculated a percentage of each distance buffer and buffer overlap was not accounted for (Geist and Lambin 2002).

3.2.6 Accuracy assessment

To assess the pilot study map accuracy, 50 randomly stratified points per class were generated for the 2014 map. These were then validated visually using Landsat satellite scenes, high resolution Google Earth satellite imagery, aerial photos and ground knowledge. Similarly, for the 1975 period map, 50 randomly stratified points per class, including the urban class, were generated and validated using MSS Landsat and Corona imagery. For both datasets, overall accuracy was calculated (Eastman 2009). Alternatively, for the composite image land cover maps spanning the periods 1984–2014, half of the training data were reserved for processing an accuracy assessment; the urban class was excluded as it was masked. Then, for each map, a confusion matrix representing overall validation expected accuracy (error) was processed using the reserved data. Finally, a qualitative assessment of each land cover map was undertaken using all available imagery.

In order to further assess the accuracy of the land cover maps generated in this study, an area adjusted accuracy assessment was additionally processed as per the method proposed by (Olofsson et al. 2013). Here, validation data is employed for estimating the adjusted change area and confidence intervals, please refer to Olofsson et al. (2013) for a complete review of the methods. Post-classification results are summarized by change matrices, which show the extent of different land cover transitions (i.e., from one land cover category to another). To map changes between two points in time, the number of variables in the to-from change matrix is the number of land cover classes squared. Therefore, in order to avoid having a matrix with 49 classes (seven land cover classes were used in this study), the land cover maps were modified to represent only binary Woodland and Non-Woodland classes (i.e., all other classes were merged into the Non-Woodland class), resulting in only four transitions in the matrix (i.e., two no change "transitions" and two changes from woodland to non-woodland, and non-woodland to woodland). In addition, the Woodland class is also the class of primary interest, and therefore only the changes from Woodland to Non-Woodland were assessed for area adjusted accuracy. The pairs of maps were then overlaid to create changes maps. An accuracy assessment of the change map was performed using a stratified random sample (independent of the sample selected for the accuracy assessment of the single date maps). We determined the reference land cover using Landsat scenes.

3.3 Results and discussion

3.3.1 Classification accuracy

Overall classification error for the pilot study map was 94.0% for 2014. In the pilot study, for the sake of feasibility, we only conducted an accuracy assessment for the present day period (2014), and assumed that the accuracy for the historical maps would be similar. In effect, an accuracy assessment for historical thematic maps is complicated by the fact that only the most recently classified maps can genuinely be compared against temporally coincident validation datasets. Similarly, as the scenes used to develop the maps and validation datasets are often temporally mismatched, we assume that there may be discrepancies in observed and mapped land covers which will affect the results of the accuracy assessment. Overall classification error for the 1975 map was of 78%, however, lower classification accuracies are likely here as not all scenes were from the same period (i.e., one scene was acquired for 1973 and two for 1979). Validation overall accuracy (errors) using reserved training data were of 99.7%, 99.8% and 99.5%, for the periods 1984–1994, 1994–2004 and 2004–2014, respectively (Table 9.2).

The equations proposed by Olofsson et al. (2013) were used to calculate the error-adjusted land change area estimate at the 95% confidence interval (please refer to Olofsson et al. (2013) for details), for the Woodland to the non-Woodland class (Table 2). Error matrices for each period are provided in the supplementary material. Here we find that although the land cover maps show high accuracies, the User's accuracy of the change category was of 30%, 54%, 28%, and 58% for the periods 1975–1984, 1984–1994, 1994–2004 and 2004–2014, respectively (Table 9.3), suggesting that the change maps were not highly accurate. Further, the extent of change estimated from the change maps falls within the 95% confidence interval of the error-adjusted estimated area, except in 2004–2014 change map. Here, the mapped area of deforestation is found to be of 4624 km^2, with an error-adjusted estimate of deforestation and ±95% confidence interval of 1556 km^2 ± 76 km^2 (Table 2). In addition, the change map had an overall accuracy of 72% (Table 9.3), however, the producer's accuracy (omission), which concerns the probability that validation dataset is correctly mapped, showed high accuracy (100%) for deforestation. This suggests that user's accuracy associated with the deforestation class was problematic. The stratified estimator of the extent of deforestation (1556 km^2) is less than half of the area of mapped deforestation. The reason for this disparity can be identified from the error matrix: it shows that all of the proportions of extents of deforestation are omitted from the map (the estimated area proportions omitted from the deforestation class were 0 and 0, column 3 (deforestation) (Table 9.3). Hence, the error-adjusted estimate of the extent of deforestation adds this omitted deforested extent to the mapped area of deforestation because: (i) it reduces the estimated area of deforestation; and (ii) had there been errors of omission, the estimated area of deforestation and 95% confidence interval would have been larger. Finally, for the 2004–2014 change map, the omission error associated with a few sample units of deforestation has a strong influence on the estimated area of deforestation i.e., every sample unit of omission error from the woodland class confers 1556 km^2 of deforestation. Similarly, each sample unit of omission error from the agricultural class confers roughly 211 km^2 of deforestation to the total error-adjusted value.

Table 3.2. The error-adjusted area of change (i.e., the transition from the Woodland to the Non-Woodland class), the 95% confidence interval of the error-adjusted estimated area, and actual change calculated from the change map.

Date	Change Estimate (km^2)	Error (km^2)	Actual Change (km^2)
1975–1984	577	20	5906
1984–1994	2161	159	7411
1994–2004	678	300	8653
2004–2014	1556	76	4624

3.3.2 Limitations

Numerous factors contribute to inaccuracies when classifying satellite imagery, especially in savannah environments (Shao and Wu 2008; Hill et al. 2011; Hanan and Hill 2011). To address these issues, we created composite images composed of all the available Landsat scenes for a single year to remove noise, included an NDVI band, and interactively classified these into the main cover types using knowledge gained from previous field visits and high resolution imagery. In addition, many limitations exist when applying hard classification techniques to heterogeneous vegetation biomes such as savannahs (Smith et al. 2003). To this effect, object-based image classification of savannah vegetation has shown promising results (Whiteside, Boggs, and Maier 2011; Johansen et al. 2010). The highest classification accuracies are associated with homogenous land covers, while heterogeneous land covers comprising vegetation with variable structures (i.e., grass, shrubs and trees of savannahs), have lower accuracies. Simply put, the primary reasons behind misclassifications are small land cover patch size (i.e., forest or grassland) and landscape heterogeneity (Smith et al. 2003, 2002). Land cover maps divide the landscape into distinct classes, but in savannahs, land cover type boundaries are not necessarily distinct. Instead, they are often distinguished by a range of vegetation functional types, patches and spatial and temporal shifts from open grassland savannah to closed forest covers. These shifts result from numerous factors, including fire, variable rainfall, grazing and anthropogenic impacts such as deforestation and urbanization (Asner and Lobell 2000). The inherent landscape variability coupled with, the pronounced woodland deciduousness, is therefore presumed to have contributed to the low accuracy assessment results for the change maps (Asner and Lobell 2000; Gessner et al. 2013; Childes 1988). Furthermore, the agricultural landscape is composed of a mosaic of different land uses and land covers, leading to potential mis-classifications and confusions with other land cover classes, i.e., the "Wetland" and "Woodland" classes (Table 9.4). Finally, we assume that both the Woodland and Agriculture classes are highly heterogeneous and composed of numerous different plant functional groups (Table 1). Accordingly, the results presented must be interpreted with caution and as a best estimate of the aerial extents of these classes over time.

3.3.3 Change area, distribution and transitions

Over the whole study period (1975–2014), the most extensive land cover class to change was woodland. Between 1975 and 2014, woodland area declined by −460,689 ha (4.3% of the study area), while agricultural land increased by 431,545 ha (4% of the study area) during that same period. The extents of all classes, as well as losses and gains in the Agriculture and Woodland classes are plotted for the entire study area (Figure 4).

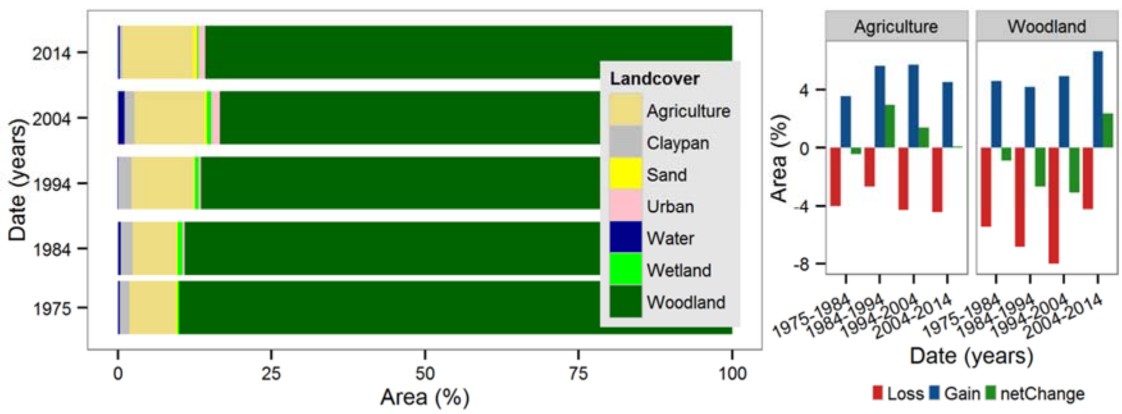

Figure 3.4. Bar graph illustrating the extents of the main land cover classes as a percentage of the study area (study area = 107,994 km^2) at decadal time scales. It shows an overall decline in the Woodland class and concurrent increase in the Agricultural class until 2004, followed by an increase in the Woodland class and decrease in the Agricultural class. Also included are the losses, gains and net change in the Agriculture and Woodland classes.

The overall trend for the whole study period was of a loss in woodland and an associated increase in agricultural classes except during the last decade, where woodland cover appears to be increasing. For all land cover classes, losses and gains took place simultaneously, i.e., between 1975 and 1984 woodland lost −5.47% and gained 4.59%, resulting in a net change of −0.87% of the study area. The pattern is similar for the intervals 1984–1994 and 1994–2004, however, between 2004 and 2014, woodland gains (6.64%) outweigh losses (−4.28%), resulting in a net positive change of 2.36%. Similarly, we see that during the 1994–2004 period, the highest woodland cover loss (−8%) was accompanied by the most important agricultural expansion (5.71%). For the whole study area, the predominant land cover transitions at each time interval were changes from woodland to agricultural classes, followed by changes from agricultural to woodland classes. For example, the predominant change trajectory between 1975 and 1984 as a percentage of the study area, included agriculture to woodland (3.54%) and woodland to agriculture (3.06%). These findings imply the woodland and agricultural land cover classes are dynamic and changeable, exhibiting relatively large losses, gains and exchanges over the intervals compared (Table 9.4). Correspondingly, 73% of the study area underwent no change; yet it is very likely that minor land cover changes, such as forest fires, could have taken place between study intervals. We mapped burnt area for each interval using the same approach but with single scenes from May to August, and found increases from 3.3% of the study area in 1975 to 11.5% in 1994, but constituted only 0.1% and 0.6% in 2004 and 2014, respectively.

The composite DSMP OLS images reveal urban area increased from 0.3% to 1.42% of the study area between 1994 and 2004, respectively. Urban areas experienced significant growth since the 1990s, in fact, Namibia's urban population more than doubled between 1981 and 2001 (John Mendelsohn and el Obeid 2002). As shown by the change matrix (Table 9.4), increases in the extent of urban areas (1994–2004) resulted mainly in the loss of agricultural land, while urban expansion in the latter period (2004–2014) primarily caused woodland losses. However, changes in the spatial extent of urban areas should be interpreted with caution, as urban growth may not always be linked with electricity (Röder et al. 2015). Nevertheless, this method provides an alternative method for estimating of the extent of human influence on the landscape.

Our analysis revealed a gradual reduction in the area of woodland and an increase in agricultural and urban land covers. Woodland conversion to agricultural land uses occurs as a continuous small-scale (2 ha) process of extraction and utilization of resources, driven by a need for permanent grazing pasture, construction timber and fire wood, and arable land for rain-fed cropping (Erkkilä 2001; Röder et al. 2015) (Figure 5a,b). Correspondingly, the process of cropland fallowing and subsequent woodland succession is constrained by diverse factors, chief among them being water availability, soil nutrient depletion, alterations and diminution of seedbanks, increased likelihood of fire disturbance and continual grazing pressure (John Mendelsohn and el Obeid 2005) (Figure 5c,d).

Figure 6 displays land cover maps for the main land cover class transition (i.e., Woodland to Agriculture classes) for each time interval: yellow (1975–1984), orange (1984–1994), dark orange (1994–2004) and red (2004–2014). The encroachment the Agricultural class into the Woodland class as well as the small-scale nature of the changes, are clearly visible for each time interval. For example, gradual decreases can be noted in proximity to the urban area of Rundu, which suggest urban expansion and small-scale cropping (Figure 6).

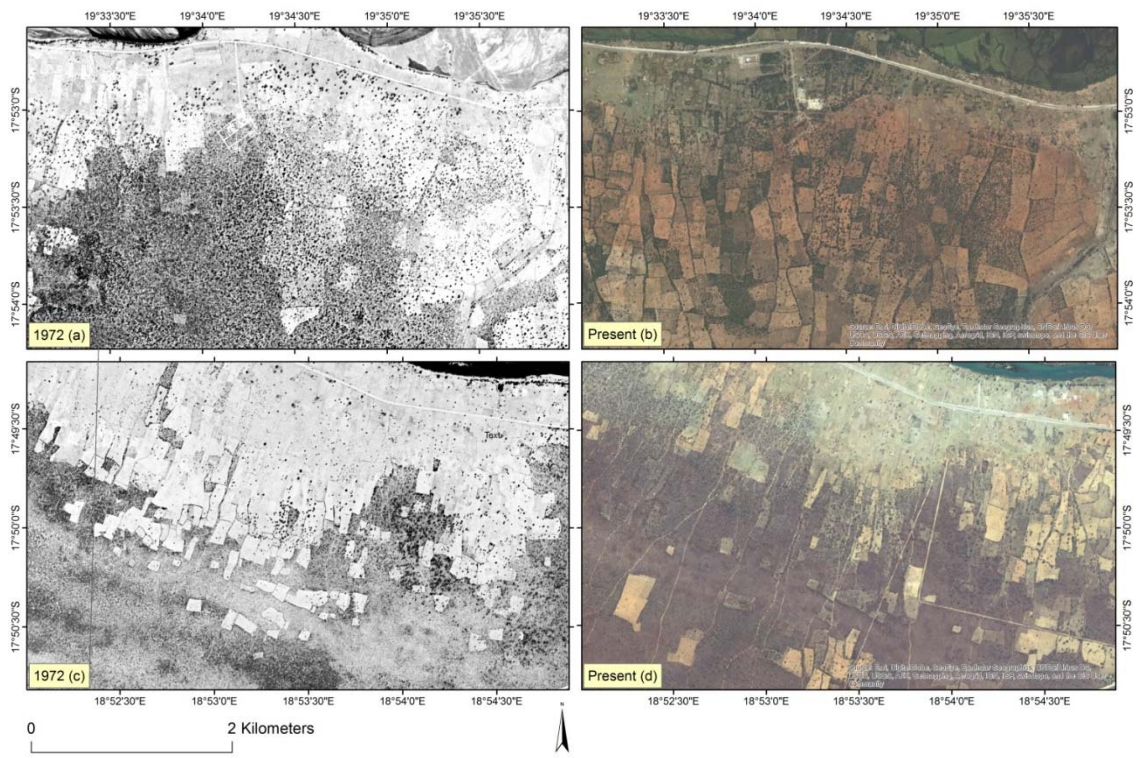

Figure 3.5. Corona image from 1972 (a) compared with present day satellite imagery (b) revealing small-scale agricultural growth (i.e., Woodland class loss); and a Corona image from 1972 (c) compared to present day satellite imagery (d) showing woodland succession and crop land fallowing (i.e., Woodland class gain).

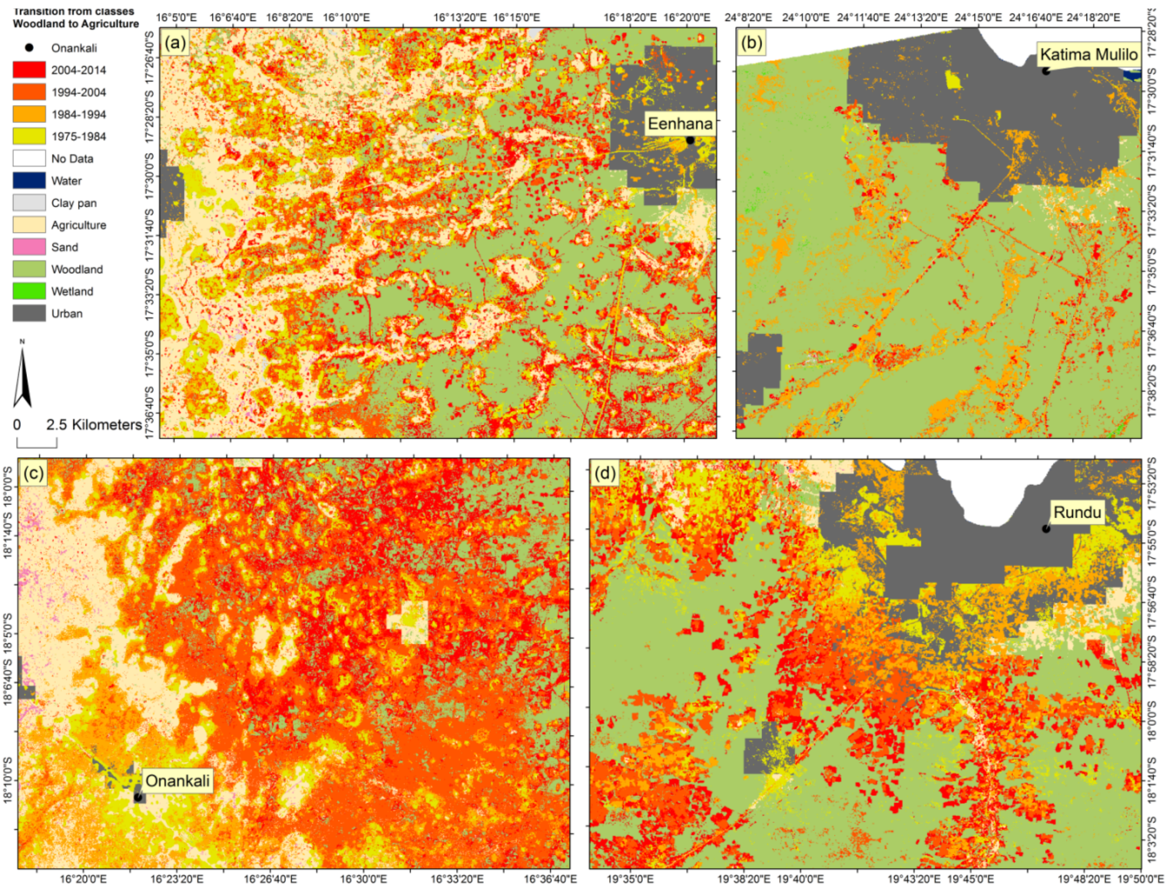

Figure 3.6. (a–d) Maps show the transitions from the classes Woodland to Agriculture for each time interval: yellow (19751984), orange (1984–1994), dark orange (1994–2004) and red (2004–2014). The encroachment the Agricultural class into the Woodland class as well as the nature of the changes, are evident for each time interval.

3.3.4 Land cover changes per administrative region

The administrative regions assessed vary importantly in terms of land-use categories, populations and geographic extents (John Mendelsohn and el Obeid 2002). We therefore expect to find differences in the relative amounts of change. In effect, the Woodland class persistently declined in Ohangwena region, with consistent net losses. A similar pattern is evident for Oshikoto and Caprivi regions; however, a net positive change is evident for the 2004–2014 era (Figure 7).

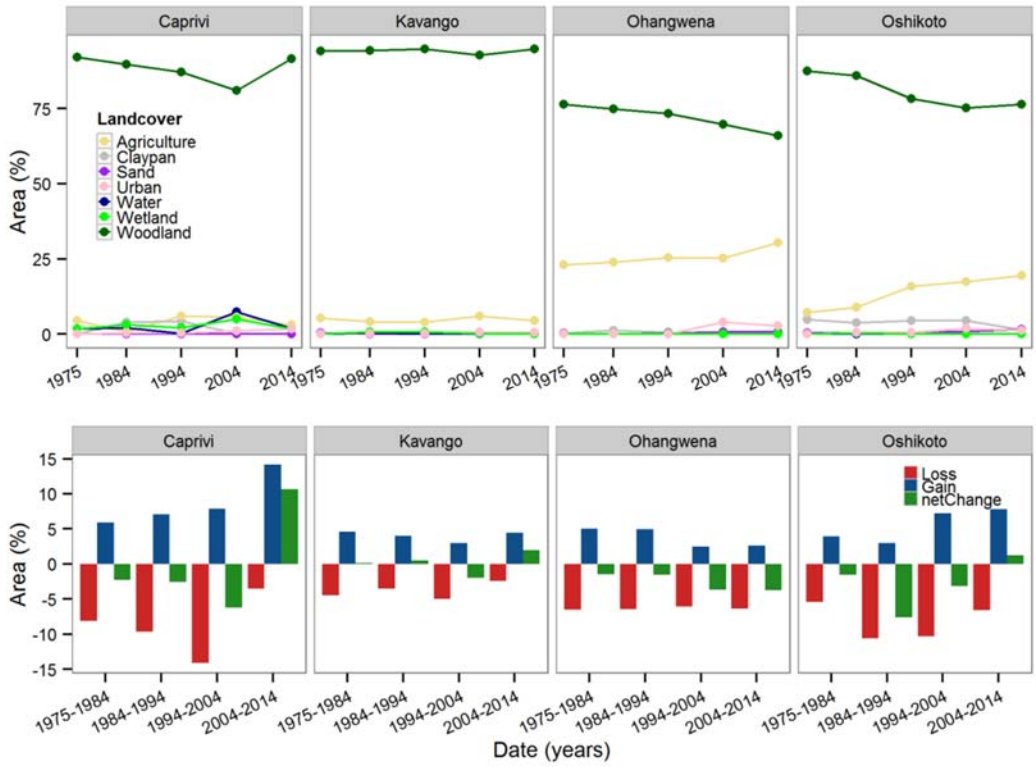

Figure 3.7. Plots showing the extent of all land cover classes (above) and the changes (i.e. losses, gains and net change) of the woodland cover class (below), by administrative region.

Contrastingly, Kavango region showed a gradual increase from 94.20%, 94.31%, 94.80%, 92.81% and 94.78% in 1975, 1984, 1994, 2004 and 2014, respectively (Figure 5). These results stand in contrast to studies finding decreases in woodland cover within the region of Kavango and therefore should be interpreted with caution (J. M. Mendelsohn and El Obeid 2003; Erkkilä and Löfman 1999; Röder et al. 2015; Pröpper et al. 2010). Our results are likely due to a number of different factors, including: (i) the selection of broad land cover classes, i.e., Woodland and Agriculture, which encompass and range of different cover types, which are themselves highly susceptible to changes from anthropogenic and climatic drivers (Vicente-Serrano et al. 2015; Asner et al. 2004); (ii) the method used to validate the maps, here, the earliest map (1975) was validated using a limited number of sample points, while the maps for the following eras were validated using half of the training data in combination with a qualitative assessment of each land cover map (Figure 2B); and (iii) the different temporal and spatial scales of the analyses. For example, the study by Erkkilä et al. (1999) focused on a small portion of the Ohangwena region and found decreases in woodland. The study by Röder et al. (2015) centred upon the town and Rundu and encompassed part of the Eastern and Western Kavango provinces (Namibia) and part of the Cuando-Cubango province (Angola) covering an area of 15,000 km^2, at two time intervals (1990 and 2010). Had this study encompassed the entire region, their results may have been comparable. Further, Mendelsohn (2003) (J. M. Mendelsohn and El Obeid 2003) find that for Kavango region, 26,140 ha of woodland were cleared by 1943, then, 72,100 ha (1.48%) in 1972 and 194,550 ha in 1996 (3.99%), resulting in a mean annual rate of increase of 3.9% from 1943 and 1996, but does not indicate which aerial imagery or satellite data were used. In comparison, for the same region, we found that in 1975, agricultural land constituted 260,839 ha (5.35%), and in 1994, it constituted 189,378 ha (3.89%), or a very similar mapped extent. The most important differences occur in 1970s period and may be attributable to the low spatial resolution (60 m) and variable quality of the MSS images used in this study (Chander, Markham, and Helder 2009). Similarly, Pröpper et al. (2010) found decreases in woodland cover for Kavango but do not provide exact aerial extents. We propose our results are likely due to both vegetation succession and woody encroachment occurring in areas previously dominated by grassland cover (Ward 2005; O'Connor, Puttick, and Hoffman 2014; Mitchard and Flintrop 2013).

The predominant land cover class transition (i.e., Woodland to Agriculture) is assessed in relation to the different land-use categories, in order to identify which categories are the most important contributors to change for each region. Figure 8 shows the predominant transition as a percentage of each administrative region, for every land-use category. It is evident that for all regions, the greatest proportion occurs on "small scale agriculture on communal land", this is particularly obvious for Ohangwena region (Figure 8). Similarly, for all regions except Caprivi, we find that "large scale agriculture on communal land" is the third largest contributor to the predominant land cover transition. For Caprivi, Kavango and Oshikto, the second largest proportion of changes occurred on State Protected land (Ohangwena has no protected areas), suggesting land cover change impacts sites of conservation interest. Monitoring land cover changes in protected is essential, indeed, loss of habitat by deforestation and conversion to arable land are likely the most important threats to biodiversity (Pimm et al. 2014). As demonstrated by (Szantoi et al. 2016), detection of land cover changes, especially in mixed vegetation types such as grass and shrub land, is essential for facilitating numerous conservation activities, including the enforcement of protection and contributing to the work of managers and conservation scientists.

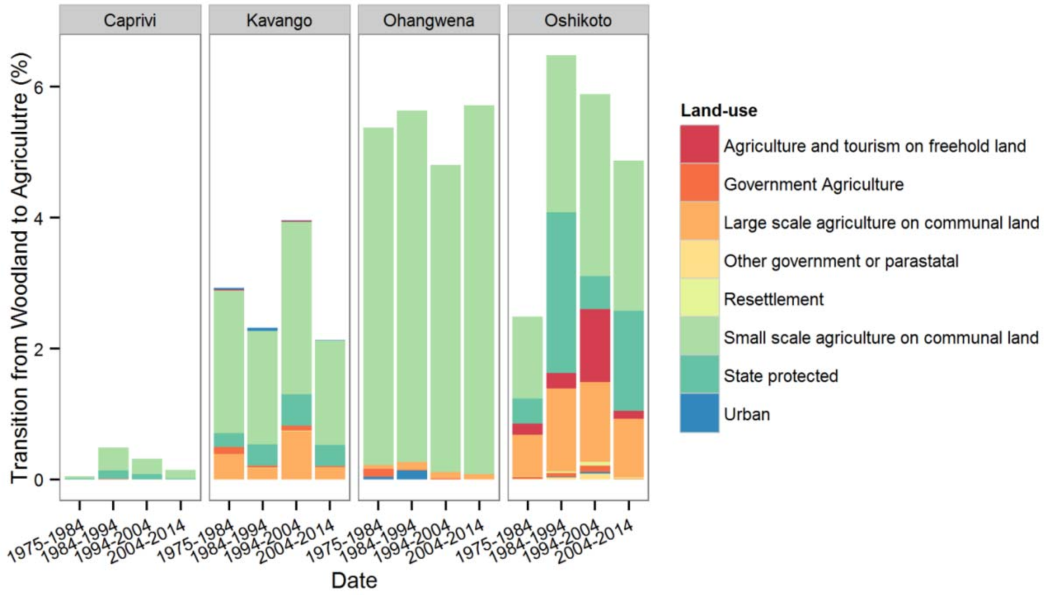

Figure 3.8. The predominant land cover transition (i.e., from Woodland to Agriculture) as a percentage of each administrative region, for every land-use category.

3.3.5 Drivers, consequences and implications of land cover changes

The observed trends in woodland extent are likely explained by the current and historical Namibian socio-political context. Northern Namibia has benefited from a period of political and social stability and a strong drive for economic growth as of independence in 1990 (Malan 2009). This is evidenced by the expansion of the urban areas, for example, Rundu within the study area. The associated development of modern road networks has heightened the flow of goods between markets throughout the region, and consequently also access to and commercialization of communally held resources including, timber, pasture, thatch and access to remoter arable lands (Röder et al. 2015; John Mendelsohn and el Obeid 2002; John Mendelsohn 2006). The majority of conversions from woodland to agricultural land cover classes, in terms of area, took place in the first two buffer zones in proximity to villages, rivers and roads, and the area of changes decreased with distance from these. For example, for the period 2004–2014, conversions from woodland to agricultural land in buffers zone 1 for "minor town", "major town" "rivers" and "roads" were of 4.56%, 1.95%, 4.88% and 4.03%, respectively. Except for "major towns", these values are more than double the values from the further zones, thus highlighting the correlation between proximity to villages, roads, and rivers and conversions from the woodland to the agricultural class. This analysis used the predominant land cover class transition (i.e., woodland to agriculture), and variables included proximity of villages, rivers and roads. The area of change decreased with increasing distance from all proximal variables, as evidence by significant Pearson's product-moment correlation coefficients (Table 9.5). All variables exhibit a clear and similar pattern (except distance to major towns), where the most important rates of conversion are found adjacent to the variable, and decrease with growing distance (Figure 9). As an avenue for future research, modelling transitions between categories as functions of environmental variables should be considered.

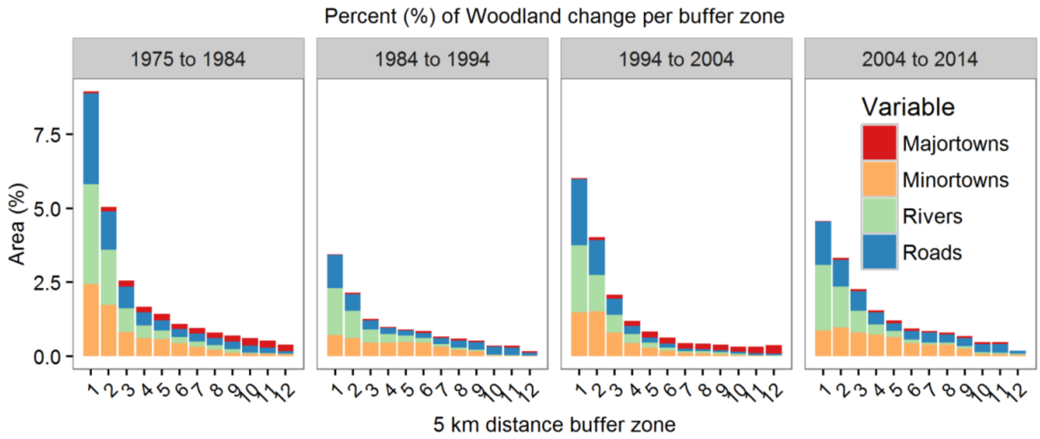

Figure 3.9. Bar graphs show the area of the predominant land cover class transition (i.e., woodland to agriculture per 5 km distance zone), as a percentage of each buffer zone, for each proximal change variable (i.e., rivers, roads, villages and major towns), calculated using Euclidean distance.

To illustrate this, ephemeral and perennial rivers are associated with more fertile, arable soils; in fact, river courses have been shown to be the preferred location for subsistence agriculture because of the higher soil fertility and access to water (Gröngröft 2013). Ephemeral and major rivers, as well as floodplains, including the Okavango River and Cuvelai basin, respectively, have historically been regional centres of agriculture (Gröngröft 2013; Oldeland 2013). Importantly, therefore, the area available of potentially arable land is limited and decreasing.

The conversion of land to intensive, conventional agricultural uses on the continent is clearly exposed by recent, continental scale land cover studies (Baccini et al. 2012; Hansen et al. 2013). In NE Namibia, however, woodland losses appear to be chiefly the result of small-scale subsistence farming (Figure 8). These changes are explained as being the result of expanding population pressure, better access to and commodification of natural resources, as well as an ineffective legislation to manage land use and its distribution (Röder et al. 2015). However, the observed trend of woodland conversion to subsistence agriculture is described as being unsustainable because, as subsistence agriculture spreads into increasingly marginal areas (in terms of agricultural potential and soil fertility), as a result of an ever decreasing amount of arable land, it increases the likelihood of soil becoming nutrient depleted sooner, thereby accentuating the need for more arable land (Oldeland 2013). An additional issue identified by various authors is the increased competition for grazing and other resources within commonage areas between wealthy farmers, who can afford both more stock and man power, and resident subsistence farmers (John Mendelsohn 2008). Wealthy land users have been shown to be responsible for fencing off large tracts of commonage, often to the detriment of local residents. The enclosure of large tracts of woodland which were previously held as commonage, reduces the grazing intensity and woodland clearing within the enclosed area, however, these processes are in all likelihood displaced elsewhere (John Mendelsohn and el Obeid 2002). In consequence, the increasing competition for land and grazing resources may be driving local land-use intensification, in the form of increased woodland clearing for cropping and resource extraction. In this context and given their wide extent, savannah woodland biomes are globally significant and constitute an important carbon sink if appropriately managed. Because of their potential for carbon sequestration, investments in the conservation and management of woodlands can provide African countries with benefits from carbon trading (Zahabu et al. 2007; Jindal, Swallow, and Kerr 2008; Bond et al. 2010). Although African savannahs provide for the livelihoods of a great many people, their capacity to furnish environmental services is not well understood and numerous constraints act to preclude their development, including a lack of valuation studies for such services, poorly defined tenure and markets, and a shortage of technical and institutional resourcefulness (Chidumayo and Gumbo 2010).

3.4 Conclusions

This study successfully develops a regional scale analysis of land cover change over four decades in NE Namibia. By processing and comparing multi-sensor Landsat scenes over five time intervals between 1975 and 2014, and across four administrative regions in NE Namibia, we observe an overall trend towards a reduction in woodland extent. The conversion of woodlands to arable land was the prevailing land cover transition process in terms of area, during all intervals, followed to a lesser extent by the succession of agricultural land to woodland. These transitions suggest that woodland clearing, followed by arable land abandonment and woodland succession, are widespread. The variable classification results obtained in the final analyses highlight the complexities of applying post classification change detection methods to spatially and temporally heterogeneous woodland savannah environments which are heavily impacted by grazing, fire and woodland clearing over decadal time scales (Hill et al. 2011; Hanan and Hill 2011). The clearing and conversion of woodlands to other land uses appears to be primarily driven by subsistence-based, rain-fed cropping, with pastoralism, timber extraction, but also urban and infrastructural expansion, such as the creation of new roads, forming an integral part of the change process (Röder et al. 2015). In effect, we look at the predominant land cover changes in relation to distance from towns, villages, rivers and roads, and find most changes occurred in proximity to these, and decrease with distance from these. Furthermore, the predominant land cover changes were found to occur mainly within land designated as communally held, followed by state protected land, suggesting land cover changes had a relatively high impact on conservation areas (Szantoi et al. 2016). Finally, a lack of concise tenure rights regulating access to commonage grazing land may, in part, be driving the intensification of land-use. Here, subsistence farmers are compelled to compete for resources (primarily grazing and arable land) with wealthier farmers, who also often have the assets to fence large tracts of commonage, resulting in some areas, in what many perceive to be a typical "tragedy of the commons" situation. NE Namibia has extensive tracts of woodland savannah which provide numerous globally significant ecosystem services, such as carbon sequestration and biodiversity conservation, but also a wealth of natural resources critical to the livelihoods of communities in the region (John Mendelsohn and el Obeid 2005).

Ecosystems around the world are continuously changing as a result of anthropogenic and natural causes. In the present study, we investigate abrupt changes from one land cover class to another. However, ecosystem changes can also be gradual, with subtle changes in vegetation and surface biophysical properties occurring even over short time scales (Coppin et al. 2004). The availability of new satellite archives at dense temporal resolutions present novel opportunities to study these changes, through the analysis of trends in land surface dynamics. In effect, time-series analyses which have typically been carried out on dense temporal and coarse spatial resolution sensors such as MODIS and Advanced Very High Resolution Radiometer (AVHRR), are now applicable to high resolution datasets, for example, by combining Landsat 8 and Sentinel-2 archives (Drusch et al. 2012). Identifying and understanding the continual changes to our planet is essential for informing policy makers, managers and stakeholder about which ecosystems are at risk, what actions can be taken to better manage them and finally how effective these management actions might have been (Kuenzer, Dech, and Wagner 2015; Pettorelli et al. 2005).

Supplementary Materials: The following are available online at www.mdpi.com/link, Table 9.1: Google Earth Engine code, Table 9.2: Evaluation error matrixes indicating overall accuracy, errors of commission and omission, and total training data pixels, Table 9.3: Error matrices for each period showing adjusted change area and confidence intervals. The transition from woodland to non-woodland is labelled deforestation. Error matrix entries are expressed as the estimated area proportion. Map classes represent rows and reference classes the columns, Table 9.4: Cross tabulation matrices showing change trajectories as a percentage of the study area [50], Table 9.5: Pearson Pearson's coefficient (*r*) showing the relation between the aerial extent of main land cover class transition (i.e., woodland to agriculture) in each 5 km distance zone, and each proximal change variable for each interval assessed. Figure 9.1-3: arable farming.

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Author Contributions: V. Wingate designed the study, produced the datasets, collected the field data, carried out the analyses, interpreted the results, created the figures and wrote the manuscript. All other authors supervised the designing of the study, discussed the results and edited the manuscript.

Conflicts of Interest: The authors declare no conflict of interest. The founding sponsors had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, and in the decision to publish the results

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Chapter 4

Estimating aboveground woody biomass change in Kalahari woodland: combining field, radar and optical datasets

4 Estimating aboveground woody biomass change in Kalahari woodland: combining field, radar and optical datasets

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Abstract

Maps that accurately quantify aboveground vegetation biomass (AGB) are essential for ecosystem monitoring and conservation. Throughout Namibia, four vegetation change processes are widespread, namely, deforestation, woodland degradation, the encroachment of the herbaceous and grassy layers by woody strata (woody thickening), and woodland regrowth. All of these vegetation change processes affect a range of key ecosystem services, yet their spatial and temporal dynamics and contributions to AGB change remain poorly understood. This study quantifies AGB associated with the different vegetation change processes over an eight-year period, for a region of Kalahari woodland savannah in northern Namibia. Using data from 101 forest inventory plots collected during two field campaigns (2014-2015), we model AGB as a function of the Advanced Land Observing Satellite (ALOS) Phased Array L-band Synthetic Aperture Radar (PALSAR and PALSAR-2) and dry season Landsat vegetation index composites, for two periods (2007 and 2015). Differences in AGB between 2007 and 2015 were assessed and validated using independent data, and changes in AGB for the main vegetation processes are quantified for the whole study area (75,501 km^2). We find that woodland degradation and woody thickening contributed a change in AGB of -14.3 Tg and 2.5 Tg over 14% and 3.5% of the study area, respectively. Deforestation and

regrowth contributed a smaller portion of AGB change, i.e. -1.9 Tg and 0.2 Tg over 1.3% and 0.2% of the study area, respectively.

Keywords: Aboveground Biomass; Time-series; Random Forest; Landsat; Namibia; Savannah; ALOS PALSAR; Woodland; SAR; ICESat; LiDAR; Change detection

4.1 Introduction

4.1.1 Dryland vegetation

Dryland ecosystems encompass hyper-arid to sub-humid regions which include savannahs and associated woodlands and forests (Pachauri et al. 2014). Dryland vegetation provides such essential ecosystem services as biodiversity conservation, forage, timber and water, critical for human livelihoods (Adeel et al. 2005). These ecosystems cover roughly 41% of the planet, but are heavily impacted by anthropogenic pressures, such as deforestation, land degradation and urbanization (Sörensen 2007; Scholes and Archer 1997; Bastin et al. 2017). Consequently, high rates of land-use and land cover change (LULCC) in drylands contribute significantly to global carbon (C) emissions (Ahlström et al. 2015; Liu et al. 2015).

Maps of vegetation carbon, or aboveground biomass (AGB), in these ecosystems are essential for modelling vegetation carbon dynamics, assessing the impact of different land-use and management strategies and monitoring vegetation change processes (Hall et al. 2011; Birdsey et al. 2013; Jantz, Goetz, and Laporte 2014; Carreiras, Melo, and Vasconcelos 2013). Despite their importance, AGB in drylands has received little attention compared to humid biomes, since drylands are thought to be less significant in terms of carbon storage (Liu et al. 2015). Yet, woodlands in sub-Saharan Africa were found to sequester a quantity of carbon comparable to that of the Congo basin humid forests (Ryan et al. 2016; Nasi et al. 2009). Moreover, a number of studies have clearly demonstrated their importance to global biogeochemical cycles, including net ecosystem carbon balance (Scheffer et al. 2001). For example, savannah biomes in Africa and Australia are a significant component of the carbon cycle (Liu et al. 2015), and semi-arid vegetation in the southern Hemisphere is an important carbon sink. In contrast, tropical humid forests are a major source of C emissions due to widespread deforestation (Poulter et al. 2014; de Jong et al. 2013). Due to their global significance, a number of recent studies have focused on mapping AGB change in drylands (Brandt et al. 2017; Naidoo et al. 2015; Mograbi et al. 2015; Wessels et al. 2013; Odipo et al. 2016) but also vegetation cover (Scanlon et al. 2002; Hansen et al. 2003).

Two processes affect AGB in drylands, (i) the persistent disappearance of herbaceous and woody vegetation, and (ii) the thickening or encroachment of the woody strata with a consequent loss of the herbaceous layer (Hudak and Wessman 1998; Mitchard and Flintrop 2013). Both these functional and structural changes affect ecosystem processes, services, biodiversity as well as the way the land is used economically (Scholes and Archer 1997; Briggs et al. 2005). Drivers of vegetation loss include deforestation, urbanization and land-use intensification (Bai et al. 2008). Woody encroachment, which occurs in Australia, America, Africa, the northern latitudes and at altitude (Jia, Epstein, and Walker 2003; Archer, Schimel, and Holland 1995; Hudak and Wessman 1998; Fensham, Fairfax, and Archer 2005; Ward 2005; Mitchard and Flintrop 2013; O'Connor, Puttick, and Hoffman 2014; Caviezel et al. 2014), is driven by rising atmospheric carbon dioxide (Bond and Midgley 2000; Donohue et al. 2013), shifts in fire activity (Bond and Midgley 2000; Bowman, Murphy, and Banfai 2010), over stocking, (Asner et al. 2004), loss of browsers (Ward 2005), long-term rainfall changes (Fensham, Fairfax, and Archer 2005) and the synergy of these (Ward 2005). Nevertheless, there are very few studies looking at the effect of rising CO_2 in drylands and there is an overall paucity of ground data (Stevens et al. 2017).

Notwithstanding, satellite and field-based studies have uncovered complex climate-vegetation interactions and subtle change processes, characterized by alternating positive and negative vegetation cover trends, present throughout drylands and in particular the African Sahel savannah (de Jong et al. 2013; Bai et al. 2008; Dardel et al. 2014; Nutini et al. 2013; Martínez et al. 2011). Some of these studies have established extensive "greening" and challenge the widely accepted view that land degradation is occurring, yet, in many instances what the observed greening trend represents in the field has yet to be fully explored (Herrmann and Tappan 2013). For example, processes associated with soil degradation, such as erosion, are exacerbated by the loss of herbaceous strata and replacement by hardy shrubs, with consequent species impoverishment; these process are often concealed or masked from satellite-based studies showing greening trends (Brandt 2014; Archer, Schimel, and Holland 1995) (Brandt et al. 2014; Herrmann and Tappan 2013; Gonzalez 2001).

4.1.2 Remote sensing woodlands and AGB

Tropical dry deciduous forests, hereafters referred to as woodlands, are an important component of savannah biomes globally and occur as forests with sparse, discontinuous canopies, composed of a mixture of trees, shrubs and grasses. They cover over 36% of Africa and thus constitute a large but low density AGB stock (Mayaux et al. 2004; Dewees et al.

2010). However, African countries harbouring woodland often also have large and rapidly growing populations and consequently, high rates of LULCC, resulting in these ecosystems contributing substantially to Africa's overall carbon emissions (FAO 2010; Mayaux et al. 2004).

Mapping woodland vegetation communities with satellite remote sensing is challenging, as they consist of mixed tree-grass strata and, in contrast to tropical humid forests, they undergo significant intra- and inter-annual changes in vegetation biophysical properties in each strata (Adams, Goudie, and Orme 1996; Lanly 1982; Grainger 1999). They are distinguished by marked phenological cycles manifesting as pronounced deciduousness and seasonality of the woody and herbaceous strata. Also contributing to the fluctuations of these cycles are variable rainfall and anthropogenic impacts such as fires and urbanization (Houghton and Hackler 2006; Ryan et al. 2012). Furthermore, African woodlands are generally characterized by small-scale (approximately 1 ha) and sometimes shifting cultivation, usually in combination with timber extraction and extensive grazing, so that the resulting mosaic landscape is highly variable over space and time (Ryan et al. 2012).

Remote sensing data are fundamental tools for measuring AGB in woodlands (Röder and Hill 2009), yet a critical drawback of freely available optical sensors is their saturation at closed canopy and moderate to high biomass densities (i.e. tropical forests) (Ahl et al. 2006; Zhang et al. 2003; Fensholt et al. 2012; Tucker et al. 2005; Jensen 1983). Similarly, L-band Synthetic Aperture Radar (SAR) is more sensitive to a greater range of AGB, approximately 100 t ha^{-1}, as indicated in the majority of studies focused on boreal, temperate and tropical humid forests (Austin, Mackey, and Van Niel 2003; Dobson et al. 1992; Dobson et al. 1995; Fransson 1999; Hoekman and Quiriones 2000; Imhoff 1993; Le Toan et al. 1992; Lucas, Armston, et al. 2010a; Luckman et al. 1997; Saatchi et al. 2007). Combining data sources in a multi-sensor strategy can take advantage of each sensor's relative sensitivities for biophysical modelling, and overcome some of the limitations associated with measurements using single classes of sensors. For example, to quantify AGB, this can be achieved by using the complementary data on forest vertical and horizontal structure, as well as greenness by fusing Light Detection and Ranging (LiDAR), radar and optical sensors (Montesano et al. 2013; Cartus et al. 2012b; Lu et al. 2016; Baccini et al. 2011).

4.1.3 Aims

This study maps and discusses AGB and its changes for part of the Namibian Kalahari woodland biome. This region provides the natural resources for the livelihoods of greater part of the Namibian population, yet its spatial and temporal dynamics and associated four vegetation change processes (i.e. deforestation and woodland degradation, woody encroachment, and woodland regrowth) remain poorly quantified (Strohbach 2001; Mendelsohn and El Obeid 2002; Wingate et al. 2016; Mendelsohn and el Obeid 2005a; Tian et al. 2016). Hence, we use field measurements of AGB in combination with high spatial resolution multi-temporal maps L-band SAR and dry season Landsat vegetation index composites for two periods (2007 and 2015) to define the extent, intensity and severity of these change processes. In quantifying AGB changes, we aim to and address the following research questions,

(a) Can AGB be mapped and validated using independent data?

(b) Can AGB changes resulting from the four vegetation change processes be identified?

(c) Within which land-use categories are the most important AGB changes taking place and which vegetation change processes are they associated with?

(d) How much AGB has been lost and gained as a result of the different vegetation change processes?

4.2 Methodology

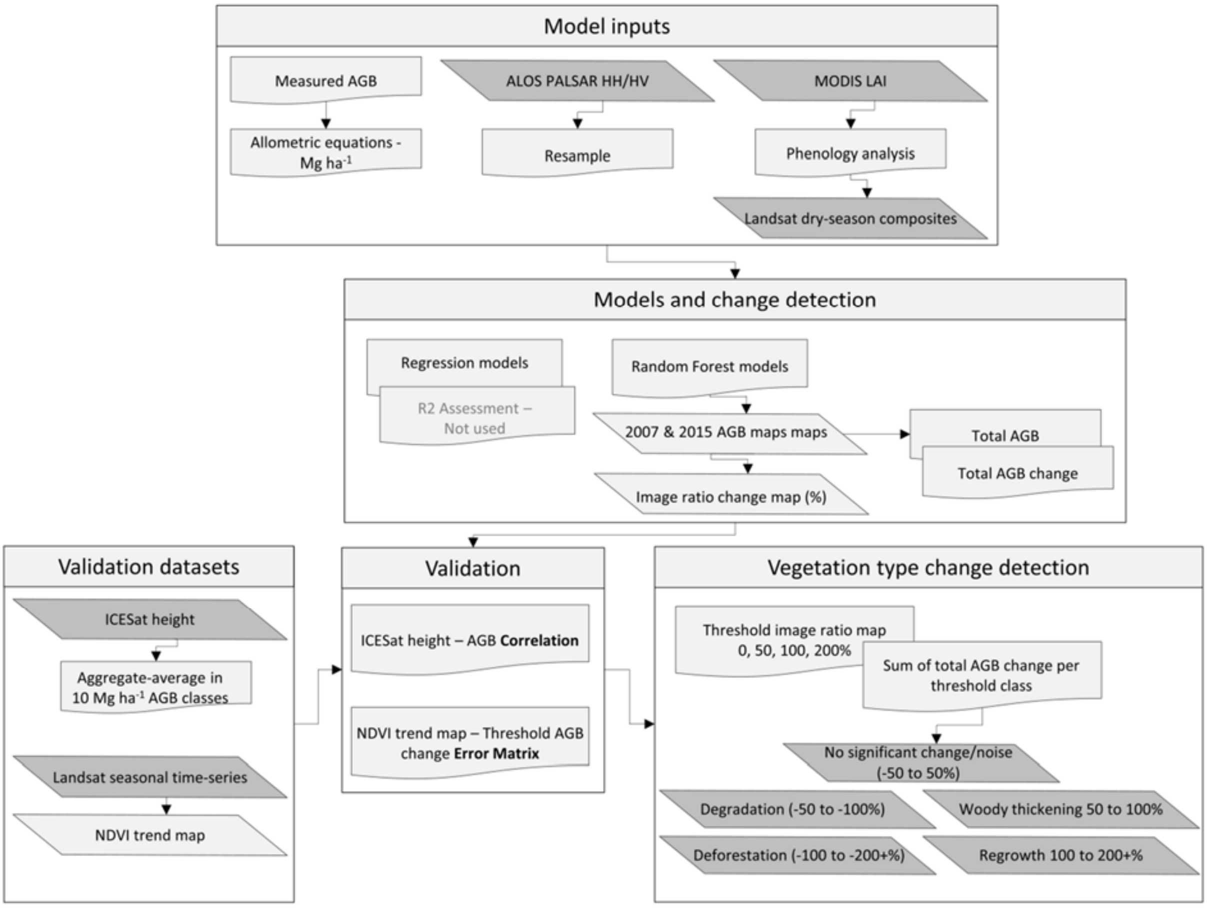

Figure 4.1. Workflow schematic illustrating datasets, initial processing and methodological steps taken for the modelling, change detection, validation and quantitative analysis of this study.

4.2.1 Study area

Namibia has three predominant land-uses with a number of subdivisions, namely, commercial (urban, government agriculture, agriculture and tourism on freehold land and other government and parastatal), communal (small and large scale agriculture on communal land and resettlement) and conservation (state protected), which occupy 45%, 40%, and 15% of the land area, respectively (Van der Merwe 1983). A long standing debate remains as to the sustainability of these land-uses; it is widely believed that commercial farming better manages resources, while communal farming is resulting in a typical “tragedy of the commons” situation (Hardin 1968; Strohbach 2001). Permanent vegetation loss and woody encroachment with the consequent loss of economically important herbaceous layer species, are the principal environmental concerns faced by both farming sectors and these processes are also believed to be impacting conservations areas (Tian et al. 2016; Ward 2005; Wingate et al. 2016; Ward and Ngairorue 2000). Changes in AGB resulting from deforestation or degradation are often limited to approximately 2 t ha^{-1} due to lack of mechanical means, while woody encroachment occurs at regional scales (approximately 10,000 ha^{-1}) (Wingate et al. 2016; De Klerk 2004b).

The study area encompasses part of the Kalahari woodland biome in north eastern Namibia, forming part of the Miombo forests of southern Africa (Frost et al. 1996) (Figure 2). This includes the communally held regions of Oshikoto, Kavango and Ohangwena. The area's main vegetation types include mopane savanna in the western-most region, mostly composed of *Colophospermum mopane*, and Kalahari woodland composed mainly of *Burkea Africana* and *Pterocarpus angolensis* comprising the remaining area. Tree species are semi-deciduous or deciduous and grow on the Kalahari sand sheet (Verlinden and Laamanen 2006; Verlinden and Dayot 2005; Campbell et al. 2007; Wang et al. 2007). The region extends over 75,501 km^2 with a mean elevation of 1,100 m and annual precipitation ranging from 400 to 800 mm $year^{-1}$. Communal land-use is characterised by labour-intensive and subsistence-based farming, with limited conventional input and use rather than ownership rights defining tenure, as well as a relatively high population density (Mendelsohn and El Obeid 2002). Agriculture is distinguished by agro-silvo-pastoralism with widespread small-scale pearl millet (*Pennisetum glaucum*) cultivation (Erkkilä 2001; National Planning 2012; Verlinden and Kruger 2007). Cultivation is depends on rainfall for plant growth and this results in the arable land being free of crop cover for the greater part of the year, with crops being harvested four to five months after planting between April and July (Mendelsohn 2006). In contrast, commercial farming centres mainly on ranching, tourism and conventional irrigated cropping. Land cleared of woodland for small-scale cultivation and urbanization has increased in extent. For example, cleared land increased from 6% to 12% since 1975, with new roads allowing access to arable land, although land abandonment and vegetation succession also occur (Wingate et al. 2016). Woodland loss is thought to be driven principally by widespread urbanization and small-scale pearl millet cultivation on approximately 2 ha plots, the expansion of these and small-scale timber extraction. In addition, areas which were once open woodland with a well-developed grass and herbaceous layer are being replaced with a denser woody layer. The predominant factors believed to be driving this vegetation change process are high stocking densities, loss of browsers and altered fire regimes (Mendelsohn and El Obeid 2005b; Wingate et al. 2016; Ward 2005; Tian et al. 2016; Strohbach 2001).

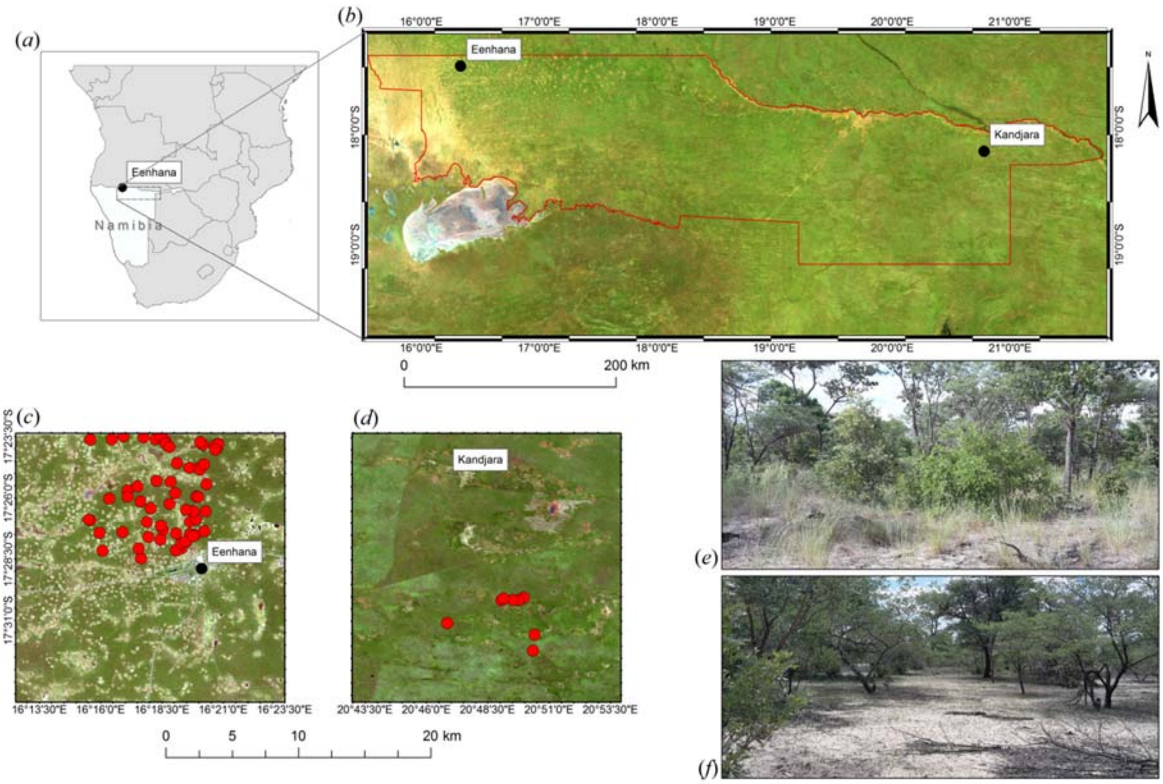

Figure 4.2. Study area in southern Africa (a, b); sample sites visited in 2015 adjacent Eenhana (c), and Kakekete (Kandjara) (d); well-developed herbaceous layer (Kakekete) (e); limited herbaceous growth (Eenhana) (f).

4.2.2 Field dataset

We measured woody AGB in Mg ha^{-1} as this constitutes the main biomass component and omit estimates for dead trees, litter and grasses (Figure 9.4). Field data were collected at two sites, (i) adjacent to the town of Eenhana (Figure 2f) within an un-gazetted community forest, and (ii) within Kakekete (Kandjara) village (Figure 2c). Measurements of diameter at breast height (DBH) and species were collected for all trees with a circumference > 10 cm (diameter > 3.2 cm) in geo-located 30 × 30 m plots (900 m^2), and time-averaged GPS coordinates with an accuracy of <5 m were taken from the centre of each plot. Tree height was not measured, since the allometric biomass equation selected uses DBH as the main predictor. Here, we used a pantropical allometric model which includes wood density, trunk diameter, and the compound bioclimatic variable (E). Mean woody density for Zambia (0.69) was used, since measurements from this region were assumed to be the most closely related, both climatically and eco-floristically, to our study site and a mean E value (0.87) calculated from the spatial area of our study site, as described in (Chave et al. 2014). Data were collected during two field campaigns (January-March) in 2014 and 2016, which resulted in a total of 101 sample plots. At the Eenhana field site, measurements were collected using a defined sampling protocol (Pearson, Walker, and Brown 2005): high spatial resolution aerial imagery (0.5 m) was used to stratify the sampling area into two different apparent vegetation density classes (i.e. high and low woody cover) using supervised classification to account for landscape heterogeneity, then measurements from a preliminary set of field plots were taken. A minimum number of sites per stratified class were sampled in order to provide a statistically robust estimate for each strata and achieve an acceptable level of precision (i.e. error of 10% of the mean 95% confidence interval), with the aim of providing representative vegetation samples and appropriate statistical probability. The Kakekete field site was only stratified into density classes and plots then sampled along transects (due to limited time and access constraints). An additional "very low" biomass class was included in the final dataset, representing sparsely vegetated areas (i.e. more than half of the plot consisting of bare ground), where AGB was visually estimated based on previous field measurements gained from the forest inventory surveying, in an attempt at capturing coincident satellite data variability. At these sites, an average AGB value for shrubs (DBH = 2-5 cm; AGB = 0.02 t ha^{-1}), trees (DBH = 5-20 cm; AGB = 0.2 t ha^{-1}) and large trees (DBH = 20-100 cm; AGB = 4.1 t ha^{-1}) was calculated based on previous inventory measurements, and these estimates were multiplied by the number of trees or shrubs present. Hence, field data distribution is assumed to be representative of the satellite data. Subsequently, plots were assessed against Landsat scenes for disturbances (i.e. fire and deforestation), to ensure no occurrence before satellite data acquisition. Although each plot was found to not have been affected by deforestation during the study period (2007-2015), more gradual changes, for example, due to encroachment or degradation, cannot be qualitatively accounted for. AGB was then estimated for each measured species, summed and scaled to Mg ha^{-1} units (Lucas, Armston, Fairfax, Fensham, Accad, Carreiras, Kelley, Bunting, Clewley, Bray, et al. 2010).

4.2.3 Space-borne Radar

Synthetic Aperture Radar (SAR) facilitates the mapping of AGB due to its effectiveness at penetrating cloud and its sensitivity to woody canopy components (i.e. stems and trunks), thus providing a more direct link to the three dimensional forest structures than optical data. This is especially true in low biomass vegetation communities, despite signal saturation being identified for biomass values ranging from 40 to 180 Mg ha^{-1} (Cartus, Santoro, and Kellndorfer 2012; Le Toan et al. 1992; Dobson et al. 1992; Ranson and Sun 1994; Lucas et al. 2006; Lucas, Armston, et al. 2010b; Sandberg et al. 2011; Mitchard et al. 2009). An active SAR sensor emits a pulse of energy while simultaneously quantifying the return echoes, which is measured as a unitless variable and referred to as backscatter intensity or normalized radar cross section. Backscatter is quantified as a ratio of the energy returning from an area of ground, assuming it scatters at the same intensity for any angle (isotropic). Hence, energy returning to the sensor is affected by the amount of incident energy reflected by the land surface as well as its directionality. It follows that energy pulses of distinct wavelengths interact differently with varying land surface components. L-Band, 23 cm wavelengths show a strong coefficient of determination with woody vegetation components, such as tree trunks, branches and canopy, with higher backscatter intensities (more return energy), being associated with higher woody biomass. In this study, the coefficient of determination is shown as 'R^2' and the Pearson's correlation coefficient as 'r'. Notwithstanding, backscatter intensities vary as a function of many confounding factors often unrelated to biomass, including soil and canopy structure and water content, which impacts scattering directionality and proportion, respectively. For example, the relationship between biomass and signal saturation varies across vegetation classes and moisture, phenological and seasonal conditions (Lucas et al. 2000; Mitchard et al. 2009; Mitchard et al. 2011b; Le Toan et al. 1992; Woodhouse 2005). Saturation levels for biomass retrieval with SAR sensors ranged from 40 to 180 t ha^{-1}, rendering it adequate for the biomass mapping of the Kalahari woodland biome (Le Toan et al. 1992; Lucas et al. 2006; Lucas, Armston, et al. 2010a; Mitchard et al. 2009).

4.2.4 ALOS PALSAR

The Advanced Land Observing Satellite's Phased Array-type L-Band Synthetic Aperture Radar (ALOS PALSAR) is an L-Band, 23 cm wavelength SAR capturing cross-polarized data in horizontal send vertical receive (HV) and horizontal send and horizontal receive (HH), which have been used to map AGB at regional scales (Mitchard et al. 2011b; Lucas, Armston, Fairfax, Fensham, Accad, Carreiras, Kelley, Bunting, Clewley, Bray, et al. 2010; Mitchard et al. 2009; Morel et al. 2011). HH and HV polarizations are highly correlated yet the latter are more correlated to AGB. For this study we use the global 25 m resolution PALSAR/PALSAR-2 seamless mosaic for the years 2007 and 2015, distributed by the Japan Aerospace Exploration Agency (JAXA) (Shimada et al. 2014). Data are in gamma naught and both polarizations were used as model inputs, as they were found to reduce the error when modelling AGB in a regression equation (Rignot et al. 1994). Imagery speckle was not assessed as the ALSO PALSAR mosaic generation process already successfully addressed this using the 16-looks approach (Shimada et al. 2014). Several authors demonstrated a reduction in noise, speckle, positional errors associated with GPS localization and a strengthening of the SAR polarization – AGB relationship, with an averaging of the polarization data to a higher spatial resolution (Mitchard et al. 2011a; Carreiras, Vasconcelos, and Lucas 2012), hence to account for these sources of error all predictor layers were resampled to a 60 m resolution. The datasets were resampled from the original using bilinear resampling, which calculates the value of each pixel by averaging the distance weighted values of the four pixels adjacent and is suitable for continuous data. Digital Numbers (DN) were converted to gamma naught values (γ^0) using the following equation:

$$\gamma^0 = 10\log_{10}(\mathrm{DN})^2 + (\mathrm{CF}) \tag{1}$$

were the calibration factor (CF) is equal to -83.0 (Shimada et al. 2009). DNs were first converted to backscattering intensity then averaged to a 60 m spatial resolution, before being converted to gamma naught values in decibel units (dB), in order to calculate the arithmetic rather than geometric averages (Lucas, Armston, Fairfax, Fensham, Accad, Carreiras, Kelley, Bunting, Clewley, Bray, et al. 2010; Mitchard et al. 2009). Small-scale deforestation may go undetected by moderate to coarse resolution (i.e. 250 m – 8 km) satellite analyses, but can effectively be detected with high resolution imagery, such as ALOS PALSAR (Ryan et al. 2012), which allows change be mapped at a spatial resolution sufficient to capture deforestation, but also a temporal scale sufficient to identify woody encroachment (Chidumayo 1997; Williams et al. 2008). A qualitative comparison of the ALOS PALSAR imagery with Landsat scenes in relation to permanent landscape features (i.e. road intersections) revealed minor geo-referencing discrepancies (i.e. approximately on the order of 1-5 pixels). Here, we omit co-registration due an important lack of permanent landscape features proportionately distributed through the study area (i.e. the study area is mainly savannah with very few roads and buildings identifiable at the imageries resolution), therefore we assume geo-positional errors.

4.2.5 Landsat vegetation index time-series

Trends in satellite-derived time-series are extensively used to monitor vegetation change in drylands (Fensholt et al. 2009), while the increasing availability of high resolution Landsat data make such analyses possible for these sensors (Kuenzer, Dech, and Wagner 2015). Satellite derived vegetation indices (VI) including the Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI), merge reflectance measurements from different parts of the electromagnetic spectrum, for instance the red: near-infrared ratio, to create new biophysical information on vegetation productivity. These include vegetation leaf area biomass and physiological mechanisms such as the fraction of absorbed photosynthetically active radiation (Baig et al. 2014; Myneni et al. 1995), and correspondingly, they have been used to estimate vegetation change processes (Higginbottom and Symeonakis 2014; Eisfelder, Kuenzer, and Dech 2012). In addition, the estimation AGB in semi-arid regions based on low-resolution optical imagery and seasonal integrated VI metrics with herbaceous biomass measurements has been successfully been carried out (Tucker et al. 1985). Similarly, a high degree of correlation was also found between field measurements of AGB and NDVI in savannah biomes (Sannier, Taylor, and Plessis 2002; Eisfelder, Kuenzer, and Dech 2012).

4.2.6 Seasonal time-series

The creation of radiometrically consistent seasonal reflectance mosaics often requires considerable data, therefore we use Landsat 5 Thematic Mapper (TM), 7 Enhanced Thematic Mapper plus (ETM+), and 8 Operational Land Imager (OLI), Top of the Atmosphere Reflectance imagery (2007-2015), which provide high resolution (30 m) multi-spectral data (Roy et al. 2014; Kuenzer, Dech, and Wagner 2015). The Fmask algorithm was first applied to all scenes to remove cloud and cloud shadows (Zhu and Woodcock 2012; Zhu, Wang, and Woodcock 2015). All scenes were then composited into a time-series of seasonal images by taking the median pixel value of all available images for four seasons, namely, January-March, April-June, July-September, and October-December, (i.e. four images representing distinguishable seasons were created for each year resulting in an 8-year 2007-2015 seasonal time-series). To reduce data gaps, Landsat 5 and 7 datasets were merged The time-series attempts to capture part of the seasonal phenological vegetation variation, while simultaneously it maximises the use of low quality images (i.e. by removing clouds and cloud shadows) and reduces image noise from extreme pixel values, such as may result from disturbances including fire, by taking the seasonal median value.

Seasons were derived based on phenology metric analysis of the Moderate Resolution Imaging Sprectroradiometer (MODIS) MCD15A3H product, consisting of a time-series of averaged leaf area index (LAI) values over the whole study area (2007-2015) , and calculated using the methods proposed by (Forkel et al. 2015; White, Thornton, and Running 1997). For the study period, the mean start of season (SOS) and end of season (EOS) was a Julian day of the year (DOY) of 340 +/- 8.2 and 130 +/- 16 days, respectively, corresponding to 6 December and 10 May. Similarly, positions of seasonal maximum and minimum values occur at DOY 50 +/-24 and 230 +/- 4.7 days, respectively, corresponding to 19 February and 18 August (Figure 9.5). The first season available was from January to April 2007, and quarterly composites were created up until December 2015, resulting in a total of 35 images. These time intervals were assumed to be representative of the rainfall and vegetation phenological, annual seasonal cycle, in that they correspond roughly to four obvious seasons (Mendelsohn and El Obeid 2002). Finally, trend analyses were applied to the resulting dataset.

4.2.7 Dry Season composite imagery as model predictors

Seasonal composites allow the phenological differences between the woody and herbaceous strata to be distinguished: during the early dry season, the difference between the woody canopy and herbaceous layer are the most pronounced, as the trees generally remain in leaf while the herbaceous layer dries out (Archibald and Scholes 2007; Ryan et al. 2017; Verlinden and Laamanen 2006). Therefore, in addition to the 8-year time-series, EVI and short wave infrared (SWIR) composites based only on Landsat 5 (i.e. to bypass the Landsat 7 SLC-off issue) (Chander, Markham, and Helder 2009), coincident with the year of the ALOS PALSAR imagery (i.e. 2007 and 2015), were generated for the period between the EOS and SOS (i.e. the dry season), to accentuate the presence of the woody canopy. Since reflectance from the SWIR band shows a strong relationship with field-measured AGB (Avitabile et al. 2012; Baccini et al. 2012), this band composite was also included as a model predictor.

4.2.8 Univariate analysis

Biophysical modelling has often relied on mapping a given dependant variable as a function of single or multiple independent (or predictor) variables, using parametric linear regression models. Several assumptions are inherent to these models, namely, normal distribution of values and associated error, and homoscedasticity (Jensen 1983). As such, predictor layer data were extracted for coincident AGB field plots, and linear logarithmic models fitted to estimate the strength of the relationship.

4.2.9 Random forest algorithm

Machine learning algorithms including Random Forest (RF) are frequently applied to regression and classification problems with large datasets (Lu 2010), as they allow the inclusion of multiple variables with different predictive strengths (Moisen and Frescino 2002), for instance, correlated, categorical or continuous variables, while being computationally effective (Breiman 2001). The algorithm is increasingly used in ecological studies due to its capacity to rank multiple variables by their predictive power and not “over-fit” data (Cutler et al. 2007; Breiman 2001). Compared to parametric models, it does not presume particular statistical distributions of the data, nor assume any distinct relation (i.e. logarithmic), between dependent and independent variables, and in addition to being multivariate it requires no assumption of normality (Prasad, Iverson, and Liaw 2006). This modelling approach uses modified non-parametric ensemble techniques derived from the classification and regression tree (CART) method (Breiman et al. 1984; Breiman 2001). Rather than selecting the “best split” from all variable options, it instead samples variables randomly for every node and subsequently selects the best from these (Breiman et al. 1984).

4.2.10 Random forest in remote sensing

RF is increasingly used by remote sensors to scale measurements of biophysical variables to satellite data (Foody, Boyd, and Cutler 2003; Baccini and Asner 2013), and has been used extensively for broad-scale biophysical mapping, due to its ability to capture non-linear relationships and effectiveness at fusing of multi-sensor datasets (Baccini et al. 2012; Simard et al. 2011; Avitabile et al. 2012; Baccini and Asner 2013). It has been used to map tropical AGB with different data sources (Avitabile et al. 2012; Baccini 2004; Baccini et al. 2008), for instance, by modelling forest inventory measurements as a function of ALOS PALSAR backscatter (Karlson et al. 2015; Mishra and Crews 2014; Baccini 2004; Baccini and Asner 2013; Carreiras, Melo, and Vasconcelos 2013). We therefore use this algorithm to model AGB by combining seasonal Landsat metrics, ALOS PALSAR backscatter and forest inventory measurements.

4.2.11 Model inputs and validation with training data

A predictive RF model of AGB as a continuous variable was calibrated using field-measured AGB (training data), both HH/HV polarizations and Landsat dry season EVI/SWIR composites, and measures of model accuracy were then computed (Freeman, Frescino, and Moisen 2009; Breiman et al. 1984). Here, a separate model for each period (2007 and 2015) was created using the training data. Model parameters included 500 trees, predictors at every node were calculated as the square root of all predictors, and to assess the relative importance of the predictor the model was calibrated using different combinations of these.

RF model validation diagnostics are usually performed with out of bag estimation (OOB), which we use in this study (Liaw and Wiener 2002). For every model tree grown, the algorithm makes predictions on the OOB data (data excluded from the bootstrap sample from which it validates the models dynamically with a fraction of observations withheld from the model fit). To measure the error for every prediction, the coefficient of variation (CV) was calculated (pixel-wise), by taking the standard deviation of a modelled observation divided by the corresponding average values.

Models were created from the training data and these were validated with an independent test set, namely, the OOB predictions on the training data, where the training data was randomly divided into training and test sets (20%). We plot variable importance, measured as (i) percentage change in mean standard error (MSE) with the random permutation of each predictor layer, and (ii) mean increase in node purity (NP) of the residual sum of the squares, of the OOB sample or from all the splits in the forest. This results from the inclusion of every predictor and is measured using the gini coefficient. Pearson's and Spearman's correlation coefficients and Root Mean Squared Error (RMSE) are included for the observed and modelled values.

4.2.12 Vegetation change processes and change detection

The change detection method aims to gain an estimation of the change in AGB resulting from the main vegetation change processes (i.e. deforestation, woodland degradation, woody thickening and woodland regrowth). Over the time-scale of this study, woodland degradation is characterized by small and gradual changes in woody biomass, often resulting from the felling on individual trees, while deforestation is identified by large and abrupt woody biomass changes generally cause by land clearing and burning. Similarly, woodland regrowth is characterized by relatively large and rapid woody biomass gains, characteristic of fast growing, post-disturbance or successional woody species. In contrast, woody thickening is distinguished by small, gradual changes in woody biomass, which corresponds to the slow growth rate of the shrub species functional type associated with woody thickening, (e.g. *Acacia mellifera* subsp. *detinens*, *Dichrostachys cineria*, *Terminalia sericea*, *Terminalia prunioides*, *Acacia erubescens* and *Acacia reficiens*) (De Klerk 2004a). Therefore, in order to differentiate between the two "gain" process (i.e. woodland regrowth and woody thickening) we assume that only a difference in the magnitude of change between the two dates. The same assumption applies the two "loss" processes.

To detect these changes, we use the image ratioing method, which calculates the relative differences (giving emphasis to differences at the low end of the scale), and effectively discriminates noise from change in SAR imagery (Ryan et al. 2012). Since the result of ratioing is not linear or symmetrical about the zero, the natural logarithm transformation is applied using the following formula:

$$(\text{Image Ratio}) = \ln \frac{(AGB)_{2015}}{(\text{AGB})_{2007}}$$

(2)

where AGB_{2015} and AGB_{2007} are the modelled datasets at both dates. The resulting image ratio change map has values ranging from 2.05 to -2.31 (205% to -231%). Here, AGB in 2015 is shown as a percentage of AGB in 2007; values greater than 0% signify AGB increases while values lower than 0% signify decreases.

As outlined above, deforestation implies relatively large AGB losses (>20 Mg ha^{-1}), while woodland degradation and woody encroachment imply low AGB gains, manifesting as AGB increases over several years (i.e. 1.4–2.0 Mg ha^{-1} year^{-1}) (Chidumayo 1997; Williams et al. 2008; Ryan et al. 2012). In order to distinguish AGB changes characteristic of the four vegetation change processes under investigation, thresholds of change were applied to the image ratio change map to create different classes. These aim to capture the magnitude of AGB fluctuations associated with the different vegetation change processes between the periods assessed. Here, values ranging from 50 – 100% were assumed to constitute woody thickening, and from 100 – 200%+ regrowth. Similarly, all values ranging from -50 – -100% were assumed to represent degradation, and values from -100 – -200%+ deforestation (Table 1). All values ranging from 50% to -50% were considered as no significant AGB change or noise. Here, we assumed that 95.5% of the AGB Mg ha^{-1} values are due to normal variation while 2.3% in each "tail" constitute significant change. To choose relevant thresholds, we compared an area of know deforestation (i.e. an 80 km road approximately 70 m wide, built between the two periods assessed and visited during field campaigns), to subjectively assess the validity of the chosen vegetation change classes. To illustrate this, a pixel with a value of 39.5 Mg AGB ha^{-1} in 2007 decreased to 12 Mg AGB ha^{-1} in 2015, a loss of the -27.5 Mg AGB ha^{-1} and equivalent to a log ratio of -1.19 or -119%, which places the pixel in the deforestation class. In contrast, a pixel with a value of 12.5 Mg AGB ha^{-1} in 2007 increased to 43 Mg AGB ha^{-1} in 2015, a gain of the 31 Mg AGB ha^{-1} and equivalent to a log ratio of 1.14 or 114%, which places the pixel in the regrowth class. A number of assumptions and limitations are implicit in this approach. Firstly, the vegetation change process in question is identified simply based on the magnitude of the observed change. For example, in the regrowth class, we do not assume a low starting AGB value, as would be expected from woodland regrowth after clearing; instead, we simply identify the process based on the fraction of AGB in found 2015 compared to 2007. Therefore, the change classes constitute proxies for different vegetation change processes.

Total AGB for both dates and comparison maps was calculated by aggregating each pixel to the resolution of a ha (using bilinear resampling), summing the each pixel value in Mg ha^{-1}, and converting to Tg. To quantify total AGB change for each vegetation change process, the various vegetation change classes were used to extract the difference between the 2015 and 2007 AGB maps. The sum of the values then represents the amount of AGB lost or gained per vegetation change class (Tg ha^{-1}). Finally, the amount of AGB changed per vegetation class was converted to a percentage, both of the total AGB found in the study area in 2007 and within each land-use category.

4.2.13 Validation

Independent data were used to validate modelled and changed AGB: (i) the change map was compared to a classified trend map derived from a time-series Landsat seasonal Normalized Difference Vegetation index (NDVI) composites using an error matrix; (ii) regression and correlation analysis were undertaken for LiDAR derived height metrics with modelled AGB at both dates, and (iii) results were compared to published biomass datasets.

4.2.14 Trend estimation

A validation dataset is generated to estimate of the accuracy of the change map. Here, we apply a trend estimation method to the Landsat seasonal NDVI composite time-series and map trends in vegetation greenness (Forkel et al. 2013). Trend calculation is dependent on the time-series length, its temporal and spatial resolution, data quality and method of analysis (Sulkava et al. 2007; Badreldin and Sanchez-Azofeifa 2015). The various approaches for calculating trends produce comparable results with regard to significant trends, although differences occur for weaker trends (de Jong et al. 2011). In this study we identify overall trends using seasonal trend model (STM); please refer to Forkel et al. (2013) for details. Calculated trends were classified as either significantly negative or positive (p=0.05), signifying vegetation loss or gain, respectively, and no significant trend suggesting no vegetation shifts. We compare this validation map to the change map, which is the map of applied thresholds aggregated into positive and negative change, using an error matrix and calculate the user's, producer's and overall accuracy. Please refer to Foody (2010) for a discussion on implementing accuracy assessments.

4.2.15 ICESat

The space-born LiDAR sensor Geoscience Laster Altimeter System (ICESat) provides continuous observations of Earth (2003-2009) and is used to measure a range of environmental variables including vegetation structure (Lefsky et al. 2005; Simard et al. 2011). ICESat is a waveform sampling LiDAR sensor with a 70 m footprint spaced at 170 m intervals; due to its limited sampling area it is often used in conjunction with other sensors (Badreldin and Sanchez-Azofeifa 2015; Cartus et al. 2012a). It emits short duration (5 ns) laser pulses and records the echo of those pulses as they reflect from the ground (Zwally et al. 2002). When the surface is vegetated, the return echoes (waveforms) are a function of the vertical distribution of vegetation and ground surfaces. For forests on flat ground, stand height is calculated as the difference between the elevation of the first returned energy minus the mean elevation of the ground return (Harding and Carabajal 2005). LiDAR waveform metrics are related to vertical forest structure, which in turn are correlated with AGB (Lefsky et al. 2002; Drake et al. 2003; Baghdadi et al. 2014; Baccini and Asner 2013; Simard et al. 2011), such that ICESat has been used to map continental scale vegetation vertical structure and AGB (Saatchi et al. 2011; Koch 2010; Scarth 2014).

The linear relationship described by the R^2 between LiDAR height metrics and AGB is used as an independent proxy method for validating the AGB models (Baccini et al. 2008; Lefsky et al. 2005). An ICESat metric proposed by (Scarth 2014) for 134,282 waveforms (2003-2009) was aggregated within 5 Mg ha^{-1} modelled AGB classes, averaged and correlation statistics calculated. Aggregated height metrics were also converted to AGB; these were first multiplied by the mean number of stems per ha (as measured from both field campaigns), converted to DBH, and finally, to AGB Mg ha^{-1} using the equations proposed by (Mugasha, Bollandsås, and Eid 2013) (Mugasha et al. 2013). The equation by (Mugasha, Bollandsås, and Eid 2013) was modified to allow for the modelling of low height values by changing "1.3" (i.e. DBH) to "0.4", where:

$$\text{Height} = 1.3 + \exp(10.5116 - 10.6039 \times (\text{DBH})^{-0.0823}) \tag{3}$$

The temporal mismatch between the ICESat returns and modelled AGB, as well as spatial autocorrelation, were not accounted for.

4.2.16 Published map comparison

A comparison with published maps derived from different data sources is essential to evaluate model accuracy. Comparison datasets include Baccini et al. (2008) (BAC) (Baccini et al. 2008), and Saatchi et al. (2011) (SAA) (Saatchi et al. 2011). Comparative statistics were calculated, while covariance, variance correlation matrices are also included (Table 4.2) (Snedecor and Cochran 1989). Finally, pixel values of all maps coincident with the field plots were plotted and variances compared. The temporal mismatch between published and modelled data was not accounted for.

4.3 Results and discussion

4.3.1 Field data

A total of 7,435 trees of 36 species were measured during the course of two field campaigns. AGB estimates for the 101 sample sites varied from 0 to 108.3 Mg ha^{-1}, with a mean of 36.1 Mg ha^{-1}, median of 38.7 Mg ha^{-1}, standard deviation of 29.6 Mg ha^{-1} and standard error of the mean of 3.8 Mg ha^{-1}. Training data are skewed towards lower AGB values, whereas those of modelled predictions are not (Figure 3a); such an uneven frequency distribution may have biased model results. Training data frequency distribution may have resulted from the (i) inclusion of visually estimated low AGB plots, and (i) sampling of low biomass areas (i.e. lacking large trees).

Observed and predicted data (Figure 3b), and show that the modelled AGB is able to reproduce the 101 field AGB measurements with a moderate degree of accuracy (R^2 = 60%) and RMSE = 20 Mg ha^{-1} (Figure 3b). However, results from the Baccini et al., (2008) model with both and modelled AGB and field measured AGB, show a lower level of agreement (R^2 = 40%; RMSE = 16.1 Mg ha^{-1} and R^2 = 30%; RMSE = 27 Mg ha^{-1}, respectively) (Figure 3 c, d).

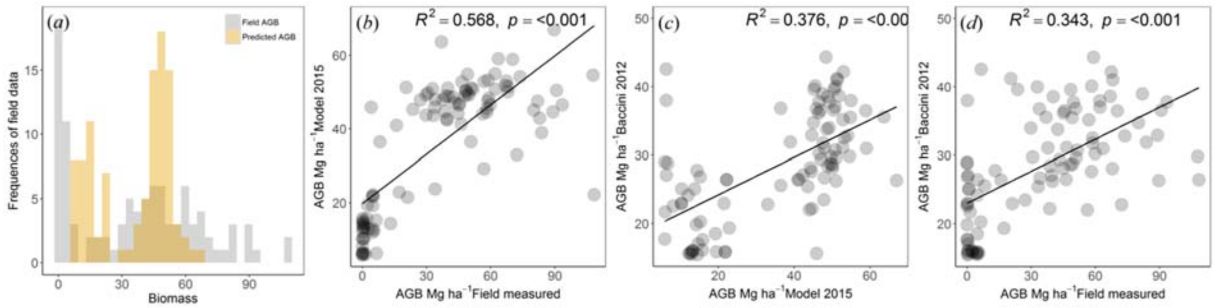

Figure 4.3. Frequency distribution of training data showing skewed distribution (grey) and modelled output for 2015 (yellow) (a); regression plot of measured and modelled AGB for each field site (b); observed and predicted results compared to published results, respectively.

Tree cover, canopy structure and AGB in Miombo woodlands are inherently spatially and temporally variable; a response compounded by the often pronounced anthropogenic impact, yet, mean field-measured AGB (36.1 Mg ha^{-1}) is comparable to analogous field studies. For example, Tanzanian woodland AGB varied from 13 – 30 Mg ha^{-1}; AGB in Mozambique varied between 31 – 45 Mg ha^{-1} (Carreiras, Melo, and Vasconcelos 2013; Ryan, Williams, and Grace 2011), while AGB ranged from 58 – 92 Mg ha^{-1} for Kenyan coastal dry forest (Glenday 2008).

4.3.2 Univariate analysis

The proportion of the variance explained by fitting the equations were low, with the strongest coefficients of determination found for the HV polarizations, in accordance with previous studies, explaining 74% of the variance for 2015 (Figure 4a) (Lucas et al. 2006; Mitchard et al. 2009). Weak relationships may be due to (i) heterogeneous vertical and horizontal woodland structure. Indeed, sample sites contained a wealth of structural form, vegetation functional types and growth stages, counting mixed aged tree species and transition zones from forest to woodland and grassland, resulting in a broad range of AGB values (0 to 108.3 Mg ha^{-1}) and hence DBH (Mendelsohn and el Obeid 2005a); (ii) sample plot size, which is known to impact the correlation between SAR polarization and field-measured AGB: larger plot sizes increase the strength of the relationship, hence where vegetation structural characteristics are heterogeneous, sample plots covering larger areas would be more effective (Carreiras, Vasconcelos, and Lucas 2012); lastly, (iii) the low biomass plots for which AGB was visually estimated may have resulted in inaccurate results.

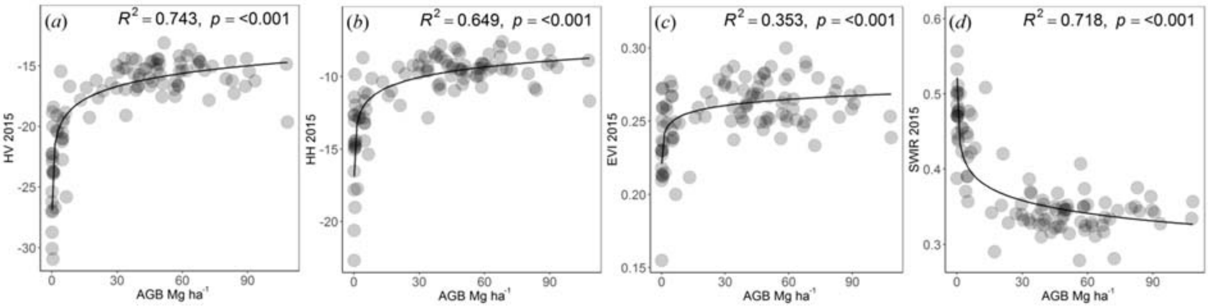

Figure 4.4. Linear logarithmic models for HV/HH polarizations (a, b) and dry season EVI/SWIR composites (c, d) with field measured AGB (n = 101).

4.3.3 Model output validation

Observed and predicted AGB resulting from fitting the RF model to a subset of the training data, show that the 2007 and 2015 models explained 88% and 92% of the variance of the OOB data, respectively (Figure 5 a, d). Regression plots of the CV and modelled AGB are shown (Figure 5 c, f). The coefficient of variation ranges from 0.13 – 1.33% and 0.12 – 1.33% in 2007 and 2015, respectively.

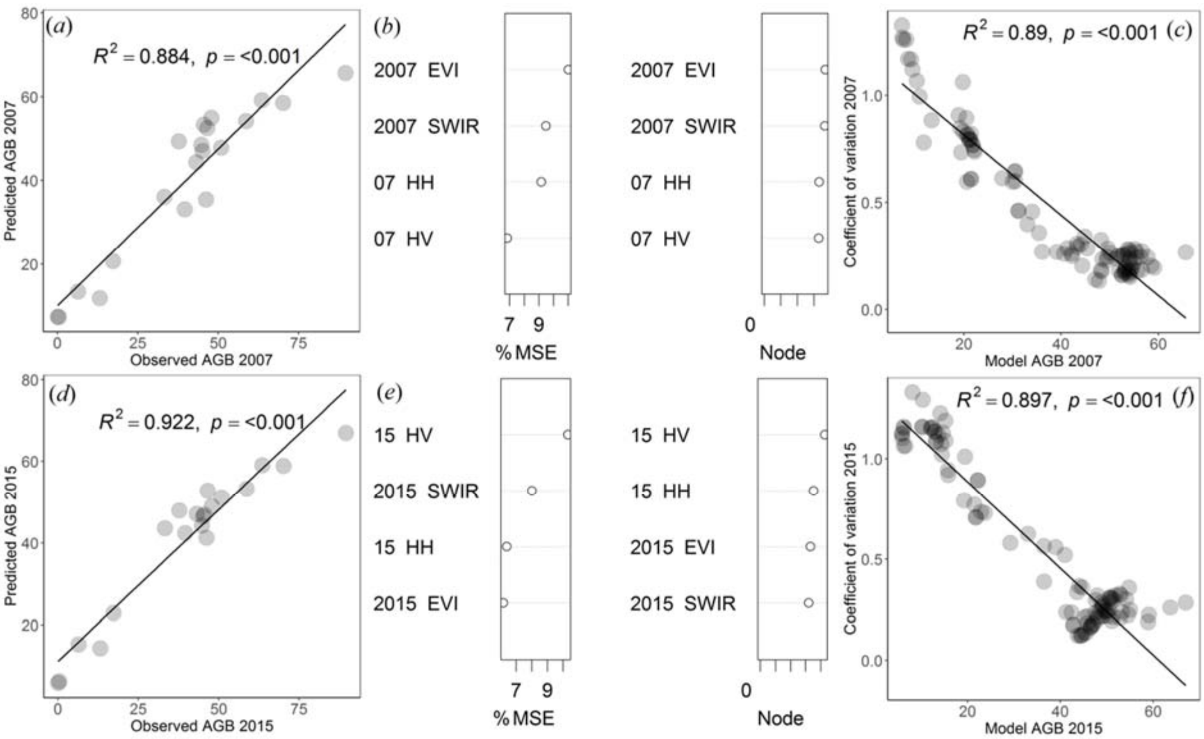

Figure 4.5. Observed verses predicted values resulting from the fitting of the Random Forest model. RMSE = 7.63; Pearson's correlation coefficient = 0.95; OOB estimate of error rate = 241 (a); RMSE = 7.85; Pearson's correlation coefficient = 0.96; OOB estimate of error rate = 245 (d). Predictor layer importance as measured by the MSE and NP (b, e). In 2007 (b), both Landsat metrics were the most important predictors, while in 2015, HV, HH, and SWIR were. The coefficient of variation plotted against model predictions with all samples corresponding to field sites (c, f).

Predictor variable importance plots show EVI is the most important predictor, followed by SWIR in 2007 (Figure 5b), while HV, HH and SWIR were the most important predictors in 2015 (Figure 5e). The weaker importance of the HV polarization in 2007 may indicate confounding factors influencing model outcome (i.e. variations in soil and canopy moisture), accentuated in low biomass sparse cover forests (Cartus et al. 2012a).For instance, Radar backscatter intensity (and subsequent AGB estimates), in particular from the HH polarization, may have been affected by, (i) the roughness and exposure of the soil, (ii) and the sparse and deciduous canopy cover and consequent strong influence of the woody vegetation components (Rignot et al. 1994; Carreiras, Melo, and Vasconcelos 2013). Sample sites were often located in areas close to farms and villages, with important amounts of bare ground exposed through the canopy and low biomass density, resulting from the influence of human activity (i.e. intensive grazing, fire, small-scale timber extraction). The important role of the SWIR band in predicting AGB for the 2007 model is in agreement with earlier studies (Baccini et al. 2008; Baccini 2004; Avitabile et al. 2012).

4.3.4 Change detection

Changes in AGB and respective areal extent are shown in Table 1, while Figure 6 illustrates the change detection results (image ratio) and the image ratio map with thresholds applied to distinguish the vegetation change processes under investigation (thresholds). Plots of AGB change (Tg) and areal extents (%) of the change for each change class are also included (Figure 6a,b). We find that most changes in AGB are associated with the “degradation” class (-14.3 Tg), followed by the “thickening” (2.5 Tg), “deforestation” (-1.9 Tg) and “regrowth” (0.2 Tg) classes. This pattern is also reflected by the areal extent of changes, where we see that woodland degradation affected the largest portion of the study area (14%), followed by woody thickening (3.5%), deforestation (1.3%) and regrowth (0.5%). The area of the “No change” class also contributed to the overall change in total AGB (i.e. -16.5 Tg and 81% of the total area), suggesting widespread but low intensity change.

Table 4.1. Spatial extent of vegetation change (km2 and percentage of study area), as well as the change in AGB (Tg) and percentage of 2007.

Thresholds	Vegetation change	Area (km^2)	Area (%)	AGB change (Tg)	AGB change since 2007 (%)
100% to -200%	Deforestation	957.5	1.3	-1.9	-4.2
-50% to -100%	Degradation	10555.0	14.0	-14.3	-31.5
-50% to 50%	No change	61188.1	81.0	-16.5	-36.5
50% to 100%	Thickening	2648.6	3.5	2.5	5.5
100% to 200%	Regrowth	151.4	0.2	0.2	0.4

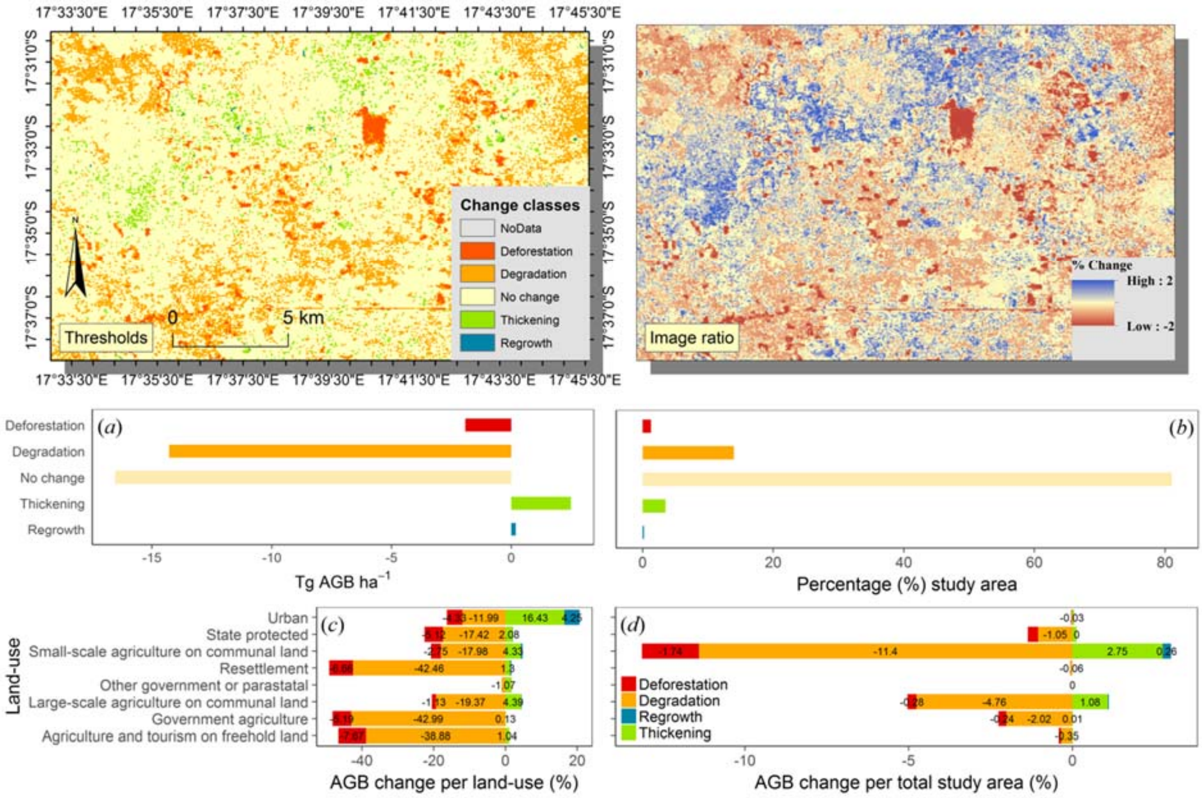

Figure 4.6. Map of the thresholds applied to the image ratio map (50%, 100% and 200% +) to identify the degree of AGB change and hence the vegetation change processes. Plots of AGB (Tg) change between each date, for each class (a), and its respective area (b) as a percentage for each vegetation change class. Changes in AGB for each vegetation change process as a percentage of the total AGB contained within each land-use in 2007 (y-axis) (c). Likewise, the changes in AGB for each vegetation change process, as a percentage of the total AGB of the study area, in 2007 (y-axis) (d).AGB change in relation to land-use

Figure 6 (c, d) summarises the AGB changes and associated areal extents of those changes, undergone by the different vegetation change processes, in relation to land-use. We find that in terms of percentage of the total AGB per land-use category, deforestation was most pronounced on land designated as “agriculture and tourism on freehold land” (7.8%), followed by “resettlement” (6.7%), “government agriculture” (5%), “state protected” (5.1%) and “urban” (4.3%). In terms of degradation, the most important AGB changes were associated with “government agriculture” (43%), “resettlement” (43%), “agriculture on and tourism on freehold land” (39%), and “small scale agriculture on communal land” (18%). Woody thickening was most prevalent on “urban” (16.4%), “large scale agriculture on communal land” (4.4%) and “small scale agriculture on communal land” (4.3%), while regrowth was most widespread on “urban” land (4.3%). However, for the whole study area, the highest percentage of AGB change associated with deforestation (1.7%) and degradation (11.4%) occurred on communal land. These results are reflected by the areal extent of each vegetation change process for every land-use, shown both as a percentage of the respective land-use and study area. However, for the whole study area most deforestation and degradation occurred on communal land.

4.3.5 Validation

4.3.5.1 Map comparison

Differences in model date were not accounted for in the comparison and hence may have contributed to amplifying differences. We compare only the 2015 map as it is most coincident with the date of the field data collection. Mean model AGB for 2015 was 25.3 Mg ha^{-1}, an estimate which is higher than for studies conducted by BAC and SAA. The maximum value (98.8 Mg ha^{-1}) is comparable to those of the published maps, but the minimum value (5.9 Mg ha^{-1}) is higher. Pearson's correlation coefficients suggest a weak linear relationship between maps (i.e. 0.3 and 0.5 for BAC and SAC, respectively), while the RMSE shows comparable results between maps (Table 2). A moderate relationship exists between model predictions and those of BAC (Figure 3 c, d), (R^2 = 40%), while for those of SAA none is apparent.

Table 4.2. Descriptive and comparative statistics for model and published AGB predictions: Root Mean Squared Error (RMSE) and Pearson's correlation coefficients are included for all three maps.

AGB model	Min	Max	Mean	SD	RMSE				*r*			
1=Model 2015	5.90	68.80	25.30	12.10		1	2	3		1	2	3
2=Baccini et al. (2008)	0.00	97.00	24.91	8.18	1	1.00	12.40	21.10	1	1.00	0.30	0.05
3=Saatchi et al. (2011)	1.00	80.42	10.11	11.96	2	12.10	1.00	17.90	2	0.30	1.00	0.30
					3	21.50	17.90	1.00	3	0.50	0.30	1.00

4.3.5.2 ICESat and model validation

ICESat height metrics and modelled AGB in 2015 revealed a strong relationship (R^2 = 85% and 87%, respectively). This relationship weakened for the higher biomass classes (i.e. standard error and deviation), suggesting decreased model accuracy with at higher AGB estimates (Figure 7). The weak R^2 in the lowest biomass class (0-5 Mg ha^{-1}) suggests inaccurate values. This may be linked to the ICESat sensors known lower accuracies when sampling short vegetation. This comes as a result of the interplay between the sensors footprint diameter (90 m), the terrain slope and roughness of the terrestrial surface and the transmitted pulse width, which when acting together render it highly complex to derived short vegetation from the actual ground return (Scarth 2014). Both correlations lend support to model predictions (i.e. vegetation height is strongly correlated with biomass) (Baccini et al.

2008; Lefsky et al. 2002), while providing an independent validation method. A similar relationship is evident when the height metric is converted to AGB (Figure 7b).

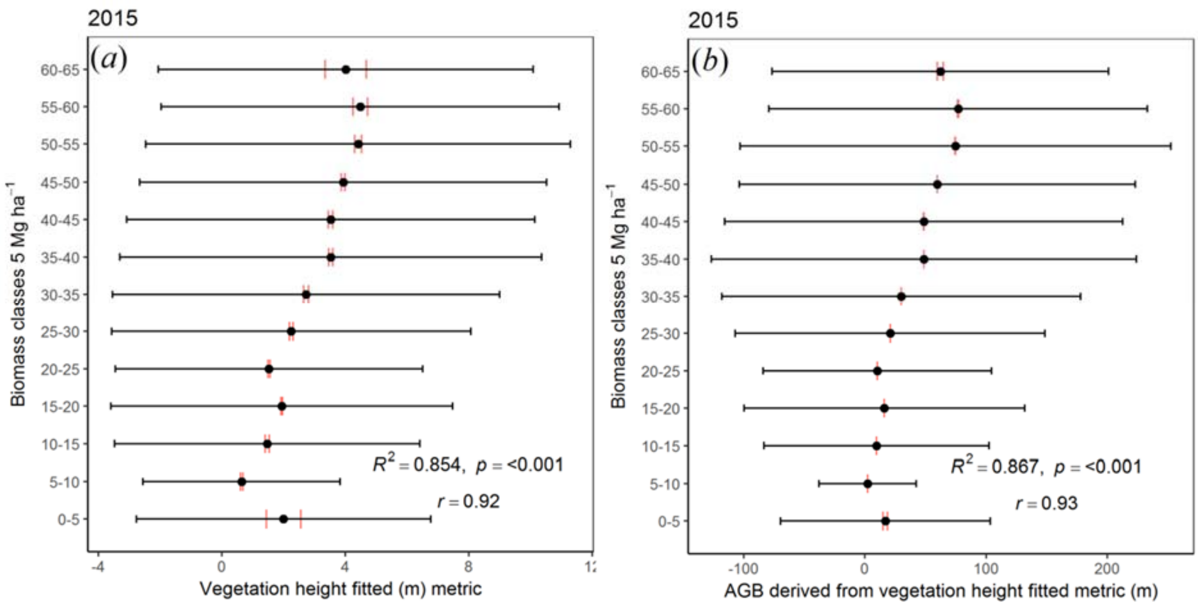

Figure 4.7. R^2 and Pearson's coefficients (r) resulting from ICESat height metrics and modelled AGB 2015 (a), and ICESat height metrics converted to AGB (b). Red error bars show standard errors and black error bars show the standard deviation.

4.3.5.3 Change detection validation

Overall accuracy was 65% when comparing all available pixels of the STM reference map and threshold change map for part of the study area, however, when applying the mapped area proportions variable (W_i) (Olofsson et al. 2014) overall accuracies decreased to 22% (Table 9.6 and 9.7). User's accuracies tended to be higher than producers accuracy. Results indicate that although there was a moderate parallel between model and validation datasets (overall accuracy), most of the equivalence was found in the "No change" class, followed by "Deforestation/Degradation", with very little relationship between the "Thickening/Regrowth" classes (user's accuracy) .

4.3.6 Total AGB estimates

Estimates of total carbon stocks for the study area in 2007 where of 221 Tg and 191 Tg in 2015 (overall loss of 30 Tg). These results are proportionate to the comparison maps (i.e. 187.08 Tg for BAC and 75.82 Tg for SAA). Similarly, Ryan et al. (2012) (Ryan et al. 2012) found AGB for their >1000 km^2 study site in central Mozambique to be of 2.13 ± 0.12 Tg in 2007 (equivalent to approximately159.75 Tg for the same area). Our results are slightly higher than those of published maps, which may be the result of including small stem diameter classes. In effect, the above studies did not include <5 cm stems in their model. In order to test this, we ran the models with the stems <5 cm excluded and found that total AGB in 2007 was 211 Tg while in 2015 it was 199 Tg, revealing a net change of only 12 Tg. These result suggest the exclusion of the small stems from the model has caused an overall decrease in estimates of carbon density (Mg ha^{-1}) in both models and hence smaller estimate of the total change in AGB between the periods assessed, and has therefore resulted in a marked effect upon model carbon density estimates (Figure 8).

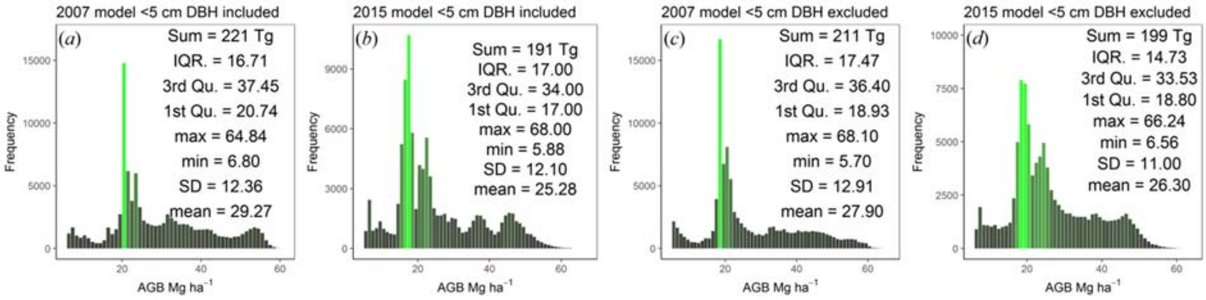

Figure 4.8. Descriptive statistics (interquartile range, upper quartile, lower quartile, max, min, sd and mean) and sum of the carbon density (Tg) for modelled AGB including stems with a diameter <5 cm in 2007 and 2015 (panels a and b, respectively), and excluding stems with a diameter <5 cm in 2007 and 2015 (panels c and d, respectively). Results show that the exclusion of <5 cm diameter stems impacts the overall estimates of carbon density (Mg ha^{-1}).

4.4 Conclusion

We modelled AGB for a part of the Kalahari woodland savannah biome in Namibia using ALOS PALSAR backscatter, dry season Landsat metrics and field measurements DBH. We then quantify the changes between two dates for the four main different change processes (i.e. deforestation, woodland degradation, woody thickening and woodland regrowth). Variance explained from fitting both RF models was high, with comparable RMSE values. Model validation using independent data was successfully carried out, with ICESat height metrics and model predictions revealing strong coefficients of determination, supporting model validity. However, change map validation using a reference dataset demonstrates only moderate overall classification accuracy with intermediate to low accuracies for change classes. Although our models give slightly higher biomass estimates compared to published maps, we suggest this small effect is likely due to our sampling, and inclusion in model calibration, of smaller stem diameters. To test this, we ran the model with <5 cm stem diameter classes excluded and find that overall estimates of carbon density are lower. We use the image ratio change detection method to measure the degree of AGB change between the two dates compared, which serves as a proxy to identify the four main types vegetation changes expected. We then apply thresholds to distinguish AGB changes associated with the four different vegetation change processes. Results demonstrate that most change in AGB is associated with woodland degradation, followed by woody thickening. Deforestation and regrowth contribute a smaller portion of AGB change, a pattern which is also reflected by the areal extent of these. Change in AGB in relation to different land-uses categories were also assessed, revealing that land designated as “agriculture and tourism on freehold land” experienced the greatest amount of AGB losses associated with deforestation, while degradation was most prevalent on “resettlement” land. These results are in agreement with previous studies, which identify both extensive greening but at the same time small-scale deforestation and woodland degradation. The Kalahari woodlands are structurally complex, presenting a range of plant functional groups with contrasting stand ages and successional stages, and this variability is exacerbated by intensive anthropogenic influences. Accurately mapping AGB in such a dynamic biome is hindered by a number of issues, chiefly environmental variability and consequent vegetation phenological fluctuations which affect satellite data, together with field datasets which may not adequately describe the biophysical parameter being measured, lead to variable estimates.

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Chapter 5

Mapping trends in woody cover in Namibian savannah with MODIS seasonal phenological metrics and field inventory data

5 Mapping trends in woody cover in Namibian savannah with MODIS seasonal phenological metrics and field inventory data

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Abstract

Woody vegetation is an integral component of savannas. Here, two main change processes alter woody vegetation, namely shrub encroachment and deforestation. Both impact a range of ecosystem services and functions across scales. Accurate estimates of change, including spatial extent, rate and drivers are lacking. This is primarily due to savanna vegetation comprising woody and herbaceous vegetation, each of which exhibit divergent phenological characteristics, and vary importantly in their response to climatic and environmental factors. This study uses phenological metrics derived from the MODIS MOD13Q1 NDVI time-series to model woody cover as a function of field measurements, and to map trends across Namibia. These metrics enhance the contrasting phenological characteristics of woody and herbaceous vegetation, and standardizes their annual response to climatic and environmental factors by integrating short term variation. Trends in woody cover are excellent indicators of shrub encroachment and deforestation. Trend significance was computed using the Mann-Kendall test, while change statistics, including the rate and spatial extent of change were derived using the Theil-Sen slope. Change was evaluated in relation to drivers including land-use, population, biomes and precipitation. An overall decrease in woody cover was identified, with the most pronounced decreases found in urban and densely populated areas. Decreases in woody cover were not homogenously distributed; losses predominated in tropical desert and dry forests, but gains were found across shrub lands.

Key words: Time-series; woody cover; trends; savanna; MODIS; Theil-Sen; precipitation; NDVI; phenology metrics; land surface phenology; tropical dry forests.

5.1 Introduction

Savannas constitute one of the most extensive biomes, covering over a fifth of Earth's land surface and providing a livelihood for a substantial number of people (Scholes and Archer 1997; Sankaran et al. 2005). Savanna vegetation is characterized by the co-occurrence of trees, shrubs and herbaceous species with a distinguishing feature being their contrasting phenologies. The proportions of woody and herbaceous species vary widely, forming forests, grasslands and shrub lands (Archibald and Scholes 2007; Murphy and Bowman 2012; Frost 1996). Woody vegetation is an important component of savannas (Emmanuel N Chidumayo and Gumbo 2010; Sánchez-Azofeifa et al. 2005); it is essential not only at the local scale, where it provides resources for rural communities ranging from forage to timber, but also at the global scale, where it contributes key ecosystem services functions affecting biodiversity, carbon and water cycling, surface energy balance and climate (Duveiller, Hooker, and Cescatti 2018; Turner, Lambin, and Reenberg 2007; Foley 2005; Le Quéré et al. 2017; Alkama and Cescatti 2016; Adeel et al. 2005). Woody vegetation is closely linked to biomass, carbon stocks, net primary productivity (NPP) and surface energy balance (Foley 2005; Le Quéré et al. 2017; Alkama and Cescatti 2016). Quantifying its dynamics is therefore an important global environmental issue and research priority (Poulter et al. 2014). For instance, it has been shown that both the trend and inter-annual variability of the CO_2 uptake by terrestrial ecosystems are dominated by semi-arid ecosystems, of which savannas and woody vegetation are an important component (Ahlström et al. 2015). Moreover, recent research has shown that tropical dry forests, which are closely linked to savannas in sub-Saharan Africa, are far more extensive than previously thought, thereby highlighting the need for a greater understanding of ecosystem functions and services provided by these biomes (Bastin et al. 2017; Scholes and Archer 1997; Parr et al. 2014).

Throughout sub-Saharan Africa, the need for arable land and forest products, such as charcoal, is driving widespread deforestation and forest degradation (Brink and Eva 2009; Baccini et al. 2012; Achard 2002). Simultaneously, a contrasting land degradation process is also widely reported, namely, the thickening of the woody layer and associated loss of herbaceous vegetation (i.e. shrub encroachment) which is of vital economic importance for rural communities relying on cattle (Liu et al. 2015; Ward 2005). Both processes involve changes in woody vegetation cover and are often associated with pervasive land degradation and desertification (Reynolds et al. 2007; Bond et al. 2010). At the same time, several authors questions whether shrub encroachment is a sign of declining ecosystem functioning, and suggesting that encroachment may limit degradation, boost carbon sequestration especially through the drylands (Eldridge et al. 2011; Poulter et al. 2014; Maestre et al. 2009; Soliveres and Eldridge 2014). Thus, there is an inadequate understanding of the scale of woody vegetation change in relation to environmental and socio-economic and environmental drivers. In fact, separating trends in woody and herbaceous functional groups is an active area of research (Helman et al. 2015; Roderick, Noble, and Cridland 1999; Brandt, Hiernaux, Tagesson, et al. 2016). As such, monitoring trends in woody cover and deciphering its relation to climatic and anthropogenic drivers, including precipitation and land management, respectively, is fundamental for sustainable land management and planning (Fensholt et al. 2012).

5.1.1 Satellite remote sensing

Satellite remote sensing offers a convenient tool to study trends in woody cover, due to its synoptic coverage and cost-effectiveness once calibrated and validated. Several continental-scale tree cover products, available at the spatial resolution of Landsat and Moderate Resolution Imaging Spectroradiometer (MODIS), are widely used to monitor processes such as deforestation (Broich et al. 2014; M. C. Hansen et al. 2013a; Matthew C. Hansen et al. 2016). These products use very high resolution (VHR) scenes to train a vegetation cover algorithm based on high to moderate resolution imagery. However, our current knowledge of the extent of tree cover and forests in drylands is limited. This is illustrated by substantial spatial disagreements between recent satellite-based global forest maps (Sexton et al. 2016, 2013; M. C. Hansen et al. 2013a) and by the scarcity of large-scale studies of dryland biomes (Durant et al. 2012). Moreover, savannas exhibit pronounced land cover heterogeneity (Sexton et al. 2013, 2016; M. C. Hansen et al. 2013b; Durant et al. 2012), ranging from open grassland to closed forest while exhibiting high intra- and inter-annual variability in vegetation photosynthetic activity and phenology, which is often enhanced by marked anthropogenic disturbances, including fire and grazing (Matthew C. Hansen et al. 2016; Gessner et al. 2013; M.C Hansen et al. 2002; Bastin et al. 2017).

Within this context, satellite-derived indicators of vegetation dynamics are fundamental to identifying environmental change processes such as land degradation. These indicators are often derived from spectral vegetation indices of satellite imagery, which are related to the photosynthetic potential of vegetation canopies. For example, a time-series of Normalized Difference Vegetation Index (NDVI) effectively captures variation in photosynthetic activity, whether it results from phenological cycles or anthropogenic disturbances such as deforestation (Myneni et al. 1995, 1997; Kuenzer, Dech, and Wagner 2015; Sankaran, Ratnam, and Hanan 2008).

The spatial and temporal resolution of MODIS is especially effective for continental-scale monitoring of land surface phenology, which refers to the seasonal and inter-annual variation in surface vegetation photosynthetic activity as measured by satellite vegetation indices (Friedl et al. 2006). In addition, its high temporal imaging frequency allows the negative effects of cloud cover to be overcome; this is important in biomes which are seasonally impacted by cloud cover (M.C Hansen et al. 2002; Jacquin, Sheeren, and Lacombe 2010). Regional-scale modelling of woody cover using MODIS is strengthened by including seasonal phenological metrics which describe contrasting stages in seasonal vegetation growing cycles (i.e. green-up and senescence), rather than simply metrics which represent temporal snapshots (Broich et al. 2014). Such metrics enhance the phenological differences between woody and herbaceous vegetation, and constitute good proxies of woody cover, including all shrubs and trees, and have effectively been used to map trends in woody vegetation for large parts of sub-Saharan Africa (Horion et al. 2014). In addition, MODIS has successfully been used to monitor vegetation phenology (Zhang et al. 2003) and been used in conjunction with satellite-derived precipitation estimates (Zhang et al. 2005).

5.1.2 Phenology of Namibian savannas

In sub-Saharan savannas, important plant phenological events often occur in response to the seasonal availability of water, although it is widely reported that several vegetation phenophases do not follow this pattern. For instance, pre-rainy season leaf-flushing, as observed across much of sub-Africa, is thought to be driven mainly by photoperiod and temperature cues; here, woody species flower and leaf-out before the onset of the rains

(Childes 1988; Ryan et al. 2017). The many woody species found throughout Namibia exhibit different phenophases and vary in the timing of leafing and leaf senescence. However, for most deciduous tree and shrub species, senescence occurs in response to a drop in soil moisture and the onset of lower daily minimum temperatures (Childes 1988). The leaf-on period takes place shortly before the onset of the rainy season (September-October) and leaf-off period ensues throughout the middle of the dry season (April-August). Various species are evergreen, keeping at least a portion of their leaves throughout the dry season, but the majority are strongly deciduous, losing effectively all their leaves during the dry months and experiencing a leaf flush independently and before the first rains. For example, a pre-rainfall leaf flush and synchronized flowering is commonly observed in three tree/shrub species which are widespread in the northeast, in particular, *Terminalia sericea*, *Ochna pulchra* and *Pterocarpus angolensis*. In contrast, several common species in closed savanna woodland often demonstrate asynchronous flowering periods, notably *Baikiaea plurijuga* (Childes 1988). Trees and shrubs retain their foliage longer than herbaceous vegetation during the dry season (John Mendelsohn and el Obeid 2005a; Verlinden and Laamanen 2006). The annual growth of herbaceous biomass relies on the first precipitation events to initiate photosynthesis and remains photosynthetically active during the rainy season, as it is largely dependent on the spatio-temporal distribution of annual precipitation. Senescence of herbaceous vegetation then takes place at the onset of the dry season once the plants have completed their annual life cycle, while in addition, intense grazing pressure throughout the country contributes to promptly grazing the pasture throughout much the country. Importantly, this results in woody vegetation remaining photosynthetic during part of the year, while herbaceous vegetation is entirely desiccated.

Woody vegetation dynamics in savanna biomes can be broadly divided into intra-annual (seasonal) fluctuations, and inter-annual trends (occurring over a period of years). Seasonal fluctuations are mainly controlled by seasonal precipitation and short-term anthropogenic disturbances, such as burning, grazing and vegetation clearing. Environmental factors such as soil type, vegetation community composition and land-use history, also affect the seasonal growth of woody vegetation. Concurrent to shifts in canopy foliar density, are the associated leaf and plant phenology changes, including timing of flowering and leaf senescence; for most tree and shrub species, these are in turn regulated by seasonal water availability and temperature. For instance, the timing of plant phenological stages may vary for a given year, as a function of the seasonal availability of water in certain species, such as leaf flush occurring as a result of early rainfall onset. At the same time, these phenological stages may be influenced by the climatic, anthropogenic and environmental factors listed above (Childes 1988; Ryan et al. 2017; E. N. Chidumayo 2001; Wagenseil and Samimi 2007; Kuenzer, Dech, and Wagner 2015). Importantly, these different processes, their interactions and synergies, contribute to creating a marked variation in the seasonal NDVI signal across savanna biomes. Finally, different plant functional types, including in particular herbaceous vegetation, also have a pronounced seasonal effect on the NDVI signal (Kuenzer, Dech, and Wagner 2015).

In contrast, inter-annual trends impact woody vegetation dynamics over multiple years and thereby encompass the life cycle of trees and shrubs. For example, a minimum period of 5 years is thought sufficient to capture any increases in woody biomass, which is related to woody cover, using satellite indices (Williams et al. 2008; Ryan et al. 2012a; Asner et al. 2003). This is due to the fact that forest inventory parameters used to monitor tree growth, such as diameter at breast height, height, canopy cover and basal area, change slowly over the course of several years (i.e. gradual changes). However, they are also subject to abrupt negative changes, often triggered by deforestation, encroacher bush control or forest fires (Ryan et al. 2012b; Williams et al. 2008; Emmanuel N Chidumayo 1997).

5.1.3 Aims

Against this background, land surface phenology across Namibia is highly variable over time, yet simultaneously reveals clear annual cycles at regional scales (10^4 km^2) (V. R. Wingate et al. 2018). It is to a large extent driven by the distinctive rainy season (December-April) and the variable proportion of herbaceous and woody vegetation. These display divergent phenologies, which can be exploited to map either vegetation functional type (Hüttich et al. 2009; John Mendelsohn and el Obeid 2005a). In addition, vegetation change processes, including deforestation and woody encroachment are reported to be widespread in Namibia, yet their spatial and temporal dynamics remain little studied. In particular, the relation of these change processes to land-use, biomes, population density and precipitation trends, are poorly known (John Mendelsohn and el Obeid 2002a, 2005a; Curtis and Mannheimer 2005; V. Wingate et al. 2016; V. R. Wingate et al. 2018). The aims of the following study are therefore to 1) exploit the relationship between phenological metrics and field measurements of woody vegetation cover to create a time-series of percentage woody cover, 2) map trends in woody cover across Namibia, including the rates, trajectory and spatial extent, and 3) evaluate the relationship between trends in woody cover and potential anthropogenic drivers, as well as environmental and climatic gradients, namely, land-use and population density, as well as biomes and precipitation, respectively.

5.2 Materials and methods

5.2.1 Approach

An empirical/statistical approach based on the Random Forest algorithm was used to map percentage woody cover (Colombo et al. 2003; Breiman 2001). Here, phenological metrics derived from a MODIS NDVI time-series, together with 484 field-based measurements of percent woody cover sampled over three years (2012, 2014 and 2016), were used to model percentage woody cover at annual intervals, resulting in a study period spanning the period from 2001 to 2016. Outliers NDVI values were attenuated by applying a temporal filter to the original MOD13Q1 NDVI time-series, and subsequently creating monthly mean composites. Phenological metrics which integrate seasonal fluctuations into a single annual metric, characterising the phenology of a particular plant functional types were used to enhance long-term trends by suppressing inter-annual variation. The approach enables a maximum amount of noise and variation to be integrated, and hence enhances gradual trends and changes associated with woody vegetation. A fundamental underlying assumption of these metrics is that the observed NDVI signal during the dry season is derived only from woody vegetation. Thus, phenological metrics act as indicators of woody vegetation cover, while also effectively separating the woody NDVI signal from the herbaceous one. Estimates were validated using independent measurements of tree cover, which are closely correlated with woody cover and hence constitute a proxy. Trend significance was computed using the Mann-Kendall test and the annual rate, trajectory and spatial extent of change was derived using the Theil-Sen slope. These were then evaluated in relation to potential drivers including land-use, population biomes and precipitation. Finally, hotspots of change were selected for further discussion (Figure 5.1).

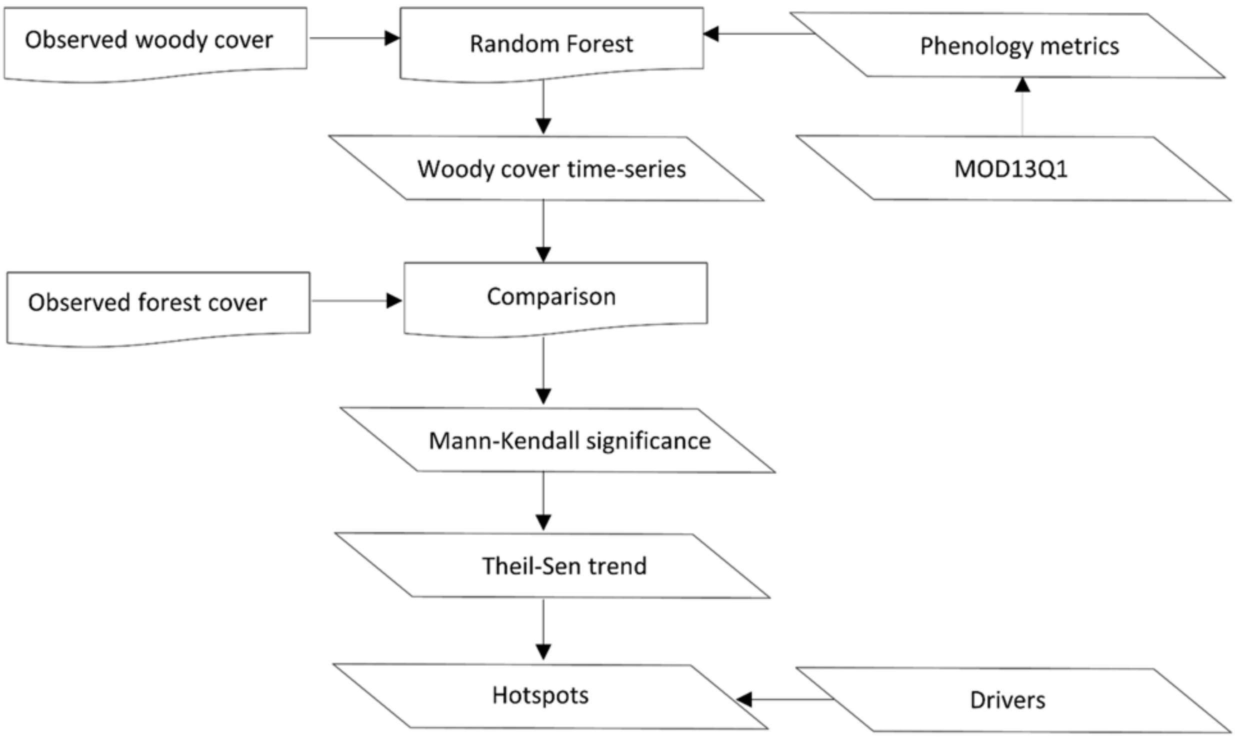

Figure 5.1. Schematic workflow diagram illustrating the datasets and approach used to map and evaluate trends in percentage woody cover.

5.2.2 Study region

The study area comprises the whole country of Namibia and encompasses an extensive and biogeographically diverse southern African savanna biome (Figure 5.2). The area is semi-arid to arid, with precipitation across the country varying from an annual average of 650 mm in the northeast, to 50 mm in the southwest. Rainfall events are variable both within and between years for any given period. In the north and central regions, precipitation is concentrated during the five summer months (December to April), while in the southernmost regions it occurs especially in the austral winter (Desmet and Cowling 1999; John Mendelsohn and el Obeid 2005a). Agriculture ranges from subsistence small-scale cropping and ranching on commonages, predominantly across the northern areas, to large-scale commercial ranching and wildlife tourism enterprises on private (free-hold) lands in the central and southern areas; most of the land which is not set aside for conservation being used for livestock grazing or subsistence agro-pastoralism.

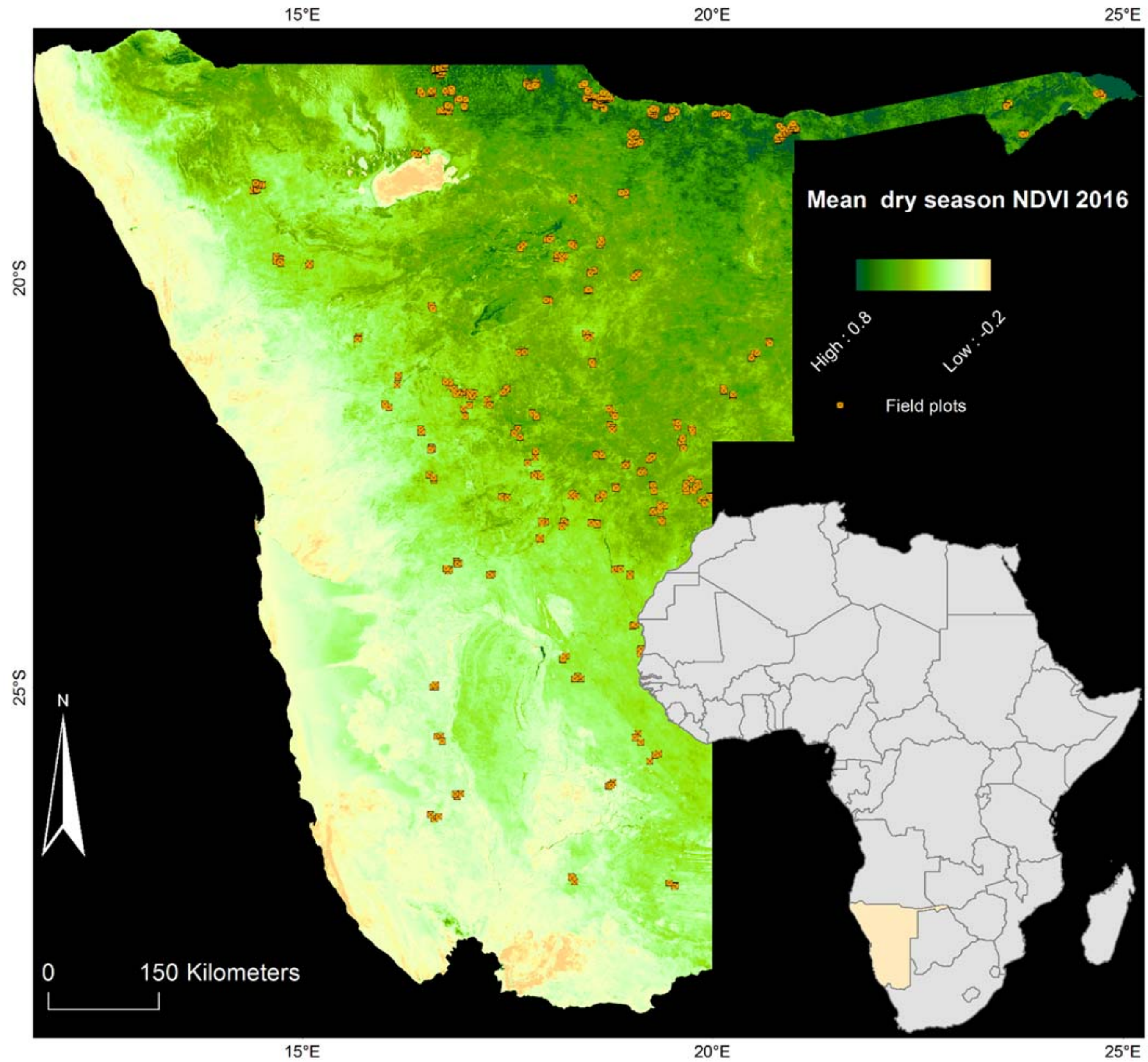

Figure 5.2. The study area encompasses Namibia (822,634 km^2). The background image is a MODIS mean dry season NDVI image (2016), which enhances the presence of woody vegetation since herbaceous vegetation has already senesced.

5.2.3 MODIS Data

The MODIS MOD13Q1 NDVI time-series gridded level-3 product collection 6 has a number of advantages over the previous collection, making it suited for land surface phenology parameter estimation. A number of improvements have been made on the MODIS vegetation index algorithm, which minimize the confounding effect of bidirectional reflectance distribution functions (Didan 2015). The product is available at 250m spatial resolution, is masked for water, clouds, heavy aerosols, cloud shadows and merged into 16-day composites, which allows only the highest quality values to be used, thus minimizing the impact of cloud cover (Didan 2015). Pixels flagged as low quality were masked and a Savitzky-Golay smoothing filter was applied to each pixel of the time-series to interpolate missing values, smooth outliers and minimize the effects of low quality data resulting from noise and cloud cover, and the time-series was aggregated to mean monthly values. The computation of smoothing filters is recommended since observations over time are often noisy, especially in drylands (Broich et al. 2014).

5.2.4 Field Data

Field measurements of percentage woody cover were made at three separate periods, 2012 (July), 2014 (May-June), and 2016 (April-May), across three separate regions and amalgamated into a single calibration dataset, resulting in a total of 483 samples. Only woody cover was used in this study since it aims to map vegetation associated with both deforestation and shrub encroachment, and woody cover is assumed to be representative of either plant functional type (i.e. trees and shrubs). Thus, woody vegetation encompasses both tall and short vegetation, counting trees and shrubs. Field data were collected using the point cover observation method described in Herrick *et al*. (2013), as part of the Land-Potential Knowledge System (J. E. Herrick et al. 2013), and consisting of stratified point intercept measurements of plant canopies in a 50 × 50 m area (Jeffrey E Herrick et al. 2010). Sample sizes were 100 intercept points in 2012 and 2014, but were increased to 160 points in the 2016 survey. The post-processing and sampling effort was also different for the 2016 dataset, in which data were processed to fractional cover values. Therefore, in order for the 2012 and 2014 datasets to be included in the analysis, fractions of the three primary components (i.e. woody, herbaceous and bare ground) assessed were normalized so that their sum would correspond to 100 percent. In order to ensure the normal distribution, each variable was logarithmically transformed (Zandler, Brenning, and Samimi 2015). Samples with a measured percent woody cover <10% were excluded (n=25) from this analysis in order to apply log transformations, which otherwise would have resulted in negative values, this resulted in a total of 458 available for model calibration.

5.2.5 Scaling field data

Importantly, a key challenging in the use of field data in remote sensing research is making sure that the in situ field measurements provide a representative sample; this problem is especially pertinent in studies which cover large spatial areas with moderate spatial resolution data. In particular, when using plot-level field data to calibrate and validate remote sensing models at moderate spatial resolutions, the field data needs to be up-scaled to the resolution of the remotely sensed observations (Baccini et al. 2007). In this study, the field plots were not scaled to the resolution of MODIS (250 × 250 m) using spatial averaging; instead, the average percentage woody cover within the 50 × 50 m field plot was compared with the corresponding MODIS pixel values. We make the assumption, therefore, that the 50 × 50 m field plot adequately captures the average percentage woody cover within the corresponding MODIS pixel. We justify this assumption since the field plots were sampled in homogenous vegetation strata (Baccini et al. 2007).

5.2.6 Spatial data

To investigate the observed trends in terms of potential drivers, a number of additional datasets were acquired. Land-use data were acquired from the Atlas of Namibia (J Mendelsohn et al. 2002). Biomes distribution was downloaded from the Food and Agricultural Organization Global Forest Resources Assessment. For Namibia, they comprise tropical desert, tropical dry forest, tropical mountain system and tropical shrub land; the latter two being very similar (Simons et al. 2001). Population density data were obtained from the Worldpop, high resolution global gridded dataset at 100 m resolution, which gives an estimation of the number of people per km^2 (Lloyd, Sorichetta, and Tatem 2017). This dataset was classified into four classes, with population densities per pixel ranging from 0-9, 9-53, 53-127, and 127-483 people per 100 × 100 m pixel. The average trends in percentage woody cover were then evaluated for each land-use type, biome and population density class.

5.2.7 Rainfall data

Monthly precipitation was computed using the Climate Prediction Center Morphing technique (CMORPH) dataset, in which precipitation estimates are from satellite-derived passive microwave and infrared data, and available at a resolution of 0.0727° (Joyce et al. 2004). The CMORPH dataset was aggregated to mean annual values and converted to anomalies. To evaluate the correlation between rainfall and modelled woody cover, the CMORPH anomalies time-series was regressed, as the independent variable, against the time series of annual percentage woody cover anomalies. In contrast to NDVI which is highly correlated with precipitation (i.e. NDVI integrates the signal from herbaceous vegetation which responds quickly to precipitation), we expect a low correlation between precipitation with predicted woody cover. This is because wooded regions undergo a pre-rainy season green-up (Fensholt et al. 2012; Nicholson and Entekhabi 1987; Herrmann, Anyamba, and Tucker 2005; Nicholson, Tucker, and Ba 1998; Ryan et al. 2017; Childes 1988).

5.2.8 Modelling woody cover

The Random Forest algorithm was selected since it is effective at estimating predictor variable importance, integrating multiple predictor variables with different predictive power, not ‘over-fitting’ data, not assuming normal statistical data distribution or any particular relation (i.e. exponential) between dependent and independent variables, in addition to being multivariate (Breiman 2001; Moisen and Frescino 2002; Cutler et al. 2007; Prasad, Iverson, and Liaw 2006).

Models were created by taking plot measurements of percent woody cover, with the coincident pixel values of each of the five metrics (Table 5.1), for every year. In other words, the coincident pixel values of each of the five metrics do not correspond to the timing of the field data; rather the field data, which have been aggregated into a single dataset, are related to each annual time-step of satellite data. This resulted in an annual time-series of modelled percentage woody cover for the period from 2001 to 2016.

Phenology metrics were extracted using TIMESAT, which has been extensively used for measuring seasonal land surface phenology in drylands (Jönsson and Eklundh 2004; Horion et al. 2014; Herrmann and Tappan 2013; Fensholt et al. 2012). Three phenological metrics found to comprise an indirect measure of woody canopy cover were selected as model predictors (Table 5.1). They include the dry season index (DSI), described in Brandt et al. (2016) (Brandt, Hiernaux, Rasmussen, et al. 2016), the mean annual dry season values (MeanDS), and the dry season integral (DSINT) defined in Brandt et al. (2016) (Brandt, Hiernaux, Tagesson, et al. 2016). These metrics reduce the confounding effects of herbaceous vegetation on woody vegetation, by taking advantage of the seasonal period when herbaceous vegetation photosynthetic activity and biomass are at their minimum (i.e. the dry season).

In order to test the sensitivity of these metrics to predicting woody cover from field measurements, two phenological metrics known to be related to herbaceous vegetation cover were included in the model. Predictor variable importance metrics were then computed to contrast their effectiveness at predicting observed woody cover. They include, the maximum annual values (MaxWS) taken for each wet season, and the integral of the difference between the function describing the season and the base level from season start to season end or the small seasonal integral (SINT) (Jönsson and Eklundh 2004). Calculation of the SINT used values spanning the start of season (SOS) and end of season (EOS), as described in Jönsson and Eklundh et al. (2004) (Jönsson and Eklundh 2004), where the onset of the rainy season is inferred by assigning a percentage threshold of 20% of the yearly NDVI amplitude value. Although this threshold is well established for the SOS, it should be interpreted with caution for the EOS, since a number of factors are likely to influence this period, for example, wetlands and cropland remaining photosynthetically active longer than the surrounding herbaceous layer, or a particularly wet year may result in vegetation remaining photosynthetic for longer.

Table 5.1. Phenological metrics used in this study, their abbreviation and concise description.

Phenological Metric	Short form	Description
Annual dry season index	DSI	Dry season index, calculated as per Brandt *et al.* (2016)
Mean annual dry season value	MeanDS	The mean annual values taken for the duration of the dry season
Maximum annual wet season value	MaxWS	The maximum annual values taken for each wet season
Annual small seasonal integral	SINT	Integral of the difference between the function describing the season and the base level from season start to season end
Annual dry season integral	DSINT	Dry season integral described in Brandt *et al.* (2016)

5.2.9 Model accuracy and comparison

The paired observed and predicted values were used to compute two accuracy metrics, namely, the Root Mean Squared Error (RMSE) and the coefficient of determination (R^2) (Willmott 1982; Stehman et al. 2012). For the Random Forest algorithm where the output is a continuous response, the pixel-wise prediction represents the average of the model trees. Hence, the individual tree predictions offer the opportunity to compute uncertainty metrics including the coefficient of variation (CV) and standard deviation (SD); a large CV and SD suggests higher variability (L. Zhu and Southworth 2013). Finally, model predictions were compared to the recently published 4,684 sample calibration/validation dataset of percentage tree cover from Bastin *et al*. (2017) (Bastin et al. 2017); each data point consists of a 0.5-ha plot, visually assessed for tree cover percentage using very high resolution imagery. This dataset is assumed to act as a good proxy for percentage woody cover, since interpretation of contemporary high resolution imagery was used and it provides the latest estimate of tree cover in drylands. In addition, we find observed tree cover percentage and observed woody cover percentage, sampled as part of this study, to be highly correlated (r=0.83).

To test the correlation between modelled percentage woody cover and the validation dataset, model predictions were firstly classified into 5% increment classes; the validation dataset was then aggregated and averaged within these classes. The mean values of the validation dataset were regressed with the corresponding values of 5% increment class values, and the R^2 and RMSE computed. This approach aimed to reduce the spread of values from the large number of validation points. No validation has been conducted in the temporal domain due to a lack of long-term field data which would have allowed validating past land cover changes.

5.2.10 Trend analyses

Key aspects surrounding trend estimation from Earth Observation (EO) time-series include temporal and spatial resolution, as well as data quality (Sulkava et al. 2007; Badreldin and Sanchez-Azofeifa 2015). Although trend estimation using linear regression analysis is widely employed, it contravenes several statistical assumptions (Eklundh and Olsson 2003; deBeurs and Henebry 2004). Hence, non-parametric tests which overcome these limitations were applied (i.e. Mann-Kendall and Median Theil Sen trend analyses) (Forkel et al. 2013; deBeurs and Henebry 2004). Furthermore, limitations are incurred by temporally aggregating, for example, to the annual scale, by diminishing temporal resolution. On the other hand, annual aggregation may strengthen trend analysis by eliminating seasonal cycles, which have been found to add seasonal correlation structures and thus augmenting uncertainties (Forkel et al. 2013). In this study, by aggregating NDVI values to average monthly scales, we assume fluctuations due to climate, fire or anthropogenic activity are effectively integrated, permitting the quantification of anomalies, such as deviations from long-term averages, and the strengthening of the signals under investigation, namely that of woody vegetation.

The time-series was first converted to anomalies before applying the trend analysis (Eastman 2009). Subsequently, the statistical significance of the trend was defined by applying a pixel-wise Mann-Kendall trend test to the woody cover time-series. Areas which exhibited no significant trend ($P \geq 0.05$) were masked out and assumed to represent no change. For areas which demonstrated a significant trend ($P \leq 0.05$), the Theil-Sen trend test was applied to the time series. This approach smooths the annual time-series using a linear trend, and is generally recommended for looking at rates of change in noisy or short time-series, since it is robust in identifying trends and insensitive to outliers (Hoaglin, Mosteller, and Tukey 1983). Additionally, it has been extensively used to measure trends in EO time-series (Fensholt et al. 2012; Z. Zhu et al. 2016; Guay et al. 2014; N Andela et al. 2013)..

The percentage woody cover time-series was created with the aim of reducing both inter- and intra-annual fluctuations; however, important inter-annual fluctuations in the percentage woody cover time-series values remained apparent. These can be attributed to a variety of factors, including variable atmospheric and weather conditions, together with changing vegetation phenology. In light of these fluctuations, simply applying an image differencing change detection method to estimate annual change would not be reliable; hence, the Theil-Sen trend slope was used. By multiplying the slope by the number of years, the annual rate of change rate can be computed, thereby providing an estimate of change in percentage woody cover between 2001 and 2016. The resulting annual slope was then spatially aggregated by taking the mean (spatially aggregated mean annual net change) to the country level, land-use types, population density classes and biomes; the mean slope, minimum and maximum change estimates reported. Subsequently, two layers were derived from the significant annual slope image, the percentage woody cover gain (positive slope) and loss (negative slope). Pixel-wise loss and gain were then aggregated (mean values) at the level of the country and land-use types, to estimate gross gain and loss (i.e. loss and gain) (Table 2). All datasets were projected to the WGS_1984_UTM_Zone_33N projected coordinate system, and annual slope values we converted from the MODIS resolution (250 × 250 m) to km^2 (1000 × 1000 m) by multiplying by and expansion factor (1.6), where:

Equation (1)

$$exapnsion\ factor = \frac{100{,}000m^2}{62{,}500m^2}$$

5.2.11 Multi-temporal imagery evaluation

To qualitatively assess what the observed trends represent on the ground, in terms of land cover change, a visual assessment was undertaken using a range of multi-temporal, high resolution scenes, including Google Earth imagery. The assessment aimed to identify direct drivers namely, human driven land-use and land cover change, such as urbanization and deforestation, as well as indirect drivers, including land cover changes driven by a combination of climate and human land-use, such as woody encroachment.

Two classes were created representing areas mapped as either positive or negative trends, with slopes ≥25% (≥-25). 10 randomly sampled points were then generated within each class and subjectively assessed for vegetation changes using Corona satellite imagery (6 feet spatial resolution, 1972), contemporary aerial images (0.5 m, 2010), pan-sharpened Landsat 7 imagery (~15 m, 2000), Sentinel-2 imagery (10 m, 2016) and multi-temporal (time-slider tool) Google Earth imagery.

5.3 Results

5.3.1 Predictor layer importance and model uncertainty

The evaluation of predictor importance yielded a clear pattern: the maximum annual wet season value (MaxWS) and annual small seasonal integral (SINT) were consistently the weakest predictors (expect for the 2007 model, in which the DSINT is the weakest, potentially implying an anomalous year). Predictor importance (2008) is plotted in (Figure 5.3); two measures are used to assess variable importance, including percent increase in Mean Standard Error (MSE) following random permutation, and increase in node purity resulting from all the splits in the forest based on a particular variable, as computed using the gini criterion. Plots for the remaining years (2001-2015) are provided in the supplementary material (Figure 9.6). A plot of CV shows that model uncertainty is higher for the arid coastal and southern regions, where percentage woody cover lower and most likely more variable; where percentage woody cover is high and more stable, a lower CV is identified (Figure 5.3). These results indicate that in areas of lower woody cover, model predictions are the least accurate and should be interpreted with caution.

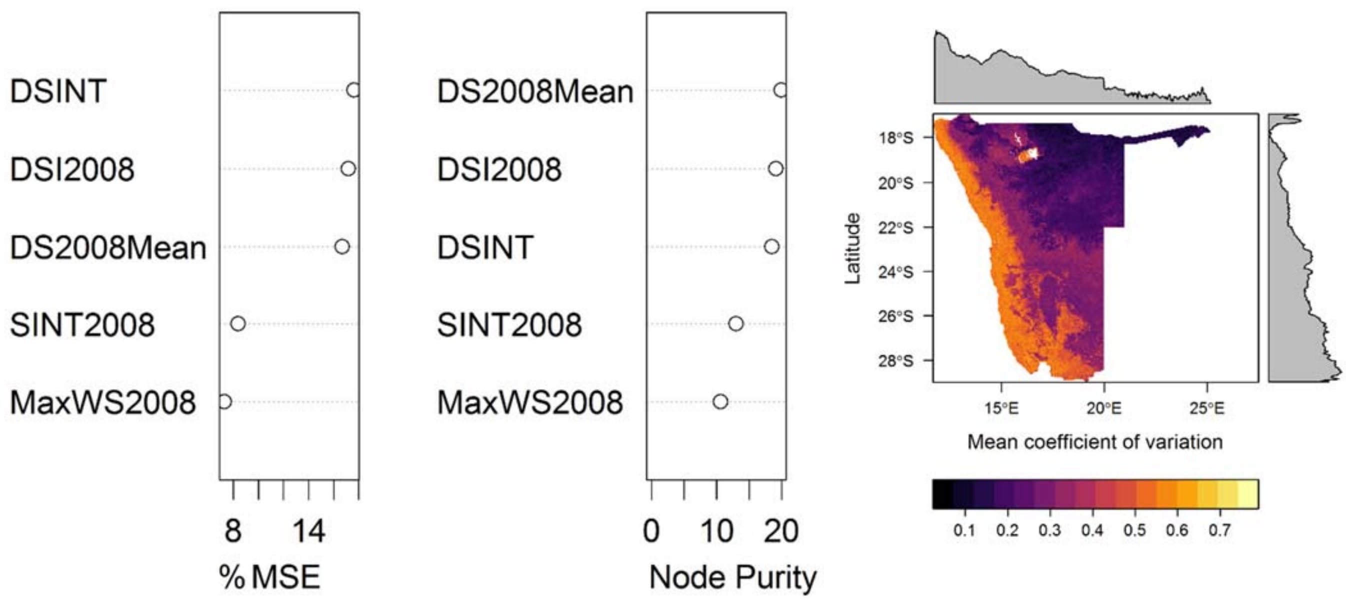

Figure 5.3. Predictor importance (2008) generated using the Random Forest algorithm. Mean coefficient of variation.

5.3.2 Model accuracy and comparison

Moderate correlations were found between observed and predicted (2001-2016) percentage woody cover. Figure 5.4 illustrates the linear relation between observed and predicted (2016) percentage woody cover, yielding an R^2 of 0.47 and an RMSE of 14.47%. Between the 2001 and 2016 models, the R^2 values ranged from 0.4 to 0.5, and the RMSE ranged from 14.14% to 15.43%. Plots for the remaining years are provided in the supplementary material (Figure 9.7).

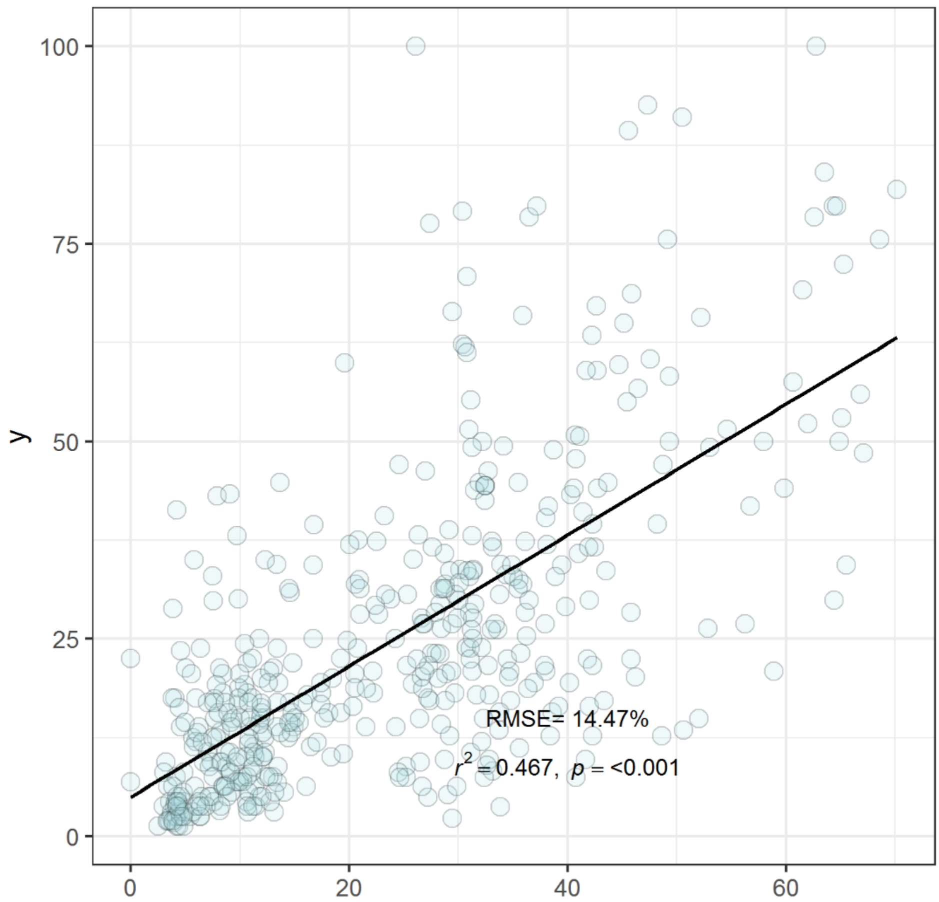

Figure 5.4. Linear relation between observed and predicted (2016) percentage woody cover.

Each annual model prediction was compared to the Bastin *et al.* (2017) percentage tree cover dataset (Bastin et al. 2017). Figure 5.5 illustrates the linear relationship between percentage woody cover at 5% increment classes (2016), and percentage tree cover, yielding an R^2 of 0.77 and an RMSE of 3.94%. Between the 2001 and 2016 models, the R^2 values ranged from 0.13 to 0.96, and the RMSE varied from 3.52% to 4.10%. Plots for the remaining years (2001-2015) are provided in the supplementary material (Figure 9.8).

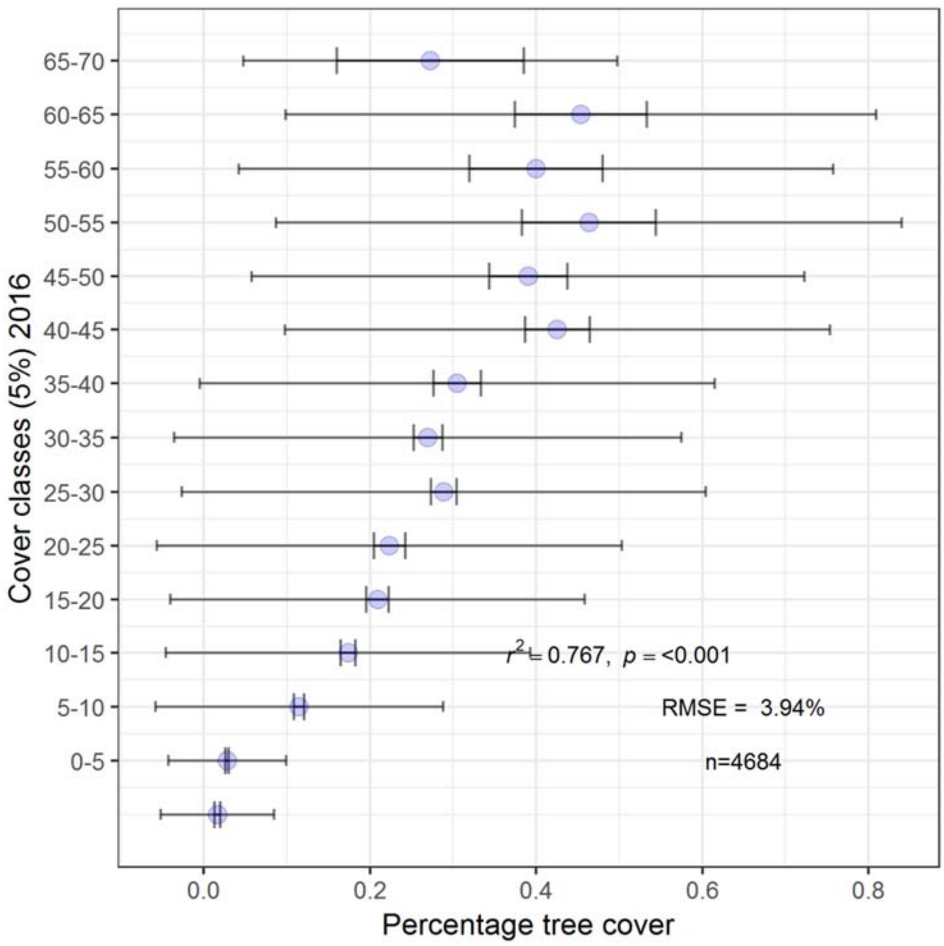

Figure 5.5. Linear relationship between percentage woody cover at 5% increment classes, and percentage tree cover.

5.3.3 Trends in relation land-use, biomes and population

Trend analysis results for Namibia and its constituent land-use classes are presented in Table 5.2. The areal extent of modelled woody cover in 2001 (km^2), the spatially aggregated mean annual net change (i.e. slope [% km^2 yr^{-1}] and minimum and maximum values [% km^2 yr^{-1}], and total change (i.e. loss and gain) (% km^2 yr^{-1}) are shown. The average annual slope for Namibia is negative (-4.38 % km^2 yr^{-1}). In term of land-use types, large-scale communal and urban lands show a positive average annual slope with 8.42 % km^2 yr^{-1}, and 0.37 % km^2 yr^{-1}, respectively. For the remaining land cover types, mean annual slope was negative, suggesting an overall loss of woody cover (Table 5.2).

Table 5.2. Change in woody cover (annual slope) in relation to land-use, estimated using Theil–Sen trend test, of the time series of annual percentage woody cover area. The 2001 percentage woody cover area, Min and max slopes are included. P represented a Mann–Kendall trend test with P < 0.05 used to define statistically significant trends, with a sample size of n = 16 years. Total change in percentage woody cover was estimated pixel-wise using the Theil-Sen trend test, with losses and gains being summed and converted to km^2 to compute total loss and gain.

Percent woody cover area (2001)							
		Mean annual net change				Total change	
Land-use	**Woody cover/km^2**	**Slope/ km^2 yr^{-1}**	**Min/ km^2 yr^{-1}**	**Max/ km^2 yr^{-1}**		**Loss km^2 yr^{-1}**	**Gain km^2 yr^{-1}**
Namibia	774588	-4.38	-4.82	5.42		-303	257
Large-scale communal	354332	8.42	-3.55	4.05		-21	20
Resettlement	5257	-12.59	-3.17	2.42		-21	12
Government agriculture	48697	-8.11	-2.58	3.65		-20	27
Other government	16159	-12.32	-3.07	2.72		-18	6
Urban	6741	0.37	-4.67	5.42		-18	21
State protected	246907	-6.26	-3.58	2.98		-18	15
Small-scale Communal	88852	-14.94	-3.57	3.87		-19	16
Freehold	6982	-7.76	-4.82	4.14		-20	11

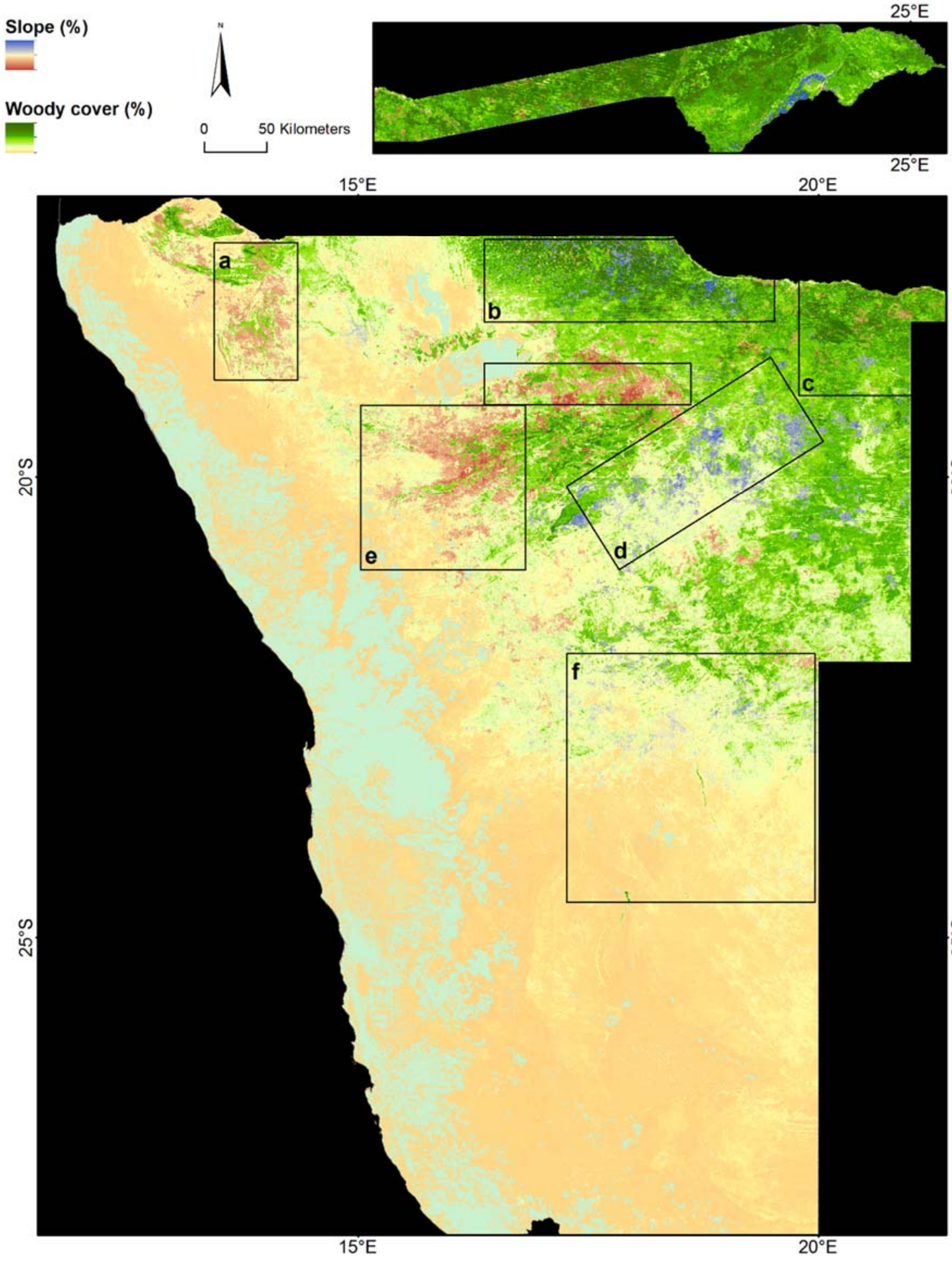

Figure 5.6. Maps the significant positive (negative) Theil-Sen trend slope, including hotspots of change selected for further discussion marked in black rectangles (c-h), overlaid on modelled percentage woody cover for the study area in 2016. Positive trends are shown in blue and negative in red.

Tropical shrub land manifested very minor decline (-0.17 % km^2 yr^{-1}) in woody cover and associated tropical mountain system an increase (3.76 % km^2 yr^{-1}), respectively. The tropical desert biome displayed a pronounced decrease (-4.64 % km^2 yr^{-1}) in woody cover, while the tropical dry forest biome experienced the most striking decline (-7.39 % km^2 yr^{-1}) (Table 5.3).

Table 5.3. Change in woody cover (annual slope) in relation to biomes.

		Mean annual net change			Total change	
Biome	**Woody cover/km^2**	**Slope/ km^2 yr^{-1}**	**Min/ km^2 yr^{-1}**	**Max/ km^2 yr^{-1}**	**Loss km^2 yr^{-1}**	**Gain km^2 yr^{-1}**
Tropical desert	2698569	-4.64	-31.96	36.68	-8.70	1.76
Tropical mountain system	182080	3.76	-25.23	27.43	-8.34	7.59
Tropical shrubland	3421476	-0.17	-48.24	37.50	-11.27	9.58
Tropical dry forest	1432130	-7.39	-46.78	54.29	-12.79	15.31

Most of the country (>99.86%) has a low population density, with between 0-9 people per km^2 (Table 5.4). Areas of "no data" cover a relatively large area (0.11%), while the remaining population density classes (0-9, 9-53, 53-127, 127-483 people per km^2) occupy 0.03% of the remaining land area. The average slope values for each population density class are listed in Table 4. All population density classes show an average negative trend, with the strongest decline being in the middle 9-53, 53-127 classes, (-11.10 % km^2 yr^{-1}, -8.12 % km^2 yr^{-1}, respectively).

Table 5.4. Change in woody cover (annual slope) in relation to population density classes.

		Mean annual net change			Mean annual change	
Population density	**Woody cover/km^2**	**Slope/ km^2 yr^{-1}**	**Min/ km^2 yr^{-1}**	**Max/ km^2 yr^{-1}**	**Loss/ km^2 yr^{-1}**	**Gain/ km^2 yr^{-1}**
NoData	573.42	-3.43	-50.40	69.31	-22.23	24.08
0-9	773104.77	-4.38	-77.18	86.86	-18.93	16.08
9-53	223.32	-11.10	-48.55	7.60	-13.61	3.95
53-127	20.65	-8.12	-23.98	-3.52	-8.12	0.00
127-483	6.74	-4.20	-4.20	-4.20	-4.20	0.00

5.3.4 Trend assessment using multi-temporal imagery

Of the 20 randomly sampled points assessed for each trend slope class (i.e. ≥25% and ≥-25%), two examples exhibiting characteristic land cover changes were selected for further discussion. They include a direct human impact, namely land clearing (shown in Figures 5.7a and 5.7b), and an indirect impact, potentially manifesting as greening (shown in Figures 5.8a and 5.8b). For the remaining randomly sampled points in the ≥25% trend class, no clearly apparent land cover changes could be distinguished, using the available imagery and sampling method.

Figure 5.7. Randomly sampled point for an area exhibiting a significant negative slope (≥-25%), visible as land clearing for small-scale agriculture and indicative of direct land cover change. These are identified using a 1972 Corona image (a) and a 2010 aerial othrophoto (b).

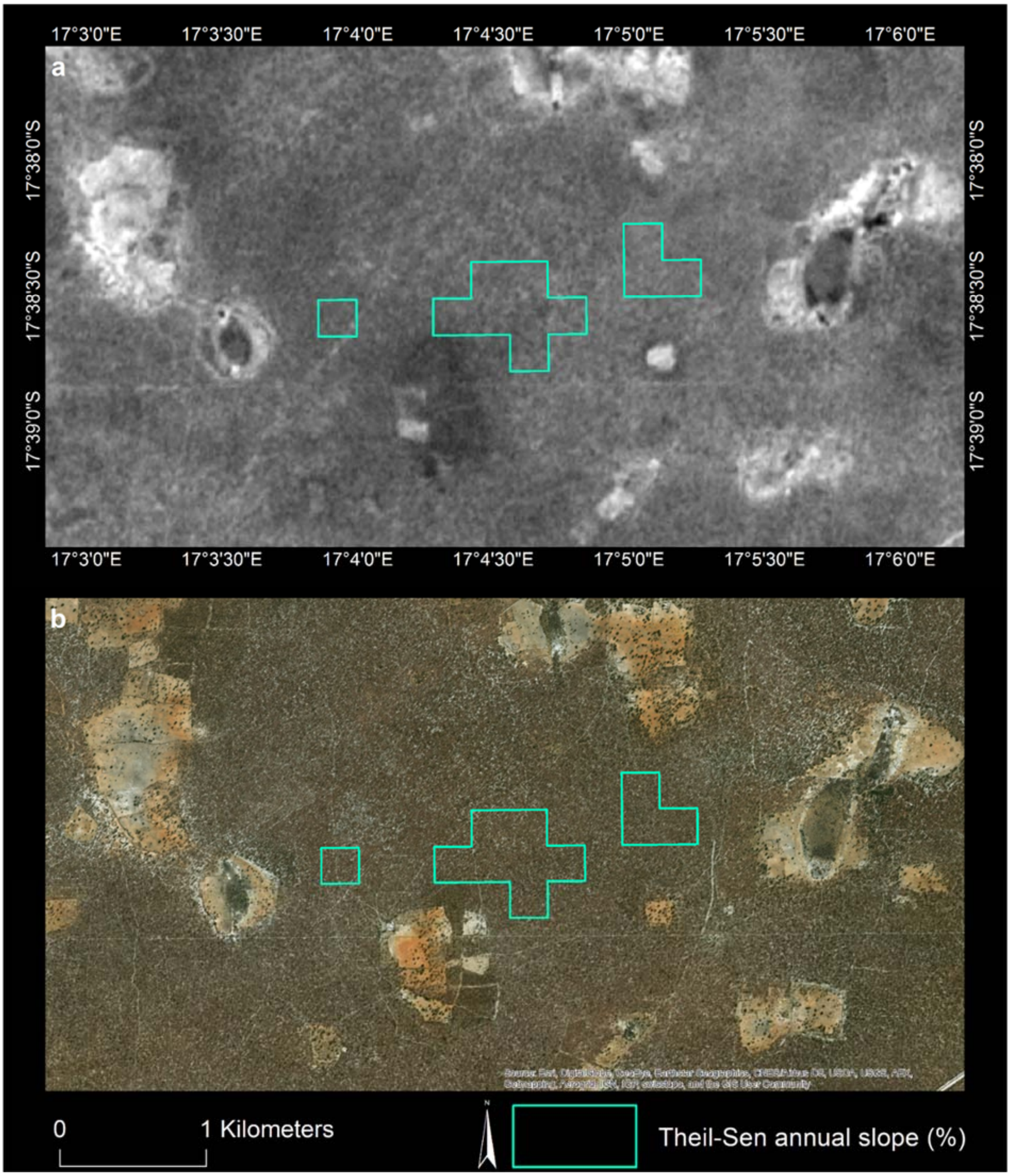

Figure 5.8. Randomly sampled point for an area exhibiting a significant positive slope(≥25%); no apparent change can be identified from a 1972 Corona image (a) and a 2010 aerial othrophoto (b). Results may be indicative of indirect change.

5.3.5 Trends in relation to precipitation

The linear regression between mean annual precipitation anomalies (independent) and annual percentage woody cover anomalies (dependent), reveals that the majority of R^2 values are low, signifying no significant linear relationship. The result implies that anomalies in precipitation are not coupled with those of percentage woody cover for most of the country, except along the western escarpment (Figure 9.9).

5.4 Discussion

5.4.1 Trends in relation to biomes

Globally, arid and semi-arid (desert) biomes have recently been found to exhibit large decreases in short vegetation (≤5 m in height) and important increases in bare ground, with both trends pointing to long-term land degradation; simultaneously, the world's tropical shrub land biome is reported to have experienced a considerable areal increase in short vegetation and a concurrent bare ground loss, and these results are postulated to be the result of woody encroachment (Song et al. 2018). In contrast, the tropical dry forest biome is found to have undergone significant levels of deforestation (Song et al. 2018). When evaluating the results from Song et al. (2018) for Namibia only, an overall greening trend from 1982 to 2016 can be identified. On average for each FAO biome, a decrease in bare ground and a simultaneous increase and short vegetation can be noted, while a gain in tree canopy is seen across the tropical dry forest biome. Our results differ in that we identify an overall browning trend with an average slope of -4.38 km^2 yr^{-1}, with an especially marked decrease in woody cover across the tropical dry forest biome (-7.39 km^2 yr^{-1}). These contrasting results may be due to the different spatial (0.05° × 0.05° compared to 250 m × 250 m) and temporal (1982-2016 compared to 2001-2017) scales of the studies. Importantly, they serve to highlight how these two factors can lead to substantially differing results when analysing EO time-series.

Of the four biomes which Namibia encompasses, large parts of the country are desert (38.45%), shrub land (including mountain system) (43.74%) and dry forest (17.81%) (Simons et al. 2001). Tropical shrub land showed only a very small decline in woody cover (-0.17 % km^2 yr^{-1}), and the closely related tropical mountain system an increase (3.76 % km^2 yr^{-1}), indicating overall woody encroachment. In contrast, the tropical desert biome showed a marked decline (-4.64 % km^2 yr^{-1}) in woody cover, suggesting long-term land degradation. Lastly, the tropical dry forest biome experienced the most pronounced decline in woody cover (-7.39 % km^2 yr^{-1}), pointing to extensive deforestation (Table 5.3).

Overall, our results point to the occurrence of contrasting land cover change processes, with both gains and loss in woody cover. We find that woody cover loss is associated with the more humid areas (tropical dry forest) and is therefore potentially the result of deforestation/forest degradation , which has been shown to be taking place (V. Wingate et al. 2016; V. R. Wingate et al. 2018). The desert biome also exhibited a woody cover loss; such losses in arid biomes are often associated with desertification and land degradation (Song et al. 2018b). In contrast, the tropical shrub land and mountain biomes demonstrated an increase woody cover suggesting greening and in turn shrub encroachment (Saha, Scanlon, and D'odorico 2015). Our results mirror those recently publish by Brandt et al. (2017); in their pan-African study on trends in woody cover, the authors found that negative trends were preferentially associated with humid, high biomass forest biomes, while positive trends were mostly found across drylands, except very hot xeric ecoregions or tropical deserts (Brandt et al. 2017).

5.4.2 Trends in relation to land-use and population

The overall positive trend in percentage woody cover (8.42 % km^2 yr^{-1}) identified for large-scale agriculture on communal land agrees with previous studies, in that a high density of encroacher species, at early growing stages, were identified in these regions (De Klerk 2004a). However, they may also result from other land management practices, such as agro-forestry and large-scale fencing of commonage, which are known to cause an overall increase in woody and herbaceous vegetation (John Mendelsohn and el Obeid 2002b). However, this result is also unexpected, since the land-use type has been shown to be experiencing substantial land clearing for cropping and ranching (V. Wingate et al. 2016; V. R. Wingate et al. 2018). The limited increasing trend (0.37 % km^2 yr^{-1}) observed for urban land areas is again unexpected, since rapid urbanization, associated with vegetation cover losses, is occurring throughout Namibia (V. Wingate et al. 2016).

A decrease of -14.94 % km^2 yr^{-1} in woody cover is identified across small-scale agriculture on communal land; while a similar loss of -12.59 % km^2 yr^{-1} can be noted on resettlement land. This trend is most likely the result of widespread vegetation clearing for small-scale cropping and ranching (John Mendelsohn and el Obeid 2002a; V. Wingate et al. 2016). Importantly, it is likely that as a consequence of the moderate spatial resolution of MODIS, much of the small-scale deforestation is being concealed; in fact its resolution has been shown to hide up to 50% of small-scale deforestation (Anderson et al. 2005; Hammer, Kraft, and Wheeler 2014; Matthew C. Hansen and Loveland 2012). The negative trend identified across protected areas (-6.26 % km^2 yr^{-1}) is unexpected, since conservation efforts in Namibia, especially in the Kalahari woodland ecoregion, focus on the preservation of woodlands and forests (John Mendelsohn and el Obeid 2005b). However, long-term fire-scar monitoring studies throughout the northern regions of the country, where much of the conservation areas are found, identify increasing fire frequencies. More frequent fires are associated with a decrease in tree stem diameters, densities and species diversity, and is potentially being driven by more intensive land management ('Ministry of Agriculture, Water and Forestry. 2017. Monthly Burned Area Report, August 2017' 2017; Sankaran, Ratnam, and Hanan 2008; De Cauwer et al. 2016; John Mendelsohn and el Obeid 2005b) (Table 5.2).

An important environmental and socio-economic question for much of northern Namibia and neighboring countries is the expansion of small-scale arable cropping into marginal land (Pröpper et al. 2010). The primary reason for this expansion is the demand for farm land due to population growth; in addition, the on-going land reform is introducing land privatization and hence important changes in land-use on commonages, for instance, large-scale fencing (John Mendelsohn and el Obeid 2005b). Furthermore, since the end of the civil war in 1990, the region has undergone important infrastructural developments, with new roads connecting much of the north and neighboring countries, together with the establishment of water and power infrastructure. These have greatly facilitated access to and settlement of remote regions, promoting the expansion of new farmsteads and villages. The greater need for arable land and the consequent heightened pressure on it for the extraction of natural resources such as timber, lead to a reduction in woody cover (Pröpper et al. 2010; Röder et al. 2015; Anne Schneibel et al. 2017; A Schneibel et al. 2013; V. Wingate et al. 2016; De Cauwer et al. 2016).

Across agriculture and tourism on freehold land, the negative trends observed (-7.76 % km^2 yr^{-1}) may be the result of encroacher shrub control (De Klerk 2004a). This land management activity is widely implemented on commercial farm land in order to favor herbaceous vegetation growth which supports livestock production (John Mendelsohn and el Obeid 2005c) (Table 5.2).

The 9-53, 53-127 population density classes exhibited the largest declines in woody cover (-11.10 % km^2 yr^{-1}, -8.12 % km^2 yr^{-1}, respectively), suggesting densely populated regions are responsible for most land cover changes associated with decreases in woody vegetation cover. Table 5.4 shows the mean trend values for each population density class as being largely negative, indicating that overall, decreases in woody cover occur across population density classes, and implying that population density may have a role in explaining the observed trends.

5.4.3 Trend assessment using multi-temporal imagery

Qualitative analysis of historical and contemporary high resolution imagery, using a random sample of ten points distributed in areas with slopes ≥25% (≤-25%), enabled the observed trends to be interpreted as specific land cover changes. In particular, negative trends were chiefly identified as a general reduction in vegetation cover, together with a concurrent increase in bare ground cover, vehicle tracks and farm plots, thereby indicating a direct human impact (Figure 5.7a and b). However, when evaluating areas exhibiting positive trends, land cover changes were harder to conclusively identify. For instance, no apparent change can be seen in Figures 5.8a and 5.8b, yet this area was mapped as having undergone a significant positive trend. These results suggest the occurrence of indirect impacts manifesting gradually; as such they may comprise increases in vegetation density.

5.4.4 Trends in relation to precipitation

Low R^2 values, resulting from the linear regression between percentage woody vegetation cover anomalies and precipitation anomalies, are seen across much of the country. The of cause of this may be that much of the country's densely wooded areas are photosynthetically active before the on-set of the rainy season i.e. pre-rainfall leaf flush (Childes 1988; Ryan et al. 2017). In other words, anomalies in NDVI and hence woody vegetation cover, were anticipated to occur independently of anomalies in precipitation. Hence, from the un-coupled relationship observed between both variables, we may conclude that the model is, to a certain extent, effective at predicting woody cover, with the low R^2 supporting the effectiveness of using dry season phenological metrics to predicted woody cover. Finally, the high R^2 values observed throughout a portion of the western escarpment region may be a response specific to vegetation communities or species avoiding drought by not leafing-out in dry years, such as the widespread *Senegalia reficiens* (pers. comm. C. van der Waal, 2017).

5.4.5 Regional hotspots

Namibia is comparatively heterogeneous in terms of eco-floristic regions and climate and consequently land-use, due to the pronounced altitudinal and climatic gradients (John Mendelsohn and el Obeid 2005c). Large parts of the south and western coast of the country are hyper-arid to arid and have very low woody vegetation cover, which may help explain why little or no significant trends were identified here. In these regions the land is mainly used for extensive grazing with little or no cropping being practiced due to the extreme aridity (J Mendelsohn et al. 2002). Figure 5.6, which illustrates significant trends in woody cover across Namibia, suggests that there are important differences in the spatial pattern of trends across the country; based on this observation, six areas were qualitatively selected for further discussion (Figures 5.6a to f).

The Kaokoland region (Figure 5.6a) exhibits important negative trends in woody cover; this region is primarily composed of mopane woodland which are often used as coppice stands harvested for building material. Being sparsely populated during the civil war, the mopane woodland in this region is thought to have widely regenerated and may now be extensively utilized (John Mendelsohn and el Obeid 2005c).

The Ohangwena and Kavango West border regions (Figure 5.6b) display significant positive trends; these findings are somewhat unexpected, since the area is known to be experiencing small-scale deforestation for urbanization and rain-fed crop farming (V. Wingate et al. 2016). However, evidence suggests shrub encroachment is also occurring in these areas, potentially contributing to explaining the observed greening trends (De Klerk 2004b; Erkkilä, A 2001). Further, the moderate spatial resolution of MODIS is probably masking small-scale deforestation which is likely to be co-occurring adjacent to greening trends.

In the Kavango East region (Figure 5.6c), a spatially heterogeneous pattern of trends can be observed, with negative trends predominating. Increasing fire frequency is the likely cause of this, as demonstrated by the long-term Namibian fire monitoring data ('Ministry of Agriculture, Water and Forestry. 2017. Monthly Burned Area Report, August 2017' 2017). These data agree with a recent study demonstrating regional increasing fire activity (Niels Andela et al. 2017).

Figure 5.6d highlights widespread positive trends; this area comprises both large and small-scale agriculture on communal land in the southeastern portion of the rectangle, as well as agriculture and tourism on freehold land on the north-western side. Despite the different land-uses present within the demarcated area, a very homogeneous trend is observed, possibly suggesting widespread encroachment by *Senegalia mellifera* and *Dichrostachys cinerea* occurring across land-use types (De Klerk 2004b).

Important negative trends in woody cover were identified across the region south of Etosha National Park (Figure 5.6e). These may be the result of several consecutive low rainfall years and a high density of elephants (*Loxodonta africana*), which in combination led to a net decline in woody cover (de Beer et al. 2006). The central eastern area (Figure 5.6f) which comprises freehold land again reveals widespread positive trends, pointing to the occurrence of shrub encroachment by *Senegalia mellifera* (De Klerk 2004b).

5.4.6 Trend analysis

Recent studies find a greening trend in satellite-derived vegetation proxies across southern Africa; however, interpreting these trends in terms of ecologically meaningful, measureable and identifiable vegetation properties, for instance, in terms of plant functional type, is often problematic (Song et al. 2018; Saha, Scanlon, and D'odorico 2015; Brandt et al. 2015; Z. Zhu et al. 2016). We find woody cover has decreased overall and several recent studies corroborate these findings; for example, decreases in NPP were identified in the adjacent Okavango, Kwando and upper Zambezi catchment areas over a 29-year period using MODIS (L. Zhu and Southworth 2013). Similarly, Andela et al. (2017) find an increasing trend in fire activity across much of the north east of the country which implies less woody cover (Sankaran, Ratnam, and Hanan 2008; De Cauwer et al. 2016; Niels Andela et al. 2017). These results stand in contrast to those of Tian et al. (2016) (Tian et al. 2016), who identify increases in woody density across southern Africa, and Fensholt et al. (2012) (Fensholt et al. 2012) who identify greening trends. However, both these studies rely on coarse spatial resolution data (i.e. 0.25°, 8 km and 0.05°× 0.05°, respectively) and cover different time periods (2000-201 and 1981-2007, respectively). Furthermore, they do not provide country-specific change statistics, but only regional approximations.

The south-north and west-east gradient of increasing percentage woody cover reflects the different eco-floristic regions (Figure 5.6). Northern regions consist of Kalahari and mopane woodlands, whereas the southern regions are made up of grass and shrub land, which exhibit lower woody cover densities (J Mendelsohn et al. 2002; John Mendelsohn and el Obeid 2005b). The overall decline in woody vegetation cover is therefore likely to be occurring in the north of the country, and be associated with declining tree and shrub stem numbers; these variables are related to aboveground biomass, as well as foliar and canopy density (Asner et al. 2003; Asner and Heidebrecht 2005; Asner and Lobell 2000). In effect, Wingate *et al.* (2018) identified a net loss of aboveground woody biomass for the northern Kalahari ecoregion (V. R. Wingate et al. 2018). Based on our results, we may conclude that decreases in vegetation biomass associated with woody vegetation are also taking place, especially in the desert and tropical dry forest biomes; however, since the approach used does not permit the direct estimation of change in carbon stocks, a precise inventory of loss and gains cannot be undertaken. Several anthropogenic and biophysical factors are known to drive decreases in woody cover. In particular, they include long-term changes in precipitation patterns, disturbances resulting from cattle grazing, high densities of browsers, fires, timber extraction and land clearing (Sankaran, Ratnam, and Hanan 2008; Sankaran et al. 2005; De Cauwer et al. 2016).

Gains in woody cover are thought to be driven by factors including reforestation, conservation land management activities and raising atmospheric CO_2 concentrations, which under certain conditions have been found to favor C3 plants over C4, and the interaction of these factor presumably leading to shrub encroachment (Donohue et al. 2013; John Mendelsohn and el Obeid 2005a; Saha, Scanlon, and D'odorico 2015). Finally, most of the study area (92.2%) exhibits no significant trends, which agrees with several long-term studies demonstrating vegetation to be remarkably stable in the region (O'Connor, Puttick, and Hoffman 2014; Buitenwerf et al. 2012; Rohde and Hoffman 2012).

5.4.7 Model accuracy and limitations

Both predictor layers MaxWS and SINT are proxies for herbaceous vegetation; their low ranking is indicative of the higher correlation between field measurements of woody cover and phenological metrics characterizing woody vegetation. Similarly, when model predictions are compared to percentage tree cover, an increasing spread of values can be noted in the higher predicted percentage woody cover classes, as indicated by the black standard error bars (Figure 5.5) (Bastin et al. 2017). The low RMSE error observed suggests both datasets show a moderately good agreement, in spite of the fact that the datasets measure distinct variables using different methodologies, which makes their comparison prone to a multitude of confounding factors. Low R^2 values are the result of single outliers (percentage tree cover) within woody cover classes.

The low R^2 found when comparing observed and predicted values result from several limitations related to the phenological metrics, field measurements and nature of the savanna system. Limitations associated with the phenological metrics include, pixel resolution, spectral limitations, the use of monthly averages causing the lose of the full suite of variation in NDVI values, and the temporal mismatch between the field observations and the coincident pixel phenological metric values (John Mendelsohn and el Obeid 2005a). Limitations associated with field measurements include, the different sample sizes (e.g. 100 point observations per site for the 2012 and 2014 datasets, compared to 160 point for the 2016 dataset); date of field data collection (i.e. 2012, 2014, 2016); and a modified methodology adopted for the samples collected in 2016. Moreover, the small field plot size may not be adequately representative at the spatial resolution of the MODIS data, and similarly, the field sample sites may not be sufficiently representative of the variability within predictor metrics (i.e. more variability within a pixel that between pixels) (Baccini et al. 2007). The seasonal phenological cycles of woody and herbaceous vegetation in response to precipitation and temperature cues, results in a variable NDVI signal for any given period. This causes the computed phenological metrics to vary annually, in relation to the static field plot estimates. Furthermore, management actions, such as grazing and fire are likely to have impacted both the sample sites and the coincident pixel values of each metric. In particular, fire scars, which are often extensive, cause the NDVI signal to fluctuate importantly and hence affect the phenological metrics. Fire is an important factor shaping vegetation structure and composition across Namibia, with certain areas routinely experiencing grass fires during the on-set of the dry season (John Mendelsohn and el Obeid 2005c). Lastly, the diverse vegetation characteristics, including species composition and structure, encompassed within the field sites used for model calibration, are likely to not be fully representative of the overall local to regional vegetation characteristics, resulting in decreased model accuracy (Carreiras, Vasconcelos, and Lucas 2012; V. R. Wingate et al. 2018). These may include for example, among other biotopes, wetlands and floodplains which are ephemerally submerged in water, and where herbaceous perennial plants can remain green for longer periods (Hüttich et al. 2011).

Several additional limitations are are likely to have introduced inaccuracies into the modelling of woody cover. For instance, NDVI is well correlated with vegetation chlorophyll content, leaf color, vegetation density and depth, soil color and moisture, as well as being a good indicator of NPP in drylands. However, it is limited by effects of soil and senesced vegetation background and signal saturation at high biomass levels, while in addition not being directly correlated with woody cover (Sellers et al. 1992; Asrar et al. 1984; Prince 1991; Pettorelli et al. 2005). Furthermore, savanna biomes are often characterized by several vegetation strata, ranging from tall tree canopies to shrub and herbaceous layers, all of which exhibit distinct phenophases (E. N. Chidumayo 2001). Taken together, this variability in these factors contributes to impacting the regularity and rigorousness of the phenological metrics extracted.

5.5 Conclusion

This study provides a new estimate of change in woody cover across Namibia. Annual maps were created based on contemporary field measurements and MODIS NDVI metrics aimed at enhancing the distinct phenophases of woody and herbaceous vegetation. The resulting time-series was used to map trends in woody cover, which are excellent indicators of vegetation changes, including shrub encroachment and deforestation. The annual rate, trajectory and spatial extent of change was evaluated in relation to potential drivers, including biomes, land-use, population density and precipitation.

On average, a loss of woody cover was identified; specifically, the desert and tropical dry forest biomes displayed a marked decline in woody cover, pointing to long-term land degradation, and deforestation/forest degradation, respectively. In contrast, tropical shrub lands demonstrated increases in woody cover, suggestive of woody encroachment. These results reflect those of a recent pan-African study on trends in woody cover (Brandt et al. 2017). Here, we identify contrasting change processes, where woody cover loss is associated with more humid areas (tropical dry forest), and very arid areas (tropical desert), while woody cover gain predominated across the intervening tropical shrub lands.

Certain land-uses exhibited pronounced declines, notably protected areas; here these changes may be due to woody vegetation die-back caused by large herbivores and below average rainfall. Similarly, a negative trend was identified in resettlement and small-scale communal agricultural land, and is likely the result of increases in urbanization, deforestation and fire frequency; similarly, a negative trend on freehold might be the result of encroacher shrub control. Greening trends across large-scale agriculture on communal land could be indicative of shrub encroachment, agro-forestry and fencing causing decreased grazing intensity. Importantly, no significant trends in woody cover were found across most of the country.

Qualitative high resolution image interpretation allowed the nature of observed land cover changes to be evaluated; in particular, our trend analysis effectively captured direct human impacts such as land clearing. However, greening could not be conclusively identified using available imagery, and is probably the result of indirect impacts. Lastly, trends in woody cover and trends in precipitation are unrelated for most of the study area; their un-coupled relationship supports the validity of using metrics which enhance the distinct phenophases of woody and herbaceous vegetation. Our results point to a landscape substantially affected by direct human impacts, resulting from the expansion of agriculture and urbanization, but also from indirect impacts, manifesting as long-term gradual vegetation changes. Moreover, distinct change processes prevails across different biomes. Both instances have important implications for the provision of long-term ecosystem services, and evaluating the response of biomes with large proportion of C4 species to changing atmospheric CO_2 concentrations.

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Chapter 6

Contemporary trends in NDVI and precipitation: mapping anthropogenic vegetation change processes

6 Mapping precipitation-corrected NDVI trends across Namibia

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Abstract

Savannas comprise a major component of the Earth system and contribute ecosystem services and functions essential to human livelihoods. Monitoring spatial and temporal trends in savanna vegetation and understanding change drivers is therefore crucial. Widespread greening has been identified across southern Africa; yet its drivers and manifestations on the ground remain ambiguous. This study removes the effects of precipitation on an NDVI time-series, thereby identifying trends not driven by rainfall. It utilizes the significant correlation between vegetation and precipitation as captured using MODIS and rainfall estimates. A linear regression between variables was used to derive its residual (corrected) time-series, and the rate and spatial extent of trends were evaluated in relation to biomes. A random sample-based qualitative interpretation of high spatial resolution imagery was then used to evaluate the nature of the trend on the ground. 2.88% of the country, including all biomes exhibited positive trends. We propose that greening may be related to a reduction in woody species richness, loss of the large trees and a shift towards drought tolerant shrub species, as has been shown in other sub-Saharan environments. 0.88% of the country exhibited negative trends, which were mostly associated with more humid (forested) regions pointing to deforestation as a cause; these manifested as vegetation clearing, identifiable using high resolution multi-temporal imagery. Greening trends could not be identified using this approach; instead, they point to the occurrence of gradual vegetation change caused by indirect drivers.

6.1 Introduction

Land cover change is increasingly impacting Earth system processes, from biodiversity, the carbon and water cycles, to the global surface energy balance and ultimately, climate (Turner, Lambin, and Reenberg 2007; Foley 2005; Le Quéré et al. 2017; Alkama and Cescatti 2016; Duveiller, Hooker, and Cescatti 2018). Recent land-use intensification and climate changes have caused widespread vegetation structural and functional shifts in savannas, which are highly sensitive to both precipitation and anthropogenic disturbances (Adeel et al. 2005). Savannas are characterised by the co-occurrence of woody (trees and shrubs) and herbaceous (grasses and forbes) vegetation and provide key ecosystem services and functions locally and globally, from forest and forage resources to the regulation of carbon and hydrological cycles, as well as the Earth's surface energy balance. For instance, savannas in the southern hemisphere are a major carbon sink (Adeel et al. 2005; Poulter et al. 2014; Scheffer et al. 2001; Liu et al. 2015), and African savannas, which cover 36% of the continent, contribute significantly to the carbon cycle (Poulter et al. 2014; Ahlström et al. 2015; Liu et al. 2015), being responsible for 14% of global Net Primary Productivity (NPP) (Grace et al. 2006). Moreover, African savannas are of great agricultural, economic and environmental importance to a large part of the continent's rural population, who comprise a substantial proportion of the continent's total (Jacquin, Sheeren, and Lacombe 2010; Fensholt et al. 2013; Pettorelli et al. 2017). Thus, any change in savanna vegetation is likely to have a large impact on social and ecosystem processes. Yet important uncertainties remain concerning the role of African savanna vegetation in these processes, as well as the extent and drivers of its change. For instance, recent studies find widespread greening in dryland areas, the carbon sequestration effects of which are potentially being offset by important deforestation in humid regions (Ciais et al. 2009; Hansen et al. 2013; Brandt et al. 2017; Saha, Scanlon, and D'odorico 2015).

Against this background, vegetation change in southern African savannas takes two principal forms. Firstly, the persistent disappearance of all vegetation (i.e. deforestation and desertification), and secondly, a shift towards a woodier condition where herbaceous vegetation layers are replaced with hardy, often unpalatable shrub species (i.e. shrub encroachment) (Hudak and Wessman 1998; David Ward et al. 2000; Erkkilä 2001; Mendelsohn and el Obeid 2005a; D Ward 2005; Mitchard and Flintrop 2013; Tian et al. 2016; Wingate et al. 2016). Both these processes are widespread and result in a new equilibrium state with a modification of ecosystem service provision, processes, functions and biodiversity

(Anyamba and Tucker 2005; Olsson, Eklundh, and Ardö 2005; Saha, Scanlon, and D'odorico 2015). Although findings are often nuanced for shrub encroachment, it has generally been observed that both processes exacerbate soil erosion, reduce land productivity, animal and plant diversity including valuable forage species (Briggs et al. 2005; Scholes and Archer 1997).

Change processes are generally attributed either to direct human activities or indirect drivers, such as climate change (Song et al. 2018). For instance, deforestation is most often the result of direct human activities, including urbanization and land-use intensification. Others drivers remain poorly understood and can often be attributed to indirect causes, for example, those responsible for shrub encroachment (S. Archer, Schimel, and Holland 1995; Hudak and Wessman 1998; Fensham, Fairfax, and Archer 2005; D Ward 2005; Mitchard and Flintrop 2013; Caviezel et al. 2014; O'Connor, Puttick, and Hoffman 2014; Adeel et al. 2005). They include, shifts in fire activity (Bond and Midgley 2000; Bowman, Murphy, and Banfai 2010), overstocking and the removal of browsers and the herbaceous layer (Asner et al. 2004; D Ward 2005), long-term rainfall changes and climate changes (Fensham, Fairfax, and Archer 2005), and the interaction and synergy between these (D Ward 2005). Lastly, rising atmospheric carbon dioxide concentrations have been shown to cause a shift away from the predominance of recently evolved C4 grasses, adapted to low CO_2 and found extensively in savannas, to the older C3 shrubs and trees (Bond and Midgley 2000; Donohue et al. 2013).

Satellite remote sensing has proved invaluable for quantifying environmental change and identifying its drivers, over the last five decades. In particular, the available moderate to high resolution sensors, including MODIS, Landsat and Sentinel-2, continuously provide synoptic measurements at spatial and temporal scales which allow the quantitative detection of land cover changes processes (Coppin et al. 2004; Singh 1989; Drusch et al. 2012). Satellite-derived spectral vegetation "greenness" indices such as the Normalized Difference Vegetation Index (NDVI), are fundamental tools for monitoring trends in global vegetation cover and condition (Myneni et al. 1995; Olsson, Eklundh, and Ardö 2005). In addition, a number of rainfall data sets have been providing consistent daily precipitation estimates over the past three decades, including the Tropical Applications of Meteorology using SATellite data and ground-based observations Research Group (TAMSAT). It is based on Meteosat thermal-infrared (TIR) observations across Africa, and yields estimates comparable to analogous remotely sensed precipitation datasets (Maidment et al. 2014). Studies integrating multi-data sources, for instance, NDVI and rainfall among others, provide key insights into regional vegetation shifts resulting from climatic and human drivers, and are fundamental tools for studying their temporal and spatial relationship (Herrmann, Anyamba, and Tucker 2005; S. E. Nicholson, Tucker, and Ba 1998). Specifically, they have contributed towards addressing questions pertaining to NPP, carbon sequestration, and ecosystem responses to climatic shifts and anthropogenic disturbances (C. Tucker et al. 1983; Anyamba and Tucker 2005; Archibald and Scholes 2007; Donohue, McVicar, and Roderick 2009; Andela, Liu, van Dijk, et al. 2013; Fensholt et al. 2006, 2012).

NDVI consists of the spectral reflectances from the normalized ratio of the near-infrared (NIR) and red bands. It is used as a proxy for vegetation "greenness", cover, biomass and gross primary productivity (Pettorelli et al. 2005). However, several constraints are associated with NDVI for vegetation mapping generally, including: illumination and observation geometry, soil background effects in areas with exposed soil, atmospheric noise, a non-linear response at low and high vegetation density levels. Further issues arise in multi-layer canopies due to the different phenologies of understory vegetation strata, for instance grasses (herbaceous) and canopy trees (woody), and are of particular concern in savannas (E. N. Chidumayo 2001; Soudani et al. 2012). These limitations become apparent when attempting to quantify vegetation changes in savannas, and arise primarily as a result of the spatially and temporally patchy nature of tree, shrub and herbaceous vegetation together with their stratification. Indeed, savanna vegetation composition often ranges from open grassland and shrub land to woodland and forest (Scholes and Archer 1997; Asner and Lobell 2000; Herold et al. 2008); moreover, it typically exhibits high inter- and intra-annual variability in response to climate, fire and anthropogenic land-use - herbaceous vegetation in particular. Collectively, these factors render change detection using NDVI in savannas more complex than for forests with closed canopies (Donohue, McVicar, and Roderick 2009; Z. Zhu et al. 2016). For instance, NDVI measures vegetation "greenness", but does not distinguish between vegetation functional types; hence, shifts from herbaceous to woody vegetation, such as would be expected from shrub encroachment, may not be directly measured using NDVI. In other words, changes in vegetation composition, where the "greenness" signal characteristics do not change, may be concealed (Brandt et al. 2016; Horion et al. 2014). Thus, a degradation process which is not characterized by decreases, but instead by increases in "greenness", such as shrub encroachment, may exhibit positive trends in NDVI. Lastly, several methods have been proposed to distinguish between different vegetation functional types and density characteristics, including NDVI signal amplitude (Wagenseil and Samimi 2006; Olsson, Eklundh, and Ardö 2005).

The availability of water and precipitation, often highly variable both seasonally and inter-annually, are the main controls on vegetation structure, composition and distribution in savannas; thus, precipitation greatly impacts the amount of vegetation present in any given year. In effect, the dynamics of savanna vegetation in relation to precipitation have been monitored at continental scales, and were found to be sensitive to climatic fluctuations within relatively short time scales (i.e. months) (Scanlon et al. 2002). Across most of the African continent, inter-annual fluctuations in rainfall were found to not often trigger much variability in NDVI (Goward and Prince 1995; Fuller and Prince 1996). Yet, in some regions a strong relationship between rainfall and NDVI has been identified. In particular, over much of southern Africa and in so called "marginal zones" found between areas of high and low annual rainfall, several authors identify a strong response of NDVI to inter-annual precipitation fluctuations (Goward and Prince 1995). This response is presumed to result from the relative proportions of woody and herbaceous vegetation in these zones; these areas encompass the bulk of the study area, hence the NDVI signal is expected to show a strong correlation with rainfall (Goward and Prince 1995; Herrmann, Anyamba, and Tucker 2005).

In the Sahel region in particular, the correlation between precipitation and vegetation has been extensively studied (S. E. Nicholson 2001; Fensholt et al. 2012; Brandt et al. 2015). For example, NDVI was found to be increasing in line with rainfall for part of the Sahel between 1982 and 1999 (Eklundh and Olsson 2003). Several studies have used models to investigate the effects of precipitation on vegetation proxies (Andela, Liu, Van Dijk, et al. 2013; Tian et al. 2016). For instance, a linear relationship was identified between NDVI and precipitation in the Sahel in areas where rainfall reached 1000 mm per year; this relationship was log-linear for large parts of eastern Africa with similar annual rainfall regimes (S. E. Nicholson, Davenport, and Malo 1990). Further, the observed relationship was often significant enough to use NDVI as a proxy for variations in precipitation (C. J. Tucker and Nicholson 1999). In Botswana, which has a similar climate and vegetation composition to Namibia, a linear relationship between NDVI and precipitation for regions with less than 500 mm of rainfall per year was identified. Above this threshold, a "saturation" response could be established with a much reduced rate of NDVI increase (S. Nicholson and Farrar 1994). In southern Africa, several studies have focused on the interconnections between NDVI and rainfall estimates, to investigate NPP (L. Zhu and Southworth 2013), phenology (E. N. Chidumayo 2001; Azzali and Menenti 2000), the relationship between NDVI and precipitation (Richard and Poccard 1998; Chamaille-Jammes, Fritz, and Murindagomo 2006; S. Nicholson and Farrar 1994), land degradation (Wessels et al. 2007) and vegetation trends in relation to climate and human drivers (Herrmann, Anyamba, and Tucker 2005; Evans and Geerken 2004).

6.1.1 Model theoretical basis

Building upon these studies, we explore vegetation trends using an approach to remove the precipitation signal from the NDVI time-series (Evans and Geerken 2004; Herrmann, Anyamba, and Tucker 2005; Wessels et al. 2007; Li, Wu, and Huang 2012; Andela, Liu, Van Dijk, et al. 2013; Fensholt et al. 2013; Saha, Scanlon, and D'odorico 2015). The theoretical basis for this centres on the observed linear relationship between precipitation and NDVI, identified throughout large parts of sub-Saharan Africa with a mean annual precipitation of up to 600 mm. This linear relationship implies that rainfall is the main driver of vegetation photosynthesis and hence NDVI signal (C. J. Tucker and Nicholson 1999). Such an equation computes predicted NDVI from observed precipitation estimates and observed NDVI, and hence the residuals. The approach theoretically permits the precipitation signal to be removed from the NDVI time-series, enabling the main vegetation changes not associated with precipitation to be detected. Using this approach, the following model assumptions are made: if there is a significant anthropogenic effect, as opposed to precipitation effect, on the NDVI signal, it may be identified in the residuals. More specifically, removing the effects of precipitation from NDVI time-series (i.e. corrected NDVI) allows the remaining signal changes to be attributed to anthropogenic disturbances. For instance, areas exhibiting negative trends in corrected NDVI may be undergoing vegetation losses due to anthropogenic disturbances rather than drought. Conversely, areas experiencing positive trends may be undergoing vegetation gains due to factors other than precipitation increases, for example, land management. However, such an approach is dependent on a strong linear relationship between NDVI and precipitation, and is complicated by factors which reduce the strength of this relationship. They include gradients in precipitation and vegetation density, differing responses of eco-floristic regions to rainfall patterns, and distinct ratios of herbaceous and woody vegetation together with their respective phenologies. In particular, these factors are expected to affect the corrected time-series by causing marked and irregular seasonality and thus constituting an important limitation in terms of model accuracy.

6.1.2 Aims

Considering the widespread vegetation changes identified across southern Africa, together with the uncertainty surrounding their cause, extent and rate of change, there is a pressing need for quantitative and reproducible assessments of long-term (> 15 years) land cover change, as well as an identification of their drivers (Strohbach 2001). Such an assessment will permit the intensity change processes, including shrub encroachment, land degradation and deforestation to be quantified, and hence serve for developing, implementing and revising sustainable land management, policy, practices and conservation objectives (Wessels et al. 2004; Jacquin, Sheeren, and Lacombe 2010). To address these gaps, this study maps trends in corrected NDVI, with the purpose of measuring the extent and rate of vegetation changes unrelated to precipitation across Namibia. The main hypothesis is that precipitation-corrected NDVI can be used to map vegetation changes resulting anthropogenic disturbances. The aims of the study are to: i) quantify the rate, trajectory and spatial extent of trends in corrected NDVI, ii) evaluate these results in relation to the main biomes, and iii) attribute observed change to direct and indirect drivers. These aims are addressed through the following objectives: a) model the relationship between precipitation and NDVI using linear regression; this allows predicted NDVI and hence residual NDVI (corrected NDVI) to be computed; b) compare trends in the corrected NDVI time-series with those of the original or raw (uncorrected) time-series; and finally, c) qualitatively evaluate a random sample of plots exhibiting marked changes with high resolution multi-temporal imagery (Saha, Scanlon, and D'odorico 2015).

6.2 Materials and methods

We investigate the country of Namibia, which lies in southern Africa, and its constituent Food and Agricultural Organization (FAO) biomes (Figure 6.1). The climate ranges from subhumid to hyper-arid, with rainfall extending from an annual average of 650 mm in the northeast, to 50 mm in the southwest. Precipitation is highly variable over space and time, both intra- and inter-annually, with frequent drought events occurring for any given period. It is concentrated within the five summer months from December to April in the northern and central plateau regions, while in the southernmost regions, it occurs predominantly during the austral winter, although it has also been observed throughout the year (Desmet and Cowling 1999; Mendelsohn and el Obeid 2005b). Small-scale subsistence cropping based on pearl millet (*Pennisetum glaucum*), agro-forestry and ranching, is prevalent on commonages in the northern areas. In contrast, large-scale commercial ranching and wildlife tourism is prevalent on private or freehold lands throughout the rest of the country. Most of the population depends either directly or indirectly on the land's natural resources, with a large proportion of the country being used for livestock grazing. Conservation areas in which large mammals predominate are also an important landscape feature. Namibia is situated in a transition zone between the hyper-arid Namib Desert along the western coast and the semi-arid interior. It encompasses a dynamic and variable tropical savanna biome, which is sensitive to climate and anthropogenic disturbance. As for most of the African continent's savannas, Namibia's vegetation has continuously been subject to the effects of large mammals, anthropogenic fire for land management, together with extremes of climate including droughts and floods. All of these factors have historically contributed to moulding the current structure and composition of the vegetation (Mendelsohn and el Obeid 2005a). Contemporary land-use practices are currently greatly modifying the country's savannas in ways which are still not fully characterized or quantified.

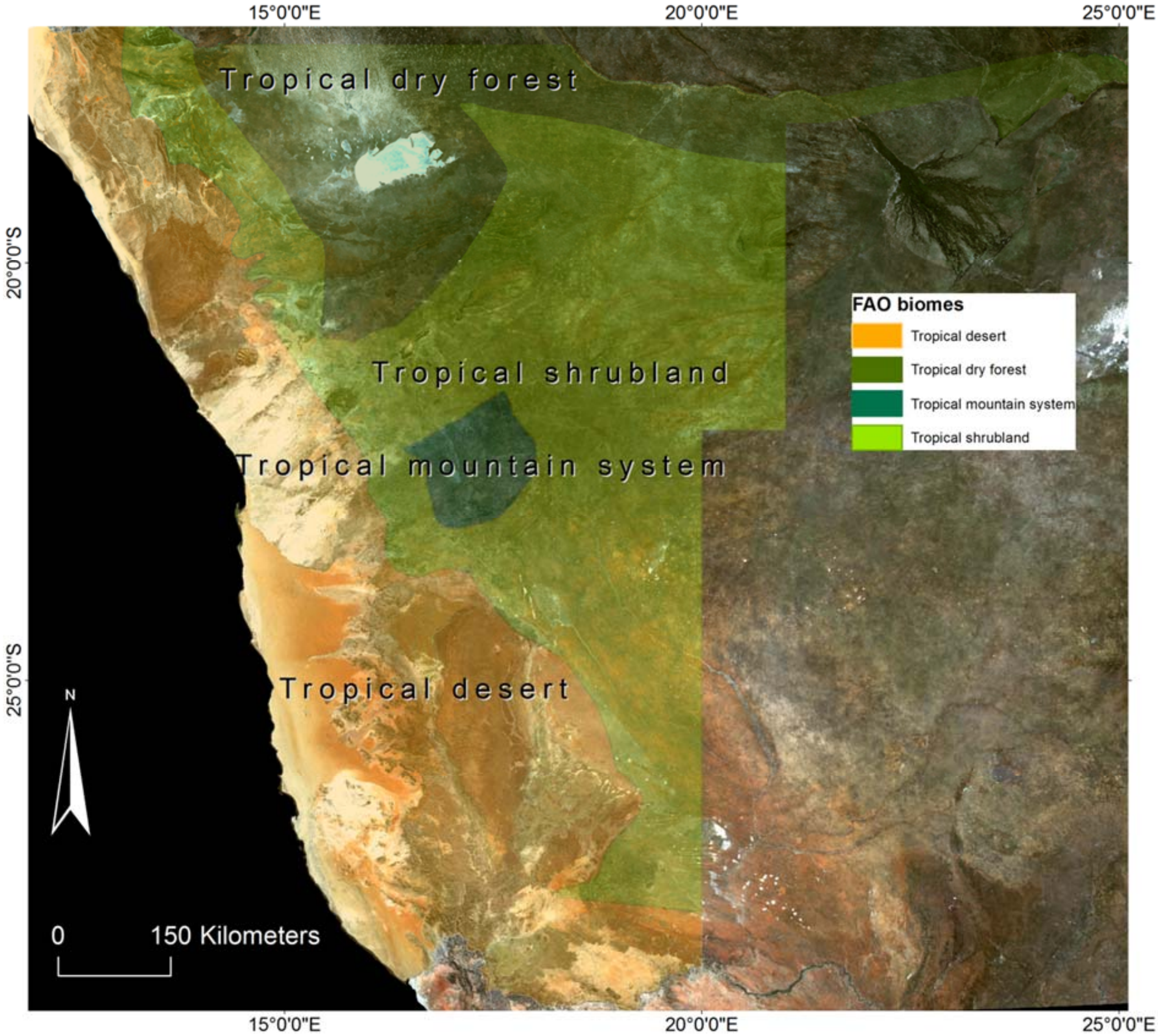

Figure 6.1. Namibia (study area), the background scene is a natural colour (bands 4, 3 and 2) Sentinel-2 early dry season composite (April to end of June 2017). Also included are the main FAO biomes for which the rate, trajectory and spatial extent of Theil-Sen trend slopes are evaluated.

6.2.1 Datasets

6.2.1.1 NDVI time-series pre-processing

The MODIS MOD13Q1 NDVI gridded level-3 product (version 6), available at 250 m spatial resolution and computed from atmospherically corrected bi-directional surface reflectances was processed for this study. The product has masks for water, clouds, heavy aerosols and cloud shadows applied, with scenes merged into 16-day composites. This approach permits only the best quality values to be used and minimizes the impact of cloud cover. From this dataset, a monthly time-series of mean NDVI was generated for the period from 2000/02 to 2017/01 as follows: pixels flagged as low quality were masked and a Savitzky-Golay temporal filter computed for each pixel of the time-series, so as to interpolate missing values and smooth outlier values. Finally, the time-series was aggregated to monthly mean values, resulting in a total of 204 observations. These processing steps further reduce the effects of low quality values resulting from noise and cloud cover, as well as helping to normalize the dynamic spatio-temporal NDVI signal observed for the region (Broich et al. 2014).

6.2.1.2 Precipitation and biome data

The TAMSAT research group produces daily rainfall estimates for all of Africa at a spatial resolution of 0.03758° in latitude and longitude, or approximately 4 km at nadir. The archive spans from 1983 to the delayed present with pan-African coverage. The TAMSAT dataset merges geostationary Meteosat data with ground-based gauge observations (Maidment et al. 2017). We used the cumulative monthly precipitation product re-projected and re-sampled, using bilinear interpolation, into the MODIS Sinusoidal projection and resampled to a 250 m resolution. Although this approach created a large number of replicate pixels, with no gain in the dataset spatial resolution, it enabled their comparison by retaining the MODIS resolution. Monthly estimates were converted to anomalies and evaluated for significant trends slopes; in addition, monthly estimates were aggregated to an annual mean in order to map 100 mm isohyets, which were then evaluated in relation to trend slope. Data for the main biomes were downloaded from the FAO Global Forest Resources Assessment and include tropical desert, tropical dry forest, tropical mountain system and tropical shrub land; for this study, we assumed that the latter two are analogous (Simons et al. 2001).

6.2.2 Approach

A schematic workflow diagram illustrating the datasets and approach used is included (Figure 6.2). Here, a linear regression between MODIS NDVI and TAMSAT precipitation was evaluated for different lag periods yielding the highest correlation coefficients. A linear regression between both variables was then used to derive a map of coefficients of determination; subsequently, the residuals (corrected NDVI) were computed from observed and predicted values. Trend significance in corrected NDVI was evaluated using the Mann-Kendall test, and significant trends were converted to annual rate of change using the Theil-Sen slope. Lastly, change was evaluated in relation to the main FAO biomes and explored using high resolution imagery.

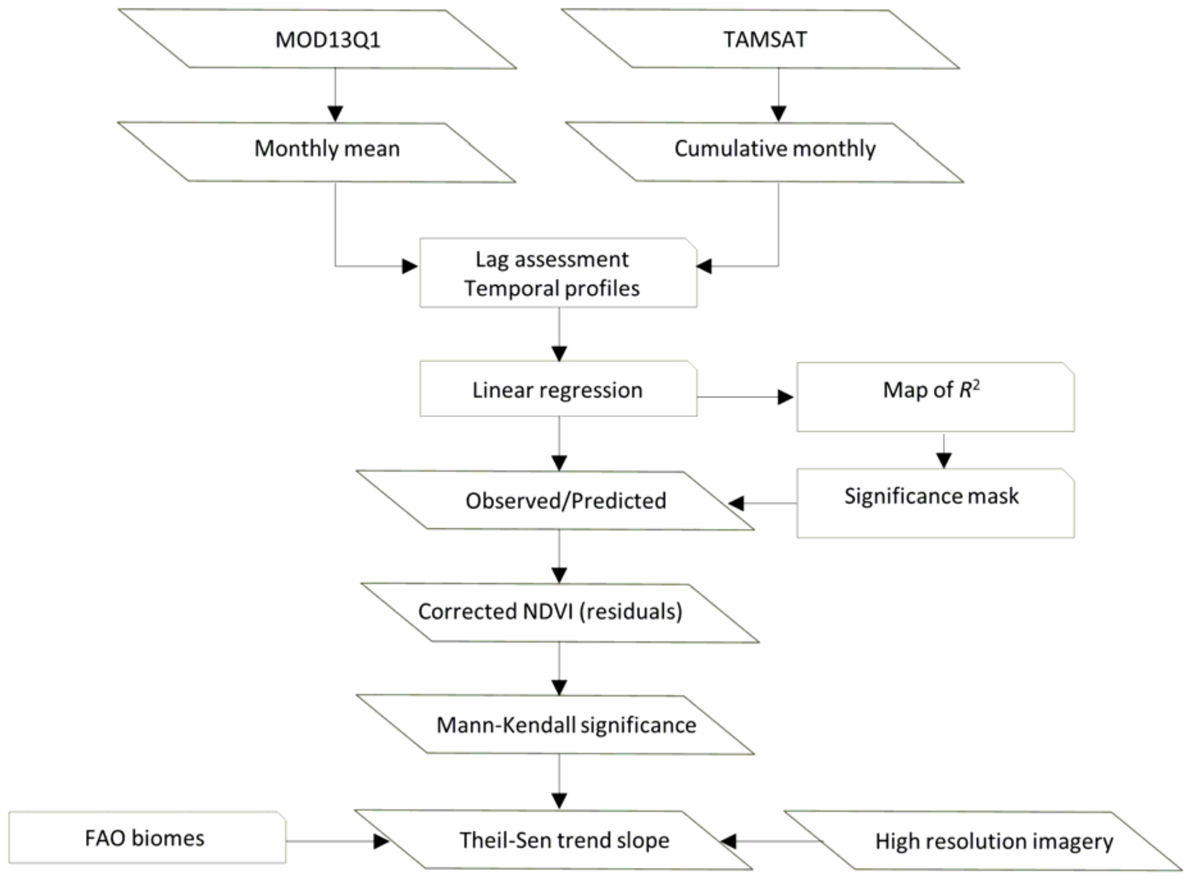

Figure 6.2. Schematic workflow diagram illustrating the datasets and approach.

6.2.3 Lag assessment

To test the strength of the linear relationship between NDVI and precipitation, correlation coefficients (*r*) were calculated between both variables for different vegetation eco-floristic regions, which extend from desert to tropical dry forest biomes. Temporal profiles consisting of the full NDVI and precipitation time-series are used in the correlation analysis, therefore, the correlation coefficient is computed for all years. Lag periods were tested by taking the spatially averaged NDVI and precipitation values for a particular eco-floristic region; the resulting temporal profiles were evaluated using the correlation coefficient (*r* value), and a range of positive and negative time-lags (months) were tested. For example, a lag of 0 means the dependent and independent variables are compared at matching (concurrent) time steps, while a negative lag shifts the independent variable (rainfall) to an earlier time step (89). Over an area as large as Namibia, a single precipitation lag period is unlikely to yield an optimal correlation with NDVI; rather, optimal lag periods are likely to vary as a function of different biomes. However, since our study is countrywide, the linear regression model was run for whole study area, rather than individual eco-floristic regions, with different lag periods. The resulting R^2 image was then evaluated by taking the mean value; here, a lag period of 0 resulted in the highest overall mean coefficient of determination (R^2) value. (0.33%); (lag +1=0.11%; lag -1=0.26%) (Hielkema, Prince, and Astle 1986; Yang, Yang, and Merchant 1997; Du Plessis 1999; Schmidt and Karnieli 2000).

6.2.4 Linear regression

NDVI was used as the dependent variable and precipitation as the independent variable in the linear regression. The intercept and slope were calculated pixel-wise and are assumed to account for local variation in the precipitation-NDVI response. Predicted and residual NDVI were computed (i.e. difference between the observed and predicted) (E. R. Archer 2004; Herrmann, Anyamba, and Tucker 2005). We assume that residuals describe the fraction of observed NDVI which is not related to precipitation; however, this assumption is dependent on the strength of the relationship between the dependent and independent variables, hence all values with a coefficient of determination (R^2) lower than 0.5 were masked. Aside from integrating noise in the time-series, the residual are also assumed to integrate the effects of vegetation change drivers other than precipitation, which are not included in the regression model. It follows that any significant trend in the residuals points to drivers aside from precipitation impacting vegetation.

6.2.5 Trend analyses

Trend significance of all datasets was evaluated using the Mann-Kendall test; areas exhibiting no significant trend ($P \geq 0.05$) were masked and assumed to represent no change. A median Theil-Sen test was computed for pixels demonstrating significant trends ($P \leq 0.05$); here, the values given by the trend slope in NDVI units we converted to rate of change ($km^2\ yr^{-1}$), or net linear increase or decrease, by multiplying for the number of months (204) (Brandt et al. 2016; Song et al. 2018). The Theil-Sen test computes the median slopes of all pixel-wise combinations, and smooths the time-series using a linear trend. It is based on non-parametric statistics, effective for short noisy time-series, robust in identifying trends and insensitive to outliers (Hoaglin, Mosteller, and Tukey 1983). Additionally, it has been extensively used to measure trends in satellite time-series across drylands (Fensholt et al. 2012; Z. Zhu et al. 2016; Guay et al. 2014; Andela, Liu, Van Dijk, et al. 2013; Herrmann, Anyamba, and Tucker 2005; Olsson, Eklundh, and Ardö 2005). Mean slope values were converted from the MODIS resolution (250 × 250 m or 62,500 m^2) to km^2 (1000 × 1000 m or 100,000 m^2) by multiplying by an expansion factor (1.6), where:

$$expansion\ factor = \frac{100{,}000\ m^2}{62{,}500\ \mathrm{m}^2}$$

We report the i) spatial area of significant trends (km^2 and percentage of the study area), ii) mean and sum ($km^2\ yr^{-1}$) of positive, negative and all slopes combined, and iii) 95th quantiles, which are representative of strong trends (Saha, Scanlon, and D'odorico 2015).

Comparing the spatial area of significant trends with the mean slope is an indicator of the intensity of the change processes occurring; for instance, spatially extensive positive trends with weak slopes may indicate small and gradual vegetation change, while in contrast, localized negative trend with pronounced slopes may signify large and abrupt vegetation changes.

6.2.6 Temporal profiles

To understand which vegetation types are experiencing changes, we evaluated mean annual slope and spatial extent of trends in relation to the main FAO biomes. Temporal profiles, which allow for the comparison of each variable's temporal dynamics, were extracted for each biome using the mean values of the NDVI residual time-series. Finally, temporal profiles were extracted for predicted, observed and corrected (residual) NDVI, as well as precipitation, for selected areas mapped as exhibiting marked trends in corrected NDVI, where slopes were > or < than 2σ (standard deviations).

6.2.7 Verification of trend results

Regional-scale, coarse resolution remote sensing products are difficult to validate; ideally, this step would require long-term and spatially extensive field datasets beyond the scope of this study. Instead, a visual evaluation of high resolution multi-temporal imagery was undertaken to assist in identifying any land cover change associated with significant trends. In addition, it allows significant changes to be attributed to specific change drivers, for instance, a loss of vegetation cover can be attribute to direct human disturbances. Here, in regions mapped as having undergone pronounced change (trends slopes > or < than 2σ standard deviations), a random sample of 10 points per class was evaluated using high resolution imagery. Scenes comprised 10 m spatial resolution Sentinel-2 imagery (2017) and 15 m spatial resolution Landsat Enhanced Thematic Mapper (ETM+) panchromatic (2000) seasonal composites. Due to the relatively low spatial resolution of these datasets, this approach is limited with respect to the identification of vegetation changes, in particular, the gradual process of shrub encroachment; two representative examples are selected for further discussion.

6.3 Results

6.3.1 Linear regression

The R^2 image derived from the linear regression between mean monthly NDVI and concurrent cumulative monthly TAMSAT precipitation (2000-2017) is plotted in Figure 6.3. Rainfall and NDVI show a strong correlation (R^2 > 0.5) across 11.52% of the country (95,071 km^2). Higher coefficients are evident across the northeast, with western and southern-most regions showing the lowest values. Low R^2 values were found in hyper-arid areas (little or no precipitation or NDVI signal), and in regions where the temporal dynamics of NDVI and precipitation are not coupled.

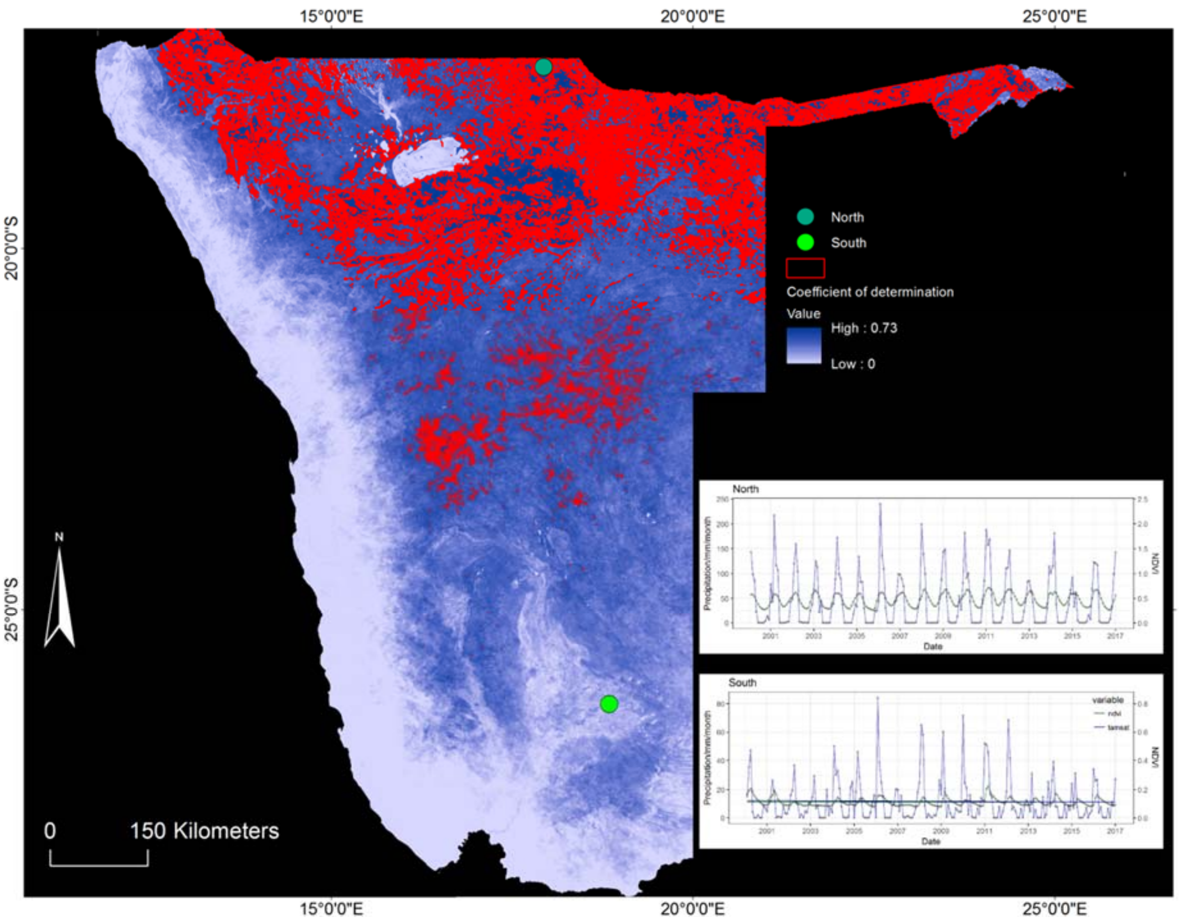

Figure 6.3. ***R*^{2} image derived from the linear regression between mean monthly NDVI and concurrent cumulative monthly TAMSAT precipitation; *R*$_2$ values greater than 0.5 are highlighted in red. NDVI and precipitation in northern regions show more regular annual cycles and amplitude values compared to southern areas.**

6.3.2 Trend analyses

6.3.2.1 Corrected NDVI

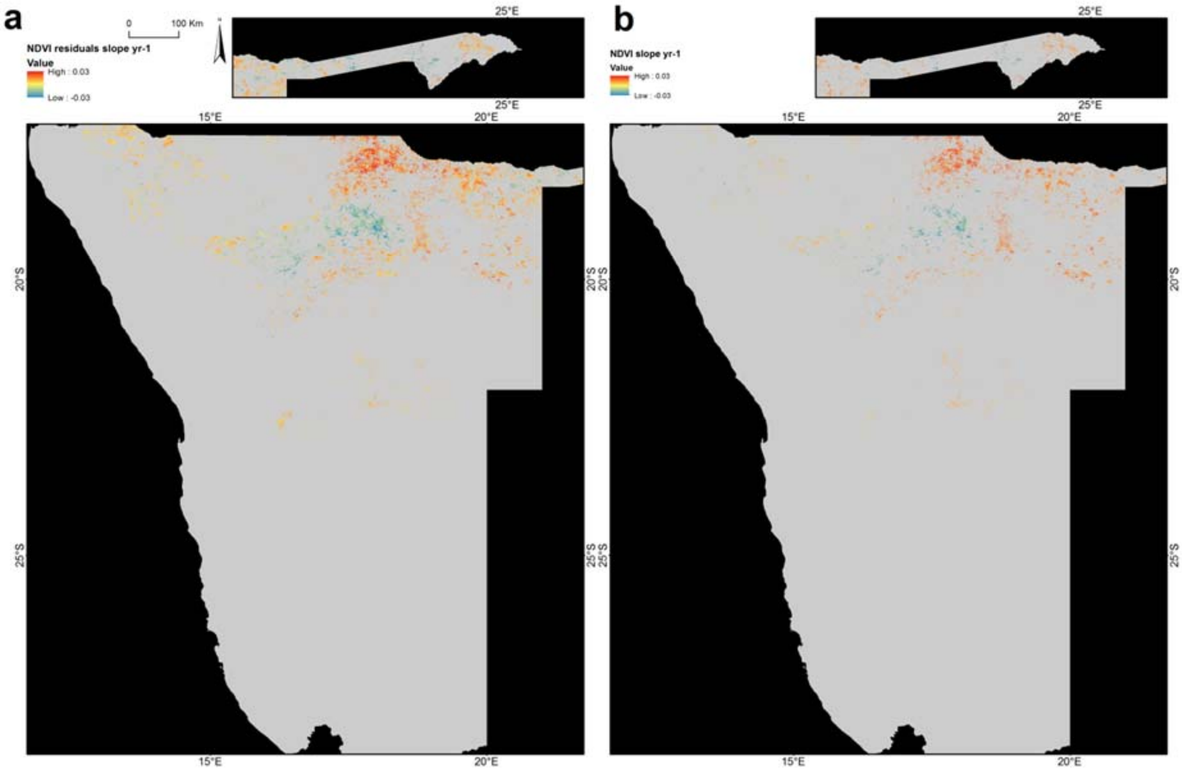

Figure 6.4. Significant Theil-Sen trends (NDVI residuals slope yr^{-1}) in corrected NDVI (a) and un-correct NDVI (b), with Mann-Kendall and R^2 significance masks applied.

Figure 6.4 illustrates the extent of significant trends in corrected NDVI (a) and un-correct NDVI (b). Table 6.1 presents the results of the corrected and un-corrected NDVI trend analyses; it reports aerial extent of significant trends in km^2, percentage of the study area, as well as the mean annual slopes and sums (km^2 yr^{-1}) of negative, positive and all significant slopes. For the corrected trends, we find 31,045 km^2 (3.75% of the country) exhibited significant trends in NDVI residuals, with a mean slope of 0.004. Of this, 23,745 km^2 (2.88%) were positive with a mean slope of 0.006, and 7,302 km^2 (0.88%) were negative with a mean slope of -0.006; the remaining 794,166 km^2 (96.24%) exhibited no significant trend and hence no slope was computed.

Table 6.1. Results of the trend analyses (corrected and un-corrected NDVI) reporting aerial extent of the significant trends (km^2 and percentage of the study area), mean negative annual slope and sum (loss), mean positive annual slope and sum (gain), and total significant mean annual slope (km^2, yr^{-1}).

Significant trends corrected NDVI (residuals)				
	Spatial extent		Change	
Trend	**Area (km^2)**	**Percent (%)**	**Mean slope ($km^2\ yr^{-1}$)**	**Sum ($km^2\ yr^{-1}$)**
Negative	7,302.02	0.88	-0.006	-710.78
Positive	23,745.00	2.88	0.006	2,454.66
Not significant	794,166.16	96.24	0.00	0.00
Significant	31,045.00	3.76	0.004	1,740.56
Significant trends un-corrected NDVI				
	Spatial extent		**Change**	
Trend	**Area (km^2)**	**Percent (%)**	**Mean slope ($km^2\ yr^{-1}$)**	**Sum ($km^2\ yr^{-1}$)**
Negative	3,877.00	0.47	-0.007	-427.05
Positive	11355.24	1.38	0.008	1,370.00
Not significant	809,979.00	98.15	0.00	0.00
Significant	15232.20	1.85	0.004	941.40

We find 15,232 km^2 (1.85% of the country) exhibited significant trends in un-corrected NDVI, hence, these were less extensive than for corrected NDVI; however, the mean slope was identical (0.004). When comparing between trend signs, we find positive trends were less extensive 11,355 km^2 (1.38%), but with an identical mean slope (0.008). Negative trends were less extensive, covering 3,877 km^2 (0.47%), although the mean slope was less pronounced (-0.007). Thus, the slopes of the un-corrected NDVI time-series are slightly greater than those of the corrected NDVI. Finally, areas exhibiting no significant trends were greater, with 809,979 km^2 (98.15%).

The strengths of corrected and un-corrected NDVI trends are explored by comparing the relative number of pixels in the quantiles, or distribution tails, which are representative of stronger trends, and are illustrated using density plots (Figure 6.5). We find that the intensity of the slopes in the tails or 95th quantiles, are slightly more pronounced (0.0113%), compared to corrected NDVI trends (0.0109%).

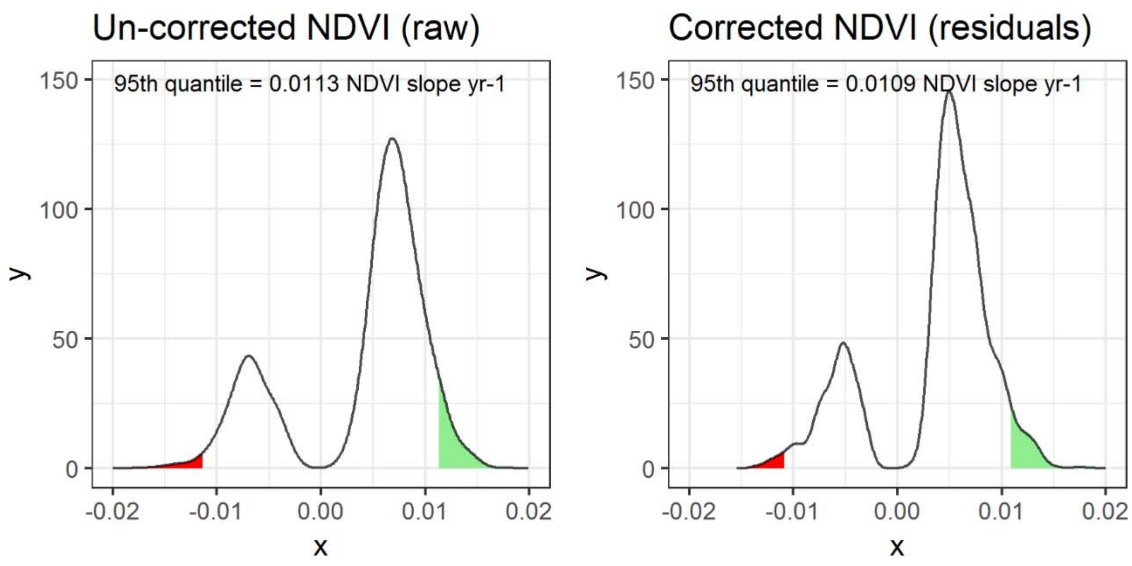

Figure 6.5. Density distribution of corrected (raw) and un-corrected (residual) Theil-Sen slopes.

For both corrected and un-corrected NDVI trend slopes, greening tends to be more pronounced than vegetation loss, with the ratio of greening to browning pixels being 3:2; this is further illustrated by the larger spatial area and more pronounced trend slopes. The corrected NDVI dataset indicates that 2.88% of the country is greening at an average annual rate of 0.006 over the 16 year study period, which is equal to a cumulative change of 0.10 NDVI units. Considering the country exhibited a maximum NDVI value of 0.82 for the 2016 dry season, it is clear that the greening measured in this study is both spatially extensive and of a high magnitude. Overall, accounting for the effects of rainfall enhanced greening and browning, trends in corrected NDVI closely resemble - in terms of spatial patterns of variability - those of un-corrected NDVI, although they are in general more extensive.

6.3.2.2 Trend in relation to precipitation and biomes

Figure 6.6a presents the results of the trend analysis in relation to mean annual precipitation. The positive trends are most pronounced in the 0-100 mm, 100-200 mm and 400-500mm isohyets. The most pronounced variation (largest upper and lower quartiles) is found in the 200-300 mm, 300-400 mm and 500-600 mm isohyets. Negative trends predominate in the driest the wettest (600-700 mm). Figure 9.12 reveals that greening trends are prevalent in all biomes except tropical desert, which underwent a mostly negative trend.

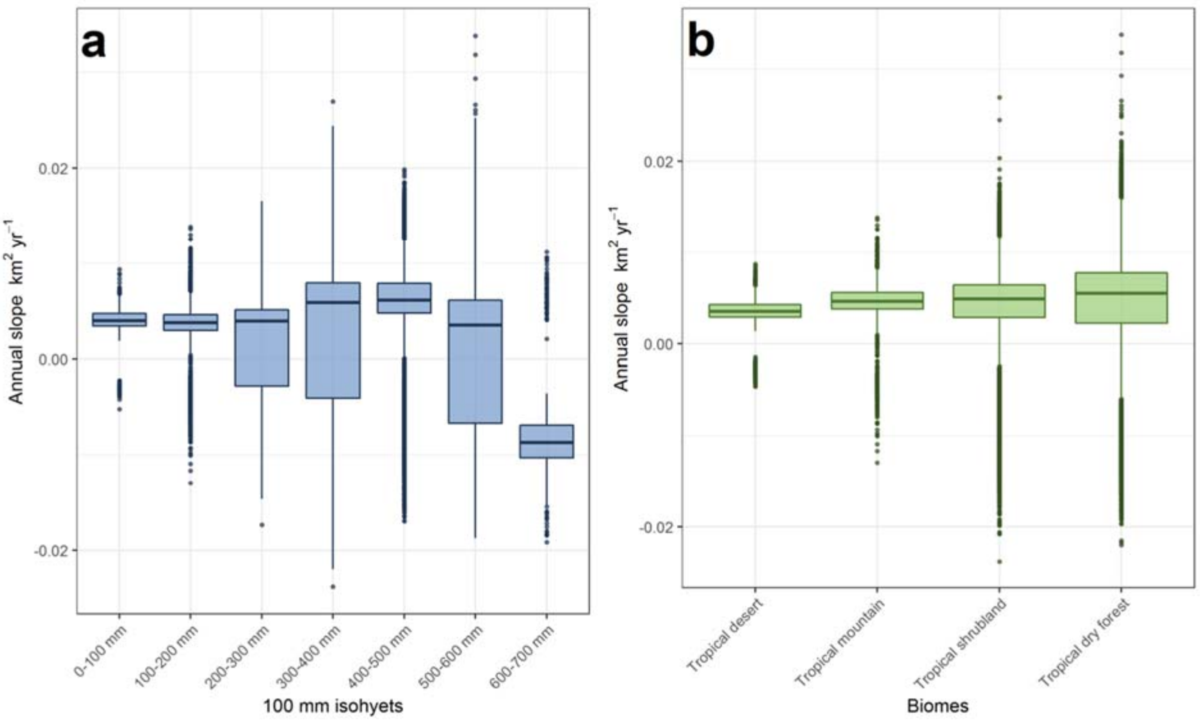

Figure 6.6. The distribution of annual slope (km^2 yr^{-1}) in corrected NDVI, extracted for mean annual precipitation amount (1983-present) with 100 mm bins (a) and FAO biomes (b).

Figure 6.6b presents the results of the NDVI residual trend analysis in relation to biomes. Here, we find a persistent greening trend across biomes. Table 6.2 presents the same results but also includes the spatial extent of significant trends in km^2 and as a percentage of the total area, as well as the mean and sums of annual slopes (km^2 yr^{-1}). All biomes show marked increases, with tropical mountain system and tropical dry forest exhibiting the most pronounced (0.004). Mean slope values and density distributions are included in the supplementary material (Figure 9.11).

Table 6.2. Results of the trend analysis for corrected NDVI, in relation to the main biomes. Aerial extent of the significant trends in km^2 and percentage of the study area, as well as mean annual slopes and sums (km^2, yr^{-1}) are reported.

	Significant trends corrected NDVI (residuals)			
	Spatial extent		Change	
Biome	**Area km^2**	**Percent (%) total area**	**Mean slope km^2 yr^{-1}**	**Sum km^2 yr^{-1}**
Tropical desert	618.01	0.07	0.003	34.25
Tropical mountain system	238.70	0.03	0.004	16.80
Tropical shrubland	12,849.60	1.56	0.003	632.81
Tropical dry forest	17,306.30	2.10	0.004	1056.64

6.3.3 Temporal profiles

Temporal profiles were extracted for observed, predicted and corrected NDVI, as well as precipitation, for randomly selected regions showing negative and positive trends (slopes > or < than 2σ, respectively) (Figures 7); these were not extracted for areas showing no significant trend, as it was assumed that no land cover changes had occurred there. Figure 6.7a shows a negative trend in residual and observed NDVI, while the trend in precipitation and predicted NDVI has remained stable. Figure 6.6b shows a positive trend in NDVI-precipitation residuals and observed NDVI. In addition, temporal profiles of corrected NDVI were extracted for each biome, and comprise the mean of all values (Figure 6.8); they illustrate the predominant trend as tabulated in Table 6.2.

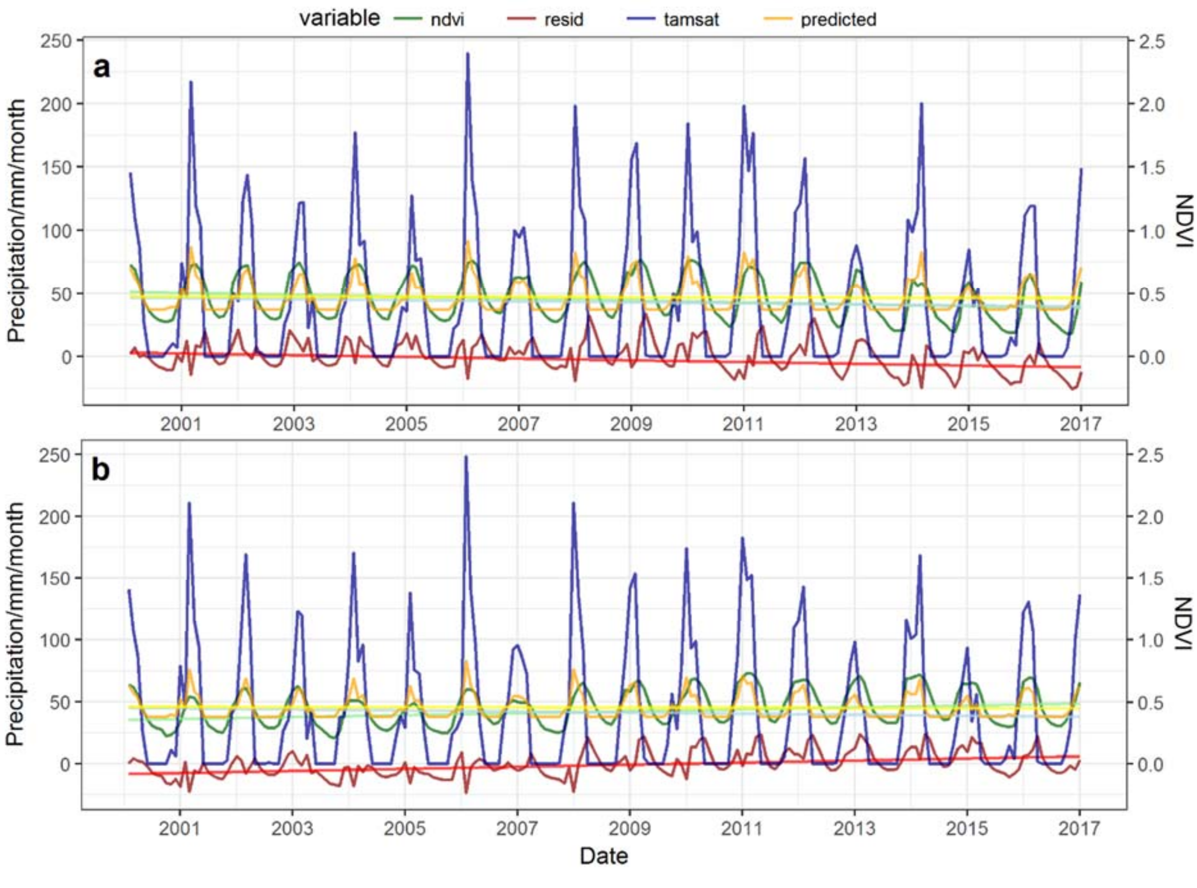

Figure 6.7. (a) Temporal profiles extracted for an area showing a significant negative trends (slopes ≤ 2σ) in corrected NDVI (resid), observed NDVI (ndvi), predicted NDVI (predicted) and precipitation (mm/month) (tamsat). (b) Temporal profiles extracted showing significant positive trends (≥2σ) in corrected NDVI.

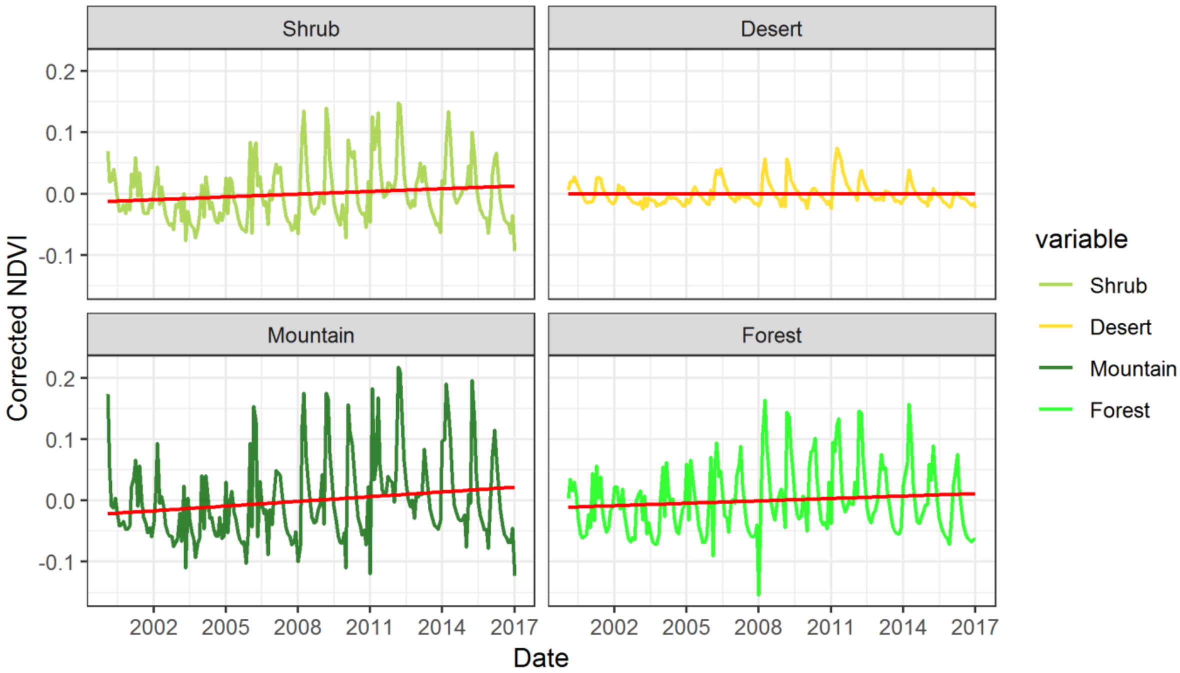

Figure 6.8. Temporal profiles extracted for each biome using the mean values of the corrected NDVI time-series, illustrating the overall positive trend.

6.3.4 Image interpretation

For randomly sampled areas exhibiting significant trends in corrected NDVI, multi-temporal Landsat 7 pan-sharpened and Sentinel-2 composite imagery, for the dry seasons of 2000 and 2017, were qualitatively assessed for marked changes in land and vegetation cover (Figure 6.9).

In Figures 9a to 9d, two randomly sampled regions where a distinct loss in vegetation cover has taken place were selected for further discussion. Specifically, Figures 9a and 9b show a region in northern Namibia where woodland clearing for small-scale agriculture has taken place. Figures 6.9c and 6.9d plot a region in central-western Namibia where the land has been excavated and covered with mine tailings from an open cast mine.

In Figure 6.10, areas which were mapped as undergoing significant positive trends in NDVI-precipitation residuals are shown; here, no apparent change in vegetation cover appears to have occurred. Instead, these areas are most likely to have undergone gradual or indirect vegetation changes, such as shrub encroachment or a general increase in vegetation density, only quantifiable using time-series and trend analyses. Such qualitative interpretations are particularly limited by the resolution of the Landsat 7 imagery used (i.e. 15m).

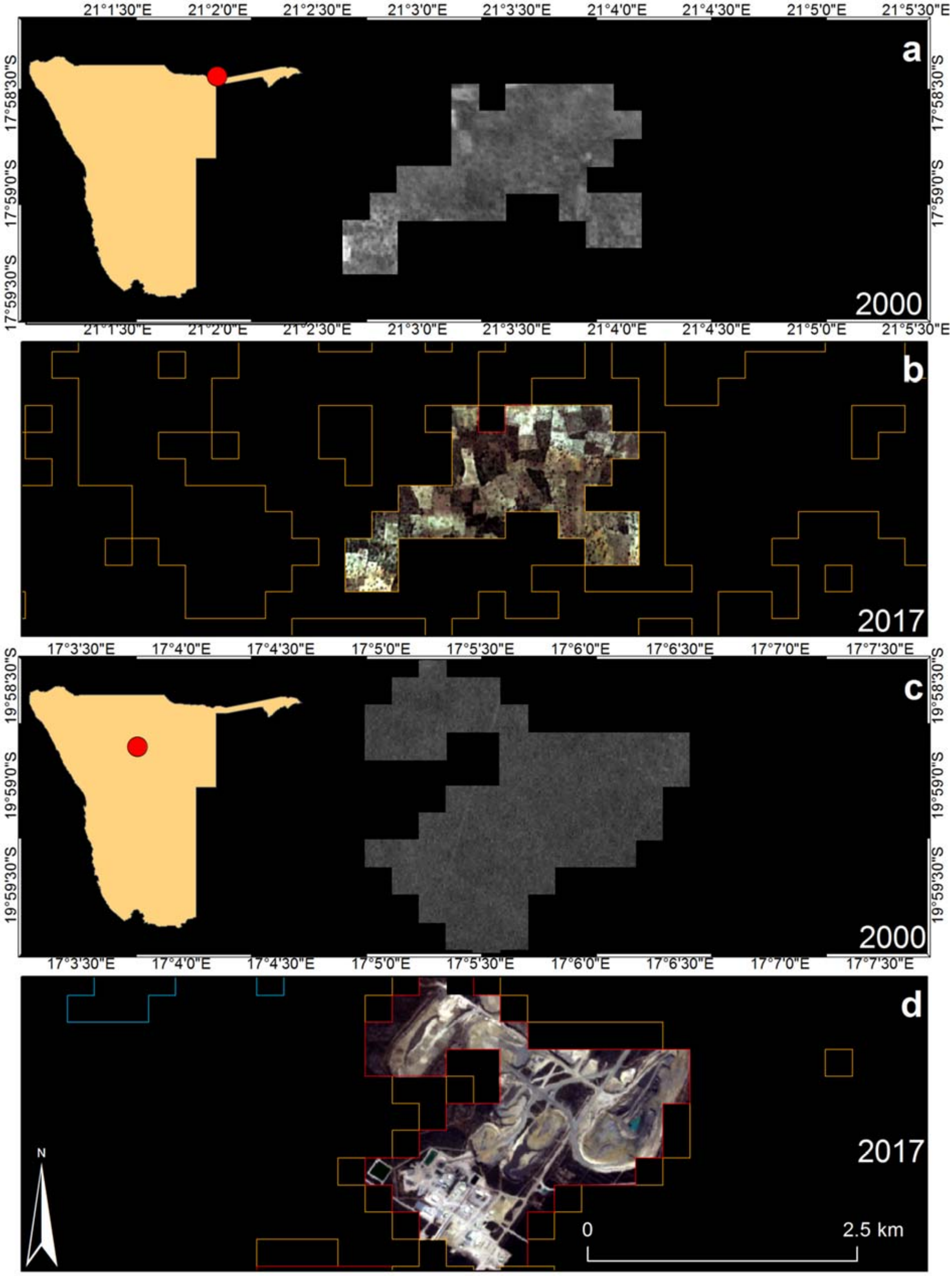

Figure 6.9. Landsat 7 panchromatic (2000) (a, c) and Sentinel-2 (2017) (b, d) dry season imagery, for areas showing significant negative trends in corrected NDVI; (a) and (b) show small-scale land clearing (northern Namibia); (c) and (d) identify an open cast mine in the north-central regions.

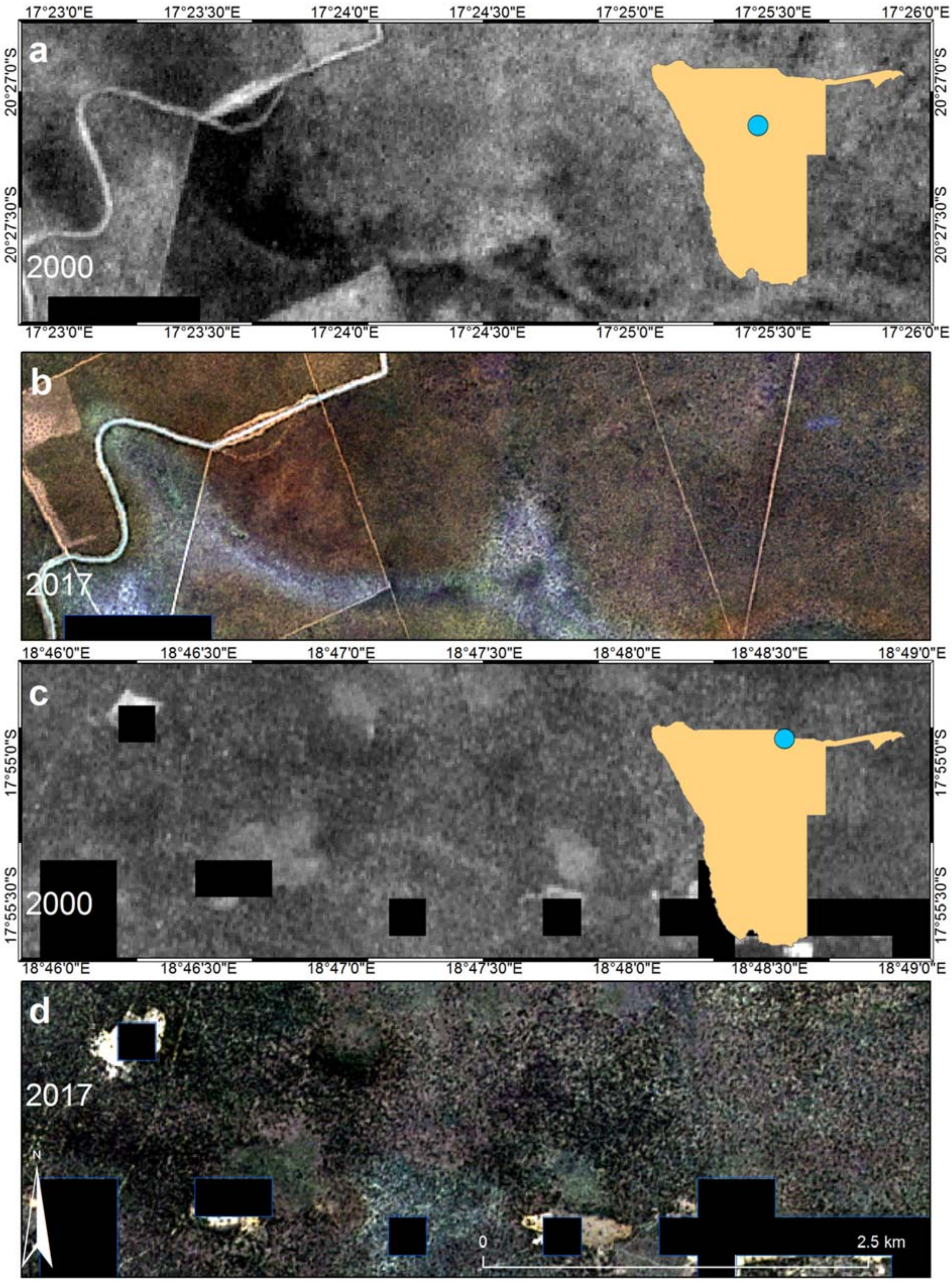

Figure 6.10. Landsat 7 panchromatic (2000) (a, c) and Sentinel-2 (2017) (b, d) dry season imagery for areas showing significant positive trends in corrected NDVI; (a) and (b) identify an area in northern Namibia under commercial farming; no changes in vegetation cover are apparent, and the observed trend is likely the result of gradual or indirect changes in vegetation cover. Similarly, (c) and (d) show an area in northern Namibia used for small-scale agriculture;

again, no clear changes in vegetation cover are apparent. Hence, significant trends in corrected NDVI are most likely the result of gradual and indirect vegetation changes.

6.4 Discussion

6.4.1 Trend analyses

6.4.1.1 Trend extent and intensity

Considering the spatial extent and intensity of the observed trends, important changes in vegetation structure and function are likely to be taking place across the country. These are likely to affect key ecosystem services and functions, which in turn will have important consequences for human livelihoods, biodiversity, the carbon and water cycles, as well as the global surface energy balance; hence, further research into these topics is required.

Correcting for the effects of precipitation increased the spatial extent of significant trends by several percent. Moreover, it enhanced the strength of negative trends, by raising the mean slope and sum (km^2 yr^{-1}), but not the magnitude of greening, as described by the 95th quantiles (Table 6.1; Figure 6.4). These results stand in contrast to those of Saha et al. (2015), who in their recent study encompassing Namibia and southern Africa found that correcting NDVI for rainfall reduced the intensity of browning; they go on to propose that this should be expected for trends driven by water availability. Therefore, from our results and those of Saha et al. (2015), we might conclude that the reason for the greater spatial extent and intensity of corrected NDVI trends is due to rainfall not playing a major role in determining the current greening, in contrast to results found in similar studies (L. Zhu and Southworth 2013; Saha, Scanlon, and D'odorico 2015).

6.4.1.2 Predominant trends

The overall trend identified in this study using precipitation-corrected NDVI is positive, pointing towards widespread greening. However, a heterogeneous spatial pattern of change, characterized by both greening and browning, was also identified throughout much of the country. In this respect, our results are in accordance with those of Saha et al. (2015), who identify widespread greening predominating over browning (Saha, Scanlon, and D'odorico 2015). Furthermore, our results agree with several additional studies which find widespread greening of satellite-derived vegetation proxies (Song et al. 2018; Z. Zhu et al. 2016; Tian et al. 2016; Fensholt et al. 2012; Andela, Liu, Van Dijk, et al. 2013). In contrast, however, research with annual minimum NDVI derived from AVHRR found no significant trends

(Andela, Liu, Van Dijk, et al. 2013). Specifically, greening trends are more widespread (2.88%) and on average are of higher intensity (slope 0.006 km^2 yr^{-1}) than browning trends, which cover only 0.88% at an intensity of -0.006 km^2 yr^1. Positive trends in corrected NDVI may be associated with gradual increases in vegetation productivity (Pettorelli et al. 2005). Such increases have been reported by several authors across southern Africa using a range of optical and passive microwave datasets, and have been attributed to shrub encroachment (Z. Zhu et al. 2016; Saha, Scanlon, and D'odorico 2015; Fensholt et al. 2012; Tian et al. 2016).

Areas of positive trends in corrected NDVI suggest that greening is more than would be expected from precipitation. Hence, they are most likely attributable to other drivers, including indirect drivers such as rising atmospheric carbon dioxide concentrations, shifts in fire activity, overstocking and the removal of browsers and the herbaceous layer, long-term rainfall changes and the synergy between these (D Ward 2005; Fensham, Fairfax, and Archer 2005; Asner et al. 2004; Bowman, Murphy, and Banfai 2010; Bond and Midgley 2000). Likewise, negative trends in corrected NDVI point to a decrease in vegetation greenness where none would have been expected from observed precipitation; in other words, vegetation greening is actually lagging behind what would be expected from the observed trends in precipitation. Drivers of the negative trends may include deforestation for arable rain-fed cropping, land clearing to remove encroacher shrub species and favour the growth of herbaceous vegetation. Within the National park boundaries, including Etosha, the impact of large mammals, in particular elephants together with low rainfall, have been shown to extensively reduce woody vegetation cover (de Beer et al. 2006). Lastly, in contrast to what has been found in the Sahel, we find no evidence of positive anomalies in precipitation (TAMSAT) responsible for driving observed trends in NDVI. In fact, only for a small portion of the south of the country were significant negative trends identified.

6.4.1.3 Trend in relation to precipitation

Plant water use efficiency is expected to increase together with rising CO_2 levels, through the process of decreased water loss via the stomata and simultaneous better carbon exchange (Bond and Midgley 2012; Donohue et al. 2013). Hence, it has been postulated that the effects of CO_2 fertilization would be most noticeable in drylands, where it has in fact been widely shown to be taking place (Fensholt et al. 2012). Figure 6.6 presents the trend slope in relation to 100 mm mean annual precipitation isohyets and FAO biomes; here, we find that greening occurs mostly across the 0 to 600 mm mean annual rainfall isohyets, which correspond dryland environments. Concurrently, the most pronounced variation is found in the 200-300 mm, 300-400mm and 500-600 mm isohyets, suggesting the occurrence of large changes (i.e. both greening and browning) occurring simultaneously. Finally, browning is most pronounced in the wettest region (600-700 mm isohyet); since the more humid regions are also those with the most important forest cover, this result may point to the impact of deforestation (Mendelsohn and el Obeid 2005b).

6.4.1.4 Vegetation change processes

Wingate et al. (2018) (in press) identify a moderate, overall declining trend in woody vegetation cover during the same period, suggesting the occurrence of complex and contrasting vegetation change processes. Specifically, their results probably indicate that the greening, observed as part of this study, is at least partially attributed to herbaceous vegetation cover. This result stands in contrast to what has recently been demonstrated for the Sahel, where much of the greening has been attributed to woody vegetation (Brandt et al. 2015; Kaptué, Prihodko, and Hanan 2015; Brandt et al. 2018). Nevertheless, for the Sahel region since the start of satellite-based studies in 1983, several authors have found that, in spite of the observed greening trends, field studies reveal an impoverishment in woody vegetation cover. This is signalled by a general reduction in tree and shrub species richness, the loss of the large trees and a shift towards the increasing dominance of drought tolerant shrub species (Herrmann and Tappan 2013; Brandt et al. 2015). Such a shift in vegetation community composition is highly plausible for Namibia, where shrub encroachment is widely reported, and occurs alongside the widespread exploitation of the timber resources (De Klerk 2004; Mendelsohn and el Obeid 2005c). Broad shifts in vegetation species composition are also likely to be a major factor driving significant trends in NDVI. In effect, positive trends in NDVI are often interpreted as an increase in biomass production; however, a lack of long-term field studies often precludes such conclusions (Brandt et al. 2015). For instance, it has been shown that certain vegetation communities with a high NDVI may have a low biomass (Mbow et al. 2013). The bulk of the study region (96.24%) exhibited no significant change; these observations are confirmed by several studies based on datasets other than satellite data which find the vegetation across the country to be surprisingly stable over long periods (O'Connor, Puttick, and Hoffman 2014; Rohde and Hoffman 2012; Buitenwerf et al. 2012).

6.4.1.5 Trends in relation to biomes

Significant trends are evaluated in relation to FAO biomes (Table 6.2; Figure 6.6); here, we find a general greening across biomes. More humid biomes (i.e. tropical dry forest) exhibit a greater variability, suggesting the occurrence of both positive and negative trends, compared to arid ones (tropical desert). These results are in accordance with studies finding tropical shrublands to be greening (Saha, Scanlon, and D'odorico 2015; Song et al. 2018), but more humid areas to be browning or undergoing deforestation (Brandt et al. 2017).

6.4.2 Linear regression

In regions where strength of the linear regression is weaker, the uncertainty associated with the trend analysis will be higher. They include, for example, flood plains and deltas where little or no correlation is apparent since in the wet season these areas are mainly flooded, with vegetation growing during the part of the ensuing dry season. The same pattern applies to extensive regions of infertile saline solonetz soils often found in conjunction with clay pans, and which frequently become flooded during the rainy season with little or no vegetation growing for the remainder of the year (Mendelsohn and el Obeid 2005b). NDVI-precipitation dynamics and hence the strength of the linear relationship, are distinct in the extreme north and south of the country. This is exemplified by the temporal profiles of NDVI and precipitation extracted from a randomly sampled area in the extreme north of the country, which reveals regular seasonal cycles, in contrast, those extracted for the extreme south show less regular cycles and lower amplitude (Figure 6.3).

The regression analysis demonstrates that across only 11.52% (95,071 km^2) of the country did concurrent rainfall and NDVI show a strong correlation ($R^2 > 0.5$). This area is smaller than expected, since the study region lies in the so called "marginal zone"; here, rainfall and NDVI are expected to be strongly correlated as a result of the high ratio of herbaceous vegetation and its coupled response to rainfall, which is the most important control on annual plant development. These results are most likely due to the many different eco-floristic regions and their differing responses to rainfall. In addition, several studies find that in semi-arid regions, vegetation greenness is more strongly correlated with lagged precipitation over a period of three months, as opposed to concurrent precipitation, thereby probably highlighting the importance of periods of high soil moisture to trigger vegetation growth or the different phenology and response of herbaceous and woody vegetation. We tested for this effect with a lag analysis, and find that lag periods yielding the highest correlation coefficient vary for different eco-floristic regions; however, across the whole study area, a lag of 0 yields the highest R^2 (S. E. Nicholson, Davenport, and Malo 1990; Herrmann, Anyamba, and Tucker 2005).

6.4.2.1 *Eco-floristic regions*

Lag periods ranging from -1 to +1 were found to result in the highest correlation coefficients. The positive lag may presumably be a function of the time required for enough soil moisture to accumulate to allow herbaceous and shrub vegetation to initiate photosynthesis, while the negative lag may be the result of the pre-rainfall leaf flush; pre-rainfall leaf flushes are triggered by changes in day and night temperature (E. N. Chidumayo 2001). A lag of 0 was found to be the most effective at integrating the contrasting response of each biome (lowest overall R^2). The areas which show the highest r values with a -1 rainfall lag are found predominantly in the eastern half. They are most likely regions comprising woodland vegetation exhibiting marked pre-rainfall leaf flushes; here, woody vegetation is already partially in leaf at the onset of the first rains (i.e. peak NDVI occurs before peak rainfall) (Figure 9.10). In contrast, eco-floristic regions showing the highest r value with concurrent and/or positively lagged precipitation are predominantly found in the central and southern parts of the country. They most likely represent regions with a high ratio of herbaceous vegetation in which photosynthesis reaches its maximum in response to precipitation, during or one month after peak precipitation (i.e. peak NDVI occurs simultaneously or just after peak rainfall) (Figure 9.11). Lastly, the carryover effects of rainfall in previous years are a key factor impacting the land surface-precipitation relationship, especially in grasslands (herbaceous vegetation) (Taylor et al. 2011). However, accounting for the carryover effects of rainfall would be beyond the scope of this study. Instead, we assume that herbaceous vegetation senesces entirely during the dry season (little to no NDVI signal), and hence any carryover effects are minimal

Temporal profiles of NDVI and rainfall for the northern and southern eco-floristic regions exhibit divergent temporal dynamics. In the drier parts of the country, including the Western escarpment and Dwarf shrub savanna, both the NDVI and precipitation temporal profiles show less pronounced seasonal cycles and a more noticeable inter- and intra-annual variability, than in the other eco-floristic regions. This may partly be due to the predominance of grasslands, in which photosynthesis is strongly coupled to rainfall. In addition, the presence of shrub species which do not exhibit pre-rainfall leaf flushes independently of rainfall, for example, *Senegalia reficiens,* but instead leaf and grow only after important rainfall events, may also contribute to the observed response (pers. comm. C. van der Waal, 2017). Lastly, rainfall in the extreme south follows a different pattern; this area borders the succulent Karoo eco-region which receives the bulk of its rainfall in the austral winter (Desmet and Cowling 1999).

Apart from the Cuvelai drainage which is a mosaic of arable land and seasonally flooded grassland, the remaining eco-floristic regions, especially the Kalahari woodlands, Northern Kalahari, Caprivi Strip and Karstveld, are characterized by tree species which are not dependent on rainfall for initiating seasonal photosynthesis and often exhibit a pre-rainfall leaf flush or “green-up”. This is clearly illustrated in Figure 9.10, where the green-up of woodland occurs before that of grassland and cropland (i.e. in August as opposed to December, respectively), which are entirely dependent on rainfall for photosynthesis.

6.4.3 Observed, predicted and corrected NDVI

Corrected NDVI shows marked and erratic seasonality, as demonstrated by the fluctuating annual cycles, suggesting that removing the effects of rainfall from the NDVI time-series did not remove the seasonal cycles (amplitude and phase) (Figures 11a and 11b). This result is most likely due to the phenology of savanna vegetation; here, herbaceous vegetation, with its pronounced response to irregular rainfall, may have contributed importantly to a variable seasonal NDVI signal. In contrast, the phenology of woody vegetation is more regular and cyclic, with photosynthesis occurring independently of rainfall, and accompanied by a distinct pre-rainfall leaf-flush, especially in the northeast.

The temporal dynamics of observed and predicted NDVI are plotted in Figure 6.11; for a randomly selected area identified as undergoing a marked negative trend in corrected NDVI, observed and predicted NDVI are initially well coupled (Figure 6.11a). From 2014 onwards, observed NDVI falls below what would be expected from the estimated precipitation. In contrast, for a selected area identified as showing a marked positive trend, observed NDVI is initially lower; from 2003 onwards it increases above predicted NDVI, or what would be expected from estimated precipitation (Figure 6.11b).

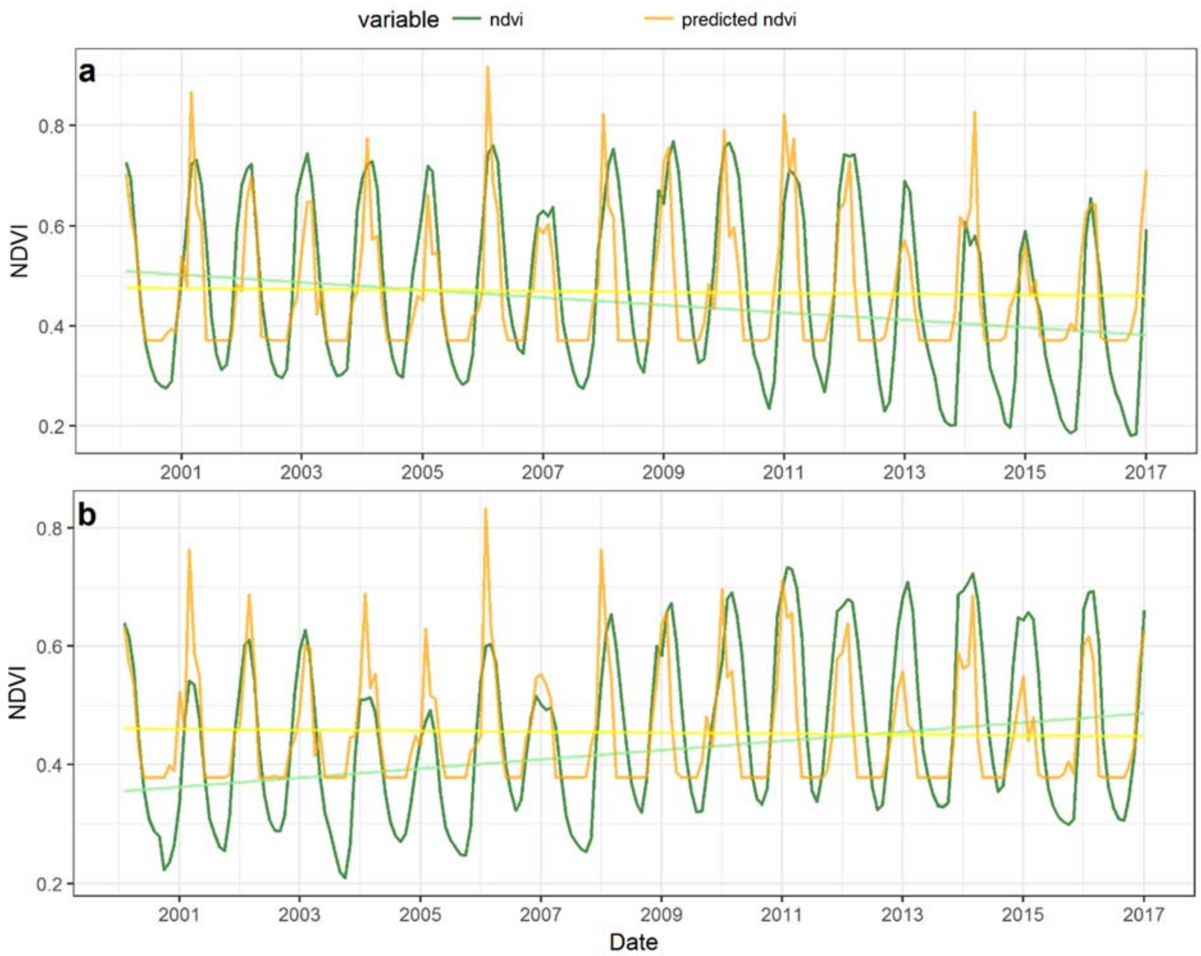

Figure 6.11. (a) Observed and predicted NDVI extracted for an area showing a negative trend in corrected NDVI; predicted NDVI is higher than observed NDVI for the last four years. (b) Observed and predicted NDVI extracted for an area showing a positive trend in corrected NDVI; initially, observed NDVI is lower than predicted NDVI, subsequently it increases above predicted NDVI.

6.4.4 Image interpretation

Trends in corrected NDVI are not validated using an uncertainty analysis; instead we focus on discussing the potential effects that the different eco-floristic regions, and their constituent plant function types, may have had on the underlying model assumptions. Further, long-term field data that would have been optimal for validating past land cover change are not available. However, we attempt to address this important deficiency by qualitatively evaluating multi-temporal high resolution imagery. This evaluation proved that negative trends manifest as obvious losses of vegetation, occurring as a result of direct human drivers. In contrast, positive trends could not be identified in this manner, and hence point to more gradual and indirect vegetation changes, requiring alternative methods to identify.

6.5 Conclusions

This study presents country-level results of a MODIS precipitation-corrected NDVI trend analyses. It confirms extensive greening in a southern African country previously reported with satellite-derived vegetation proxies. Specifically, significant greening trends cover 2.88% of Namibia, which is greening at an average annual rate of 0.006 over the 16 year study period (equal to a net change of 0.10 NDVI units). Our results stand in contrast to one recent study which finds, on an average, a declining trend in woody cover across the country, thereby implying the observed greening trend may be partially attributed to herbaceous vegetation. We further attempt to address this discrepancy by drawing a parallel to the findings of two field and satellite-based studies in the Sahel. The studies found that despite widespread greening, an impoverishment of woody cover could be demonstrated, manifesting as a decline in woody species richness, a loss of large trees, and a shift towards vegetation communities where drought tolerant shrub predominate. We suggest that such a shift in vegetation community composition is plausible for Namibia and, in fact, has been widely reported. Thus, greening may be interpreted as an increase in vegetation density unrelated to precipitation, which is likely the result of both direct and indirect drivers linked to the process of shrub encroachment.

Negative trends covered 0.88% of the country and were mainly associated with wetter and hence more forested regions, implying deforestation as a main driver. They manifested primarily as vegetation losses caused by direct human drivers and could be effectively identified using visual interpretation of high resolution multi-temporal imagery. In contrast, land cover changes associated with positive trends were difficult to identify; often no discernible change was seen to have taken place. Therefore, these results presuppose the existence of gradual and indirect vegetation changes - effectively captured using satellite time-series analyses - but requiring alternative methods for validation. In sum, our results support the use of corrected NDVI to map negative vegetation trends in particular. Similarly, time-series analysis enabled indirect ecological changes to be measured, which would not otherwise be identifiable using single date, high-resolution snap-shot data.

Precipitation is strongly correlated with NDVI for 11.52% of the country ($R^2 > 0.5$), which is lower than expected. In effect, the NDVI signal correlates differently with rainfall depending on the eco-floristic region; north-eastern regions are best correlated with a negative lag, while south-western regions a positive lag. Finally, no evidence of positive anomalies in precipitation driving trends in NDVI was identified. To conclude, our results point to important ecological shifts affecting large parts of Namibia since 2000. These changes are likely to increasingly impact ecosystem service and functions provision, and therefore require further research.

6.6 References

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Chapter 7

Comparatvie anylsis of chapter results

7 Comparative analysis of chapter results

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Abstract

The present chapter briefly introduces the thesis aims and objectvies, then describes how the constituent chapters are linked and follow each other. Subsequently, it presents the main results of each chapter, together with a comparative assessment of the main results, for a subsample of the study region (Ohangwena region). A time-seris and trend analyses based on a seasonal Landsat time-series is integrated into the discussion, in order to both (i) address the limitations implicit in previous analyses and (ii) validate the results of the previous chapters. Lastly, a disucssion and conclusion are included.

7.1 Introduction

The chapters forming this thesis aimed to quantify changes in several biophysical variables, notably, NDVI, biomass and fractional woody cover. These variables act as proxies for tropical savannah vegetation which comprises grasslands, shrub lands, woodlands and forests. Simultaneously, they constitute indicators of environmental change processes, including land degradation, ecosystem carbon dynamics, the phenological and functional response of vegetation to climate, as well as the impact of land-use and management on vegetation. Chapters 3 and 4 present high resolution land cover and biomass change analyses for the Namibian Kalahari woodland ecoregion. Chapters 5 and 6 focus on the whole country using moderate spatial and high temporal resolution MODIS time-series. As outlined in the introduction, the objectives of this thesis are:

(i) To track the degree of change experienced by the main thematic land cover classes across the Namibian Kalahari woodland ecoregion using the Landsat satellite archive data.
(ii) To estimate aboveground woody biomass change in the Namibian Kalahari woodland ecoregion by combining field, radar, and optical data sets.

(iii)To map trends in fractional woody cover across Namibia using seasonal phenological metrics and field inventory data, and investigate how these are related to anthropogenic and climatic drivers.

(iv)To monitor contemporary trends in NDVI and precipitation, and quantitatively map their spatial patterns and identify how their temporal dynamic relate.

The methods used to address the hypotheses presented in the introduction centre on the integration of multiple satellite and field datasets. They include high temporal resolution MODIS and climatic data, high spatial resolution optical, radar land LiDAR datasets spanning the past five decades including Landsat, Sentinel-2, ALOS PALSAR and ICESat, as well as vegetation biomass and cover measurements for the calibration and validation of map products. The conceptual approaches, methods discussion and conclusions are comprehensively reported as journal articles within this thesis.

7.1.1 Chapter summary and linkages

Chapter 1 introduces the key topics which are relevant to this study, such as the importance of land cover and land-use change, drylands, tropical dry forests and savannahs across the globe and in particular the African continent, and reviews the pertinent research concerning environmental change carried out over the past decades in Namibia. It then presents and discusses relevant methods and approaches with a focus on satellite remote sensing of savannah vegetation and the limitations inherent in attempting to track change in these biomes. Lastly, the knowledge gaps, problem statements and research questions are presented. This is followed by the aims and objectives, and the hypotheses. Chapter 2 gives an overview of the study area, its population, land-uses, climate, vegetation and soils, satellite and field datasets, together with processing steps and methodological approaches and analyses undertaken.

Chapter 3 makes use of the whole Landsat archive to map changes in the main thematic land cover classes from the mid-1970s across the Namibian Kalahari woodland ecoregion. It integrates Landsat MSS, TM and ETM+ data, together with multi-source calibration and validation data. By exploiting the distinct phenological phases shown by trees relative to grasses, the approach facilitates woody vegetation change detection and thus addresses some of the questions associated with mapping savannah vegetation. Natural vegetation cover was found to have decreased, predominantly due to urbanization and small-scale arable farming.

To obtain an estimate of the contribution of land cover changes to ecosystem carbon, Chapter 4 elaborates on the former analysis by quantifying aboveground biomass changes associated with the main vegetation change processes, namely, deforestation, degradation, shrub encroachment and woodland regrowth. Again, the approach takes advantage of the distinct phenological phases of woody and herbaceous vegetation functional types. In addition, it fuses satellite datasets, including ALOS PALSAR and Landsat NDVI, each of which acting as a proxy for distinct vegetation properties, namely structure and "greenness", respectively. Calibration and validation data comprised of spatially coincident forest inventory data together with canopy height estimates derived from space-bone LiDAR. Losses in biomass were found to predominate throughout the region, primarily driven by forest degradation and deforestation, thereby demonstrating the contribution of current land management practices to ecosystem carbon changes.

The analyses of Chapter 3 and 4 essentially comprise snapshot change detection studies, which besides being impacted by manifold environmental factors, including cloud cover, fires, lack of imagery data quality and noise, are limited in their ability to answer questions pertaining to gradual environmental change. Accordingly, in order to (i) establish whether vegetation biomass is declining across the country, and (ii) surmount the constraints of geographic extent and temporal resolution, Chapter 5 concentrates on developing a country-wide moderate spatial resolution time-series based on the MODIS sensor, which allows the effects of climate-driven vegetation changes to be evaluated, due to the comparable temporal resolution satellite precipitation products. Percentage woody vegetation cover is selected as a good proxy of vegetation biomass. Phenological metrics, acting as proxies for woody vegetation cover, were extracted from a MODIS NDVI time-series and used to model percentage woody cover based on a large field dataset. The mean trend in percentage woody cover for the whole country was slightly negative, suggesting a net decline; however, the spatial area of significant positive trends was larger, implying widespread but low intensity gains in woody vegetation cover. Trends were evaluated in relation to the predominant land-uses and negative trends were found to arise largely in protected, urban and communal areas. Modelled woody cover was also evaluated in relation to precipitation, which was found to have little effect on modelled woody vegetation cover throughout much of the country (i.e. low R^2), except in the arid coastal escarpment and southern regions, which receive very little and highly irregular rainfall, and where certain woody vegetation communities which leaf and flower only in response to precipitation.

Since precipitation is a primary control on both herbaceous and woody vegetation, Chapter 6 proceeds to consider its spatial and temporal relationship with NDVI, with the aim of determining to what extent observed trends in NDVI and percentage vegetation cover are driven by rainfall. Using linear regression, NDVI is modelled as a function of precipitation and the resulting NDVI residuals are assumed to describe the fraction of NDVI not explained by rainfall. Trend analysis is then applied to the NDVI residuals time-series, and extensive "greening" unrelated to rainfall is identified, despite mean annual rainfall and rainfall amplitude showing a positive trend throughout much of the country. Finally, trends in NDVI amplitude (introduced in this chapter) which was established to be a proxy for vegetation density, point to widespread shifts to a denser vegetation state.

The current chapter (Chapter 7) addresses some of the drawbacks implicit in the analyses of Chapter 3, 4, 5 and 6, namely MODIS- and snapshot-based approaches, by applying trend analysis to a seasonal Landsat time-series. The results, together with those of the previous chapters, are synthesized and discussed.

Lastly, Chapter 8 presents a synopsis in which the main thesis findings are presented. The limitations are then highlighted and the potential for future research is reviewed, whereupon overall conclusions are advanced.

7.1.2 Aims and approaches

The following study aims to compare the five vegetation parameter map products developed as part of the four previous chapters (i.e. thematic land cover change, biomass change, percentage woody cover, NDVI residuals), as well as NDVI amplitude (described in Chapter 7), within a subsample of the Namibian Kalahari woodland biome, in order to assess their effectiveness at capturing different vegetation change processes. A high resolution time-series analysis based on seasonal Landsat imagery is included, in an attempt to address the technical limitations and bridge the consequent knowledge gap inherent in the earlier analyses, as well as for model validation. In addition, an analysis of two precipitation products is presented and the results compared. By comparing the results of these analyses, the study endeavours to produce an integrated assessment of the extent, magnitude and trajectory of regional vegetation and climate change.

Based on the outcomes of Chapter 7, Chapter 8 moves on to develop the main thesis findings, while endeavouring to address the hypotheses and research questions initially set out. Since the hypotheses are closely interlinked, no attempt is made to address them separately; instead, a unified interpretation and discussion is implemented. The primary hypotheses presented in the introduction of this thesis include:

7.1.3 Hypotheses

Hypothesis 1: The widespread greening trend observed throughout much of the country is masking small-scale land clearing.

Hypothesis 2: The greening trends observed throughout much of the country are not completely related to precipitation trends. Instead, they are the result of numerous interacting environmental factors, with anthropogenic land-use being the principle factor. Collectively, they contribute to increasing woody vegetation density in certain areas. Moreover, the greening trend observed at coarse spatial scales may be also concealing land degradation, which manifests as a loss of perennial herbaceous strata, encroachment of hardy shrubs, loss of large trees and an increased susceptibility to soil erosion.

Hypothesis 3: The capacity for moderate spatial resolution satellite imagery to successfully characterize land cover changes, in particular land clearing, occurring at the scale of individual farmsteads (~2 ha) has not yet been assessed. Yet, it is likely to be highly effective at capturing regional, gradual vegetation changes and shift in land surface phenology. Contrarily, small-scale local land clearing or abrupt vegetation changes, together with modifications in vegetation biomass, can effectively be captured using high spatial resolution satellite optical and radar multi-temporal imagery and field measurements. Consequently, a multi-sensor multi-scale approach is necessarily best suited to quantitatively mapping contrasting vegetation change processes in highly dynamic savannah biomes.

7.2 Material and methods

7.2.1 NDVI amplitude

Trends (Mann-Kendall and Theil-Sen) in NDVI signal amplitude are used as a proxy of vegetation change. Figure 7.1 illustrates the underlying assumption of the approach; here, the NDVI signal temporal profile, for a pixel known to constitute a densely vegetated woodland area, is compared to one known to comprise a sparsely vegetated field and cropland mosaic area (Figure 7.1a). Seasonal NDVI minimum, maximum and amplitude for the densely vegetated woodland (Figure 7.1b) are found to be greater than for the sparsely vegetated field and cropland mosaic (Figure 7.1c). Based on this observation, we assume that NDVI signal amplitude can be used as a proxy for tracking shifts in the predominant vegetation functional type. As such, we assume that an NDVI temporal profile for a pixel showing high intra-annual amplitude (i.e. high minimum and maximum) is representative of a densely vegetated area, with predominantly woody cover. Similarly, an NDVI temporal profile for a pixel showing low intra-annual amplitude (i.e. lower minimum and maximum values relative to woody cover) is assumed to be representative of a sparsely covered area with predominantly herbaceous vegetation cover. For example, an area with declining signal amplitude (i.e. lower minimum and maximum values) would imply a decreasing vegetation density and/or a loss of woody vegetation cover, and its possible replacement with annual herbaceous vegetation, related to processes such as woodland degradation and deforestation. Correspondingly, positive trends in NDVI amplitude (i.e. higher minimum and maximum values) may translate into increases in vegetation density and/or woody vegetation cover, related to processes including shrub encroachment or woodland regrowth. The Seasonal Trend Analysis (STA), as described in Eastman et al. (2009), was applied to the NDVI time-series to derive NDVI amplitude. It applies pixel-wise harmonic regression to every year in a time-series to derive seasonality parameters, including amplitude and phase. Trend significant was computed using the Mann-Kendall trend ($P \geq 0.05$) while trend slope was subsequently derived from the Theil-Sen trend test (Ronald Eastman et al. 2009). Lastly, the slope images (NDVI amplitude and NDVI residuals) were evaluated using linear regression

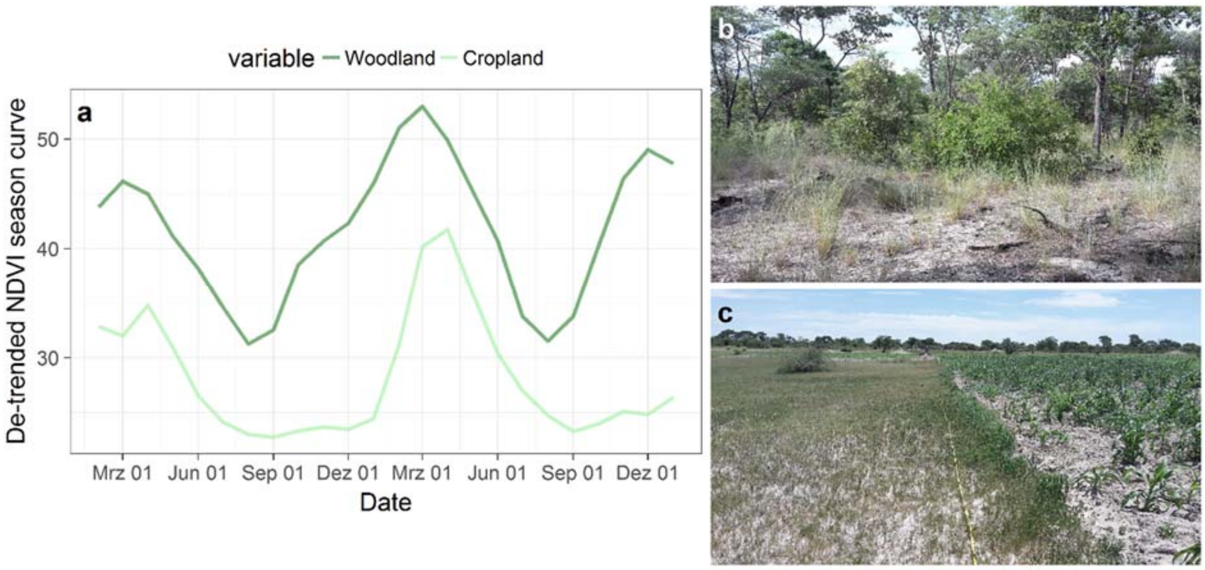

Figure 7.1. (a) Temporal profiles describing the seasonal cycle of NDVI for pixels known to comprise woodland and cropland, respectively. The NDVI signal for woodland has greater amplitude than that for field and cropland, showing higher NDVI values both during the growing season (leaf-on) and dry season (senescence). (b) Landscape photograph of woodland for which the temporal profile was extracted. (c)Landscape photograph of the field cropland area for which the temporal profile was extracted.

7.2.2 Sub-sampled study area (Ohangwena region)

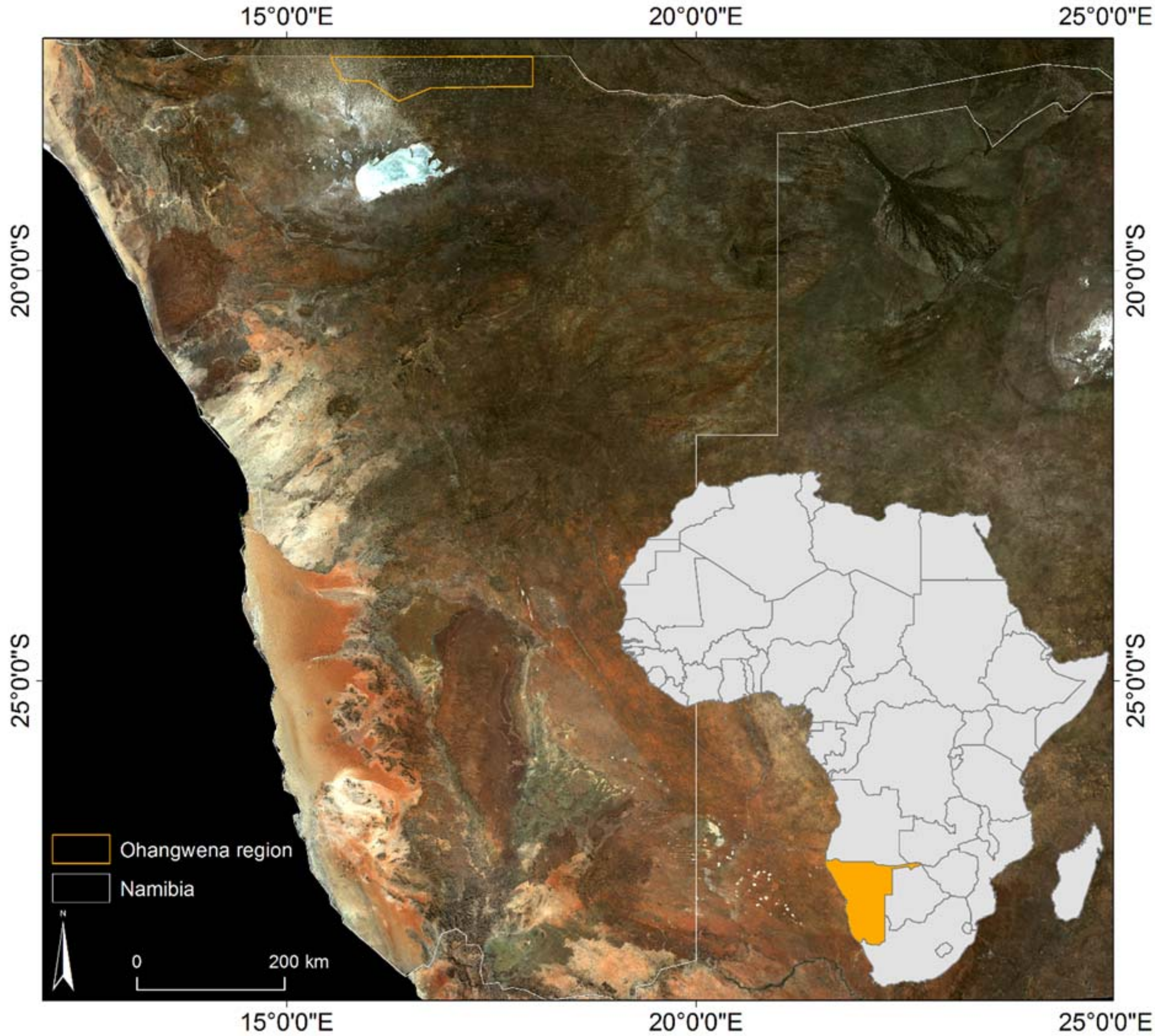

Figure 7.2. Study area encompassing part of the Namibian Kalahari woodland biome (Ohangwena region), shown at the top-centre of the figure.

The five vegetation parameter map products generated as part of the four constituent thesis chapters are assessed for the same geographic area, namely the Ohangwena region (Figure 7.2). The area was selected since it presents important environmental gradients in precipitation, soil properties, vegetation structure and composition, as well as population density, ranging from Kalahari woodland to sparsely vegetated floodplain, moreover, the greater part of the field work was carried out here. Thus, this region is representative of a large proportion of the country and extensive reference field datasets are available. In addition, since land-use is a focal aspect of this thesis and is often used as a key indicator of anthropogenic land management impacts on environmental and vegetation change, map products are assessed as a function of land-use, in an attempt to identify common tendencies between products and evaluate its effects on vegetation change.

7.2.3 Method for integrating the outputs of multiple remote sensing analyses

Since the research questions, methods and results from the four constituent chapters of this thesis are fundamentally different, in terms of the satellite sensors (i.e. optical, radar and LiDAR), spatial resolution (i.e. high, moderate and coarse), temporal scale (i.e. bi-monthly, seasonal, and annual) and anaylsis methods (i.e. image classification, image ratio change detection, time-series and trend analysis), the following qualitative and quantitative methodological approaches are adopted for their comparative assessment: (i) a brief summary of the main result of each chapter is given, ii) the spatial extents of significant trends and changes are compared; iii) coefficients of determination (R^2) are used to assess how similar the spatial patterns of significant trends between the different output datasets are (i.e. significant trends in one dataset are regressed against significant trends in another); and (iv) correlation coefficients (r) is used to assess the strength of the relationship between temporal profiles extracted for each time-series dataset, and finally (v) the relationship between datasets is evaluated, with the seasonal Landsat trend analysis serving as validation.

7.3 Results

7.3.1 Land cover and above ground biomass change

Figure 7.3a presents the areal extent (km^2) of seven land cover classes from 1975 to 2014 at decadal intervals for the Ohangwena region. A net decline of the spatial area of woodland class and a concurrent increase in the agricultural and urban classes can be noted. Figure 3d further illustrates this with a thematic land cover change map showing the losses and gains in areal extent of the woodland class which have taken place between 2004 and 2014, for a random subset of the study area, superimposed on a contemporary Sentinel-2 composite image for the early dry season (April-June) of 2017.

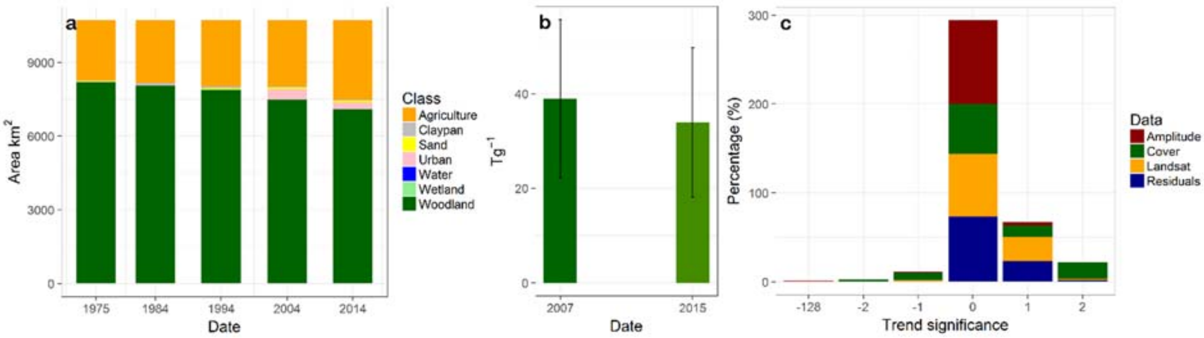

Figure 7.3. (a) Bar chart of the areal extents of the main land cover classes mapped at decadal time intervals (1975-2014) for the Ohangwena region (Chapter 3); (b) bar chart of total estimates biomass (Tg) for the study area in 2007 and 2015, showing a net decline in above ground biomass (Chapter 4); (c) Percentage of the study area (75,569 km^2) which experienced significant median Theil-Sen trends in modelled woody cover (Chapter 5), NDVI amplitude, and modelled NDVI residuals (Chapter 6), and Landsat seasonal NDVI (Chapter 7), computed as significant if slopes are > or < than 2 standard deviations from the mean.

Figure 7.3b shows changes in woody above ground biomass (AGB) between 2007 and 2015. For the Ohangwena region we find a net loss of 4.98 Tg AGB between 2007 (38.91 Tg) and 2015 (33.93 Tg) (Figure 7.3b). This analysis also estimates AGB losses and gains related to four different vegetation change processes, namely, deforestation, woodland degradation, shrub encroachment and woodland regrowth. Woodland degradation was found to be the most important contributor to AGB change (Table 7.11); a map of AGB change (Figure 7.4e), highlights areas of significant change in biomass between 2007 and 2015. A good agreement can be noted between the thematic and AGB change maps (Figures 7.4d and e, respectively). Recently cleared areas (2000-2014) correspond well to those showing significant AGB reductions and these comprise small arable plots of land (~2 ha). Thus, from the results outlined above and illustrated in Figures 7.4d and 3e, two vegetation change processes are quantitatively identified: i) a decrease in the spatial extent of natural vegetation (i.e. woodland), with a concurrent increase in the areas of cleared land (i.e. agricultural land), and ii) important declines in AGB, identified as deforestation and woodland degradation, corresponding to cleared areas.

Table 7.1. Spatial extent of vegetation change in (km^2) and as a percentage (%) of the Ohangwena region (10,705 km^2) together with the change in AGB (Tg) and percentage of 2007.

Thresholds	Vegetation change	Area (km^2)	Area (%)	AGB change (Tg)	AGB change since 2007 (%)
100% to -200%	Deforestation	112.99	1.06	-0.27	-0.71
-50% to -100%	Degradation	1212.46	11.34	-1.95	-5.01
-50% to 50%	No change	8976.65	83.94	-3.26	-8.38
50% to 100%	Thickening	375.31	3.51	0.46	1.19
100% to 200%	Regrowth	16.81	0.16	0.04	0.10

7.3.2 Areal extent of significant trends and changes

Figure 7.3c plots the spatial areas of significant trends for the three trend analyses undertaken in Chapters 5 to 7 as a percentage of the study area. A broad agreement can be noted, with the bulk of the study area experiencing no significant trends (i.e. amplitude = 94%, cover = 56% and residuals = 74%, Landsat = 71%). Amplitude shows a positive bias, with 6% of the study area experiencing positive trends and only 1% negative trends. The same holds for percentage woody cover, with 24% of the study area experiencing positive trends and 21% negative trends. A similar pattern is observed for NDVI residuals, with 18% experiencing positive trends and 2% negative trends (Table 7.2). Finally, this configuration is again observed for the Landsat seasonal NDVI time-series, with 28% experiencing positive trends and 1% negative trends. Thus, these results suggest a greening trend predominating across the region in spite of widespread deforestation.

Table 7.2. Percentage of the total study area (Ohangwena region) experiencing significant positive or negative trends in NDVI amplitude, modelled percentage woody cover, NDVI residuals and Landsat seasonal NDVI.

	Spatial area of significant Theil-Sen trends (%)	
Data	**Negative**	**Positive**
Amplitude	-1	6
Cover	-21	24
Landsat	-2	18
Residuals	-1	28

Results of three vegetation parameter trend analyses (i.e. percentage woody cover, NDVI residuals and NDVI amplitude), using the moderate resolution data of MODIS (2000-2017), are plotted for a random subsample of the study area (Figures 7.4). Figure 7.4a shows a significant median Theil-Sen slope (TS) trends in modelled woody cover. Figure 3b displays significant TS trends in NDVI residuals, derived from the linear regression between monthly NDVI and TAMSAT precipitation. Figure 3c presents significant TS trends in NDVI amplitude. The results of these trend analyses are broadly in good agreement as demonstrated by the moderate R^2 values (Figure 7.5): percentage woody cover and NDVI residuals (R^2=0.39); percentage woody cover and NDVI amplitude (R^2=0.28) show a low agreement; however, NDVI amplitude and NDVI residuals (R^2=0.61) are well correlated.

As an example to highlight the strengths of these correlations, all three trend analyses identify an area of negative change in the top left hand corner (Figures 7.4a to c). This change can be described as being a conversion of woodland to arable land (Figure 7.4d), accompanied by a significant loss in biomass between 2007 and 2015 (Figure 7.4e). From comparing the results of chapters 3 through 6, it is clear that despite widespread reductions in natural vegetation (i.e. woodland) extent and biomass, the trend analyses identified extensive greening.

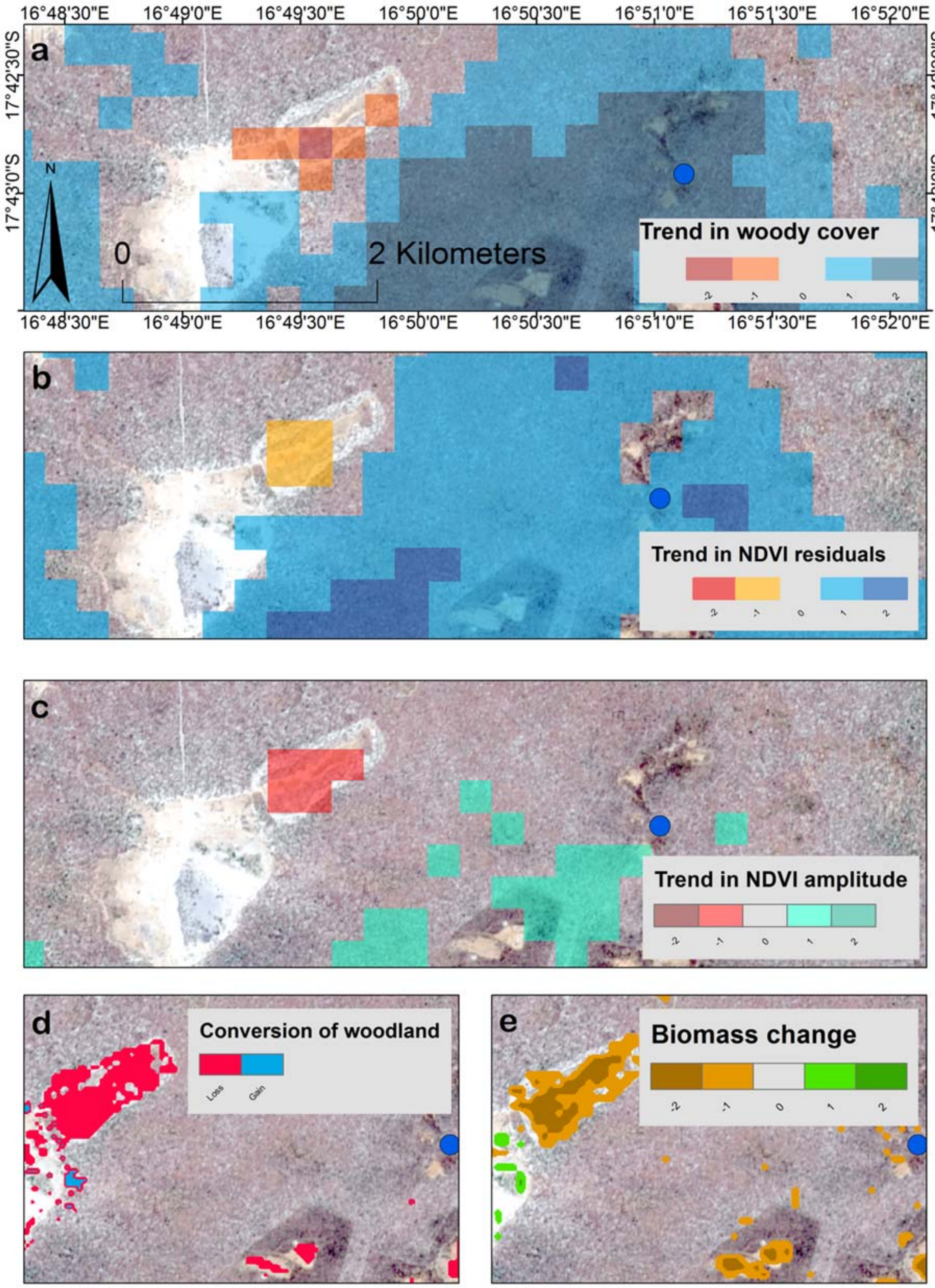

Figure 7.4. Maps comparing the different analyses undertaken as part of each thesis chapter for a random sub-sample of the study area: (a) significant median Theil-Sen slope trends (TS) in modelled woody cover; (b) NDVI residuals; (c) NDVI amplitude; (d) conversion of woodland to arable land identified using thematic land cover change maps (2004-2014); (e) significant change in above ground biomass. Background image is a Sentinel-2 natural colour composite image for the dry season (April-June) 2017.

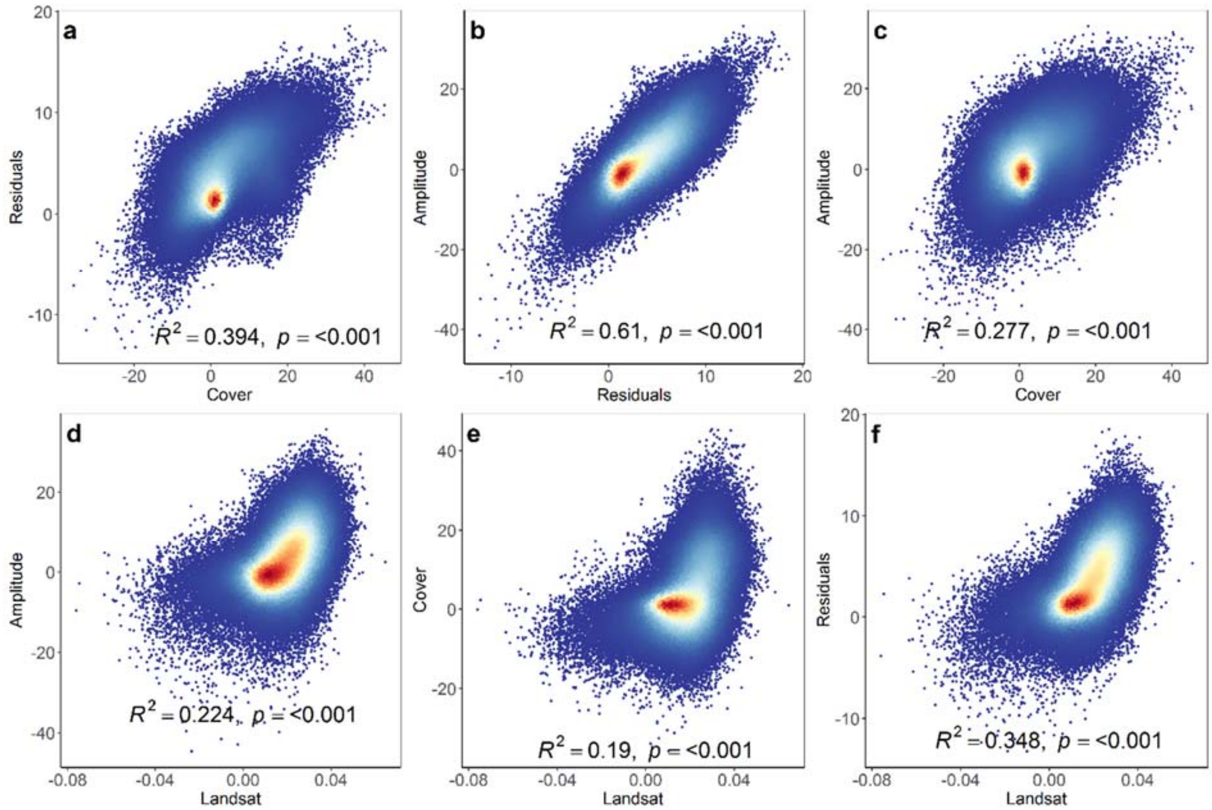

Figure 7.5. Regression plots comparing each vegetation parameter trend analysis processed; percentage woody cover - NDVI residuals (a); NDVI amplitude - NDVI residuals (b); NDVI amplitude - percentage woody cover (c); Landsat seasonal composite - NDVI amplitude (d); Landsat seasonal composite - percentage woody cover (e); Landsat seasonal composite - NDVI residuals (f).

7.3.3 Temporal profile correlation analyses

Annual temporal profiles are extracted for mean annual precipitation (TAMSAT), modelled percentage woody cover and NDVI amplitude from a selected group of pixels corresponding to positive trends in NDVI amplitude, NDVI residuals and percentage woody cover. Over the period from 2000 to 2017, TAMSAT rainfall estimates reveal a slight declining trend, while percentage woody cover and NDVI amplitude show an increasing trend (Figure 7.6). The temporal profile of percentage woody cover is poorly correlated with NDVI amplitude (r=0.09%), although both variables were expected to be well correlated. This is illustrated in Figure 7.1a, in which NDVI temporal profiles are plotted for pixels comprising woodland and grassland/cropland. Annual precipitation and percentage woody cover show a moderate correlation (r=0.23%); while a weaker correlation is found with NDVI amplitude (r=0.12%) (Figure 7.6).

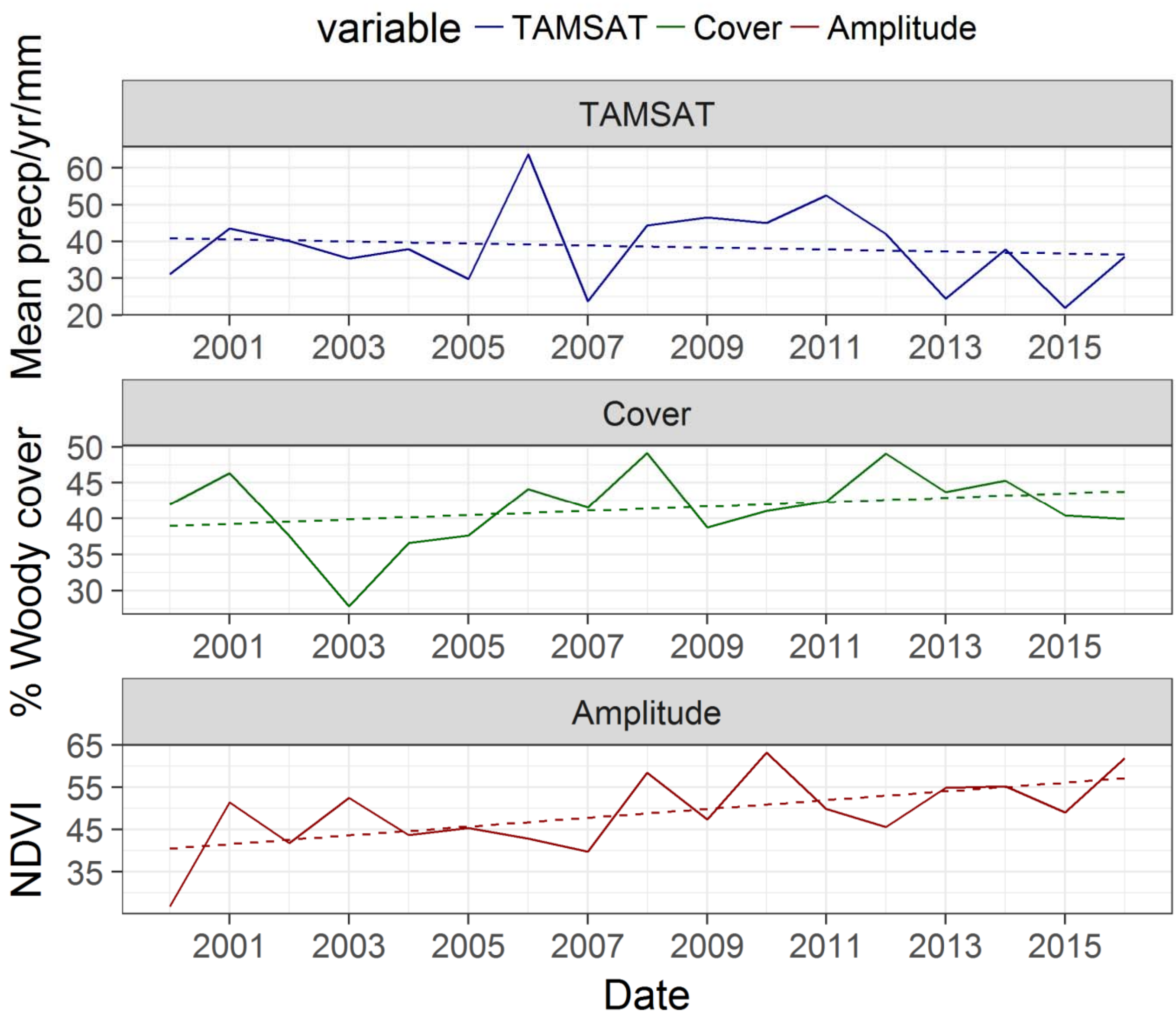

Figure 7.6. Temporal profiles extracted for a group of randomly sampled pixels displaying significant trends in NDVI amplitude, NDVI residuals and percentage woody cover. A positive trend in percentage woody cover is observed; mean annual rainfall (TAMSAT) shows a declining trend for the period between 2000 and 2016. Percentage woody cover and NDVI amplitude are unexpectedly poorly correlated (*r*=0.09%); mean annual rainfall and percentage woody cover show a moderate correlation (*r*=0.23%); a poor correlation is found between mean annual rainfall and NDVI amplitude (*r*=0.12%).

Figure 7.7 plots monthly temporal profiles (2000-2017) for precipitation, as measured using the CMORPH method, and modelled NDVI residuals extracted from the same group of pixels. CMORPH precipitation reveals a stable trend, which is in accordance with results derived from TAMSAT, moreover, both datasets are well correlated (*r*=0.86%). NDVI residuals show a marked positive trend. NDVI residuals aggregated to averaged annual values show good agreement with both modelled percentage woody cover and NDVI amplitude (*r*=0.44%; *r*=0.42%, respectively). CMORPH precipitation estimates and NDVI residuals show moderately strong correlation (r=0.51%), while the correlation is less pronounced with NDVI amplitude (r=0.32%).

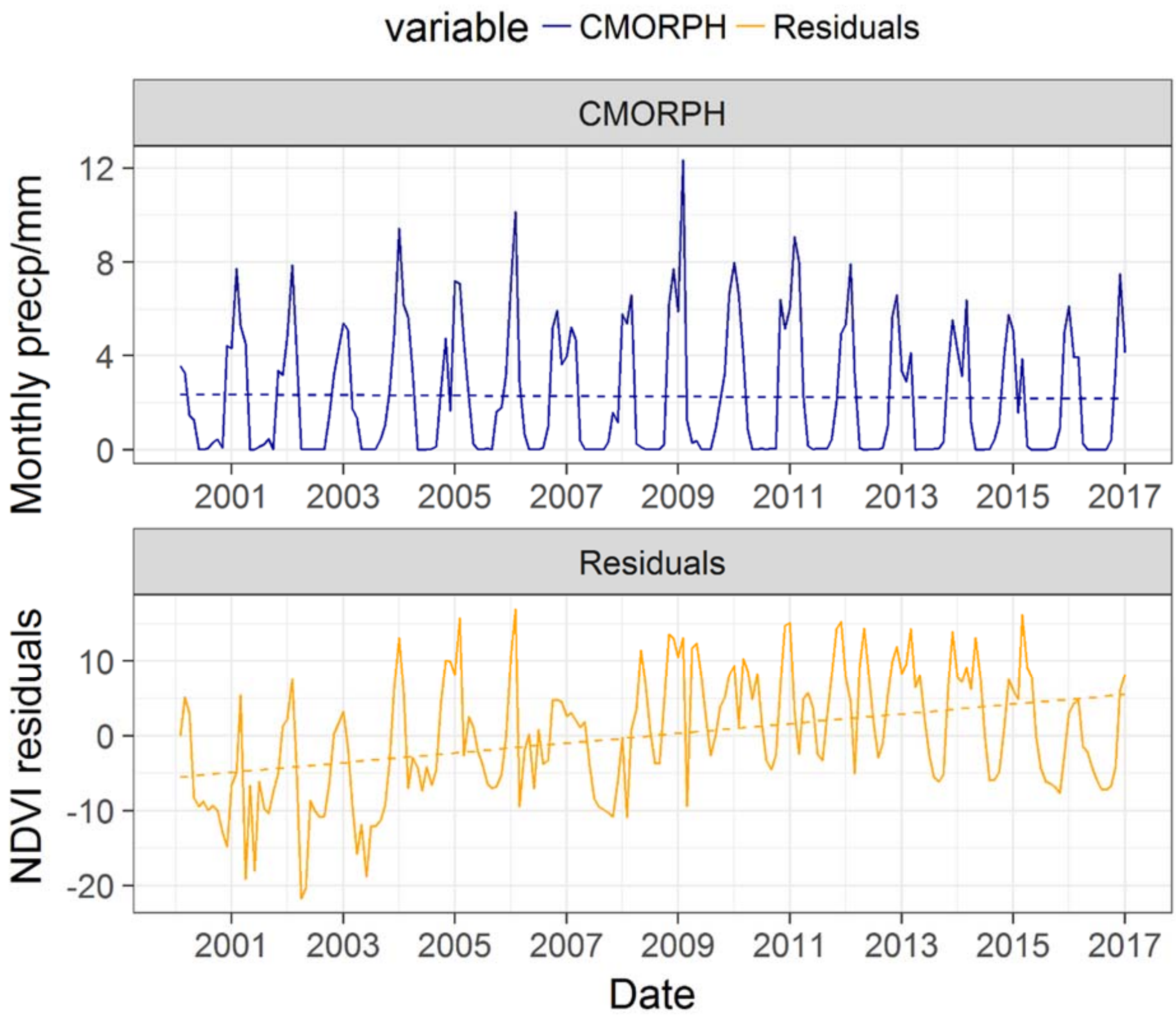

Figure 7.7. Temporal profiles extracted for a group of randomly sampled pixels displaying significant trends in NDVI amplitude, NDVI residuals and percentage woody cover. Precipitation measured using CMORPH shows a stable trend; NDVI residuals show a positive trend and good agreement with percentage woody cover and amplitude (*r*=0.44%; *r*=0.42%, respectively).

From the results presented above, we find that NDVI residuals are well correlated with percentage woody cover and NDVI amplitude. Hence, we may conclude that the greening trends are (i) not related to trends in precipitation (NDVI residuals) but are instead controlled by other environmental and anthropogenic factors; and (ii) they are likely manifest as increases in woody cover, which (iii) are presumably accompanied by increase in NDVI amplitude; this aspect is explored in depth in Chapter 6.

7.3.4 Validation using Landsat seasonal NDVI time-series

To address the limiting factors of spatial and temporal scale inherent in the MODIS-based analyses, as well as validate each map product created, a time-series of Landsat 5, 7 and 8 NDVI images was created by compositing all quarterly available images for the period from 1990 to 2016 and taking the median pixel value. Thus, four images representing distinguishable seasons were created for each year, resulting in a 26-year seasonal NDVI time-series of 104 images. A comprehensive methodological description of this dataset is found in Chapter 4. Several additional processing steps were undertaken in order to map significant trends: (i) a Savitsky-Golay temporal interpolation filter was applied to fill in the missing values and reduce noise, (ii) data were then aggregated to annual sums to bypass serial correlation likely to be present in quarterly intervals, and finally, (iii) a median Theil-Send (TS) trend slope was computed for each pixel of the time-series.

Figure 7.8a presents the median TS trend slope derived from the Landsat NDVI time-series for a random sub-sample of the study area. In addition, thematic land cover changes for woodland for the period between 1994 and 2014 are plotted in Figure 7.8b, superimposed on a Sentinel-2 natural colour composite image for the dry season (April-June) 2017. Here, a good agreement can be noted between the TS trend slope map and the thematic land cover change map. In particular, areas of pronounced negative TS trends correspond well with areas of woodland loss. Figure 7.8c plots significant biomass changes for the same area and again a good agreement can be noted with the TS trend slope map.

The correlation is validated by the results of an error matrix, using all available pixels, between the TS trend slope map (where slopes > or < than 2 and 4 standard deviations were classified as significant and highly significant trends) and the thematic land cover map (Table 7.3), which yielded an overall accuracy of 97%. An error matrix using significant AGB changes also reveals strong agreement with an overall accuracy of 99% (Table 7.4).

To evaluate the strength of the of the Landsat time-series trend results in relation to those of MODIS analyses, several regression plots were generated using the Landsat time-series TS trend slope and the three MODIS-derived TS trend slopes (Figure 7.5). A moderately good agreement between datasets is revealed, as indicated by the R^2 values: Landsat seasonal composite - NDVI amplitude R^2= 0.24% (Figure 7.5d); percentage woody cover R^2= 0.19% (Figure 7.5e); NDVI residuals R^2= 0.35% (Figure 7.5f).

In summary, the Landsat seasonal composite time-series analysis (i) could successfully identify reductions in natural vegetation extent and biomass, concurrently with all previous analyses; (ii) shows a moderate correlation with the three MODIS-derived trend analyses, suggesting the spatial patterns of trends show a good agreement, and that the Landsat time-series has successfully been able to identify both positive and negative trends; finally, (iii) the relatively low R^2 values are most likely the results of the differing time-series lengths (i.e. 26 years and 17 years for the Landsat and MODIS time-series, respectively) which would alter the spatial patterns of trends, as well as, the different spatial resolutions (i.e. 30 m and 250 m for the Landsat and MODIS time-series trend map, respectively), which are likely to hide the fine-scale variation and negatively impact the R^2 values.

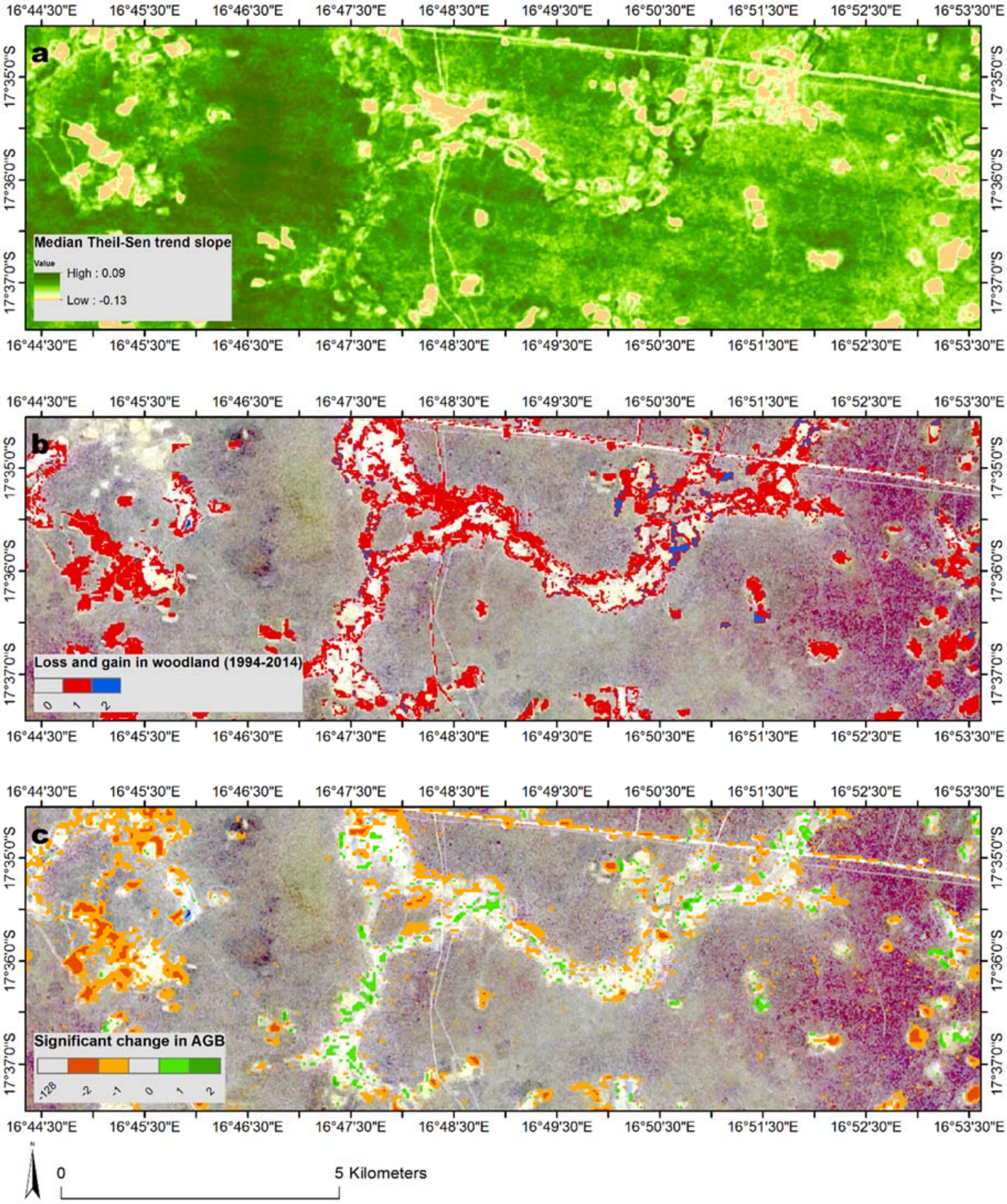

Figure 7.8. (a) Median Theil-Sen trend slope derived from a time-series of quarterly, seasonal Landsat composite images (1990-2015). (b) Thematic land cover change map showing losses and gains in woodland between 1994 and 2014 (red=loss; blue=gain); negative trends in (a) correspond well to areas having been cleared of woodland in (b), while large regions exhibiting positive trends tend to occur in intervening areas. (c) Significant gains in biomass are shown in green and losses in red; again these show good correspondence with the Landsat time-series TS trend slope.

Table 7.3. Significant Theil-Sen trends in Landsat seasonal NDVI compared to thematic land cover changes in woodland (2004-2014).

Landsat TS trend	Thematic land cover change in woodland (2004-2014)			
	Loss	Gain	Total	Error commission
0	0	15919933	15919933	1
Negative	2055254	51658034	53713288	0.96
Positive	405628	0	405628	1
Total	2460882	67577967	70038849	
Error omission	0.17	1		0.97

Table 7.4. Significant Theil-Sen trends in Landsat seasonal NDVI compared to significant changes in AGB, where slopes > or < than 2σ and 4σ (standard deviations) were classified into significant and highly significant trends.

Landsat TS trend	Significant above ground biomass changes					
	-2	-1	1	2	Total	Error commission
0	256454	52920141	13983712	37947	67198254	1
-2	31555	178339	28871	89	238854	0.87
-1	94656	498054	1658457	6390	2257557	0.78
1	21391	109788	199552	824	331555	0.40
2	1572	6966	4079	12	12629	1
Total	405628	53713288	15874671	45262	70038849	
Error omission	0.92	1	0.99	1		0.99

7.3.5 Significant trends and biomass changes in relation to land-use

Figure 7.9 presents the areas of significant TS trends in Landsat seasonal NDVI and MODIS-derived vegetation parameters, as well as significant AGB changes, as a percentage of the areas five land-uses found in the study area (Ohangwena region). For the following time-series analyses, Landsat seasonal NDVI, NDVI amplitude and NDVI residuals, the proportion of significant positive trends was highest on government agriculture and large scale agriculture on communal land. In addition, they all exhibited a positive bias or greening trend, with negligible negative trends (Figure 7.9a-c). Percentage woody cover also exhibited pronounced positive trends on government agriculture and large scale agriculture on communal land, but in addition, shows important negative trends taking place on resettlement land (Figure 7.9d). In contrast, the most important negative changes in AGB also occurred on government agriculture, large scale agriculture on communal land and resettlement land, with very little positive changes in AGB (Figure 7.9e). From this analysis, it is clear the moderate resolution analyses are providing results conflicting with those of the AGB change analyses, and not capturing the important losses in biomass which are evident from the high resolution analyses.

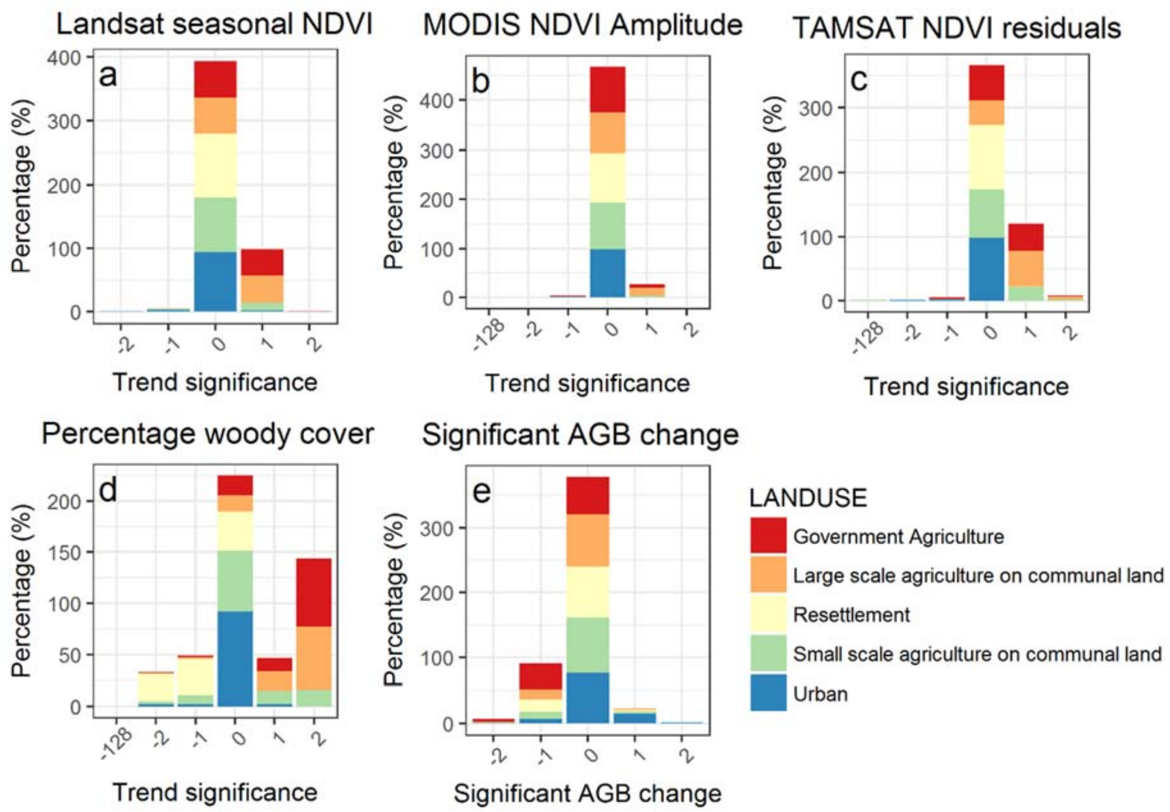

Figure 7.9. Significant Theil-Sen trends plotted as a proportion of each land-use for Landsat seasonal NDVI (a), NDVI amplitude (b), NDVI residuals (c); and percentage woody cover (d). Also included are significant changes in aboveground biomass (d). The analysis shows that the moderate resolution analyses are not capturing the important losses in biomass which are evident from the high resolution analyses.

7.4 Discussion

From contrasting the results of each analysis undertaken as part of this thesis, two vegetation change processes were quantitatively identified throughout the study area (Ohangwena region). In addition, the results were validated using a separate Landsat-based anaylsis.

(i) The high resolution land cover and biomass change analyses could successfully identify losses of natural vegetation and associated AGB. However, for the sub-sampled area (Figure 7.4), no significant increases in biomass were identified.

(ii) The moderate spatial resolution analyses could partly identify similar reductions in vegetation parameters as the high resolution analyses. These corresponding to land cover and biomass changes; however, the overall spatial extent of changes identified is negligible in comparison to the AGB change analysis (Figure 7.9).

(iii) Conversely, the moderate spatial resolution analyses additionally diagnosed positive or “greening” trends in vegetation parameters trend analyses. The R^2 values between Theil-Sens trend slope images (Figure 7.5), and the *r* values between temporal profiles (Figure 7.6 and 7.7), suggest (a) positive trends in NDVI amplitude (which acts as a proxy for increasing woody vegetation), represents a shift to a woodier or denser vegetation state, and (b) the widespread positive trends in NDVI residuals imply the increases in vegetation parameters trend analyses are not related to rainfall.

(iv) The seasonal Landsat time-series trend analysis could identify both regressive and progressive vegetation change dynamics. Moreover, the median TS trend slope map derived from the Landsat time-series shows moderate correlations with the TS trend slope maps derived from the MODIS analyses (Figure 7.5). These results highlight the validity of using seasonal Landsat NDVI time-series for (a) savannah vegetation change and trend mapping, and (b) confirms the occurrence of contrasting vegetation change processes.

(v) Positive trends were found to occur in woodland areas which were previously naturally vegetated; hence they are not the result of woodland regrowth after deforestation, but instead most likely the result of woody thickening.

To summarize, by combining the outputs from the three MODIS analyses, the positive trends identified from the three analyses can further be characterized as potentially constituting a shift in vegetation functional type to a denser and woodier condition, which is not driven by precipitation. These results are substantiated by the moderate coefficients of determination between trend maps (Figure 7.5) and correlation coefficient between temporal profiles (Figures 7.6 and 7.7). Finally, the Landsat seasonal NDVI trend analysis proved effective at identifying both regressive and progressive vegetation dynamics, as indicated by the moderate correlation coefficient with the MODIS trends analyses (Figure 7.5).

7.5 Conclusions

The datasets based on MODIS and Landsat are broadly in agreement as demonstrated by the R^2 values (Figure 7.5). Importantly, heterogeneous greening trends, identified using MODIS predominate at the regional scale, although the higher spatial resolution analysis establishes that in fact, important decreases in AGB are occurring at a local-sclae in response to small-scale deforestation.

Thus, at the spatial resolution of 250 m, the MODIS time-series analyses generalize and conceal what are in fact significant, yet highly localized vegetation losses. In effect, the analyses of Chapters 5 to 7 show that spatial patterns of vegetation change are not fully captured at a moderate resolution. As an illustration, in Figure 7.4, a proportion of small-scale (~2 ha) land clearing has erroneously been identified as having undergone a positive change but would have in fact experienced important AGB losses.

Nevertheless, the temporal resolution and hence the type of analyses permitted by the MODIS time-series, enabled certain environmental changes, which are indiscernible using higher spatial resolution but lower temporal resolution analyses (i.e. snapshots), to be elucidated. They include in particular, (i) gaining high temporal resolution data on land surface phenology, (ii) thereby facilitating the extraction of seasonal metrics and hence separating the signal of the different vegetation functional types, (iii) capturing subtle shifts in vegetation phenology, such as start of the season, and (iv) mapping trends in gradual vegetation changes, such as the gradual increases in NDVI amplitude described in Chapter 6.

Notwithstanding, with their higher spatial resolution, Landsat, Sentinel-2 and ALOS PALSAR have enabled the accurate characterization of local-scale vegetation change patterns, effectively identifying significant AGB losses which were concealed by the MODIS time-series analyses.

Chapter 8

Main thesis findings

8 Main thesis findings and synthesis

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Abstract

The following chapter presents the main thesis findings, including those developed in Chapter 7, in the context of livelihoods and sustainable development, climate, carbon, conservation and monitoring. Subsequently, an overview of the key limitations of this thesis is given. This is followed by the principle thesis conclusions, possible avenues for future research, and finally, the overall contribution to science.

Main contributions to the field of research:

• Methods and products developed as part of this thesis contribute a foundation for multi-sensor, multi-scale savannah vegetation change mapping.

• They have successfully provided a framework for integrating a range of satellite and field data in order to deliver information on environmental change at appropriate temporal and spatial scales.

• A multi-sensor multi-data source approach proved fundamental for accurately identifying vegetation changes processes.

• Intrinsic environmental variability of the savannah biome under consideration was effectively integrated using the methodological approaches outlined in the constituent chapters, as demonstrated by the high agreement between the map products resulting from this thesis.

• Regressive vegetation dynamics occur locally, especially in the forested regions, while progressive vegetation dynamics are regionally extensive. Together these processes may provoke cascading effects on ecosystems services and rural livelihoods.

8.1 Introduction

The previous chapters undertake to provide the foundations for identifying and interpreting environmental change - with a specific focus on overcoming the limitations of savannah vegetation change mapping – and quantifying the extent of deforestation and shrub encroachment. A synopsis of the main results on vegetation and climatic change processes identified as part of this thesis, are presented below, together with the relevant chapters and figures. Subsequently, the drivers and implications of change for rural livelihoods and sustainable land management, the global carbon cycle, climate conservation and monitoring, are discussed in these contexts, followed by the limitations, conclusions and future research.

8.2 Summary of results on vegetation and climatic change processes

(i) For the Kalahari woodland ecoregion between 1975 and 2014, a decline in the extent of woodland from 90% to 83% of the study area, with a resultant increase in arable land from 6% to 12%, comprised the main thematic land cover changes identified (Chapter 3).

(ii) For the same ecoregion, important losses in AGB predominate as a result of deforestation and degradation (i.e. −1.9 and −14.3 Tg, respectively). Gains associated with shrub encroachment and woodland regrowth (i.e. 2.5 Tg and 0.2 Tg, respectively) could also be quantified, although these are comparatively smaller (Chapter 4).

(iii) Woody vegetation cover is selected as an effective indicator of human impact. Throughout the country, the net change in modelled woody vegetation cover was found to be marginally negative (i.e. -0.4% ±4.80%), and the spatial area of significant positive trends was less than negative ones (i.e. 9% and 12%, respectively). Pronounced rates of negative change, as calculated using the median Theil-Sen trend slope methods, occurred predominantly on urban, state protected, resettlement and agriculture and tourism on freehold land, and are most likely due to localized land clearing. Positive trends occurred predominantly on government agriculture and large scale agriculture on communal land, and are most likely the result of shrub encroachment (Table 2; Chapter 5).

(v) Precipitation was found to not be strongly correlated with modelled percentage woody cover; this was expected since woody vegetation throughout most of Namibia is photosynthetically active independently of rainfall (i.e. woodland vegetation generally exhibits pre-rainfall green-up). In contrast, precipitation is strongly correlated with NDVI, which integrates both the woody and herbaceous vegetation signals, and hence is strongly coupled with seasonal precipitation for most of the country (Chapter 5).

(iv) Mean annual precipitation is increasing throughout the country, particularly in the north-eastern portion. Simultaneously, precipitation amplitude exhibited a weak positive trend and minor phase shifts characteristic of earlier and increased rainfall (Chapter 6).

(vi) Based on the strong correlation observed between precipitation and NDVI, NDVI residuals were calculated from a linear regression of mean monthly NDVI against cumulative monthly precipitation, as the difference between observed and predicted NDVI. Trend analyses applied to the NDVI residuals time-series demonstrates widespread greening, which is assumed to be unrelated to precipitation trends. For instance, throughout the country the spatial area of significant trends in NDVI residuals is predominantly positive (4%), with negative trends (-1%) being infrequent (Chapter 6).

(vii) The amplitude of the NDVI signal over time (i.e. NDVI amplitude), is identified as an indicator of vegetation density. Here, densely vegetated areas (i.e. woodland) exhibit high NDVI amplitude, while sparsely vegetated areas (i.e. cropland and grassland) show low NDVI amplitude. Trend analysis of NDVI amplitude also demonstrates a widespread greening trend (4%), with negative trends comprising only a small portion of change (-1.5%) (Chapter 6).

(viii) The extensive positive trends in NDVI residuals and NDVI amplitude across the country suggest the landscape may be acting as a net carbon sink. This observation is made in spite of the net decline in modelled percentage woody cover identified across the whole country, due to the inherent inaccuracies of the modelled woody vegetation cover products. Furthermore, the net decline in AGB identified for the Kalahari woodland ecoregion may not be representative of the whole country (Chapter 8).

(ix) Notably, the AGB losses found to be taking place in the Kalahari woodland ecoregion (Chapter 4) may partly be compensated by extensive, gradual and low intensity shrub encroachment, as inferred from widespread positive and co-occurring trends in percentage woody cover, NDVI residuals and NDVI amplitude (Figure 7.3, 7.4 and 7.5; Chapter 7).

(x) The results of the NDVI residuals analysis are well correlated with the modelled percentage woody cover and NDVI amplitude, both temporally (i.e. temporal profiles correlations; r=0.44 and r=0.42, respectively) and spatially (i.e. linear regression of TS trend slopes; R^2=0.40 and R^2=0.61, respectively). The strength of these correlation coefficients and coefficients of determination suggest that trends in percentage woody cover and its proxy, NDVI amplitude, are driven primarily by anthropogenic factors (i.e. land clearing and management), and to a lesser extent by precipitation trends (Figure 7.3, 7.4 and 7.5; Chapter 7).

(xi) The comparative analyses reveal that greening trends are occurring adjacent to, and at times concealing, small-scale deforestation. Specifically, in the Kalahari woodland ecoregion localized, abrupt land clearing with important losses of AGB take place concurrently to regional, gradual increases in vegetation density (Figure 7.4; Chapter 7).

(xii) Importantly, the moderate spatial resolution of the MODIS sensor (250m) failed to capture a portion of the small-scale deforestation in the Kalahari woodland ecoregion. For instance, in areas identified as experiencing positive trends in vegetation proxies, land clearing was visually identified using high resolution imagery (Chapter 7).

(xiii) The MODIS analyses identified predominantly positive changes in vegetation proxies while the AGB analysis identified predominantly negative changes in AGB. Together, the different spatial and temporal resolutions of the MODIS trend and AGB change analyses, may be the primary reasons for the discrepancy in results (Chapter 7).

(xiv) To address the issues of spatial and temporal resolution inherent in the analyses of Chapters 3 to 6, as well as validate the associated map products, a time-series of Landsat images was created based on seasonal composite imagery (Tables 7.1 and 7.2; Chapter 7). This approach successfully identifies areas corresponding to deforestation and significant AGB losses. At the same time, a good agreement was found between the Landsat and MODIS trend analyses, suggesting the Landsat time-series analysis is adequately capturing gradual increases in vegetation density (Figure 7.5; Chapter 7).

8.3 Livelihoods and sustainable land management

8.3.1 The role of agro-forestry in the Kalahari woodland ecoregion

Stringent laws and conservation measures are in place throughout much of the country to prevent deforestation, including controls on timber harvesting and forest fires. Hence, these controls may also be an important factor driving the observed trends (Alex Verlinden and Laamanen 2006). In addition, agro-forestry and pastoralism, which are the main land management practices, especially on small-scale farmsteads within the communal areas, are likely to have an important role to play in the observed greening trends.

Specifically, agro-forestry practiced by small-scale farmers in the communal regions of the Kalahari woodland ecoregion, appears to contribute to the observed greening trends (Figures 7.4a, b and c), since (i) they often take place adjacent to farmsteads, and (ii) they occur in the same geographic areas as small-scale land clearing (Figure 7.4d and e).

To explain the observed greening trends, three explanations are advanced: either, (i) the trends observed throughout much of the Kalahari woodland ecoregion are the combined result of management activities which promote vegetation growth, such as tree cultivation, rotational grazing for forage management, large-scale fencing of land previously held as commonage and fire control (Alex Verlinden and Laamanen 2006; A. Verlinden, Seely, and Hillyer 2006; A Verlinden and Dayot 1999; A. Verlinden and Dayot 2005; John Mendelsohn and el Obeid 2002). These scenarios have been described for the Sahel region, where conservation and restoration programmes were found to positively impact the NDVI signal as measured using moderate to coarse resolution satellite sensors (Spiekermann, Brandt, and Samimi 2015; Brandt et al. 2016). Or, on the other hand, (ii) the observed greening trends may only partly be the result of local agro-forestry and pastoral management, and are instead mainly precipitated by increased stocking densities in paddocks or kraals leading to shrub encroachment, which contributes to the greening trend (De Cauwer et al. 2016). A substantial body of scientific and anecdotal evidence substantiates this explanation (B. Strohbach 2001; De Klerk 2004a). Moreover, the scale at which greening trends are observed may preclude the former explanation (i.e. management activities which promote vegetation growth), which tend to be geographically limited (i.e. occurring in fenced areas or farmstead boundaries (Mendelsohn 2006; John Mendelsohn and el Obeid 2002; Mendelsohn 2009).

Lastly, fire frequency is known to be increasing throughout north-eastern Namibia (Andela et al. 2017; ‘Ministry of Agriculture, Water and Forestry. 2017. Monthly Burned Area Report, August 2017’ 2017; John Mendelsohn and el Obeid 2002). Importantly, a rise in fire frequency is known to kill large trees in broad-leaved woodlands, while repeated burns also prevent the establishment of younger trees, resulting in the older ones not being replaced. This subsequently favours the establishment of hardy trees and shrubs or encroacher species which withstand the repeated effects of fire, leading to an upsurge in small stem diameters. Through this process, the observed greening trend may also be a product of rising fire frequencies (Higgins et al. 2007; De Cauwer et al. 2016; John Mendelsohn and el Obeid 2002).

8.3.2 Feedbacks and impacts of shrub encroachment

The encroachment of savannahs with hardy shrubs has been recorded across the drylands of Africa, South America and Australia, especially after the introduction of intensive livestock raising, hence its rise is most often ascribed to excessive cattle densities (Steve Archer, Schimel, and Holland 1995). In particular, it has also been extensively documented over the past century in Namibia (Buitenwerf et al. 2012; O'Connor, Puttick, and Hoffman 2014; Rohde and Hoffman 2012; Kreike 2013). Based on the results of the various analyses undertaken in this thesis, the process of shrub encroachment appears to be widespread throughout the country.

The effects of cattle grazing in savannahs include: modifications to soil structure and chemistry, selective browsing of grasses over trees and shrubs, facilitation of woody leguminous species dispersal, as well as changes in fire intensity and frequency. Collectively, these factors impact the population dynamics of woody vegetation through the enhancement of seed production, seedling establishment and tree or shrub development and lifespan (Steven Archer 1994). Moreover, the synergy between climatic events (i.e. droughts and floods) and the biophysical impacts of grazing are very likely to have affected the magnitude and rate of shrub encroachment (Steve Archer et al. 1988; G. N. Harrington 1991).

Several additional mechanisms are postulated to lead to shrub encroachment. For example, severe climatic events, such as wet years, may facilitate the establishment of woody species. At the same time they favour herbaceous growth and hence, a consequent increase in fire intensity and likelihood, which then acts to curtail the establishment of tree and shrub species. However, if the herbaceous vegetation is heavily grazed and the fuel load thus reduced, colonization by woody vegetation might be enhanced (Seymour 2008; Rohde and Hoffman 2012; G. Harrington and Hodgkinson 1986; Swetnam and Betancourt 1990).

In addition, alterations in nutrient distribution throughout the soil profile resulting from overgrazing, may initiate a positive feedback mechanism which further facilitates subsequent shrub encroachment. Here, (i) intensive grazing prompts increases in the spatio-temporal heterogeneity of plant nutrients and water. Specifically, heavy grazing heightens herbaceous cover loss and diminishes its competitiveness; trampling then lessens water infiltration through soil compaction. The increased water run-off or overland flow gives rise to soil erosion and transport of nutrients and water. Thus, the overall impact is a decline in water and nutrient availability with a simultaneous surge in its heterogeneity. (ii) The augmented heterogeneity of these elements then facilitates invasion of encroacher shrub species, which causes further differentiation of soil nutrients and water holding capacity. (iii) Ultimately, the resulting areas of bare ground found between woody species expedite wind and rainfall erosion as well as respiration, which aggravates soil and nutrient depletion (Naito and Cairns 2011, 2011; W. H. Schlesinger et al. 1990a; Van Auken and Bush 1989; Weltz, Wood, and Parker 1989; William H Schlesinger and Jones 1984; Rostagno 1989).

Despite the removal of cattle, shrub encroachment may persist and the process has been found to be particularly hard to reverse once it has been initiated (W. H. Schlesinger et al. 1990b; Steve Archer et al. 1988; Steve Archer 1989; De Klerk 2004). For instance, severe soil erosion due to the loss of the herbaceous layer is particularly pronounced in certain regions of Namibia (Figure 8.2d; Figure 9.13). The suppression of palatable forage species by hardy and often unpalatable shrub species is the main determinant for reduced livestock carrying capacity. Such a reduction in carrying capacity is critical, since a large proportion of the country's population depends on livestock for their income and thus it comprises the foremost repercussion for rural livelihoods (Lamprey 1983; Scholes and Archer 1997).

8.4 Carbon

8.4.1 Vegetation biomass density change in the Kalahari ecoregion

Spatial patterns of vegetation loss since the 1970's indicate that in the northern Kalahari woodland ecoregion, most of the land that has been cleared is for small-scale agriculture, followed by increasing urbanization and road building. Specifically, the woodland area was found to have decreased from 90% of the study area in 1975 to 83% in 2004, and then increased to 86% in 2014, while cleared or arable land increased from 6% to 12% between 1975 and 2014 (Chapter 3).

For the same geographic area, both shrub encroachment and vegetation regrowth were prevalent, however, deforestation and forest degradation were found to be both the greatest contributors to AGB change, and the most spatially ubiquitous. For example, woodland degradation and woody thickening contributed a change of −14.3 and 2.5 Tg, over 14% and 3.5% of the study area, respectively. Deforestation and regrowth contributed a smaller portion of biomass change, i.e. −1.9 and 0.2 Tg, over 1.3% and 0.2% of the study area, respectively (Chapter 4).

Simultaneously, a greening trend was mapped for an important portion of the northern Kalahari ecoregion using moderate resolution MODIS data (Chapters 5 and 6). This suggests that low intensity or gradual increases in vegetation density are taking place that have not been fully captured by the high resolution biomass change analysis, which principally identified pronounced losses in woody biomass.

The most probable reasons for the discrepancy between the two analyses are (i) the MODIS spatial resolution is not capturing all localized vegetation change, and (ii) its lengthier temporal resolution (2000-2017) is measuring longer-term, gradual shifts in vegetation, which were not significant at the temporal scale of the biomass change analysis (i.e. 2007-2015).

The spatial area of significant trends and changes identified in Chapters 4, 5 and 6 are plotted in Figure 8.1, as a percentage of the northern Kalahari woodland ecoregion. Here, in contrast to the MODIS analyses, in which positive trends predominate, the spatial area of significant AGB losses is far more extensive than gains.

8.4.2 Vegetation biomass density change throughout Namibia

Since deforestation for arable cropping tends to occur predominantly in the northern Kalahari woodland ecoregion, with only sparse crop farming taking place in the remainder of the country due to its extreme aridity, losses in biomass may not be occurring throughout all of Namibia. However, extensive control of encroacher species or land clearing is also practiced throughout much of the remainder of the country, although the scale of this management action is not known and has not been addressed as part of this thesis, it is likely to have contributed to the observed trends.

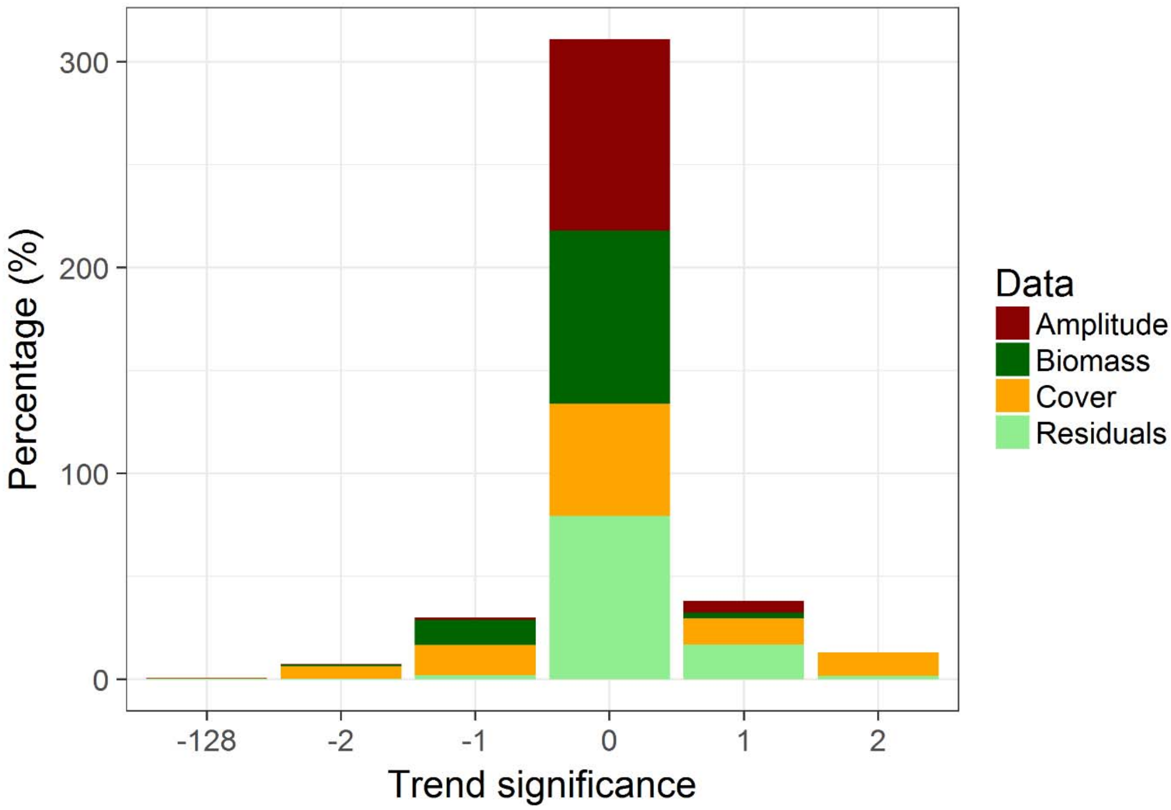

Figure 8.1. The spatial area of significant trends derived from MODIS vegetation parameter analyses, together with those of significant changes in above ground biomass (AGB). Negative AGB changes prevail, while the opposite is true for the remaining analyses. This is most likely due to the difference in spatial and temporal resolutions of the satellite sensors used in the analyses, and implies that despite important AGB losses, gradual, low-intensity increases in vegetation density are occurring.

Greening trends are prevalent across the global drylands including southern Africa and Namibia (Poulter et al. 2014). The predominance of positive trends in vegetation proxies including NDVI residuals and amplitude, which imply increases in vegetation density, provide compelling evidence that Namibia may in fact be a carbon sink. This conclusion is researched in spite of the overall decrease in modelled woody vegetation cover observed, since modelled woody vegetation cover is subject to several inaccuracies resulting from both the sampling of field measurements, and the effects of variable precipitation on phenological metrics used in the modelling approach. Furthermore, substantial AGB losses identified for the Kalahari woodland ecoregion may not be representative of the rest of country, where deforestation is not as prevalent (Tian et al. 2016; Ahlström et al. 2015; Poulter et al. 2014).

Further studies are required to quantify the ecosystem biomass content and NPP of healthy grassland versus shrub encroached rangeland, in order to establish a wall-to-wall estimate of its carbon sequestration potential across Namibia. This is especially important since increases in woody vegetation density, resulting from shrub encroachment, have been shown to not necessarily translate into increases in above and below ground biomass in savannah biomes (Eldridge et al. 2011).

8.5 Climate

8.5.1 Climate and vegetation phenology

Precipitation is thought to be the prime control on vegetation distribution and composition in savannahs (Scanlon et al. 2002). The savannah vegetation of the study area is composed of both trees and grasses, in proportions that vary substantially across the landscape in response to climatic gradients and anthropogenic pressures (i.e. grazing and fire) (Mendelsohn and el Obeid 2005). A fundamental difference between these plant functional types is their disparate leaf phenology. Shoot and leaf growth of tree species takes place in the dry season, one to three months before the on-set of the first rains (i.e. pre-rainfall green-up), while grasses are entirely reliant on seasonal precipitation for growth. The differential leafing cycles of trees and grasses suggest different factors are responsible for controlling their phenologies. In effect, the key factor controlling woody vegetation phenology across southern Africa was found to be the temporal dynamics of maximum and minimum temperature. Thus, the fluctuating phenologies of the different vegetation functional types, are the result of interacting climatic and environmental factors. This observation points to the requirement for both variables (i.e. precipitation and temperature), to be incorporated in modelling the effects of shifts in climate on savannah vegetation (Chidumayo 2001).

Monitoring and understanding these changes is highly pertinent to climate science for several reasons. In essence, they (i) are symptomatic of climatic changes, including shifts in precipitation and temperature patterns, (ii) impact vegetation biophysical properties, and hence how the land surface interacts and exchanges energy with the atmospheric system, and (iii) affect the carbon and hydrological cycles, in which any modifications are in turn likely to have cascading repercussions on ecosystem service provision.

Long-term trends in land surface or phenological metrics, apart from NDVI amplitude, were not assessed in this study, however, they provide an important avenue of future research. In particular, to identify large-scale shifts in vegetation phenology in response to environmental and climatic variables derived from satellite sensors, including land surface temperature and precipitation (D'Odorico et al. 2010; Friedl et al. 2006). For example, land cover changes alter the regional climate, as demonstrated for tropical deforestation and shrub encroachment (Asner and Heidebrecht 2005; Hulme 2001; S. Nicholson 2000). Associated transitions in vegetation functional type and phenology lead to shifts in near-surface energy balance, moisture fluxes, rooting depth, soil water balance, surface albedo, emissivity, surface heat fluxes, including long wave radiation and microclimate (Dugas, Hicks, and Gibbens 1996; Asner and Heidebrecht 2005; Friedl et al. 2006; Beltrán-Przekurat et al. 2008; Yao et al. 2017). These impacts on micro-climate result in feedback mechanisms, which in turn affect the potential for vegetation growth (Pielke et al. 1998; Scheffer et al. 2001; Bonan et al. 2002). The effects and implications of savannah woody encroachment on regional climatology and its role in feedback mechanisms, however, remains poorly quantified and little studied (W. H. Schlesinger et al. 1990a; Pielke et al. 1998; Scheffer et al. 2001; Anderies, Janssen, and Walker 2002; Van Langevelde et al. 2003; Okin, D'Odorico, and Archer 2009; He et al. 2010). For instance, in a shrub encroached dryland region, the vegetation community was found to alter the microclimate. Here, the modified microclimatic conditions initiated a positive feedback mechanism which further favoured shrub survival, as the increased area of bare soil allowed more thermal energy to be stored in the soil, thereby raising the night time land surface temperatures and enhancing the growth of shrubs over grasses (D'Odorico et al. 2010; Han and Xu 2013; Liu et al. 2016; Yao et al. 2017).

8.5.2 Drivers of precipitation variability

Mean annual precipitation may not be a good indicator of long-term trends, due to the pronounced inter-annual rainfall variability observed across savannah landscapes. Instead, spatial and temporal precipitation variability at annual to decadal scales should be taken as an indicator (Hulme 2001). These are the time-scales of rainfall variability to which the majority of social and environmental systems have adapted to and developed with, for instance, through nomadic pastoralism (Mortimore 1989). The main drivers behind long-term rainfall variability across the African continent are highly complex and centre on the shifting configurations of feedback and forcing mechanisms. These are impelled by global ocean and atmospheric circulation patterns, including the El Niño southern oscillation (ENSO) cycles (S. E. Nicholson 2001; S. E. Nicholson and Grist 2001), fluctuations in sea surface temperature (SST) unrelated to the ENSO (S. E. Nicholson and Entekhabi 1987; Giannini, Saravanan, and Chang 2003; Brooks 2004), human driven global warming (Giannini, Saravanan, and Chang 2003) and change in the land surface-atmosphere interactions through extensive land cover changes (Hulme 2001; S. Nicholson 2000).

8.5.3 Trends in regional precipitation

Vegetation in the study area was found to be highly responsive to seasonal rainfall, as evidenced not only by the high correlation coefficient (*r*) between positively lagged cumulative monthly precipitation (+1 month) and mean monthly NDVI, but also by the significant R^2 values across most of the country. Analysis of the whole TAMSAT monthly precipitation archive across Namibia reveals a largely positive trend in mean annual precipitation, especially in the north-eastern part of the country. However, when assessing a shorter time-series, from 2000-2017 using TAMSAT and CMORPH (Figures 7.6 and 7.7, respectively; Chapter 7), a stable trend is identified. This difference in results highlights the importance of temporal resolution on trend analyses outcomes. Mean annual precipitation amplitude shows a slight increasing trend, suggesting the occurrence of more very dry and wet years, while seasonal amplitude curves reveal a subtle phase shift indicative of earlier and increased rainfall at the end of the study period. Both analyses seem to point to a shift in rainfall patterns which may be in accord with climate model predictions. These anticipate longer and more frequent droughts, the overall reduction in precipitation, as well as more variable rainfall patterns (Fauchereau et al. 2003) (Chapter 6).

Importantly, human-driven shifts in climate are predicted to cause tropical savannah biomes to become more arid, resulting in a shift in vegetation composition, structure and function towards more drought-tolerante species communities. This is expected to cause a decrease in NPP and a concurrent enhancement of regional warming. Together with a rapidly growing human population, these changes are likely to exacerbate the risk of land degradation. Land degradation will negatively impact numerous ecosystem services and functions, including soil productivity, the availability of rangeland and forest resources, as well as the carbon and hydrological cycles. Ultimately, this will place added pressures on rural livelihoods (Chapter 6) (Huang et al. 2016).

8.6 Conservation and monitoring

8.6.1 Long-term ecological field data for monitoring environmental change

Greening trends derived from satellite time-series analyses need to be equated with long-term field measurements of tree densities, species composition and structure, in order to correctly interpret vegetation change processes across the landscape at the individual tree and shrub scale. For example, in their recent studies of the Sahel region, Brandt et al. (2016) and

Herrmann and Tappan (2013) show how multiple interacting vegetation change processes occur on the ground locally (Herrmann and Tappan 2013; Brandt et al. 2015). Importantly, they demonstrate that a greening vegetation trend measured using satellite remote sensing, does not always translate into a reversal of land degradation. In particular, it was often found to be accompanied by a loss of species diversity, large trees and herbaceous cover, with concurrent increases in densities of hardy unpalatable tree and shrub species and ensuing soil erosion. Thus, greening trends identified using satellite remote sensing, which would suggest increases in NPP and hence the opposite of land degradation (i.e. land recovery), can co-occur with soil and vegetation degradation processes. Notably, they also identify conservation and restoration programs as having a measurable impact on vegetation proxies measured using satellite remote sensing.

De Cauwer et al. (2016) go a long way towards addressing the issue of long-term field measurements of vegetation in Namibia. They identify significant decreases in basal area (BA) and high mortality rates among certain common, valuable timber and fruit tree species, by exploring 40 years of forest inventory data throughout the Kalahari woodland ecoregion (De Cauwer et al. 2016). These results may contribute to explaining the overall decrease in modelled woody cover identified. Although long-term field measurements are an indispensable requirement for validating biophysical trend maps, due to the associated high labour costs, they are often extremely rare. Sampling such data was beyond the scope of this study in light of the time periods involved, yet it remains an important avenue for future research. In summary, it is essential that the results of satellite trend and change detection analyses of savannah vegetation should be interpreted in conjunction with long-term field data, to ensure accurate interpretation and effective monitoring.

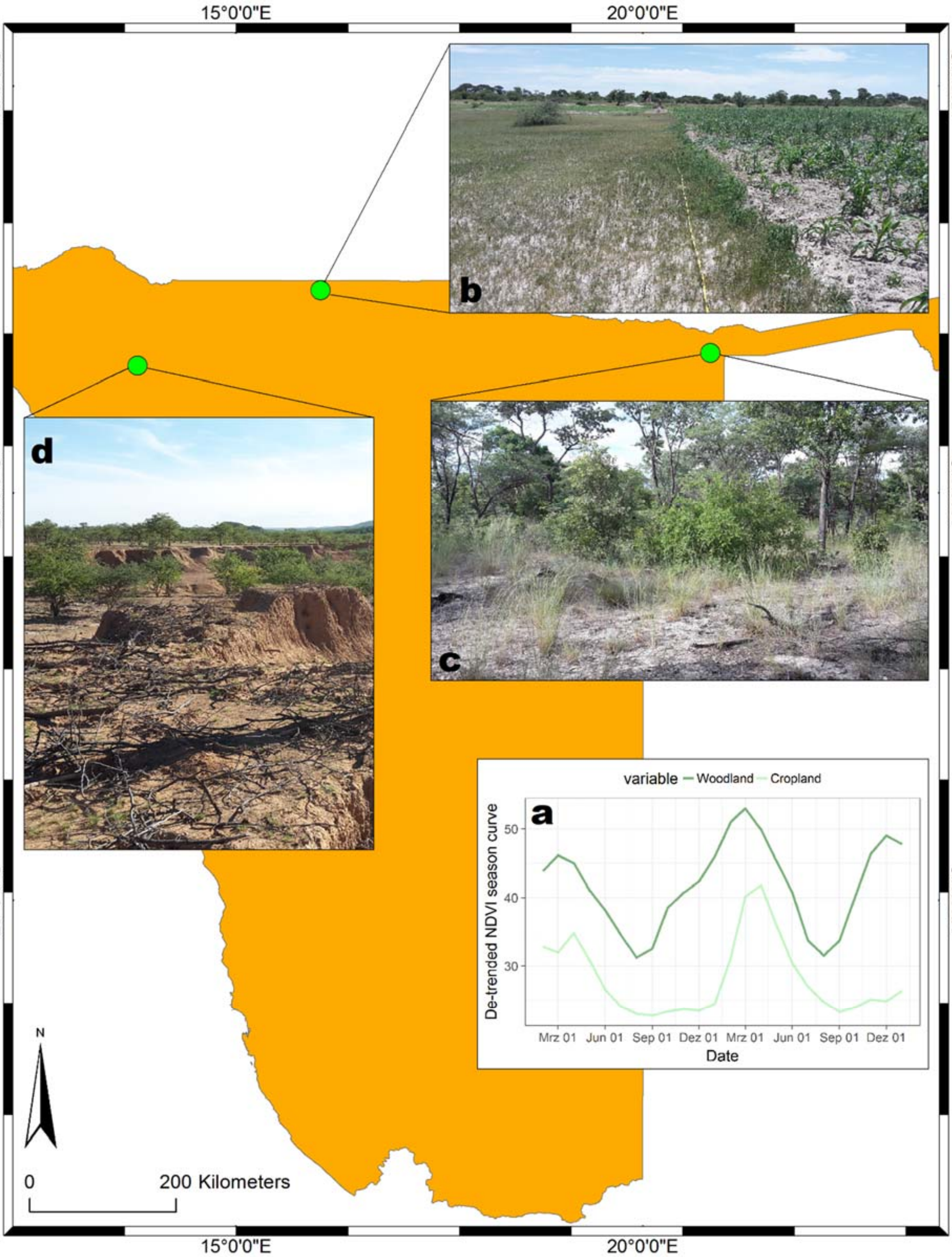

Figure 8.2. (a) Temporal profiles of pixels representing cropland (b) and woodland (c); soil erosion possibly resulting from persistent loss of herbaceous vegetation cover in western Namibiam (d).

8.6.2 Protected areas

Chapters 3 and 4 identify important decreases in woodland extent and a decline in AGB associated with deforestation and woodland degradation, respectively, throughout protected areas in the Kalahari woodland ecoregion. Moreover, Chapter 5 uncovers broad decline in modelled percentage woody cover for protected areas throughout the country. For example, large areas within the vicinity of Etosha national park were found to have experienced significant decreases in woody cover. This observation is in accord with reports of declines in tree and shrub densities throughout the park, as a result of high elephant densities and below average rainfall years (de Beer et al. 2006). Repeated fires are widely associated with decreases in tree and shrub densities, as well as woody species diversity in Namibia. In light of increasing fire frequencies identified especially in the north of the country, it is likely that fire is a leading driver of the observed decreases in percentage woody cover identified in protected areas. However, the author also argues, in Section 8.3.1, that rising fire frequency may lead to increases in small stem diameters, thereby contributing the observed greening trend (Sankaran et al. 2005; de Cauwer 2013; De Cauwer et al. 2016; Mendelsohn and el Obeid 2005).

8.7 Limitations

8.7.1 Limitations of moderate and high spatial resolution analyses

The MODIS time-series is sometimes considered too short to accurately identify long-term trends in vegetation, for instance, gradual change such as shrub encroachment. This is especially the case in comparison to very long time-series products such as the Global Inventory Monitoring and Modelling System Third generation (GIMMS3g). Nevertheless, with 17 years of data and a good agreement with analogous earth observation (EO) time-series, including the Satellite Pour l'Observation de la Terre - Vegetation, Geoland2 version 1 (GEOV1) Leaf Area Index (LAI) product and Land Long Term Data Record (LTDR) version 3, MODIS has in fact proved excellent at quantifying temporal and spatial trends in both land surface phenology and biophysical parameters (Broich et al. 2014; Baret et al. 2013, 1; Beck et al. 2011; Fensholt et al. 2009).

Abrupt, short-term processes, such as forest and grass fires, floods and crop rotations, generally have a large impact on the results of high spatial and low temporal resolution analyses (Chapters 3 and 4). In contrast, the coarse spatial resolution of MODIS allows environmental fluctuations and noise to effectively be integrated. Moreover, the dense time-series allows subtle and longer-term trends to be identified and assessed, in particular in relation to climatic variables such as precipitation, thus, permitting anthropogenic change signals to be distinguished from climatic signals. For instance, the analysis of trends in NDVI residuals (Chapter 6) specifically addresses these issues by removing the effects of rainfall on vegetation and revealing the effects of human activity as a driver of vegetation change. Nevertheless, a number of studies have shown that up to 50% of deforestation is missed, in comparison to high resolution Landsat analyses (Anderson et al. 2005; Hammer, Kraft, and Wheeler 2014; Hansen and Loveland 2012).

8.7.2 Confounding factors and the need for multi-data, multi-sensor approaches

Aside from pixel resolution, numerous confounding factors affect the biophysical property being mapped (i.e. land surface phenology, biomass cover), when measuring vegetation change in savannah ecoregions. They include the heterogeneous nature of vegetation structure, composition and function and its dynamic phenology; environmental and climatic factors, including fluctuating precipitation and climate, fire, and diverse land-uses; the imagery used, including image availability, quality, reflectances, spectral bands and algorithms used for image processing and parameter retrieval, and finally, the length of the time-series and type of trend analysis. Collectively, these factors contribute to influencing the final change and trend analysis result (Chapters 5 and 6) (Hill et al. 2011; Hanan and Hill 2011; Whiteside, Boggs, and Maier 2011; Asner and Lobell 2000). Hence, to accurately map vegetation changes in savannahs, a multi-scale, multi-sensor approach, which incorporates exhaustive field measurements into model calibration and validation, is fundamental for addressing these limitations. Such an approach facilitates the comprehensive identification and interpretation of divergent vegetation change processes (i.e. deforestation and shrub encroachment), affecting distinct plant functional types (i.e. grasses, shrub and trees), which are often subtle and occur across spatial and temporal scales.

8.8 Conclusions

The main focus of this thesis was the quantitative analysis and interpretation of satellite and field data, using multi-sensor, multi-data source methodologies, to identify vegetation change processes occurring in a savannah biome. In addition, this thesis presents mostly descriptive methods when attempting to explain the extent and drivers of vegetation changes processes. In this context, it was crucial to account for uncertainties and limitations pertaining to the data and methods used; an attempt is made to comprehensively detail these in each of the relevant chapters. Several clear patterns emerge from addressing the research questions presented in this thesis which allow a number of conclusions to be drawn.

The first aim of this thesis was to overcome some the limitations inherent in satellite remote sensing of savannah vegetation change. Savannahs exhibit a high degree of intra- and inter-annual variability which complicates vegetation change detection. In the analyses comprising this thesis, much of the intrinsic environmental fluctuations were effectively integrated, as demonstrated by the high degree of agreement between the map products. In particular, a validation time-series consisting of Landsat 5, 7 and 8 data acted to effectively integrate environmental noise and sensor disparities. Moreover, significant trends in this time-series revealed a remarkably good agreement with all the datasets created as part of this thesis, thereby emphasizing their validity. Thus, these methods are presumably highly applicable across heterogeneous and dynamic dryland biomes.

The second aim of this thesis was to quantify the intensity of contrasting vegetation change processes, identify potential drivers of change and investigate the implications for rural livelihoods and sustainable land management, the global carbon cycle, climate, conservation and monitoring, which had only previously been done in a limited context. The separate approaches adopted in this thesis establish the widespread co-occurrence of divergent vegetation change processes (i.e. gains and losses), occurring in highly heterogeneous spatial and temporal patterns. Deforestation or pervasive vegetation loss is found to be caused mainly by anthropogenic drivers, especially land clearing for urban development and arable cropping. Shrub encroachment is also most likely the result of extensive land management practices, including grazing and fire, as precipitation trends appear to present little or no influence on vegetation density trends. This is despite the fact that rainfall, as measured since 1983, shows a positive trend throughout the country, especially in the northeast. At the same time rainfall variability is increasing, which may be in agreement with predictions from global climate models. Notably, for most of Namibia, neither vegetation change process is widespread. The different vegetation proxies assessed appear relatively stable over the bulk of the territory, in that significant trends or changes occupy a relatively small portion of the country. Thus, the processes of deforestation and shrub encroachment cannot be broadly generalized across the whole study area. In fact, deforestation, land clearing and progressive vegetation loss are highly localized and occur especially in woodland regions. In contrast, greening tends, potentially constituting shrub encroachment or gradual increases in vegetation density, are found to be regionally extensive across the country, although they tend to occur at relatively low intensities.

Together these processes may provoke cascading effects on ecosystem services and rural livelihoods. For instance, shrub encroachment often leads to soil erosion and importantly, losses in annual and perennial forage species which form the basis of rural livelihoods often dependent on cattle farming. Deforestation and woodland degradation result in habitiat loss and fragmentation, as well as a decline in forest resources, ecosystem resilience and biodiversity. The Kalahari woodland ecoregion is shown to be a net carbon source as a result of these processes. Moreover, protected areas across the country are found to be particularly affected by losses of woody vegetation cover. However, the biomass losses from deforestation and degradation in this ecoregion may be compensated by widespread shrub encroachment in the remainder of the country. Here, the predominantly positive trends observed in the vegetation proxies assessed, may imply that the country as whole is a carbon sink. The results which led to this observation are in agreement with several studies demonstrating increases in vegetation density across drylands. Finally, long-term field studies are required not only to calibrate and validate models of vegetation change and results of trend analyses, but also to establish the landscape carbon storage and dynamics of different vegetation communities throughout the country.

8.9 Future research

An important amount of satellite and field data could not be included in the framework of this thesis; hence, these data constitute an important basis for future research. Notably, they include very high resolution (5 cm) aerial orthophotos, Corona satellite imagery, field measurements of fractional bare ground and herbaceous cover, multi-temporal fractional cover maps derived using the CLASlite method and spectral signatures of the predominant land cover types retrieved using a handheld field spectrometer in the 325 – 1075 nm spectral range (Asner 2009).

Two elements which were omitted from this thesis, yet also present promising avenues of research, include i) the establishment of permanent, long-term field monitoring plots that would provide valuable ecological time-series data with which to calibrate satellite-based empirical biophysical models, and ii) investigating correlations between phenological metrics and fractional herbaceous and bare ground cover. Both cover variables are fundamental components of fractional land cover products and key indicators of land degradation, grazing potential and ecosystem processes. Therefore, an anticipated study would assess spatial and temporal trends in each separate variable in relation to climatic and environmental drivers.

The recent availability of new satellite datasets, including in particular the European Space Agency's Sentinel satellite constellation, is providing a suite of data with which to monitor environmental change. For example, Sentinel-2 affords continuity to the Landsat and SPOT missions, while at the same time allowing for the creation of dense time-series and hence the application of trend and phenology analyses. Sentinel-1 is generating high resolution radar information which will contribute significantly towards vegetation biomass and biomass change mapping, while ICESat-2 will shortly be available for continental canopy height and biomass mapping. Products including land surface temperature derived from both Landsat and Sentinel constellations provide new opportunities for studying the dynamics of land surface phenology and vegetation functional type dynamcis, in relation to climatic and environmental drivers. Significantly, investigating the fusion of these datasets would allow the creation of a more accurate and contemporary high resolution time-series with which to monitor environmental change, especially in biomes encompassing heterogeneous and dynamic vegetation communities.

8.10 Contribution to scientific knowledge

Long-term trends and short-term changes in vegetation proxies were successfully mapped and validated for Namibia. The dynamics of these processes were then assessed in relation to climatic and environmental drivers. The main findings of this thesis demonstrate the i) ecosystem-level response of vegetation to change drivers, including the role of precipitation and land-use, ii) contribution of vegetation changes to the carbon cycle, and iii) contemporary impact of anthropogenic land management on regional vegetation change.

Several methods based on the integration of diverse satellite and field datasets, across multiple spatial and temporal scales, were validated and found to satisfactorily capture divergent vegetation change processes across a southern African savannah landscape. Importantly, the synthesis of multi-sensor datasets proved fundamental for accurately identifying vegetation changes processes, as single-sensor or single-resolution analyses provided an incomplete representation of actual vegetation change processes.

The analyses undertaken in this thesis provide a framework for integrating a range of satellite and field data, to expedite the delivery of information on environmental change at appropriate temporal and spatial scales. These data are relevant to both the scientific and land management communities, since they yield accurate, long-term, multi-scale map products of environmental change in savannah biomes.

The methods and map products developed contribute a foundation for multi-sensor, multi-scale vegetation change mapping of Namibia's savannahs. These have the potential to continuously be updated and refined as new satellite and field datasets become available.

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Chapter 9

Appendices

9 Appendices

9.1 Supplementary materials Chapter 3

Figure 9.1. Pearl millet field in north-central Namibia.

Figure 9.2. Recently ploughed pearl millet field, illustrating the sand nature of the soils.

Figure 9.3. Crop of peal millet with an adjacent kraal.

Table 9.1. Google Earth Engine code.

Year	Google Earth Engine Code
1984	https://code.earthengine.google.com/fdf45ca49c3e591ad21d4d2bf2b42ee4
1994	https://code.earthengine.google.com/63ce41b65b7e0d5d25001409b57a5fa9
2004	https://code.earthengine.google.com/990d662d4413283a8b71a30ccb752c18
2014	https://code.earthengine.google.com/ecf3acf4cd21c9674690bf3d488dd72e

Table 9.2. Evaluation error matrixes indicating overall accuracy, errors of commission and omission, and total training data pixels.

1975	Water	Clay Pan	Agriculture	Sand	Woodland	Wetland	Urban	Total	Error C
Water	49	1	0	0	0	0	0	50	0.0
Clay pan	0	42	0	0	8	0	0	50	0.2
Agriculture	0	0	36	0	14	0	0	50	0.3
Sand	0	1	2	28	19	0	0	50	0.4
Woodland	0	0	5	0	45	0	0	50	0.1
Wetland	0	0	1	0	0	49	0	50	0.0
Urban	5	4	15	1	0	0	21	46	0.5
Total	54	48	59	29	86	49	21	346	
Error O	0.09	0.13	0.39	0.03	0.48	0.00	0.00		
Overall accuracy									0.7804

1984	Water	Clay pan	Agriculture	Sand	Woodland	Wetland	Total	Error C
Water	896	0	0	0	0	0	896	0
Clay pan	0	540	0	0	1	0	541	0.00
Agriculture	0	0	1915	0	40	0	1955	0.02
Sand	0	0	0	99	0	0	99	0
Woodland	0	0	11	0	14475	0	14486	0.00
Wetland	0	0	0	0	1	284	285	0.00
Total	896	540	1926	99	14517	284	18262	
Error O	0	0	0.01	0.00	0.00	0		
Overall accuracy								0.9971

1994	Water	Clay pan	Agriculture	Sand	Woodland	Wetland	Total	Error C
Water	108	0	0	0	0	0	108	0
Clay pan	0	300	0	0	0	0	300	0
Agriculture	0	0	2390	4	47	0	2441	0.02
Sand	0	0	0	96	0	0	96	0
Woodland	0	0	17	0	37459	1	37477	0.00
Wetland	0	0	0	0	0	853	853	0
Total	108	300	2407	100	37506	854	41275	
Error O	0	0	0.01	0.04	0.00	0.00		
Overall accuracy								0.9983

2004	Water	Clay pan	Agriculture	Sand	Woodland	Wetland	Total	Error C
Water	297	0	0	0	0	0	297	0
Clay pan	0	182	0	0	0	0	182	0
Agriculture	0	0	1913	0	50	0	1963	0.03
Sand	0	0	0	118	0	0	118	0
Woodland	0	0	26	0	13678	0	13704	0.00
Wetland	0	0	0	0	0	206	206	0
Total	297	182	1939	118	13728	206	16470	
Error O	0	0	0.01	0	0.00	0		
Overall accuracy								0.9954

2014	Water	Clay pan	Agriculture	Sand	Woodland	Wetland	Total	Error C
Water	378	0	0	0	0	0	378	0
Clay pan	0	175	0	0	0	0	175	0
Agriculture	0	0	2130	1	38	0	2169	0.02
Sand	0	0	0	307	0	0	307	0
Woodland	0	0	13	0	30196	0	30209	0.00
Wetland	0	0	0	0	9	166	175	0.05
Total	378	175	2143	308	30243	166	33413	
Error O	0	0	0.01	0.003247	0.00	0		
Overall accuracy								0.9982

Table 9.3. Error matrices for each period showing adjusted change area and confidence intervals. The transition from woodland to non-woodland is labeled deforestation. Error matrix entries are expressed as the estimated area proportion. Map classes represent rows and reference classes the columns.

2004–2014	**Agriculture**	**Woodland**	**Deforestation**	**Total**	**Map Area**	**User's**	**Producers**	**Overall**
Agriculture	0.10	0.002	0.000	0.10	10741	0.98	0.44	0.72
Woodland	0.12	0.605	0.000	0.72	92629	0.84	0.99	
Deforestation	0.00	0.006	0.014	0.02	4624	0.58	1.00	
Total	0.22	0.613	0.014	0.84	107994			
1994–2004	Agriculture	Woodland	Deforestation	Total	Map area	User's	Producers	Overall
Agriculture	0.05	0.016	0.000	0.07	9263	0.76	0.32	0.67
Woodland	0.10	0.617	0.000	0.72	90077	0.86	0.96	
Deforestation	0.00	0.013	0.006	0.02	8653	0.28	1.00	
Total	0.15	0.645	0.006	0.80	107994			
1984–1994	Agriculture	Woodland	Deforestation	Total	Map area	User's	Producers	Overall
Agriculture	0.06	0.005	0.000	0.06	7163	0.92	0.59	0.87
Woodland	0.03	0.797	0.000	0.83	93421	0.96	0.98	
Deforestation	0.01	0.011	0.020	0.04	7411	0.54	1.00	
Total	0.10	0.813	0.020	0.93	107994			
	Agriculture	Woodland	Deforestation	Total	Map area	User's	Producers	Overall
Agriculture	0.09	0.010	0.000	0.10	12532	0.90	0.34	0.50
Woodland	0.18	0.397	0.000	0.57	89555	0.69	0.96	
Deforestation	0.01	0.005	0.005	0.02	5906	0.31	1.00	
Total	0.28	0.413	0.005	0.70	107994			

Table 9.4. Cross tabulation matrices showing change trajectories as a percentage of the study area [1].

1975	**1984**						
	Water	**Claypan**	**Agriculture**	**Sand**	**Woodland**	**Wetland**	**Urban**
Water	0.10	0.00	0.06	0.01	0.25	0.02	0.00
Claypan	0.04	0.46	0.23	0.01	1.24	0.01	0.00
Agriculture	0.01	0.43	3.55	0.06	3.06	0.00	0.00
Sand	0.01	0.01	0.08	0.07	0.00	0.00	0.00
Woodland	0.10	0.66	3.54	0.15	84.57	0.15	0.00
Wetland	0.03	0.00	0.01	0.00	0.72	0.06	0.00
Urban	0.00	0.00	0.08	0.01	0.19	0.01	0.00
1984	1994						
	Water	Claypan	Agriculture	Sand	Woodland	Wetland	Urban
Water	0.05	0.00	0.00	0.00	0.00	0.00	0.00
Claypan	0.03	0.57	0.11	0.04	1.46	0.01	0.00
Agriculture	0.05	0.55	4.42	0.06	4.98	0.02	0.00
Sand	0.00	0.00	0.13	0.07	0.00	0.00	0.00
Woodland	0.27	0.88	2.42	0.00	82.30	0.63	0.00
Wetland	0.05	0.01	0.02	0.00	0.42	0.16	0.00
Urban	0.00	0.00	0.00	0.00	0.00	0.00	0.30
1994	2004						
	Water	Claypan	Agriculture	Sand	Woodland	Wetland	Urban
Water	0.04	0.03	0.04	0.00	0.87	0.09	0.00
Claypan	0.00	0.39	0.23	0.00	0.93	0.01	0.00
Agriculture	0.00	0.43	5.76	0.04	5.22	0.02	0.01
Sand	0.00	0.02	0.20	0.11	0.00	0.00	0.00
Woodland	0.00	1.32	3.17	0.00	78.49	0.38	0.04
Wetland	0.00	0.00	0.00	0.00	0.58	0.14	0.00
Urban	0.01	0.02	0.67	0.05	0.42	0.01	0.24
2004	2014						
	Water	Claypan	Agriculture	Sand	Woodland	Wetland	Urban
Water	0.15	0.01	0.03	0.00	0.10	0.02	0.00
Claypan	0.00	0.15	0.15	0.01	0.14	0.00	0.00
Agriculture	0.00	0.31	7.02	0.10	3.78	0.00	0.32
Sand	0.00	0.02	0.23	0.22	0.01	0.00	0.06
Woodland	0.88	1.07	3.88	0.00	79.13	0.60	0.23
Wetland	0.03	0.00	0.04	0.00	0.07	0.10	0.00
Urban	0.00	0.00	0.13	0.00	0.19	0.01	0.81

Table 9.5. Pearson Pearson's coefficient (r) showing the relation between the aerial extent of main land cover class transition (i.e., woodland to agriculture) in each 5 km distance zone, and each proximal change variable for each interval assessed.

	1975–1984	**1984–1994**	**1994–2004**	**2004–2014**
Minor towns	−0.89	−0.84	−0.98	−0.96
Major towns	−0.91	−0.87	−0.63	−0.62
Rivers	−0.8	−0.85	−0.92	−0.84
Roads	−0.81	−0.81	−0.81	−0.87

9.2 Supplementary material Chapter 4

Figure 9.4. Image illustrating the predominantly woody vegetation in the study area.

9.2.1 Phenology metric extraction

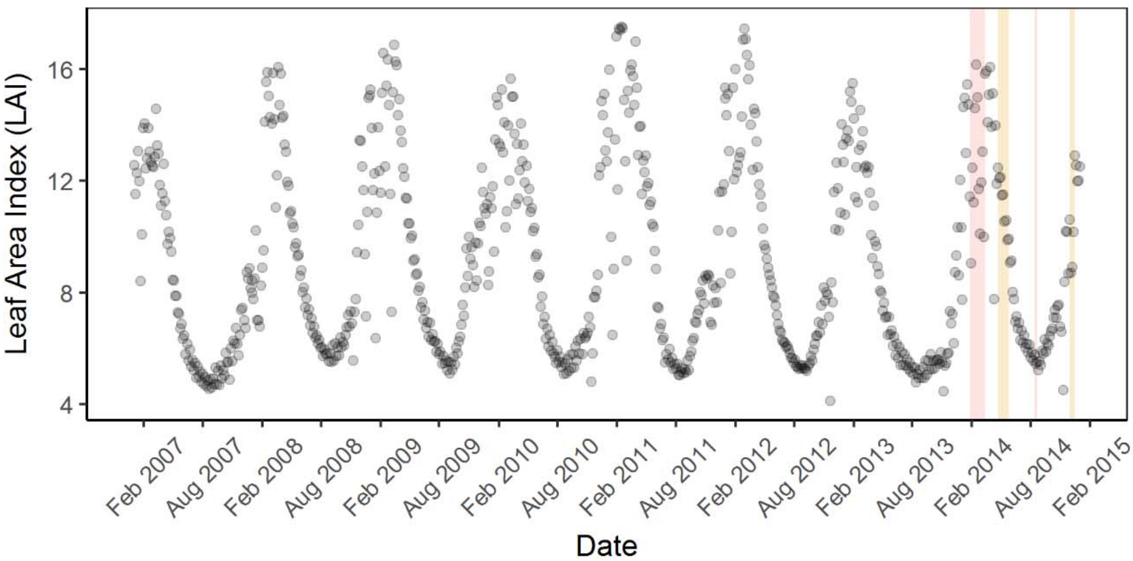

Figure 9.5. Time series of MODIS leaf area index (LAI) product averaged over the whole study area. Start of season and end of season was of 340 +/- 8.2 and 130 +/- 16 days, respectively (i.e. 6 December and 10 May) (shaded yellow). Position of peak value and trough value occur at 50 +/-24 and 230 +/- 4.7 days, respectively (i.e. 19 February and 18 August) (shaded red).

9.2.2 Trend estimation methods

Trend estimation based on linear regression analysis is commonly used (Eklundh and Olsson 2003), yet it contravenes statistical assumptions, namely independence of observation as a result of temporal autocorrelation or homogeneity (Beurs and Henebry 2004); as such, the use of non-parametric tests (i.e. Mann-Kendall) bypass these constraints (Forkel et al. 2013; Beurs and Henebry 2004). Similarly, annually aggregating diminishes temporal resolution, which is essential in estimating trend significance. Conversely, annual aggregation reinforces trend analysis by removing any seasonal cycles, which can add seasonal correlation structures increasing overall error (Forkel et al. 2013). Additionally, aggregating values to average annual scales, variation due to climate, fire or anthropogenic activity is effectively integrated, permitting the quantification of long-term anomalies, such as deviations from long-term averages. Different methods have been developed to fully exploit time-series, either by estimating and/or subtracting the seasonal cycle (Verbesselt, Hyndman, Newnham, et al. 2010; de Jong et al. 2011; Verbesselt, Hyndman, Zeileis, et al. 2010)

9.2.3 Change detection validation

Table 9.6. Error matrix comparing the threshold change to the validation map (STM trend). Overall accuracy was of 65%.

Threshold change map	STM trend map					
	Nodata	Deforestation/ degradation	No change	Thickening/ regrowth	Sum	User accuracy
Nodata	1820000	443000	3530000	150000	5944436	30.69
Deforestation/ degradation	242	71800	36100	1600	109657	65.44
No change	12500	1520000	10100000	437000	12053704	83.69
Thickening/ regrowth	1010	23900	296000	60800	381443	15.95
Sum	1840000	2060000	13900000	649000	18489240	NA
Producer accuracy	99.30	3.49	72.30	9.37	NA	65.14

Table 9.7. Error matrix comparing the threshold change to the validation map (STM trend). Overall accuracy was of 65% using the mapped area proportions (*Wi*) variable of (Olofsson et al. 2014)

Threshold change map	STM trend map									
	Nodata	Deforestation/ degradation	No change	Thickening/ regrowth	Total	W_i	Map area	User's	Producers	Overall accuracy
Nodata	0.03	0.01	0.06	0.00	0.10	0.10	21794.09	0.53	0.31	22.16
Deforestation/ degradation	0.00	0.00	0.00	0.27	0.27	0.00	402.04	0.07	0.01	
No change	0.03	0.03	22.13	0.96	23.14	26.44	44192.49	1.00	0.96	
Thickening/ regrowth	0.00	0.00	0.00	0.00	0.00	0.00	1398.48	0.00	0.16	
Total	0.06	0.04	22.19	1.23	23.52		67787.10			

9.3 Supplementary material Chapter 5

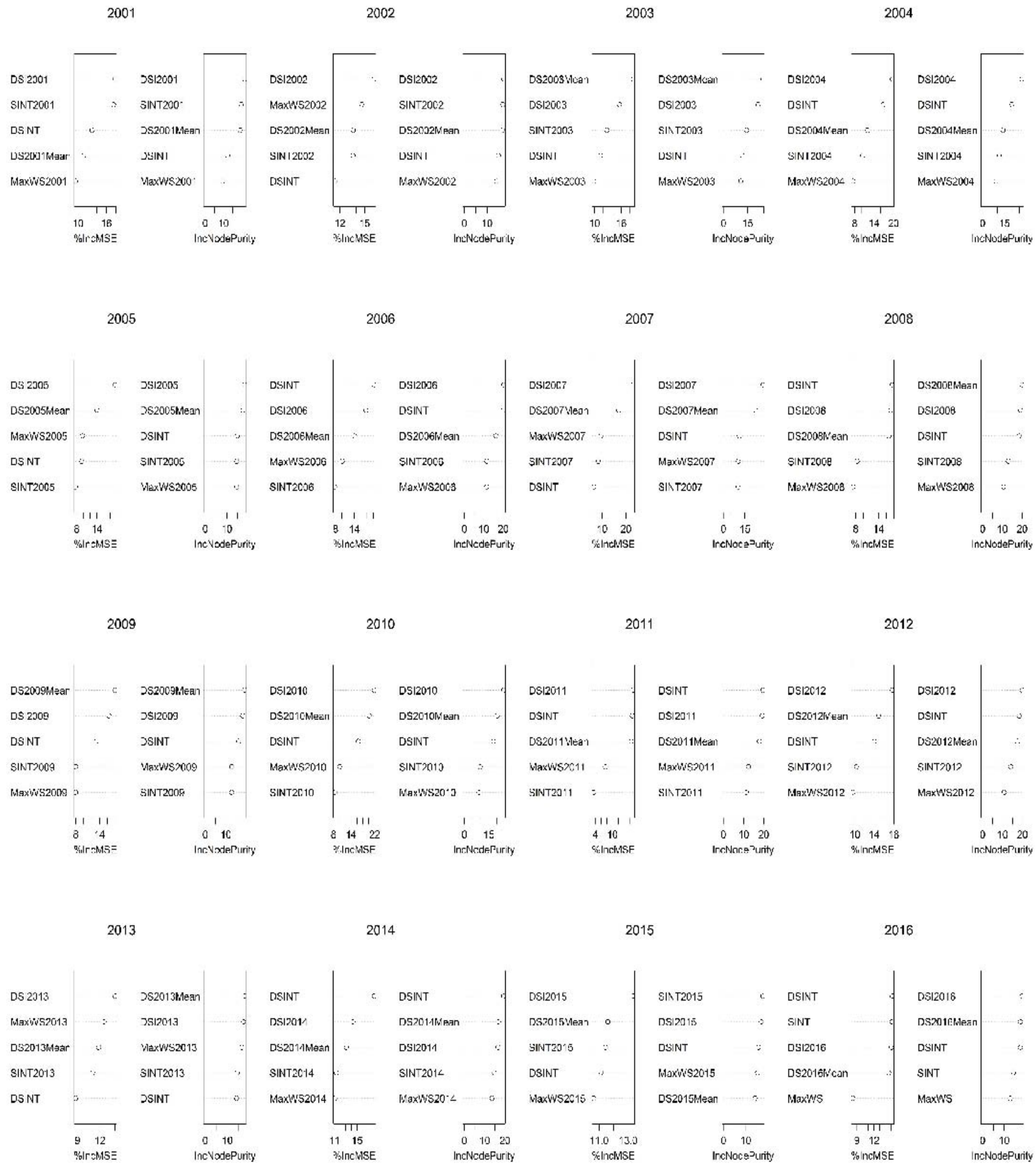

Figure 9.6. Predictor layer importance is measured using the Mean Standard Error (MSE) as each variable is randomly permuted, and the increase in node purity from each of the splits in the random forest based for each particular variable, as computed by the gini metric.

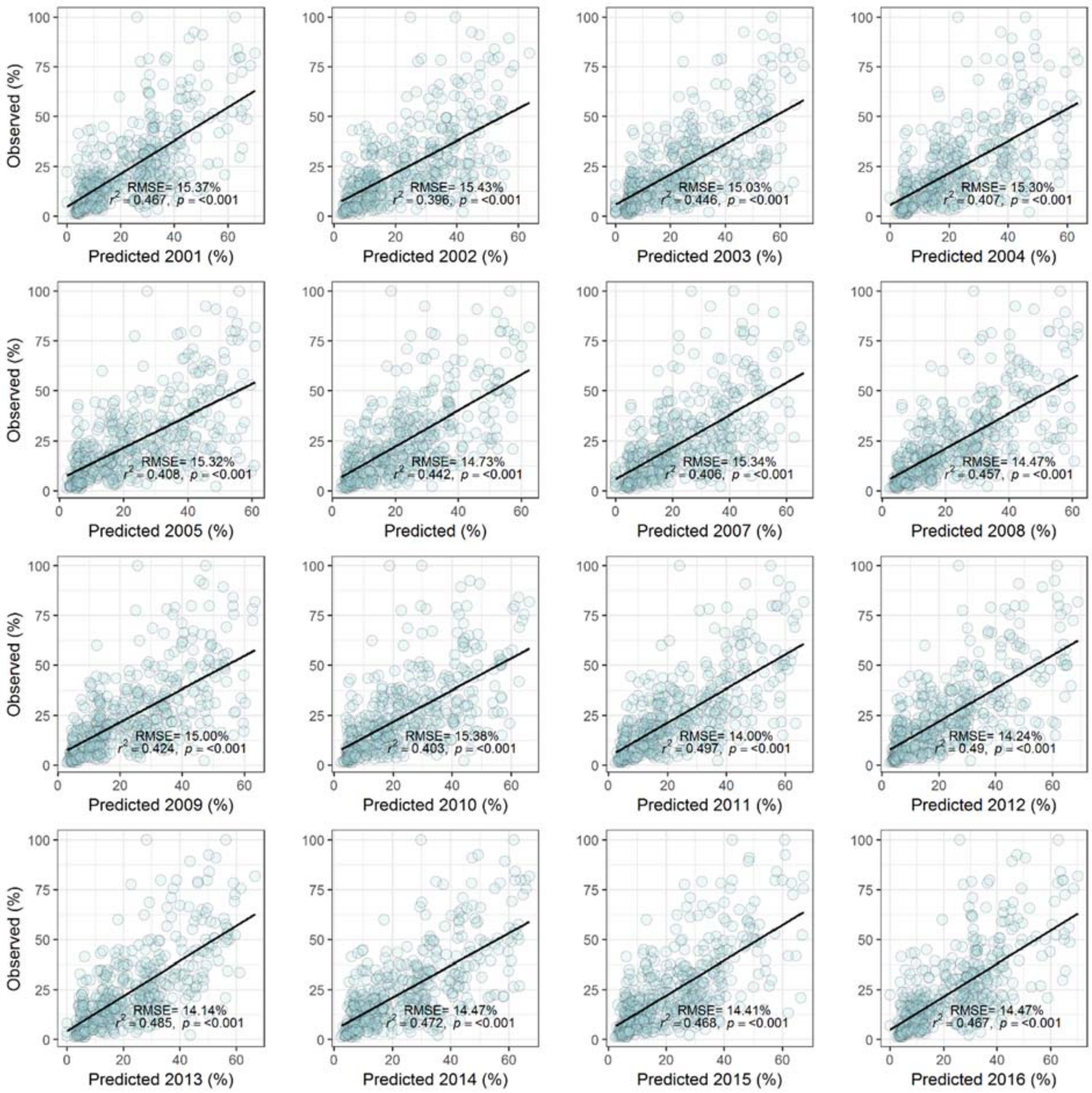

Figure 9.7. Linear regression of observed and predicted values; between the 2001 and 2016 models, the R^2 values ranged from 0.4 to 0.5, and the RMSE ranged from 14.14% to 15.43%.

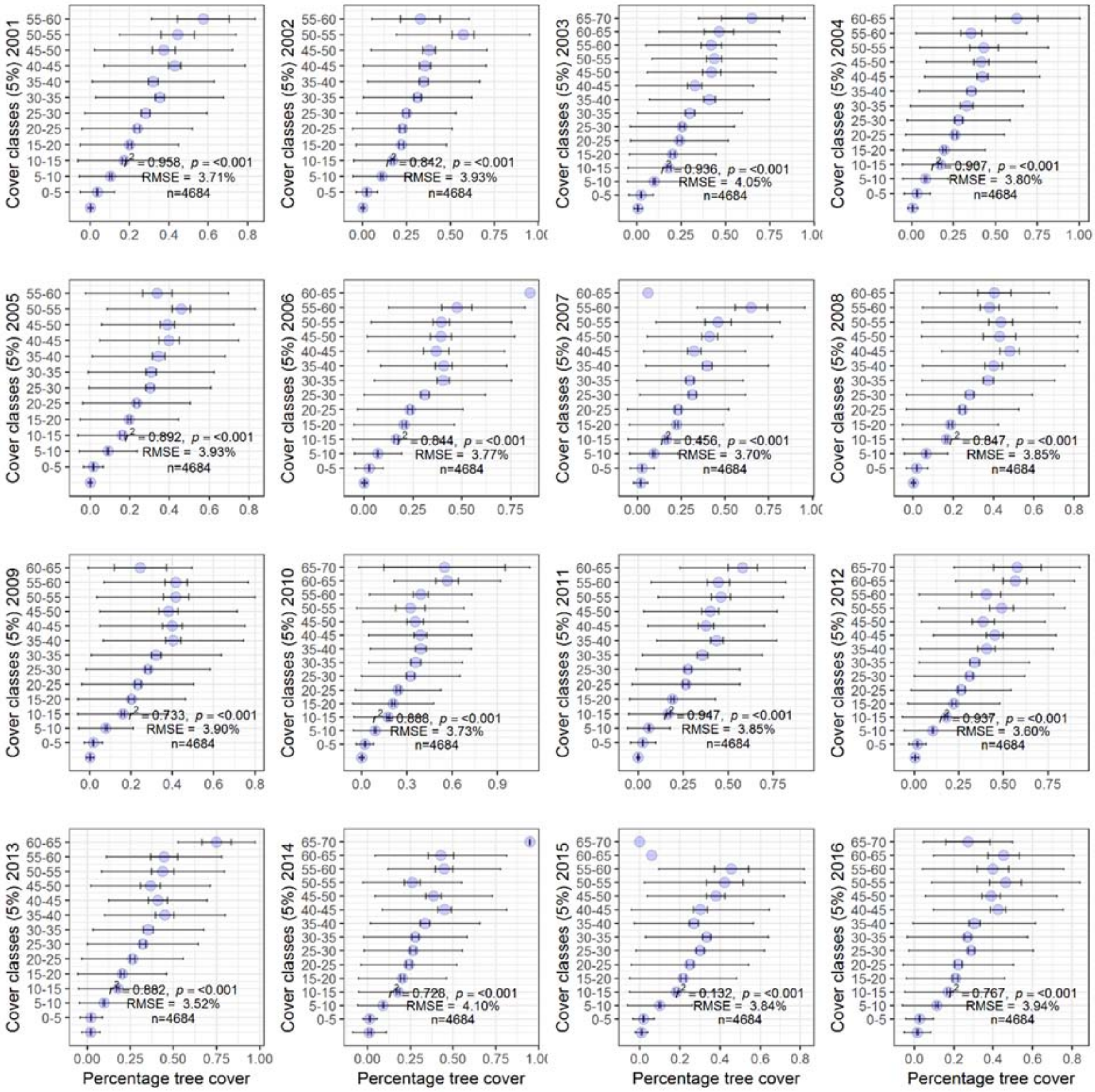

Figure 9.8. Between the 2001 and 2016 models, the R^2 values ranged from 0.13 to 0.96, and the RMSE ranged from 3.52% to 4.10%. Low R^2 values are the results of single outlier percentage tree cover (%) observation within cover classes. For example, for the 2006 model, only a single observed percentage woody cover (%) sample was identified for the 60-65 % cover class.

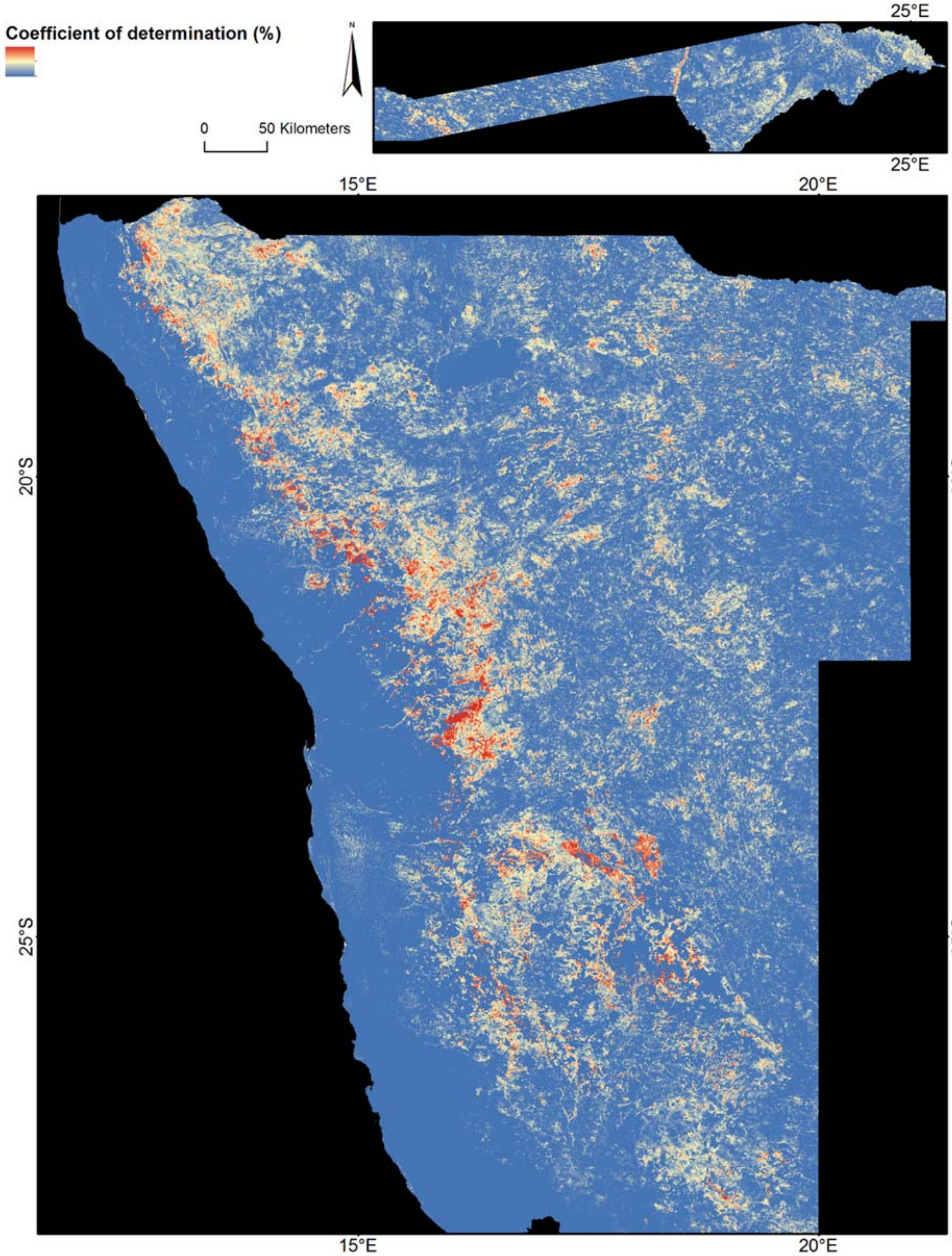

Figure 9.9. R^2 values resulting from a linear regression between mean annual precipitation anomalies (independent) and annual percentage woody cover anomalies (dependent).

9.4 Supplementary material Chapter 6

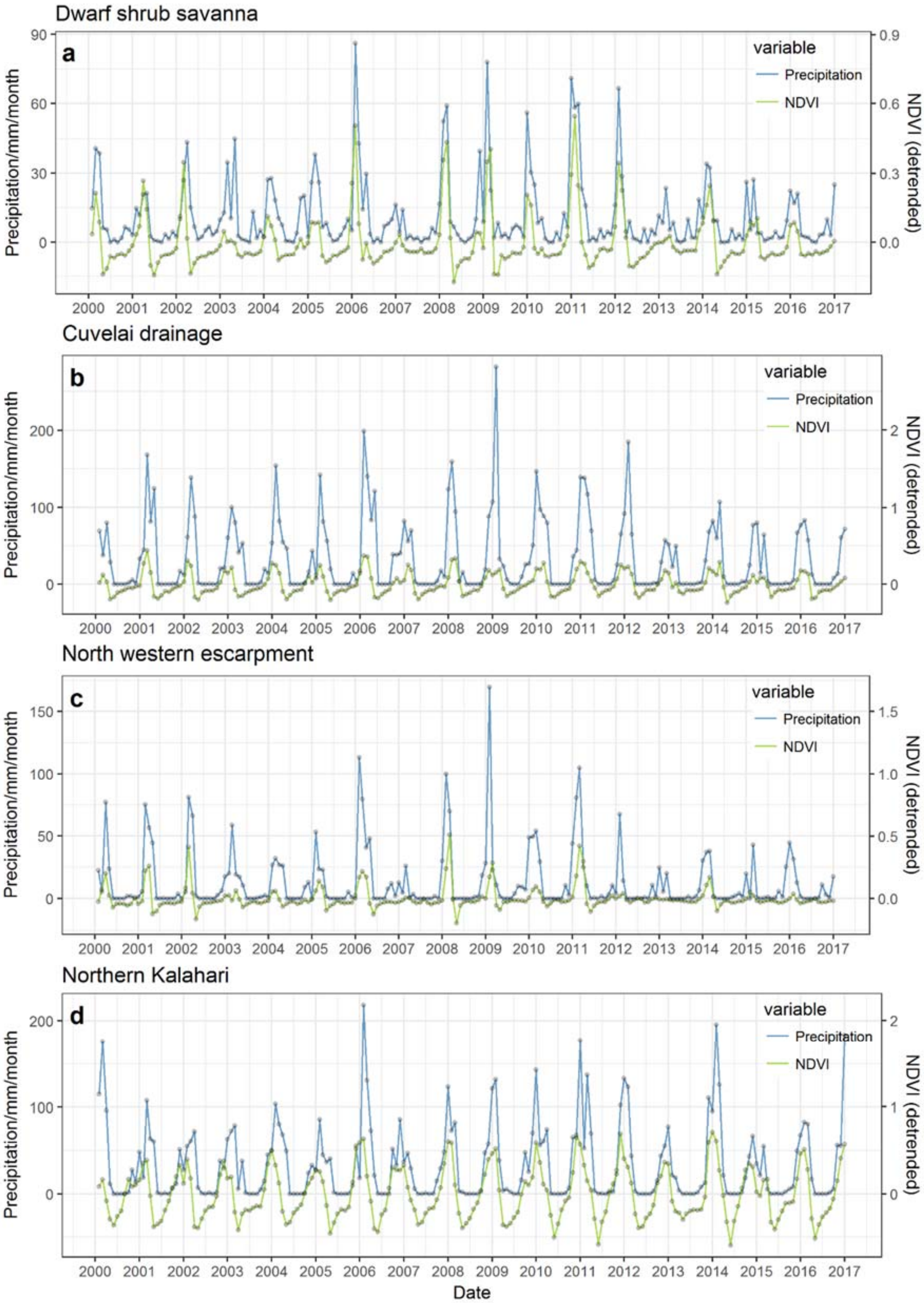

Figure 9.10. Temporal profiles of precipitation (TAMSAT) and de-trended NDVI shown without lags applied: Dwarf shrub savanna (a); Cuvelai drainage (b); North western escarpment (c); and Northern Kalahari (d).

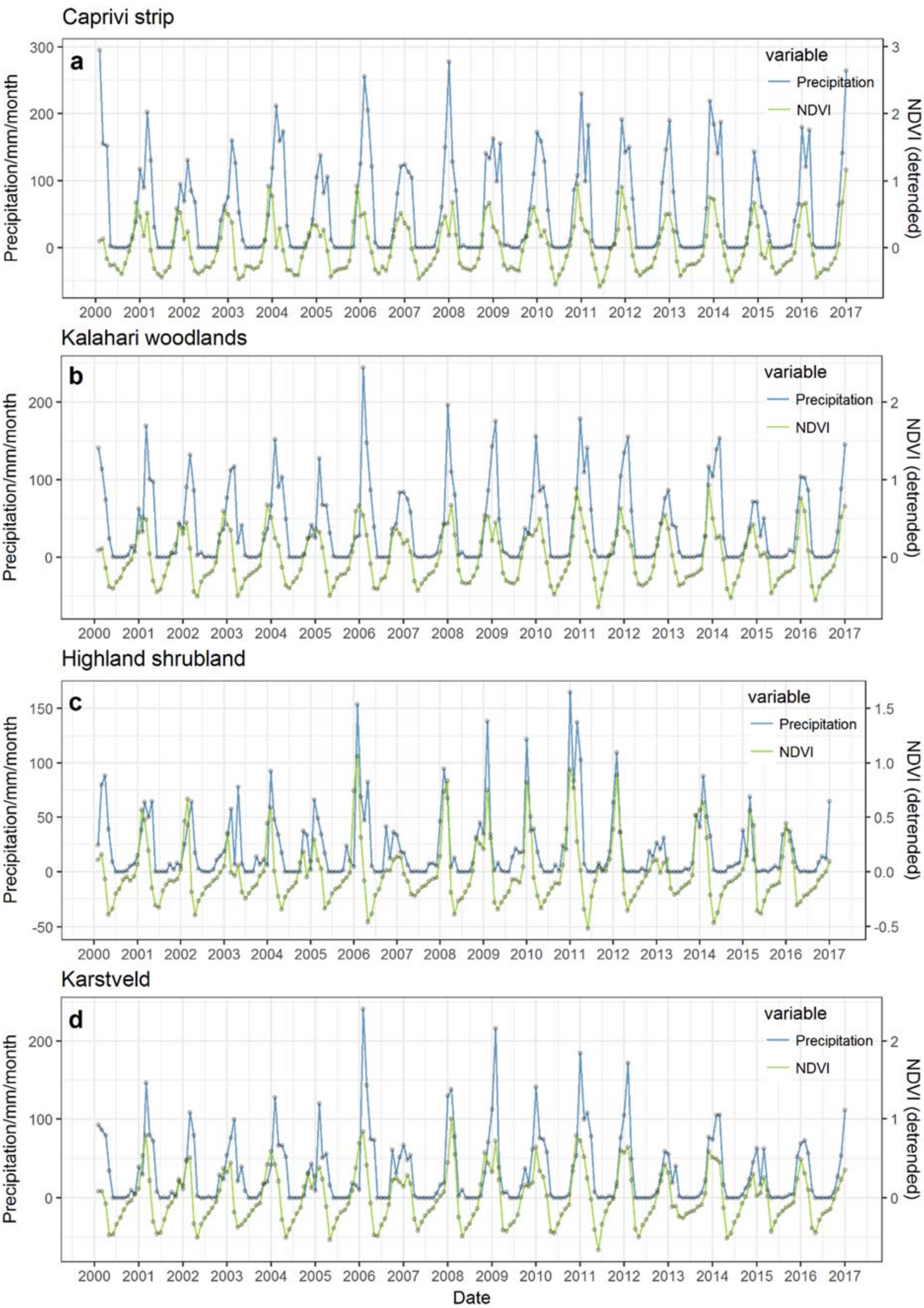

Figure 9.11. Temporal profiles of precipitation (TAMSAT) and de-trended NDVI shown without lags applied: Caprivi Strip (a); Kalahari woodlands (b); Highland shrub land (c); and Karstveld (d).

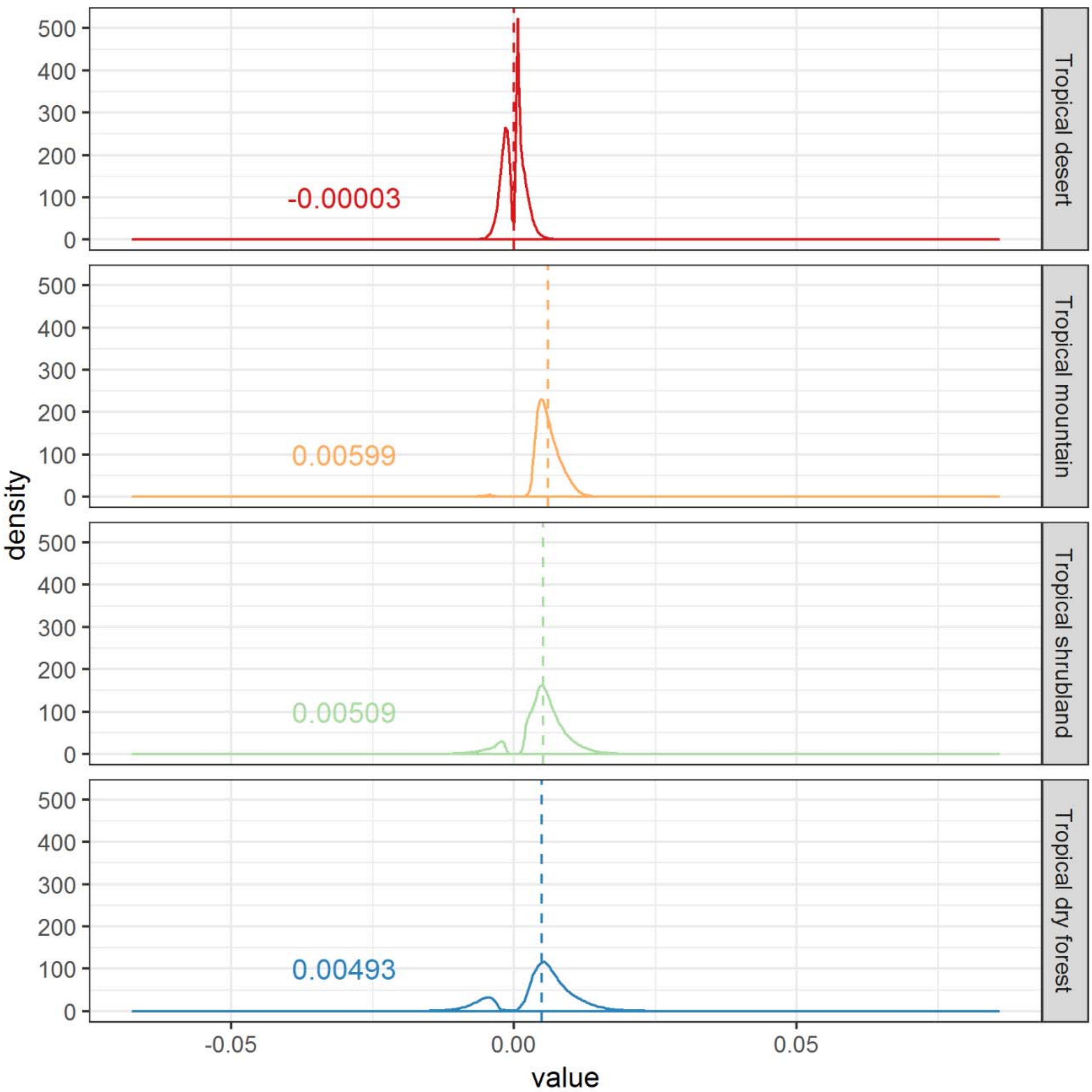

Figure 9.12. Density distributions of significant trends in corrected NDVI for each biomes.

9.5 Supplementary material Chapter 7

Figure 9.13. Soil erosion in Kaokoland, Namibia.

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EDUCATION DETAILS

2013 – 2017 **D.Phil. Geography, University of Basel**
Supervisors: Prof Nicolaus Kuhn, Physical Geography and Environmental Change
Prof Stuart Phinn, Remote Sensing Research Centre, University of Queensland (UQ)
Thesis Title: "Remote sensing environmental change in southern African savannahs: a case study of Namibia"

2010 – 2011 **Master of Science, Environmental Management, University of Stirling**
Research Projects: 1) Development of a retrieval algorithm for phytoplankton pigment concentrations and mapping phytoplankton blooms, 2) NDVI and LiDAR for mapping changes in forest growth; **MSc Thesis:** "A novel combination of a portable OSL reader, 210Pb dating and X-Ray Fluorescence to develop an erosion and pollution history for an abandoned mine site, Spain"

2006 – 2010 **BSc (Hons) Tropical Environmental Science, University of Aberdeen**
Research Project: Crops Research Institute, Kumasi, Ghana
Research Project: Madagasikara Voakajy Conservation NGO, Madagascar
Honours Project: "Leaf traits in tropical rain forest trees: the influence of ontogeny and vertical light environment of two species with contrasting shade tolerances"

WORK EXPERIENCE

April 2019 – Present **Postdoctoral researcher, Remote Sensing Laboratories, Department of Geography, University of Zurich**. Consultant at the National Point of Contact for Satellite Data (NPOC) Scientific advisory to potential EO data users; Research and development of new products. Researcher with GlobDiversity (a European Space Agency research project) aimed at engineering Remote Sensing-enabled Essential Biodiversity Variables in support of the efforts of the Convention on Biological Diversity, Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services, and Group on Earth Observations Biodiversity Observation Network to monitor biological diversity of terrestrial ecosystems from space

Jan 2018 – March 2019 **Postdoctoral researcher, Physical Geography and Environmental Change, University of Basel;** Swiss-South African Joint Research Programme, Swiss National Science Foundation grant: Source, timing and release mechanisms of cropland dust emissions: Sentinel 1-2, and, UAV and field measurements

Jan 2018 – March 2019 **Postdoctoral researcher, University of Bonn & University of Cologne**
Collaborative Research Centre Future Carbon Storage project: i) producing thematic land cover change statistics, ii) evaluating trends in Landsat time-series, and ii) remote sensing and field measurements to map savanna vegetation biomass (Kavango-Zambezi Trans-frontier Conservation Area)

Sept 2013 – Dec 2017 **PhD, Physical Geography and Environmental Change, University of Basel**

My thesis **focused on** characterising the little studied but globally relevant vegetation changes occurring in savanna environments, by integrating remote sensing (Landsat, MODIS, ALOS-PALSAR, ICESat , Sentinel-1 and 2) and field datasets (above ground biomass, percent cover, and field spectroscopy measurements).

The **aims** were to **i)** quantify trends and changes in satellite and field-derived biogeochemical, biophysical and phenological metrics, **ii)** link these metrics to change processes including deforestation and shrub encroachment, and **iii)** identify potential climatic, environmental and anthropogenic drivers of vegetation change

Sept 2013 – Dec 2017 **PhD, Physical Geography and Environmental Change, University of Basel**

A **key objective** was addressing the inherent complexities of remote sensing savanna vegetation, which varies due to climatic, environmental and anthropogenic disturbances, and distinct phenophases and gradients in plant functional types. **Outcomes** include journal articles on (i) change detection analyses using the full Landsat archive (ii) fusing optical, radar and field inventory data using empirical modelling to quantify biomass change, (iii) trends in woody cover using phenological metrics and field estimates, (iv) precipitation-vegetation dynamics using MODIS and precipitation time-series, and **on-going** work on (iv) merging Landsat and Sentinel for land surface phenology analysis, and (vi) near-surface (Phenocam) development

Aug – Sept 2016 **Visiting Scholar, Centre of Ecology and Hydrology, Earth Observation group**

Collaboration with Dr France Gerard head of the Earth Observation group, on remote sensing land surface phenology indicators in drylands

Jun – Nov 2015 **Endeavour Fellowship, Remote Sensing Research Centre, UQ**

Quantifying the extent and rate of land-cover change using forty years of Landsat satellite imagery

Jul – Sept 2013 **GIS Analyst Placement, Redland City Council, Brisbane, Australia**

Development of a GIS Geodatabase designed to provide an expression of Conservation Value within the Redland Local Government Agency boundary

Mar – June 2013 **Technical Assistant, Commonwealth Scientific and Industrial Research Organization (CSIRO), Brisbane, Australia**

Field assistant with CSIRO Ecosystem Sciences Insect Ecology department; landscape-scale monitoring of insect pest control

Oct 2011 – Jan 2012 **Environmental Technician Pacific Environment Limited, Brisbane, Australia**

Employed US Environmental Protection Agency (EPA) Methods for Emissions Monitoring across a range of process industries including smelters

June – Sept 2011 **Research Assistant, Spatial Ecology Lab, University of Queensland,**

Quantifying patterns of intertidal habitat loss across the Australasian flyway to inform conservation management of declining shorebird populations

Jan – May 2011 **Volunteer, Spatial Ecology Lab, University of Queensland**

Introduction to ArcGIS 10 and a range of its tools; introduction to Landsat archive, access, downloading and management

Nov – Jan 2010 **Field Assistant, University of Stirling, Scottish Env. Protection Agency**
Assessing the presence of, and recovering Radium-226 particle contamination, using standard experimental protocols in field environment

June – Sept 2009 **Research Assistant, University of Aberdeen, Madagasikara Voakajy Conservation NGO, Madagascar;** Research Expedition Madagascar assessing illegal hunting of the protected species *Pteropus rufus*

June – Sept 2008 **Internship, International Association for the Exchange of Students for Technical Experience (IAESTE) Crops Research Institute Kumasi, Ghana**
Student intern in the tissue culture and biochemistry laboratories

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PUBLICATIONS

Dhanjal-Adams, Kiran L, Jeffrey O Hanson, Nicholas J Murray, Stuart R Phinn, **Vladimir R Wingate,** Karen Mustin, Jasmine R Lee, James R Allan, Jessica L Cappadonna, and Colin E Studds. 2016. "The Distribution and Protection of Intertidal Habitats in Australia." Emu 116 (2): 208–14.

Wingate, Vladimir, Stuart Phinn, Nikolaus Kuhn, Lena Bloemertz, and Kiran Dhanjal-Adams. 2016. "Mapping Decadal Land Cover Changes in the Woodlands of North Eastern Namibia from 1975 to 2014 Using the Landsat Satellite Archived Data." Remote Sensing 8 (8): 681.

Wingate, Vladimir R., Stuart R Phinn, Nikolaus Kuhn, and Peter Scarth. 2018. "Estimating Aboveground Woody Biomass Change in Kalahari Woodland: Combining Field, Radar, and Optical Data Sets." International Journal of Remote Sensing 39 (2): 577–606.

Bloemertz, Lena, Martha Naanda, **Vladimir Wingate**, Simon Angombe, and Nikolaus Kuhn. 2018. Land, Livelihoods and Housing Programme 2015-18 Working Paper. Working Paper No. 10 Ecosystem Services and Small-Holder Farming Practices - between Payments, Development Support and Right- an Integrated Approach. Vol. 1. 1 10. Windhoek: Integrated Land Management Institute.

Vladimir R. Wingate, Stuart R. Phinn, Nikolaus Kuhn, Cornelis van der Waal. Mapping trends in woody cover in Namibian savannah with MODIS seasonal phenological metrics and field inventory data (In review)

Wingate, Vladimir R, Stuart R Phinn, and Nikolaus Kuhn. 2019. 'Mapping Precipitation-Corrected NDVI Trends across Namibia'. Science of The Total Environment 684: 96–112.

Dhanjal-Adams K. L., Hanson J. O., Murray N. J., Phinn S. R., **Wingate V. R,** Mustin K., Lee J. R., Allan J. R., Cappadonna J. L., Studds C. E., Clemens R. S., Roelfsema C. M., Fuller R. A. (2015) Mapped distribution of intertidal habitats in Australia between 1999 and 2014

AWARDS, SCHOLARSHIPS and GRANTS

2018	**Reisefonds für den akademischen Nachwuchs der Universität Basel,** conference
2018	**Zentrum für Afrikastudien Basel,** conference
2017	**Reisefonds für den akademischen Nachwuchs der Universität Basel,** conference
2016	**Reisefonds für den akademischen Nachwuchs der Universität Basel,** conference
2015	**Reisefonds für den akademischen Nachwuchs der Universität Basel,** conference
2015	**Swiss Geomorphological Society,** PhD Field work
2014	**Freiwillige Akademische Gesellschaft, Basel,** PhD Field work
2014	**Endeavour Research Fellowship, University of Queensland,** PhD research
2014	**Freiwillige Akademische Gesellschaft, Basel,**PhD field course, Denmark
2013	**Humer Foundation PhD Scholarship, Basel,** doctoral degree
2010	**Postgraduate Students Awards Agency Studentship, Scotland,** MSc degree
2006	**Undergraduate Students Awards Agency Studentship, Scotland,** BSc degree

CONFERENCES

Jul 2019	**World Conference of Science Journalists**, Lausanne, CH (presentation)
May 2019	**Living Planet Symposium 2019**, Milan, Italy (presentation)
Dec 2018	**Swiss Geoscience meeting 2018,** (lab poster)
May 2018	**GeoPython 2018,** Basel Switzerland (practical sessions)
Jul 2017	**International Congress on Conservation Biology,** Cartagena (poster)
Jun 2017	**4th Oxford Interdisciplinary Desert Conference,** Oxford (poster)
Apr 2017	**European Geoscience Union,** Vienna (poster x2)
Oct 2016	**Swiss Geoscience meeting 2016** (presentation)
Jun 2016	**Society for Conservation Biology 4th Oceania Congress,** Brisbane (poster)
Apr 2015	**European Geoscience Union,** Vienna (poster)
Dec 2015	**Swiss Geoscience meeting 2015** (lab poster)
Oct 2015	**Deutschen Kongress für Geographie 2015,** Berlin (poster)
Sep 2015	**3rd Namibia Research Day 2015,** Basel (presentation)
Sep 2015	**5th World Sustainability Forum,** Basel (presentation)
Sep 2015	**2nd Namibia Research Day 2015,** Basel (presentation)
Dec 2014	**Swiss Geoscience meeting 2014** (lab poster)
Oct 2014	**Third Swiss Researching Africa Days 2014,** Bern (poster)
Sep 2014	**1st Namibia Research Day 2014,** Basel (presentation)

TRANSFERABLE SKILLS

Programming	Remote sensing /modelling in R and Google Earth Engine, ArcGIS, QGIS, IDRISI, ENVI
Software	Word, Excel, PowerPoint, R, ArcGIS, QGIS, IDRISI, ENVI, Python, TIMESAT, Pix4D
Writing	Producing grant, research proposals, journal articles, posters and presentations European Space Agency project deliverables; NPOC consultancies
Collaborations	On-going research with: The Group on Earth Observations Biodiversity Observation Network (GEO BON), Professor Stuart Phinn and Dr Peter Scarth (Remote Sensing Research Centre), Dr France Gerard (Centre of Ecology and Hydrology), Dr Lena Bloemertz (University of Basel); Dr Cornelis van der Waal (Namibian rangeland monitoring); Dr Kiran Dhanjal-Adams (Schweizerische Vogelwarte); Dr Nicholas Murray (University of New South Wales); Dr Alexandra Sandhage-Hofmann and Professor Jan Börner (University of Bonn); Dr Anja Linstädter (University of Cologne)

Fieldwork Forest inventory measurement; vegetation surveys (cover and species diversity); above ground biomass measurements; time-lapse/repeat photography (Phenocam) development/placement; climate station; UAV piloting; differential GPS sampling; soil sampling, coring and profiles; social science interviews; 4WD; remote field sites

Languages English and French (mother tongues), Spanish (advanced) German (intermediate)

WORKSHOPS

Jul 2019	**GEO BON IC meeting,** Porto, Portugal
Apr 2016	**Google Earth Engine, European Geoscience Union,** Vienna, Austria
Jan 2016	**Community Land Matters Workshop,** Windhoek, Namibia
Aug 2015	**R Programming Workshop, Centre for Marine Science,** Brisbane, Australia
Jul 2015	**Endeavour Professional Development Workshops,** Brisbane, Australia

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PEER-REVIEW

Peer-reviewed journal articles for Remote Sensing and International Journal of Remote Sensing

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MEMBERSHIPS

The Group on Earth Observations Biodiversity Observation Network; Society for Conservation Biology; Swiss Association of Geography; Akademischer Alpen Club Basel; Club Alpin Suisse

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REFERENCES

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