Remote Sensing of Woodland Structure and Composition in the Sudano-Sahelian zone

Application of WorldView-2 and Landsat 8

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Abstract

Woodlands constitute the subsistence base of the majority of people in the Sudano-Sahelian zone (SSZ). Trees and grasses provide key ecosystem goods and services, including soil protection, fuelwood, food products and fodder. However, climate change in combination with rapidly increasing populations and altered land use practices put increasing pressure on the vegetation cover in this region. Low availability of *in situ* data on vegetation structure and composition hampers research and monitoring of this essential resource. Satellite and aerial remote sensing represents important alternative data sources in this context. The main advantages of remote sensing are that information can be collected with high frequency over large geographical areas at relatively low costs. This thesis explores the utility of remote sensing for mapping and analysing vegetation, primarily trees, in the SSZ. A comprehensive literature review was first conducted to describe how the application of remote sensing for analysing vegetation has developed in the SSZ between 1975 and 2014, and to identify important research gaps. Based on the gaps identified in the literature review, the capabilities of two new satellite sensors (WorldView-2 and Landsat 8) for mapping woodland structure and composition were tested in an agroforestry landscape located in central Burkina Faso. The tree attributes in focus included tree crown area (m^2), tree species, tree canopy cover (%) and aboveground biomass (tons ha^{-1}). The data processing methods encompassed object-based image analysis for tree crown delineation, and use of the Random Forest algorithm for tree species classification (WorldView-2) and estimation of tree canopy cover and aboveground biomass (Landsat 8).

The literature review revealed that the use of remote sensing has increased extensively in the SSZ, especially since 2010. Remote sensing is increasingly used by diverse scientific disciplines although the contribution from African authors remains relatively low. The main application area has been to analyze changes in vegetation productivity and broad vegetation types, while relatively few studies have used remote sensing to map tree attributes at a higher level of detail, and to analyze interactions between the vegetation cover and environmental factors.

This thesis shows that the WorldView-2 satellite represents a useful data source for mapping individual tree attributes, including tree crown area and tree species. The individual tree crown delineation achieved promising results: 85.4% of the reference trees were detected in the WorldView-2 data and tree crown area was estimated with an average error of 45.6%. Both detection and delineation accuracy was influenced by tree size, the degree of crown closure and the composition of the undergrowth vegetation. In addition, WorldView-2 data produced high classification accuracies for five locally important tree species, which are common throughout the SSZ. The highest overall classification accuracy (82.4%) was produced using multi-temporal WorldView-2 data. The dry season is recommended over the wet season for WorldView-2 data acquisition when collection of multi-temporal data is not feasible. Landsat 8 data proved more suitable for mapping tree canopy cover as compared to aboveground biomass in the woodland landscape. Tree canopy cover and aboveground biomass was predicted with 41% and 66% root mean square error, respectively, at pixel level.

The most accurate predictions were achieved when spectral, texture and phenology variables derived from Landsat 8 data were combined, which indicates that these three domains contribute complementary information about the tree cover.

This thesis demonstrates the potential of easily accessible data from two satellite systems for mapping important tree attributes in woodland areas and discusses how the usefulness of remote sensing for analyzing vegetation can be further enhanced in the SSZ.

Keywords: remote sensing; Sudano-Sahel; woodland; agroforestry; WorldView-2; Landsat 8; tree attributes; tree canopy cover; aboveground biomass; Random Forest

Sammanfattning

Befolkningen i Sudano-Sahel zonen (SSZ) är beroende av naturresurser från *woodlands* (öppen skog) för att säkra sin försörjning. Vegetationen i *woodlands* (träd, buskar och gräs) bidrar med vitala ekosystemtjänster, inklusive skydd mot jorderosion, ved, mat och djurfoder, men utsätts för närvarande av ett ökat tryck från klimatförändringar, en snabbt ökande befolkning samt en intensifierad markanvändning. Tillgången av fältmätningar av vegetationens struktur och komposition är mycket låg i SSZ, vilket utgör ett problem för forskning och miljöövervakning. Satellit- och flygburen fjärranalys representerar viktiga alternativa datakällor i detta sammanhang. De främsta fördelarna med fjärranalys är att information kan samlas in med hög frekvens över stora geografiska områden, men till relativt låga kostnader. Denna avhandling undersöker nyttan av fjärranalys för att kartlägga och analysera vegetation, främst träd, i SSZ. En omfattande litteraturstudie genomfördes för att beskriva hur tillämpningen av fjärranalys för att analysera vegetation har utvecklats i SSZ mellan 1975 och 2014, samt för att identifiera viktiga forskningsluckor. Några av de luckor som konstaterades låg till grund för de efterföljande studierna där två nya satellitsystem (Worldview-2 och Landsat 8) utvärderades för deras användbarhet att kartlägga trädtäckets struktur och artsammansättning. Ett *woodland*-område i centrala Burkina Faso användes som testplats. Trädattributen i fokus var kronstorlek (m^2) och trädslag för enskilda träd, samt krontäcke (%) och biomassa (ton ha^{-1}). Objektbaserad bildanalys användes för kartering av enskilda träd. Random Forest algoritmen användes för trädslagsklassificering (Worldview-2), samt för kartering av krontäcke och biomassa (Landsat 8).

Litteraturstudien visade att användningen av fjärranalys i SSZ har ökat i stor omfattning, särskilt sedan 2010. Fjärranalys används alltmer inom olika vetenskapliga discipliner, men bidraget från afrikanska forskare är relativt låg. Det främsta användningsområdet för fjärranalys har varit att analysera vegetationsförändringar, där fokus legat på produktiviteten och breda vegetationstyper. Relativt få studier har använt fjärranalys för att kartlägga trädattribut på en högre detaljnivå, samt för att analysera samband mellan vegetation och andra miljöfaktorer.

Utvärderingen av satellitsystemen visar att Worldview-2 är en användbar datakälla för kartering av enskilda träd i *woodlands*: 85.4% av referensträden detekterades i Worldview-2 data och kronstorlek uppskattades med ett medelfel av 45.6%. Karteringens noggrannhet påverkades av trädens storlek, graden av trädtäthet och sammansättningen av undervegetationen. Worldview-2-data producerade även hög klassificeringsnoggrannhet för de fem lokalt viktigaste trädslag. Den högsta klassificeringsprecisionen (82.4%) uppnåddes med multi-temporal Worldview-2-data. När insamling av multi-temporal data inte är möjlig rekommenderas torrperioden framför regnperioden. Landsat 8 data visade sig mer lämpade för kartering av krontäcke jämfört med biomassa. Medelfelet för karteringen var 41% för krontäcke och 66% för biomassa, på pixelnivå. Den högsta noggrannheten uppnåddes när förklarande variabler baserade på spektral information, textur och fenologi från Landsat 8 data kombinerades, vilket påvisar att de bidrar med kompletterande information om trädtäcket.

Avhandlingen visar att lättillgängliga data från två satellitsystem är användbara för kartläggning av viktiga trädattribut i *woodlands* och diskuterar hur nyttan av fjärranalys för vegetationsanalys kan ökas ytterligare i SSZ.

Nyckelord: Fjärranalys, Sudano-Sahel, woodland, WorldView-2, Landsat 8, trädattribut, trädteck, biomassa

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List of Papers

This thesis is based on the work presented in the following papers, referred to by Roman numerals in the text.

I. Karlson, M., and M. Ostwald. 2016. “Remote sensing of vegetation in the Sudano-Sahelian zone: A literature review from 1975 to 2014.” *Journal of Arid Environments* 124: 257-269.
II. Karlson, M., M .Ostwald, and H. Reese. 2014. “Tree crown mapping in managed woodlands (parklands) of semi-arid West Africa using WorldView-2 imagery and geographic object based image analysis.” *Sensors* 14: 22643-22669.
III. Karlson, M., M. Ostwald, H. Reese, H.R. Bazie, and B. Tankoano. forthcoming. “Assessing the potential of multi-temporal WorldView-2 imagery for mapping West African agroforestry tree species.” Submitted to *International Journal of Applied Earth Observation and Geoinformation*.
IV. Karlson, M., M. Ostwald, H. Reese, J. Sanou, B. Tankoano, and E. Mattsson. 2015. “Mapping tree canopy cover and aboveground biomass using Landsat 8 and Random Forest.” *Remote Sensing* 7: 10017-10041.

Papers I, II and IV are reproduced with the permission of the publishers.

Author’s Contributions

Martin Karlson contributed to the appended papers in the following manner:

I. Planned the study with the co-author. Conducted the main part of the data analysis and wrote the major part of the manuscript.

II. Planned the study with the co-authors, carried out field data collection and remote sensing data processing, and wrote the major part of the manuscript.

III. Planned the study with the co-authors, carried out field data collection and remote sensing data processing, and wrote the major part of the manuscript.

IV. Planned the study with the co-authors, carried out field data collection and remote sensing data processing, and wrote the major part of the manuscript.

Abbreviations and Acronyms

AGB	Aboveground Biomass
AVHRR	Advanced Very High Resolution Radiometer
CART	Classification and Regression Trees
CA	Crown Area
D^{20cm}	Diameter at 20 cm
DBH	Diameter at Breast Height
EMR	Electromagnetic Radiation
FAPAR	Fraction of Absorbed Photosynthetically Active Radiation
GEOBIA	Geographic Object-Based Image Analysis
GIS	Geographic Information System
GLCM	Gray Level Co-occurrence Matrix
GPS	Global Positioning System
H	Height
HCS	Hyperspherical Color Space
ITC	Individual Tree Crown
LAI	Leaf Area Index
LiDAR	Light Detection and Ranging
MAE	Mean Absolute Error
MBE	Mean Bias Error
MRE	Mean Relative Error
MS	Multispectral

NDVI	Normalized Difference Vegetation Index
NIR	Near Infrared
OLI	Operational Land Imager
OLS	Ordinary Least Squares Regression
OOB	Out of Bag
PAN	Panchromatic
PAR	Photosynthetically Active Radiation
RADAR	Radio Detection and Ranging
REDD+	Reduced Emission from Deforestation and Forest Degradation
RF	Random Forest
RMSE	Root Mean Square Error
relRMSE	Relative Root Mean Square Error
RS	Remote Sensing
SSZ	Sudano-Sahelian Zone
SWIR	Shortwave Infrared
TCC	Tree Canopy Cover
TD	Tree Density
USGS	United States Geological Survey
UTM	Universal Transverse Mercator
WD	Woody Density

Table of Contents

1. Introduction

Mixed tree-grass ecosystems, commonly referred to as savannas or open woodlands[1], occupy one fifth of the global land surface and extend over vast tropical or sub-tropical areas of South America, Africa, Asia and Australia (Sankaran et al. 2005). Trees, shrubs and grasses are fundamental components of these ecosystems by controlling rates of evapo-transpiration, primary production, nutrient cycling, soil formation, erosion and hydrology (Schlesinger et al. 1996, Scholes and Archer 1997, Lal 2004, Sankaran, Ratnam, and Hanan 2008, Beer et al. 2010). Approximately two-thirds, or 9 million km^2, of the world's woodlands are located in Africa, which makes it the main vegetation type on the continent (White 1983, Grainger 1999, Chidumayo and Gumbo 2010). The African woodlands are generally densely populated and local livelihoods are primarily based on subsistence crop and/or livestock production (Chidumayo and Gumbo 2010). In fact, the woodlands are the main zone for agriculture in Africa (Mayaux et al. 2004). A large proportion of Africa's population is therefore strongly dependent on natural resources and ecosystem services related to woodland vegetation (Chidumayo and Gumbo 2010).

The geographic focus of this thesis is on the African woodlands north of the Equator, the Sudano-Sahelian zone (SSZ), which stretches between the coasts of the Atlantic Ocean and the Red Sea (Figure 1). This is one of the poorest, most marginalized and technologically underdeveloped regions of world, ranking at the bottom of numerous global lists of life expectancies, per capita revenues, nutrition intake and other welfare indicators (Chidumayo and Gumbo 2010). Approximately 80% of the local population relies on subsistence agriculture and livestock herding, much of which is practiced in traditional agroforestry systems (i.e., managed woodlands; Boffa 1999, UNEP 2011).

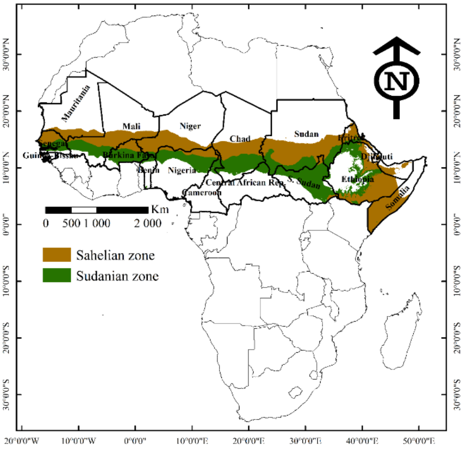

Figure 1. Map showing the Sudano-Sahelian zone defined as the area between the 200 mm and 1000 mm isohyets. The map was modified from the WorldClim dataset (Hijmans et al. 2005).

[1] The term woodland is used here on for brevity following Chidumayo and Gumbo (2010). Woodlands are defined as areas with a dry season of three months or more, where the tree canopy covers more than 10% of the ground surface.

The future of this region is of concern, in particular with projections of a tripling of the population (from ~100 to ≥ 300 million) and mean annual temperature increase of 3-5° C by the year 2050 (IPCC 2014), as well as reduced rainfall levels for the western SSZ (Roehrig et al. 2013). Low economic development and social unrest (e.g., conflicts in Mali, Nigeria and the Central African Republic) further add to the already high vulnerability of the local population. Clear signs of climate and land use induced alterations in the vegetation structure and species composition are already apparent in some areas (Gonzalez 2001, Gonzalez, Tucker, and Sy 2012, Herrmann and Tappan 2013, Maranz 2009, Achard et al. 2014). These trends suggest that natural resource management in the SSZ will face many challenges in the near future. The design and implementation of innovative land management strategies, as well as preventative and adaptive measures, aiming at sustainable use of woodland resources are therefore in high demand (Chidumayo and Gumbo 2010). Such initiatives should be based on scientifically sound knowledge about the vegetation's dynamics and functioning, and require monitoring that applies scientifically rigorous methods. A key component of research and efficient management systems is the availability of both long-term and up-to-date vegetation data (Bucki et al. 2012). However, the availability of field based datasets is highly limited throughout this area (Chidumayo and Gumbo 2010, Kergoat et al. 2011, Romijn et al. 2012, Dardel et al. 2014).

Field based (*in situ*) collection of vegetation data either involves i) measurements of structural (e.g., height and tree canopy cover), biochemical (e.g., amount of chlorophyll and nitrogen) and processual (e.g., growth and ecosystem functions) properties, which in some cases require extensive destructive sampling, or ii) visual surveying of vegetation types and species composition. These techniques are typically labor intensive and expensive, and thereby restricted to be used in samples of temporary or permanent inventory plots. While highly accurate and certainly important, such techniques and the resulting datasets are limited in their spatial and temporal coverage. An alternative, or complement, to field based data collection is provided by remote sensing (RS), including air- or space borne (i.e., satellite) systems (DeFries 2008, Ustin and Gamon 2010). RS systems can acquire spatially explicit and extensive datasets at high temporal frequencies (in particular satellite RS), which enable cost efficient, objective and systematic observations of vegetation resources. Since RS systems have been operational for a relatively long period of time (e.g., Landsat 1 launched 1972), these datasets represent unique sources of information on past vegetation conditions. Furthermore, the accessibility of RS data has improved considerably in the last decade due to changed distribution policies (Wulder et al. 2012) and the development of the internet. Consequently, RS is of particular relevance for a region such as the SSZ where programs for long-term field monitoring of vegetation are very rare (Dardel et al. 2014) and economic resources are scarce. Research concerned with the development and application of RS represents an important catalyst for accommodating the science, management and policy driven vegetation information needs in the SSZ. Historically, the advancement of RS has been crucial for a wide range of research, modeling and monitoring efforts in the SSZ, including those focusing on desertification and land degradation (Tucker, Dregne, and Newcomb 1991) and famine early warning systems (Nall and Josserand 1996).

1.1 Aim and research objectives

The main aim of this thesis is to advance the knowledge about the applicability of RS for mapping and analyzing vegetation, in particular trees, in the SSZ. The research presented in the thesis focuses on two main topics. Firstly, the thesis assesses the scientific use of RS for analyzing vegetation, with the aim to describe how this field of research has developed in the SSZ during the last four decades. Secondly, the thesis aims to determine the capability of two new satellite systems (WorldView-2 and Landsat 8) for mapping tree attributes in woodland landscapes typical to the SSZ. The following four tree attributes were selected for mapping: individual tree crown area (m^2), tree species, tree canopy cover (TCC; %) and aboveground biomass (AGB; tons ha^{-1}). The principal reason for choosing WorldView-2 and Landsat 8 was that these systems are easily accessible and provide data at a relatively low cost (WorldView) or freely (Landsat), which facilitates their practical use in the SSZ, as well as in other regions of Africa.

The specific research objectives for Papers I-IV are:

I. To review and analyze the scientific literature on RS based vegetation analysis published between 1975 and 2014 in the SSZ.
II. To determine the ability to detect and delineate individual tree crowns in WorldView-2 data using geographic object-based image analysis.
III. To evaluate the potential of using multi-temporal WorldView-2 data for mapping dominant agroforestry tree species at crown level.
IV. To test Landsat 8 Operational Land Imager data for mapping TCC and AGB at pixel level.

1.2 Thesis outline

The thesis is structured in the following way; Chapter 2 provides background information on i) the geographical context of the SSZ, ii) the basic principles of RS and iii) the application of RS in vegetation analysis and tree cover mapping; Chapter 3 describes the case study area, the datasets and the methods used in the thesis; Chapter 4 presents the main results of Papers I-IV; Chapter 5 provides the overall conclusions from the thesis work. Lastly, Chapter 6 provides an outlook by discussing the outcomes of the thesis in relation to future RS research needs in the SSZ.

2. Background

This thesis was initiated during the startup phase of a project titled "Trees, carbon and water – tradeoff or synergy in local adaptation to climate change", which was an interdisciplinary collaboration including researchers from Sweden (Swedish University of Agricultural Sciences, Linköping University and Gothenburg University) and Burkina Faso (Institut de l'Environnement et de Recherches Agricoles). This project was designed to study the influence of trees on carbon pools (soil and biomass), groundwater recharge, as well as livelihoods in agroforestry landscapes in the Sudano-Sahelian zone (SSZ). The overarching aim was to identify an "optimum" tree cover structure that improves groundwater levels, stores considerable amounts of carbon and provides people with several other important aspects for their daily life. These are all key landscape functions for increasing local capacity to adapt to climate change, especially since water scarcity is an important issue in this region. The focus on carbon was a result of the discussions to include dryland areas in the Reduced Emissions from Deforestation and Degradation (REDD+) mechanism under the United Nations Convention of Climate Change, and its importance as a soil nutrient for increasing agricultural production. The project included three components; hydrology/soil science, human ecology and "up-scaling". The research presented in this thesis constitutes the "up-scaling" component in the project. Specifically, the other two project components required mapping of a number of key land surface variables, in particular related to the tree cover, over a relatively large area (100 km^2) for landscape scale analysis and modeling of groundwater recharge and carbon sequestration. Papers II-IV were partly motivated by these needs.

2.1 The Sudano-Sahelian zone

2.1.1 Climate and vegetation

The SZZ consists of two roughly parallel ecological regions (see Figure 1), the Sahel and the Sudan, which stretches across the African continent between 10°N and 20°N latitude and includes 17 sub-Saharan countries. The Sahel is located on the fringes of the Sahara desert and extends south covering the area that receives between 200 and 600 mm mean annual rainfall, whereas the Sudanian zone receives between 600 and 1000 mm mean annual rainfall and borders the Guinean zone to the south (Nicholson 2013, Le Houerou 1980, Nicholson 1995). The climatic system of the SSZ is driven by the West African monsoon, which brings rain in May through October (Nicholson 2009). The length of the wet season is a function of latitude and is considerably shorter in the north than in the south. Temperatures in the SSZ are generally high. The warmest month is July with mean temperatures of 36°C in the north and 30°C in the south. The coldest period is during the dry season, with mean January temperatures of 20°C in the north and 22-25°C in the south.

The structure and the floristic composition of the vegetation in the SSZ is mainly a function of mean annual rainfall levels and soil characteristics, in particular nutrient content (White 1983, Le Houerou 1980, Nicholson 1995). The vegetation cover is therefore structured in distinct zonal formations where the proportion of trees and shrubs, the height of the vegetation and the vegetation density increase towards the south. The vegetation in the Sahel is composed of annual grasses and a sparse woody cover of drought resistant species, such as the *Acacia* genus. Much of the land is bare and vegetation tends to grow in patches, where the most striking example is the tiger bush (Nicholson 1995). The Sudanian vegetation, on the other hand, includes a high proportion of perennial grass species, dense shrub vegetation, woodlands and agroforestry parkland landscapes (Boffa 1999). The density of the tree layer in the Sudanian zone increases towards the south, where it forms dry forests. Vegetation growth in the SSZ is primarily limited by water availability (Philippon et al. 2005), which means that primary production mainly takes place during the wet season. The phenology of the vegetation is therefore characterized by two distinct phases. An intensive greening up stage starts shortly after the first rains in May or June. The leafing of woody vegetation generally occurs before that of grasses since it is triggered by temperature, rather than soil moisture (Seghieri et al. 2012). Grass and leaf senescence generally starts at the beginning of the dry season in October, but the start is highly dependent on the species in question (Arbonnier 2004).

The rainfall regime in the SSZ is characterized by a high degree of spatial variability (Ali and Lebel 2009) and rainfall levels vary substantially between years and decades, resulting in frequent and sustained droughts (Hulme et al. 2001, Nicholson 2001, 2013). In the years between 1970 and 1990 mean annual rainfall levels declined by up to 50% compared to the period 1950-1969, and caused widespread famine (Lebel and Ali 2009, Hulme et al. 2001). The highly variable climate, including the droughts, is caused by a combination of global scale sea surface temperature patterns and region scale interaction between the land surface and the atmosphere (Giannini, Biasutti, and Verstraete 2008, Nicholson 2013). Rainfall levels in the SSZ have generally increased since the mid-1980s (Lebel and Ali 2009, Nicholson 2013), but the risk of periodic droughts is still high. There are also signs that certain characteristics of the rainfall regime have changed compared to the period before the droughts (Nicholson 2013). For example, the spatial variability has increased, the rainfall events are less temporally persistent, the contrast between the conditions in the eastern and western part of the SSZ has increased considerably, and the peak rainfall month has shifted from August to July.

The vegetation cover in the SSZ influences both the formation of rain clouds and what happens to the rain when it hits the ground. Reduction in the vegetation cover due to overgrazing was first suggested to have caused droughts in the SSZ (Charney 1975). Charney (1975) proposed a feedback mechanism in which extensive grazing stripped the vegetation from the highly reflective soils leading to a change in surface albedo. This was assumed to enhance the radiative loss and reduce land surface temperature, which stimulate downward movement of air masses within the troposphere and leads to high barometric pressure and thus drier conditions in the SSZ. Several model simulations have established the impact of land surface changes on the Sudano-Sahelian climate (Nicholson 2013). However, it was also shown that the feedback mechanism only intensified droughts rather than it being the root cause. More recent research has shown that soil moisture and temperature heterogeneities control the spatial distribution of rainfall by influencing cloud development and convection (Nicholson 2013). Vegetation cover is an important factor for soil moisture and land surface temperature (Ramier et al. 2009, Boulain et al. 2009). The spatial rainfall patterns have been confirmed by observational research, which showed that a location that has previously received significant rainfall is more likely than other locations to receive more rainfall from future events (Taylor and Lebel 1998). However, it remains to be established whether the land surface-climate interaction only modifies the spatial distribution of rainfall, or if it also influences the amount (Nicholson 2013).

The vegetation cover also affects the distribution of rainfall when it hits the ground. Despite a general decrease in rainfall, in particular between 1968 and 1995, river discharge, groundwater tables and the number and size of ponds have increased in many areas in the SSZ (Descroix et al. 2009, Desconnets et al. 1997, Leduc, Bromley, and Schroeter 1997). Land cover changes have been shown to be the main cause of this phenomena (Descroix et al. 2009, Amogu et al. 2010), a relationship which has been termed 'The Sahelian paradox'. Changes in land cover, in particular the clearing of natural vegetation have resulted in soil erosion and crusting, including alterations in soil bulk density, porosity, hydraulic conductivity and reduced infiltrability. These changed soil conditions have led to a large increase in runoff. The rainwater is therefore transported to rivers and ponds, the latter being the main recharge areas and the cause of increased groundwater levels. However, this increased presence of water does not necessarily mean that local availability of water is improving. Specifically, this process has resulted in a reduced duration of stream flow in small rivers and streams and shorter annual floods in large rivers (Amogu et al. 2010). The increased runoff has also intensified flood disasters.

2.1.2 Land use and agroforestry parklands

The major land use strategies in the SSZ are subsistence based and closely related to environmental constraints, in particular annual rainfall levels and soil nutrient content. In the northern parts of Sahel, pastoral land use dominates, while the prospects for cropping are limited (Nicholson 1995). In southern Sahel and the Sudanian zone, the climate allows for rain-fed agriculture. The main crops consist of cereals, such as millet and sorghum, and legumes, such as cow peas, ground nuts and beans. Vegetables and rice are grown where and when rivers, dams and lakes allow for irrigation. In the southern areas of the Sudan, cash crops such as cotton and maize are cultivated on a large scale and constitute increasingly important export products.

A large proportion of the small scale subsistence cultivation is practiced in traditional agroforestry systems (Boffa 1999, Bayala et al. 2014). These systems are locally referred to as parklands and consist of cultivated land and fallows with a relatively dense tree cover. Valued tree species, including *Vitellaria paradoxa* (Shéa), *Parkia biglobosa* (Néré), *Adansonia digitata* (Baobab) and *Faidherbia albida* (Winter thorn), are deliberately retained when farmers prepare the land for cultivation. Other tree species, such as *Mangifera indica*, are planted in the agricultural fields. Parkland trees are important sources of wood fuel, construction material, food, fodder and medicinal products (Boffa 1999, Manning, Gibbons, and Lindenmayer 2009), and provide for a number of ecosystem services (Sinare and Gordon 2015), such as soil fertilization (Gnankambary et al. 2008), and water conservation, including improved groundwater recharge (Ilstedt et al. 2007, Bargués Tobella et al. 2014). On the global level, agroforestry is increasingly being recognized as a sensible land-use strategy to both mitigate and adapt to climate change (Lykke et al. 2009).

2.2 Basic principles of remote sensing

The main aim of remote sensing (RS) is to infer information on distant objects from measurements of reflected or emitted electromagnetic radiation (EMR) recorded by a sensor. Reflectance is a key component in this process: it constitutes the interaction between EMR and the object (e.g., a land surface), and varies quantitatively as a function of the optical properties of the object, EMR wavelength and the Sun-sensor geometry. RS data processing involves translating measurements of radiance into tangible information, for example, the material of a land surface (Rees 2001). The translation can be manual using human cognition, or done by a computer using a range of different statistical methods.

While the human eye can only see a narrow range of the EMR spectrum (i.e., visible spectrum; wavelengths between 390-700 nm), RS systems can be designed to collect both shorter and longer wavelengths, such as infrared (700 nm – 1 mm) and microwave (1mm – 1m) radiation, depending on their intended application. RS systems are classified as being either “active” or “passive”. Active systems, such as radio detection and ranging (RADAR) generate and emit EMR, and then record the returned signal. Passive systems, on the other hand, record the reflectance of EMR emitted by the Sun. Much of the Sun’s EMR is absorbed and scattered by the Earth’s atmosphere, for example, the ultra violet wavelengths (< 400 nm). Such wavelengths are not suitable for terrestrial RS but can be useful for inferring information about the atmosphere (Rees 2001). Passive RS systems for terrestrial applications are therefore designed to capture wavelengths for which the atmospheric transmission is high, so called atmospheric windows. The visible portion of the electromagnetic spectrum (~400-700 nm) is one atmospheric window.

The properties of different sensors and how they record radiance is often described by their spectral, radiometric, spatial and temporal resolutions (Rees 2001). RS systems usually record radiance in multiple wavelength regions, or spectral bands. The spectral resolution describes the number of recorded bands and bandwidths. Multispectral systems record radiance in tens of bands, whereas hyperspectral systems record radiance in hundreds of bands. The potential numerical range over which an RS system records the observed radiance in each band is defined by the radiometric resolution.

The recorded radiance is generally represented as pixels in images. The spatial resolution often refer to the size of the pixels, which describes the area they cover on the ground. The pixel size is primarily dependent on the instantaneous field of view of the sensor and the ground sampling distance, and RS systems are commonly categorized by their pixel size (Table 1). The size of the pixels is of importance when selecting RS data for a specific task (Strahler, Woodcock, and Smith 1986), in particular when the aim is to map woodland vegetation (Cord et al. 2010). The main reason for this is that the landscape composition in woodlands usually is highly heterogeneous and the different components (e.g., grass, trees, bare soil) alternate within close distances on the ground (Nicholson 1995). Strahler et al.

(1986) developed the concept of ‘L- and H- resolution’, which is useful for describing this situation. In an L-resolution situation, the objects of interest in the analysis are smaller than the pixel size. This may therefore result in mixed pixels when two or more objects of different types fall within a single pixel. In an H-resolution situation, the object is larger than the pixel size and can therefore be resolved by the sensor. However, since several pixels make up the objects in H-resolution, the spectral variability generally increases and may cause problems for automated RS data processing (Franklin 1991, Burnett and Blaschke 2003, Cord et al. 2010).

Temporal resolution, or the revisit period, is mostly relevant for polar orbiting or geo-stationary satellite systems and it defines how frequent a particular area can be observed. The temporal resolution is a function of the orbital altitude, the swath width, the view angle and the sensor tilting capabilities of a RS system, and the latitude of the recorded area. A short revisit period is advantageous for applications in the SSZ because it enables observation of the vegetation life-cycle events (i.e., phenology) and minimizes problems related to cloud coverage (Jönsson and Eklundh 2004, Fensholt et al. 2007)

Table 1. Common remote sensing systems categorized according to pixel size.

Category	Pixel size	Example RS system	Revisit period
Coarse	≥ 1000 m	AVHRR	≤ 1 day
Moderate	100 - 1000 m	MODIS	1-2 days
Medium	5 - 100 m	Landsat, Aster	16 days
High	≤ 5 m	IKONOS, WorldView-2	1- 5 days (off nadir) > 100 days (true nadir)

There are trade-offs between the different imaging properties of RS systems, in particular between the spatial and temporal resolution (Aplin 2006). The spatial resolution is negatively related to both the size of the area an RS system can observe in a single overpass (i.e., swath width) and to the temporal resolution. Systems that are characterized by a small pixel size generally cover smaller areas and have longer revisit periods, and vice versa. For example, the Landsat system has a pixel size of 30 m and a revisit period of 16 days, whereas the Advanced Very High Resolution Radiometer (AVHRR) system has a pixel size of 1.1 km and a revisit period of one day (Table 1). Geostationary satellites, such as the Meteosat Second Generation Spinning Enhanced Visible and Infrared Imager can have a temporal resolution as low as 15 minutes (Fensholt et al. 2010). In cases when the area of interest is larger than the image extent, multiple scenes can be combined through image-mosaicking (Homer et al. 1997).

2.3 Remote sensing of vegetation

Wavelength dependent (i.e., spectral) variability of reflectance is the main information carrier in the spectral domain for RS of vegetation (Ustin and Gamon 2010). In general, vegetation reflects low proportions of the visible wavelengths (400-700 nm) and high proportions of the near infrared wavelengths (NIR; 700-1400 nm; Sims and Gamon 2002). Leaf-scale reflectance in the visible spectrum is primarily controlled by biologically active pigments, including chlorophylls a and b, carotenoid and xanthophyll, whereas the reflectance in the NIR regions is controlled by the cell structure of leaf tissue (Tucker and Sellers 1986). Reflectance in longer wavelengths, such as short wave infrared (SWIR 1400-3000 nm) is primarily controlled by water content of leaves (Ustin and Gamon 2010), whereas microwave reflectance is controlled by water content, relative size and orientation of components (leaves, branches, trunks), and the density of the vegetation (Ulaby, Moore, and Fung 1986). Canopy scale reflectance is more complex and affected by a range of factors, in addition to the spectral properties of foliage (Asner 1998, Danson 1998). Such factors include leaf area index (LAI), leaf angle distribution, reflectance of trunks, branches and soil, and shadows. Furthermore, the reflectance of vegetation varies with time since the spectral properties are closely related to phenological events, such as bud bursts and leaf senescence (Jönsson and Eklundh 2004, Ustin and Gamon 2010).

Two main types of information can be produced from RS data, namely (i) categorical variables, that is discrete classes or objects, and (ii) continuous variables. Land cover (e.g., forest) and land use (e.g., pasture) are examples of discrete classes, and tree crowns or agricultural fields are examples of discrete objects. Classification can be performed directly on pixels (Franklin and Wulder 2002), or on objects that have been delineated in a preparatory step using image segmentation (Benz et al. 2004, Blaschke 2010). The classification algorithm assigns pixels or objects to a set of user defined categories that should ideally be non-overlapping and mutually exclusive. The other type of information that can be extracted from RS data is continuous variables. In the context of vegetation analysis, continuous variables might represent structural or bio-chemical attributes of the vegetation, for example tree canopy cover (TCC), aboveground biomass (AGB), vegetation height, primary production and LAI, among others (Cohen et al. 2003, Ustin and Gamon 2010). The proportion a land cover class occupies in a pixel can be estimated as a continuous variable using methods such as spectral un-mixing (Ustin and Gamon 2010). The mapping of continuous variables may be more suitable to characterize spatially fragmented landscapes, such as woodlands where the vegetation composition is heterogeneous and the tree canopy is open (Defries 1995, Herold et al. 2008). Furthermore, the continuous fields approach enables an objective way to define land cover or vegetation classes by combing the remotely sensed vegetation variables. It is also better suited to parameterize various environmental models (Defries 1995) and can enable more sensitive change detection analysis (Lambin and Linderman 2006).

The key to deriving relevant information from RS data is to accurately represent the relationship between the radiance recorded by the sensor and the vegetation attribute of interest. This relationship can be modeled either through physically based or empirical models. Physical models are based on radiative transfer theory and include several sub-systems, including scene, atmosphere and sensor models that describe how a specific vegetation attribute relates to the recorded radiance (Franklin and Hiernaux 1991, Lu 2006). Such models are designed to simulate the EMR reflectance of a vegetation canopy given certain conditions. When run in inverse mode and fed with RS data, physical models can generate predictions of the desired canopy variables. While physical models may be important for explanatory purposes and less site-specific compared to empirical models, their practical implementation is limited by the difficult task of specifying model parameters that often need to be calibrated using *in situ* data (Lu 2006, Dorigo et al. 2007, Eisfelder, Kuenzer, and Dech 2012). On the other hand, empirical models are fitted statistically between the vegetation attribute of interest, commonly measured in the field, and RS data. In other words, empirical models 'learn' the relationship between the sought variable and the RS data. Empirical models can then be used for predicting vegetation attributes over large areas by using RS data as input. In this context, RS data denote the explanatory variables (predictors) and the vegetation attributes represent the dependent (response) variable. Two common statistical methods for fitting empirical models in the RS context are maximum likelihood estimation for thematic classification and ordinary least-squares regression (OLS) for continuous estimates (Franklin and Wulder 2002, Cohen et al. 2003, Lu 2006, Ustin and Gamon 2010). The main drawback with empirical models is that the transferability in time and space is restricted: a model developed in one area at a specific time will not necessarily provide a good representation of the relationship for another area or at another time (Foody, Boyd, and Cutler 2003).

Different input variables from the RS data can be used for classification or prediction of vegetation attributes. The most basic of variables are the spectral bands. Another option commonly used for predicting vegetation attributes is spectral band transformations, such as spectral vegetation indices. Vegetation indices are unit-less measures where the bands have been combined mathematically to augment the radiance contributions from vegetation, whereas the contributions from external factors (e.g., soil and atmosphere) are suppressed (Baret and Guyot 1991). Vegetation indices are either based on ratios or linear combinations of spectral bands. The red and NIR wavelengths are important inputs in most vegetation indices due to their close relation to chlorophyll and leaf structure. For example, the widely used Normalized Difference Vegetation Index (NDVI; Rouse et al. 1974) makes use of these spectral bands (Equation 1).

$$NDVI = \frac{NIR - Red}{NIR + Red} \qquad \text{Equation 1}$$

Much theoretical and field based research has shown that there exists a nearly linear relationship between several vegetation indices and the fraction of absorbed photosynthetically active radiation (Myneni and Williams 1994, Fensholt, Sandholt, and Rasmussen 2004, Glenn et al. 2008). Vegetation indices can thus be related to light dependent physiological processes such as photosynthesis, and have been widely used in satellite based primary production modeling (Running et al. 2004, Song, Dannenberg, and Hwang 2013). Primary production is commonly mapped through the light use efficiency approach (Monteith 1972, Monteith and Moss 1977), where RS data can provide input variables to the models, including photosynthetically active radiation (PAR), the fraction of absorbed PAR (FAPAR) and the biological efficiency of PAR conversion to dry matter (Prince 1991, Seaquist, Olsson, and Ardö 2003, Fensholt et al. 2006).

Spatial, or contextual, information can also be derived from RS data and used as input variables in predictive models. In RS analysis, the context describes the spatial relationship between neighboring pixels, or objects, which may capture additional aspects that are not contained in spectral information (Woodcock and Strahler 1987). Context is of particular relevance in the H-resolution situation due to the increased spectral variability that may occur when the objects of interest are larger than the pixel size (Benz et al. 2004). The modeling of texture represents one way of assessing context in images (Clausi 2002). Image texture can be defined as a function of spatial variation of pixel value intensities, and is controlled by the size of the pixels or the spectral and spatial characteristics of the dominating objects in the image (Haralick, Shanmugam, and Dinstein 1973, Sarker and Nichol 2011). For example, in images representing forested landscapes, texture is dependent on the size, the spacing and the location of tree crowns. Texture features quantify spatial variation or arrangements by first placing a moving window (e.g., 3 × 3 pixels) around central pixels. Several statistics can then be calculated based on the pixel values within the window. One of the principal techniques for calculating image texture is the Grey Level Co-occurrence Matrix (GLCM; Haralick, Shanmugam, and Dinstein 1973). The GLCM characterizes image texture by calculating how often pairs of pixel values in a defined spatial relationship occur in an image. The spatial relationship is defined by the size of the moving window, the offset between reference pixel and its neighbor, and the direction in which the calculation is performed (i.e., 0-360°). Several texture features can be derived from GLCM, including contrast, dissimilarity, homogeneity, angular second moment, entropy, mean, variance and correlation. The central pixel in the moving window receives the results of these calculations. A critical step in the calculation of texture features is the identification of an appropriate size of the moving windows (Sarker and Nichol 2011, Eckert 2012). A small window size may overestimates the local variance, while a large window may have a smoothing effect, which underestimates the local variance. Consideration must also be given to the size of the pixels and to the size of the objects of interest. Several studies have found that texture features contribute significantly in predicting a range of different vegetation attributes using RS data, including TCC and AGB (Franklin, Maudie, and Lavlgne 2001, Lu 2005, Fuchs et al. 2009, Eckert 2012, Sarker and Nichol 2011, Kamusoko, Gamba, and Murakami 2014).

Temporal information represents another domain that can be used in RS based mapping of vegetation (Tucker et al. 1985). Vegetation seasonality, or phenology, is particularly useful for separating different vegetation types in woodlands, which often have similar spectral characteristics (Franklin 1991, Gessner et al. 2013). For example, trees in the Sudano-Sahelian woodlands foliate earlier and shed leaves later as compared to grasses and shrubs (Seghieri et al. 2012, Seghieri, Floret, and Pontanier 1995). Trees can support their foliage longer than other life-forms due to their ability to tap water from greater depths (Scholes and Archer 1997). Several techniques can be used to extract phenological information from RS data. The most basic approach is to acquire RS data when the spectral contrast between the different life-forms is greatest (Couteron, Deshayes, and Roches 2001). Multi-temporal datasets can also be used to either characterize the phenological development (Jönsson and Eklundh 2004), or to extract phenological variables (Defries 1995, Gessner et al. 2013), such as the minimum NDVI during the dry season (Horion et al. 2014).

2.4 Remote sensing of tree cover

Tree and forest attributes can be classified into three main groups (Table 2), including canopy, height related and composition attributes (Lefsky and Cohen 2003). Data on tree attributes can be collected at a spatially aggregated scale, such as tree stands, an inventory plot, or a pixel, or at the scale of individual trees.

Table 2. Three types of attributes commonly used to characterize trees and tree cover.

Type of attributes	Attributes
Canopy	tree canopy cover (%), leaf area index, fraction of absorbed photosynthetic active radiation
Height related	height (m), volume (m^3 ha^{-1}), aboveground biomass (tons ha^{-1}), basal area (m^2 ha^{-1}), age
Composition	physiognomy (e.g., broad leaved – needle leaved), phenological types (deciduous – evergreen), species composition

The focus of this thesis will mainly be on the attributes tree crown area (m^2), tree species, TCC (%) and AGB (tons ha^{-1}; Table 3). TCC can be defined as the fraction of an area covered by tree crowns when seen from above, whereas AGB can be defined as "all living biomass above the soil including stem, stump, branches, bark, seeds and foliage" (Ravindranath and Ostwald 2008). AGB is generally derived using allometric equations where tree attributes, such as the diameter of the stem at 1.3 m (diameter at breast height; DBH), height and wood density, are used as input variables (Henry et al. 2011, Chave et al. 2014). The allometric equations can either be species specific or generalized, which means that they have been developed for use in a geographical area or a vegetation type (e.g., tropical rainforest). The methods used in this thesis for measuring tree attributes in the field are described in Section 3.3.

Table 3. Overview of the different approaches used in the thesis.

Paper	Tree attribute	Sensor/ RS data	Analysis method
II – Tree crown delineation	Tree crown area	WorldView-2	Object-based image analysis
III – Tree species classification	Tree species	WorldView-2	Random Forest classification
IV – Tree cover mapping	Tree canopy cover and aboveground biomass	Landsat 8	Random Forest regression

2.4.1 Mapping tree canopy cover and aboveground biomass

Large area mapping of tree attributes is important for a range of natural resource management applications and has recently received increasing attention due to international efforts to understand and control the global carbon cycle (Eisfelder, Kuenzer, and Dech 2012, Goetz et al. 2009, Houghton 2007, Achard et al. 2010). Optical RS systems of medium resolution, such as Landsat 8 Operational Land Imager, are attractive for landscape scale TCC and AGB mapping due to the relatively high level of spatial detail of the data, the large swath width and freely available data. The previous Landsat sensors, in particular the Thematic Mapper and the Enhanced Thematic Mapper, have been used extensively for mapping TCC and AGB in boreal and tropical areas (Steininger 2000, Cohen et al. 2003, Lu 2006, Homer et al. 2004), including African ecosystems (Larsson 1993, Thenkabail et al. 2004). Landsat 8, launched in February 2013, has several improvements compared to its forerunners, including wider spectral range (9 bands), a higher radiometric resolution (12 bits) and an improved signal-to-noise ratio resulting from the use of a push-broom sensor (Irons et al. 2012). These improvement may enable more accurate mapping of TCC and AGB (Dube and Mutanga 2015). It is therefore of interest to test the ability of Landsat 8 to map TCC and AGB in the Sudano-Sahelian woodlands.

The reflectance in visible to near infrared wavelengths of land covered by trees is mainly influenced by tree crowns and their foliage (Lefsky and Cohen 2003) and optical imagery has shown to be most successful in predicting canopy related attributes, including TCC (Ustin and Gamon 2010). Optical RS systems do not directly capture the height dimension, and the relationship between the spectral data and tree attributes such as AGB or volume are therefore generally not as strong as the relationships to canopy attributes. Previous attempts to map AGB with Landsat imagery have mainly used spectral information, in particular vegetation indices, thus assuming a strong relationship between TCC and AGB. Outcomes have been moderately successful, with the coefficient of determination (R^2) between ground reference AGB and RS data rarely exceeding 0.6 (Lu 2006, Sarker and Nichol 2011, Eisfelder, Kuenzer, and Dech 2012). A main reason for this is that the relationship between TCC and AGB is not straightforward: AGB often continues to develop after the TCC reaches its maximum, but those changes may not be seen in the reflectance observed by the RS system (Lefsky and Cohen 2003). Recent research has shown that long Landsat time series covering several decades can be used to characterize this development by assuming stand ages and development stages and thereby provide a means for achieving more accurate predictions (Powell et al. 2010, Pflugmacher, Cohen, and Kennedy 2012, Frazier et al. 2014). However, gaps in the Landsat archive over Africa renders the acquisition of such long time series with wide spatial coverage highly problematic (Roy et al. 2010).

The TCC saturation effect is less important in open canopy conditions compared to closed forest. AGB mapping using optical data may therefore be more feasible in such situations (Lefsky and Cohen 2003, Eckert 2012), including those commonly found in African woodlands. It has been shown that optical RS systems can capture shadow structures caused by the trees, which contain information useful for inferring tree height-attributes (Greenberg, Dobrowski, and Ustin 2005, Leboeuf et al. 2007). The shadow structure is more observable in open canopy conditions because the soil background provides good contrast (Franklin and Strahler 1988). Recent research has shown that spatial RS variables, such as image texture, are correlated to AGB because they are partly controlled by the size of tree crowns and shadow structures caused by large trees (Sarker and Nichol 2011, Eckert 2012, Bastin et al. 2014). The use of image texture in empirical models has improved AGB predications based on optical imagery, especially in vegetation types with a relatively open canopy, such as the

Siberian taiga (Fuchs et al. 2009), degraded rainforest (Eckert 2012), and regenerating forests (Sarker and Nichol 2011, Lu 2005). Lu (2005) and Sarker and Nichol (2011) argue that the correlation between AGB and image texture improves with increasing openness of the tree canopy. The research on texture based mapping of AGB in African woodlands is limited, but shows promising results (Adjorlolo and Mutanga 2013, Bastin et al. 2014). Examples from the SSZ are, however, absent to date.

2.4.2 Predictive modeling techniques

The relationship between RS variables and tree attributes can be modeled through different statistical techniques. The most commonly used technique is OLS regression, where the relationship between the dependent (Y) and independent variables (X_n) is modeled and used for predictions (Cohen et al. 2003). OLS has dominated the field despite reoccurring and compelling research showing that this parametric technique is not particularly suitable for use with RS data, including for predicting tree attributes (Cohen et al. 2003, Curran and Hay 1986). The main limitations relate to two basic assumptions of OLS regression, which are violated by default when used for RS data analysis. The first issue concerns the specification of the model. In OLS regression the tree cover attribute is commonly assigned as the dependent variable, whereas the RS data are assigned as the independent variables, which implies that tree attributes are dependent on reflectance. The second issue relates to the OLS assumption about the absence of measurement error in the independent variables. Specifically, remotely sensed data, or independent variables, are influenced by numerous factors, including irradiance variations, sensor calibration error, atmospheric attenuation and path radiance and spatiotemporal miss-registration between RS data and field reference data. These errors can influence the estimations of the model parameters and lead to faulty predictions (Curran and Hay 1986). Furthermore, multi-collinearity is a common situation when RS data are used in regression analysis.

Many other methods have been suggested for calibrating models between RS predictor variables and reference data, including alternative statistical regression techniques, for example reduced major axis, Theil-Sen and Wald’s method (Curran and Hay 1986, Ardo 1992, Cohen et al. 2003); artificial neural networks (Foody, Boyd, and Cutler 2003); *k*-nearest neighbors (Fazakas, Nilsson, and Olsson 1999); support vector machines (Gleason and Im 2012); and Random Forest (RF; Breiman 2001, Powell et al. 2010, Main-Knorn et al. 2011). In recent years RF has been promoted as a well-suited and accurate technique for modeling ecological relationships, including the relationship between tree attributes and RS data (Prasad, Iverson, and Liaw 2006, Cutler et al. 2007). RF is non-parametric and can model complex relationships between predictor variables and the response variable without the need for any *a priori* assumptions about model structure. Primary advantages of RF include its insensitivity to i) measurement errors, ii) non-normal or highly skewed data distributions, iii) correlated predictor variables, and (iv) high dimensional data (Breiman 2001, Main-Knorn et al. 2011). In this thesis, RF is used for both classification (Paper III) and regression (Paper IV).

2.4.3 Random Forest for regression and classification

RF is an ensemble technique that stems from the family of classification and regression trees (CART). RF is generally considered to be robust against over-fitting in comparison to the CART approach (Breiman 2001). CART conducts recursive binary partitioning of the dataset by means of multiple predictor variables in order to produce increasingly homogeneous and successively smaller subsets. In RF, a large number (e.g., ≥ 500) of trees are built from a random sample (two thirds) of the training data that is drawn with replacements (bagging; Breiman 1996). The remaining one third of the data (out of bag; OOB) is used for internal assessments of model performance, which estimates the generalization error. The OOB data is also used for assessing the relative importance of the individual predictor variables. A subset of randomly selected predictor variables is used to identify the most efficient split at each node of the trees. For classification, the Gini impurity criterion is the most common choice to identify the split point (Hapfelmeier and Ulm 2013). The Gini impurity criterion is a measure of the probability for which a randomly selected observation in the node would be classified incorrectly if it were classified according to the class distribution within the node. Through this process, the subsequent child-nodes becomes increasingly pure in terms of the class distribution; they include increasingly more observations of the same class. When run in regression mode, the most efficient split is based upon the predictor variable and the split point that minimizes the residual sum of squares between the subset data and the node mean. In RF, the individual trees are grown to the maximum extent and no pruning is performed. The end result is an ensemble, or forest, of low bias and high variance classification or regression trees. New observations are passed through each tree and the forest determines the final outcome by averaging the predictions of the individual trees for regression, and through the majority vote for classification. The setup is relatively simple compared to other classification and regression techniques because only a small number of parameters need to be tuned, including the number of trees, the number of predictor variables to determine node splits and the node size.

A main reason for the recent popularity of RF is that it provides a framework and tools for assessing and ranking the relative importance of predictor variables (Hapfelmeier and Ulm 2013). This is of particular relevance in the RS context because the number of potential predictor variables that can be derived from RS data can be large. Variable selection has been shown to facilitate model construction and improve the predictive accuracy of RF when used with RS data (Powell et al. 2010, Mutanga, Adam, and Cho 2012). Two measures of predictor variable importance are computed from the OOB data, including the mean decrease in the Gini criterion and the mean decrease in accuracy (Breiman 2001). The mean decrease in Gini is a measure of how much each predictor variable contributes to the purity of the nodes. Each time a particular predictor variable is used to split a node, the Gini criterion for the child-nodes are calculated and compared to that of the original node. The summarized decrease in Gini is then normalized by the total number of trees in the forest. The mean decrease in accuracy, on the other hand, is derived by calculating the difference in prediction accuracy that results from excluding a particular predictor variable from the forest. This procedure is repeated for each tree and for each predictor variable and the outcome is averaged over the forest. Predictor variables that cause a large mean decrease in accuracy are considered as more important for the classification or for the regression. The mean decrease in accuracy measure has the advantage of capturing both the impact of each predictor variable, but also multivariate interaction effects (Strobl et al. 2007).

2.5 Individual tree analysis

Individual trees and their attributes can be resolved in RS data if the spatial resolution is sufficiently high (Nagendra 2001, Turner et al. 2003). The development of methods that automate individual tree crown delineation and classification using different types of RS data has been an active research field since the mid-1980s and the start of digital imagery (Ke and Quackenbush 2011). In the last decade, small footprint LiDAR has come forth as an attractive data source for individual tree and stand level analysis (Persson, Holmgren, and Soderman 2002), much due to its ability to measure vertical structure (Leckie et al. 2003, Popescu, Wynne, and Nelson 2003, Hyyppa et al. 2008). The integration of LiDAR data and aerial imagery enables improved mapping of individual tree attributes, such as height, crown size and species (Holmgren, Persson, and Söderman 2008). However, the use of LiDAR and other aerial RS systems are restricted to areas of limited spatial extent and associated with high costs, which presently limits their relevance in most parts of Africa (Cho et al. 2012). A more flexible and feasible alternative for individual tree analysis is high resolution satellite data (Turner et al. 2003). Commercial vendors, such as Digital Globe Inc., provide global coverage and easy access to high resolution data, which can also be obtained in stereo mode (i.e., allowing creation of three-dimensional data).

2.5.1 Tree crown delineation

The delineation of individual tree crowns in high resolution imagery provides the basic unit of measurement from which a number of useful tree attributes can be derived, including crown size, tree species and AGB (Hirata et al. 2014). Information on individual tree crowns can also be aggregated to derive TCC and tree density. In an image that depicts an area with trees, deciduous tree crowns are generally represented by high intensity pixels, in particular in NIR wavelengths due to the spectral properties of the foliage (Ke and Quackenbush 2011). More specifically, tree tops are represented by local maxima pixels, whereas the rest of a crown is characterized by a gradient of decreasing pixel intensity that results from the conical or spherical crown shape and the angle of the sun incidence (Leckie et al. 2003, Erikson and Olofsson 2005). High spectral contrast between tree crowns and background components, such as soil and understory vegetation facilitates tree crown delineation in optical imagery (Bunting and Lucas 2006). The three most widely used tree crown delineation algorithms, including valley-following (Gougeon 1995), watershed-segmentation (Wang, Gong, and Biging 2004) and region-growing (Culvenor 2002, Bunting and Lucas 2006), are designed to isolate this pattern and partition the RS data into homogeneous segments that represent the tree crowns.

Most research concerned with tree crown delineation algorithms has been driven by application needs in the northern hemisphere, in particular in Canada and northern Europe. Consequently, these algorithms have primarily been developed for use in coniferous forests with a relatively homogeneous tree cover in terms of age structure, crown sizes and species composition (Ke and Quackenbush 2011). The most accurate results have therefore been achieved in vegetation types that are largely different from those encountered in African woodlands. The application of tree crown delineation algorithms in deciduous forests is considered much more problematic and evaluations are considerably less frequent in the literature (Bunting and Lucas 2006, Ke and Quackenbush 2011). The algorithms may have difficulties to account for the more complex structure of deciduous forests because the canopy is often multi-layered, the species composition is heterogeneous and the tree crowns are irregular (Brandtberg and Walter 1998, Ke and Quackenbush 2011).

Although limited in number, previous studies suggest that region-growing type algorithms are most suited for use in areas with a tree cover similar to that encountered in African woodlands. Successful examples include studies in woodland/open forest in Queensland, Australia (Bunting and Lucas 2006), savanna in northern Australia (Whiteside, Boggs, and Maler 2011) and woodland in northern Senegal (Rasmussen et al. 2011). A region-growing algorithm initially identifies local maxima (seed) pixels and then evaluates neighboring pixels for similarity to the seeds. When the criteria for similarity are met, the pixels are merged to form coherent segments. In later stages of the segmentation procedure, evaluation and merging can be done on the level of image objects. User-specified criteria of local homogeneity guide this segmentation process (Baatz and Schape 2000).

2.5.2 Tree species classification

Tree species have different reflectance properties as a result of their biochemical (e.g., photosynthetic pigments and foliar nutrients) and physical properties (e.g., mass, structure and moisture content; Ustin and Gamon 2010). Tree species may also be characterized by spatial crown properties, such as size and shape (Brandtberg and Walter 1998, Immitzer, Atzberger, and Koukal 2012) and phenological traits (Cho et al. 2012). Whether such spectral, spatial and temporal signatures are unique enough determines if they can be used to separate tree species by classification algorithms. However, a number of factors can cause the spectral variability within species to be high, making RS based classification difficult. Examples of such factors include leaf age, local water availability and biotic stressors (e.g., fungi and insects; Lucas et al. 2008). Furthermore, the spectral contribution from the background (i.e., soil and understory vegetation) may be high when the foliage is senescent (Bunting and Lucas 2006). Since the spectral signatures of tree species are largely dependent on seasonal factors, the timing of RS data acquisition is of importance for tree species classification (Leckie, Tinis, et al. 2005). Multi-temporal data can capture some of this variability and be used to advantage in the classification of tree species (Reese et al. 2002).

The spectral differences between tree species may be small in comparison to the spectral resolution of the RS systems (Price 1994). However, successful results of tree species mapping have been reported, particularly in cases when data from airborne hyperspectral RS systems have been used (Cochrane 2000, Clark, Roberts, and Clark 2005, Olofsson et al. 2006, Feret and Asner 2013). Since airborne hyperspectral RS requires equipment that is generally scarce in Africa, this makes satellite RS a more attractive option. While high resolution satellite data provides a sufficient level of spatial detail, its use for tree species mapping has been considered limited due to the low spectral resolution of sensors such as

IKONOS and Quickbird (Heumann 2011). WorldView-2 represents an upgrade in the cluster of high resolution satellite systems by providing an increased spectral resolution, both in terms of a higher number of bands and narrower bandwidths. This makes WorldView-2 an interesting alternative for tree species mapping, especially in the African context. Several recently published studies have shown promising results for tree species classification using WorldView-2 data (Cho et al. 2012, Immitzer, Atzberger, and Koukal 2012, Peerbhay, Mutanga, and Ismail 2014, Waser et al. 2014). However, studies in the Sudano-Sahelian woodlands and agroforestry parklands are still lacking.

RS-based tree species classification can be performed using either individual pixels or tree crown objects as the mapping unit (Clark, Roberts, and Clark 2005, Cho et al. 2012). Previous research suggests that object-based analysis is advantageous if the pixel size is significantly smaller than the tree crowns, i.e., an H-resolution situation (Strahler, Woodcock, and Smith 1986, Clark, Roberts, and Clark 2005, Leckie, Tinis, et al. 2005, Immitzer, Atzberger, and Koukal 2012, Feret and Asner 2013). This condition applies to the analysis of tree cover in high resolution data where a large number of pixels usually cover individual tree crowns. Since image objects are composed of several pixels, a wide range of spectral and spatial features (e.g., maximum, mean, standard deviation, texture) can be derived and used for classification. Thus, the use of objects as the mapping unit enables the inclusion of more predictor variables compared to pixel based analyses (Benz et al. 2004). Immitzer et al. (2012) found the crown scale to outperform the pixel scale in terms of classification accuracy because it is based on averaged pixel values, which minimizes the effects of mixed pixels and spectral variability within the crowns caused by shadows.

To optimize object-based tree species classification, it is of importance to identify the area of the crown which provides pure spectra with a high potential for class separability (Leckie, Tinis, et al. 2005). There are several ways of calculating spectral values from a tree crown, but consensus about which is best is lacking. The basic approach is to use the mean value of all pixels included in each crown segment. However, Huang et al. (2004) found the maximum pixel within crowns to provide significantly better classification results compared to the mean value (Huang et al. 2004). Clark et al. (2005) and Leckie et al. (2005), on the other hand, recommended calculating the mean value from sunlit pixels only. Sunlit pixels can, for example, be defined as those with a spectral value higher than the average of all pixels in the crown (Leckie et al. 2005).

2.5.3 Classification algorithms

Previous research has successfully classified up to 15 tree species using RS data in both boreal and tropical ecosystems (Haara and Haarala 2002, Olofsson et al. 2006, Immitzer, Atzberger, and Koukal 2012, Feret and Asner 2013, Colgan et al. 2012). Tree species classification has been achieved using both parametric (e.g., Maximum Likelihood and Linear Discriminant Analysis) and non-parametric methods (e.g., *k*-nearest neighbor, RF). While comparative studies are rare, parametric and non-parametric methods appear to have produced similar classification accuracies (Immitzer, Atzberger, and Koukal 2012, Feret and Asner 2013). However, non-parametric methods have important advantages for RS-based tree species classification, including the ability to handle non-normally distributed datasets and to perform well in cases when the sample size used for training the classifier is small in relation to the number of input variables (Cortijo and De la Blanca 1999, Breiman 2001). For tree species classification the robustness against non-normally distributed input variables can be particularly useful when the classification is constrained to the most relevant tree species and the secondary species are pooled in a single class (Immitzer, Atzberger, and Koukal 2012). Furthermore, parametric methods usually require that the number of training samples exceeds the total number of input variables used for the classification, which can be high, especially when multi-temporal RS imagery is used (Naidoo et al. 2012). If this requirement is not met, the parametric classifier becomes affected by the 'Hughes Phenomenon' leading to poor classification accuracy (Alonso, Malpica, and Martínez de Agirre 2011). Acquiring a sufficient amount of training data samples for tree species classification can be an impractical task, in particular in cases when some of the tree species are uncommon and difficult to locate in the field. In Paper III, the non-parametric RF algorithm is used for classifying five common parkland tree species.

3. Material and Methods

3.1 Literature review

The empirical material for Paper I consists of peer reviewed articles, published in English between 1975 and 2014, which presents original research conducted within the Sudano-Sahelian zone (SSZ; Figure 1). The literature was collected using targeted searches in the Scopus and ISI Web of Science databases. Additional articles were identified in the reference lists of articles collected during the database searches and in relevant literature reviews using backward reference list checking (Gough, Oliver, and Thomas 2012). Selection criteria based on research topic and geographical location were used to identify relevant articles. The review was limited to research about remote sensing (RS) of (semi-) natural vegetation, including trees, shrubs and grasses. Thus, research where RS has been used for analyzing agriculture, including crop estimation and yield forecasting, or mapping bush fires was excluded from the selection. The search and selection procedure resulted in 268 articles where RS data had been used for analyzing vegetation in the SSZ.

The articles were categorized into three main categories defined by the objective of the research. These categories are adopted from vegetation ecology (van der Maarel 2004) and include; A) vegetation mapping, B) vegetation and environmental factors and C) vegetation change. The analysis focused on four aspects of the literature, including i) publication details (time of publication, scientific discipline of journals and author affiliation), ii) geographic information (location of study areas and spatial scale of research), iii) data usage (usage of RS systems and means for accuracy assessments), and iv) research topic (type of research and objective of vegetation analysis).

3.2 The test site

The *in situ* research was conducted in a 100 km^2 area located 30 km south of Ouagadougou in the rural commune Saponé in Burkina Faso (12° 04’ 48” N, 1° 34’ 00” W; Figure 2).

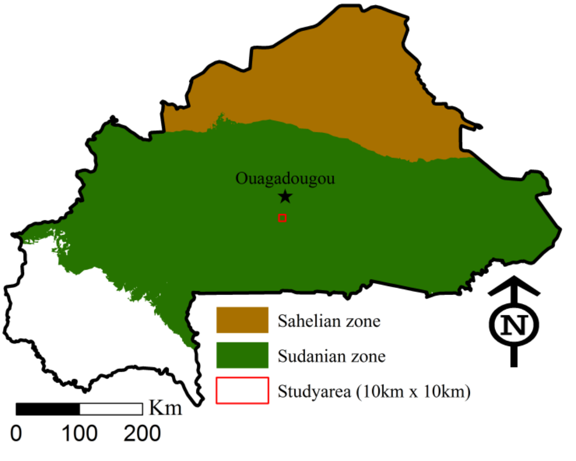

Figure 2. Map showing the location of test site. The base map was derived from the WorldClim dataset (Hijmans et al. 2005).

Field reference data were collected in Saponé during November/December 2012 (see Section 3.3). This area is mainly composed of agroforestry parkland, fallow land, woodlands and settlements (Figure 3). The area also includes denser vegetation types, such as gallery forest and sacred groves, and small scale tree plantations (*Eucalyptus camaldulensis, Tectona grandis* and *Mangifera indica*).

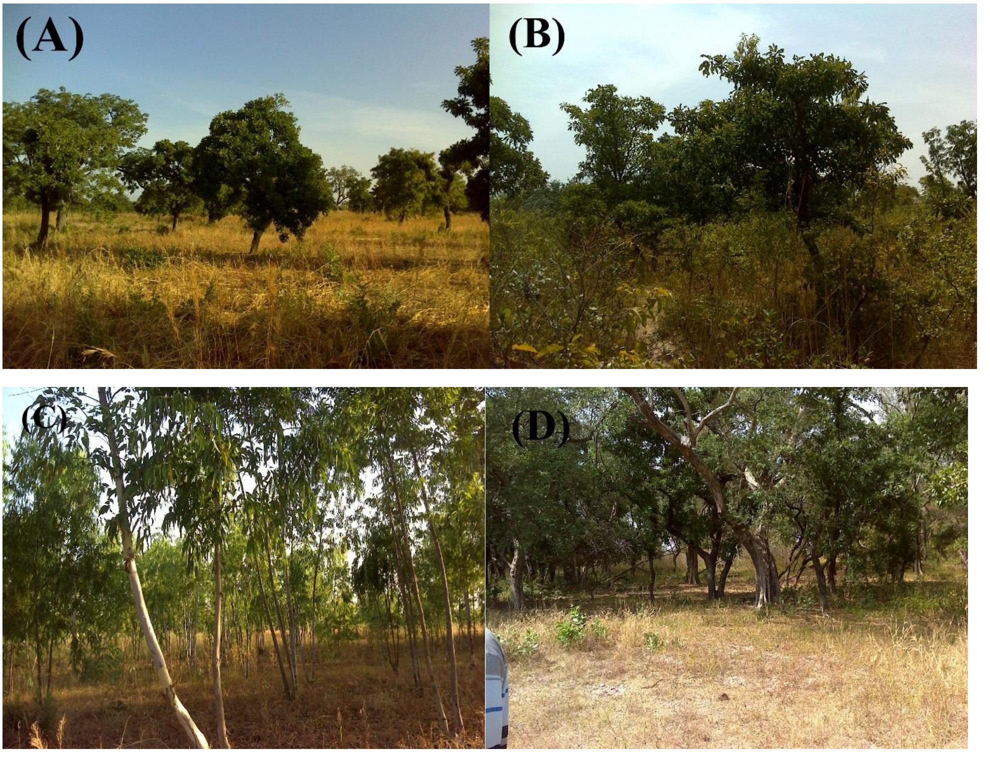

Figure 3. Pictures from the study area showing an active agricultural field (A), land in fallow (B), eucalyptus plantation (C) and woodland (D).

Saponé belongs to the Sudano-Sahelian ecotone (Le Houerou 1980) and the climate is characterized by a mean annual temperature of 28.5°C (1952-2014) and mean annual rainfall of 790 mm year^{-1} (1952-2014). The wet season starts around May and ends in October, and about 80% of the rain falls during June through September. The mean annual potential evapo-transpiration is 1900 mm year^{-1} (1974-2003), which means that the area is classified as semi-arid according to the Köppen-Geiger climate system (Peel, Finlayson, and McMahon 2007).

The study area is situated on a low relief plain (293-363 meters above sea level), where the soils are characterized by sandy clay texture and low nutrient content (Jonsson, Ong, and Odongo 1999). The composition of the undergrowth vegetation is strongly dependent on land use. A large proportion of the area is active parkland fields devoted to rainfed agriculture of staple crops, in particular millet and sorghum, which are harvested in October. The fields are regularly fallowed for 3-5 years. The fallows are characterized by relatively dense undergrowth vegetation composed of annual grasses, shrubs and tree coppice. The density of the undergrowth vegetation is related to the age of the fallow. An artificial dam is located in the south-western parts of the area and supports some irrigated cultivation of vegetables and rice. Livestock is present in the area, mainly moving on tracks and in the fallows, but is kept out of the agricultural fields during the cropping season but allowed to graze crop residues after the harvest.

The most abundant tree species in the area include; *Vitellaria paradoxa* (Shéa), *Lannea microcarpa* (African grape), *Mangifera indica* (Mango), and *Parkia biglobosa* (Néré). Other less abundant tree species include; *Azadirachta indica, Bombax costatum, Diospyros mespiliformis, Adansonia digitata, Acacia nilotica, Ficus gnaphalocarpa, Khaya senegalensis, Sclerocarya birrea, Tamarindus indica* and *Terminalia laxiflora.* A total of 37 tree species were identified during the 2012 field campaign. *Vitellaria paradoxa* and *Parkia biglobosa* are two of the most common tree species in the traditional agroforestry parklands throughout the SSZ (Boffa 1999). The nuts of *Vitellaria paradoxa* are used locally, mainly for food preparation, but the extracted Shéa butter is also becoming increasingly used in the cosmetic industry. *Parkia biglobosa* fruits are an important component of the local diet and other parts of the plant are used for medicinal purposes (Teklehaimanot 2004).

3.3 Field data

Field reference data were used for calibrating the RS data processing methods used in Papers II-IV and for validating mapping outputs. A field campaign was performed during November and December 2012 in Saponé where data on tree attributes and land use were collected in strategically located field plots (Figure 4-5). A stratified random sampling procedure was applied in order to cover the range of tree densities and vegetation types present in the landscape (Lam, Kleinn, and Coenradie 2011). The stratification was achieved by partitioning the study areas into four classes based on normalized difference vegetation index (NDVI) thresholds using an October 2012 WorldView-2 image (Figure 4-5). The NDVI was spatially aggregated to 50 × 50 m pixels, and used as a proxy variable for tree canopy cover (TCC; Lam, Kleinn, and Coenradie 2011). The first class (no trees) was omitted since it represented areas where trees were absent (Table 4). This assertion was validated during the field campaign. The field plots were distributed evenly between the three remaining strata (i.e., low, medium, high TCC) and randomly throughout the study area (Table 4; Figure 4-5). A total of 76 inventory plots with a size of 2500 m^2 (50 m × 50 m) were surveyed. The relatively large size of the plots was chosen in order ensure the inclusion of an adequate number of trees in the sample, given the open tree cover conditions. The coordinates (Universal Transverse Mercator; UTM) of the centers of the plots were extracted from the WorldView-2 image and downloaded into a handheld global positioning system (GPS; Garmin Oregon 550, Garmin, Olathe, KS, USA) device. Plot centers were then located in the field using GPS and printed WorldView-2 images of the study area.

Table 4. Characteristics of the stratification used for distributing field plots and plot statistics, including tree density (TD) per hectare, TCC and plot number.

Strata	TD ha^{-1} min	TD ha^{-1} max	TD ha^{-1} mean	TCC (%)	Plot no.
No trees	-	-	-	-	-
Low TCC	4	56	24	10.1	25
Medium TCC	6	64	47	18.8	28
High TCC	24	208	114	28.5	23
Total	4	208	60	18.6	76

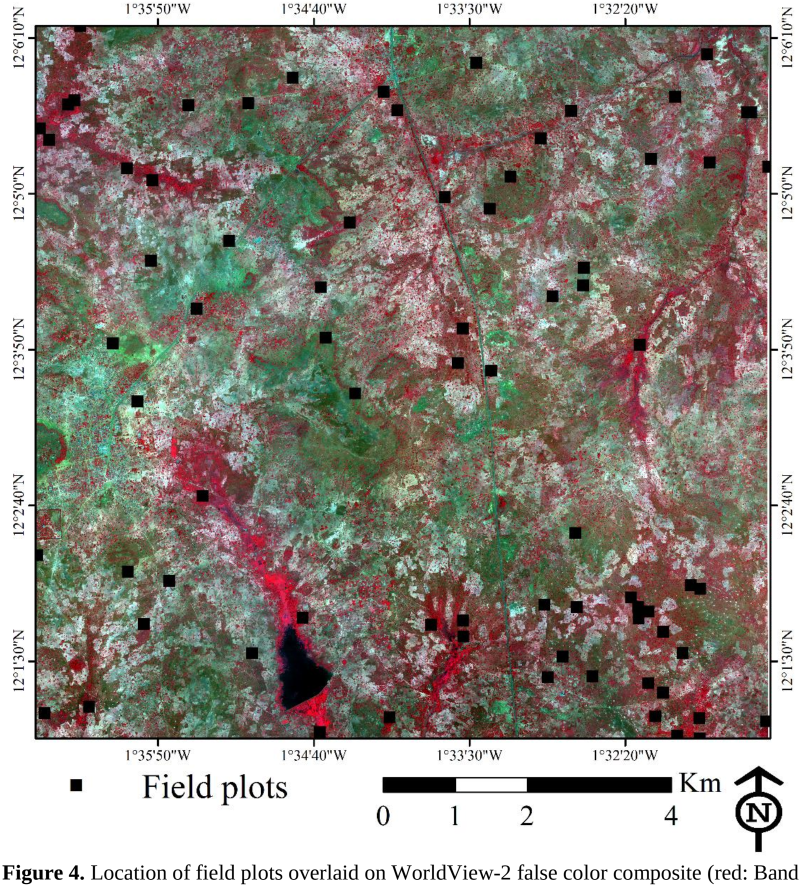

Figure 4. Location of field plots overlaid on WorldView-2 false color composite (red: Band 7; green: Band 5; blue: Band 4).

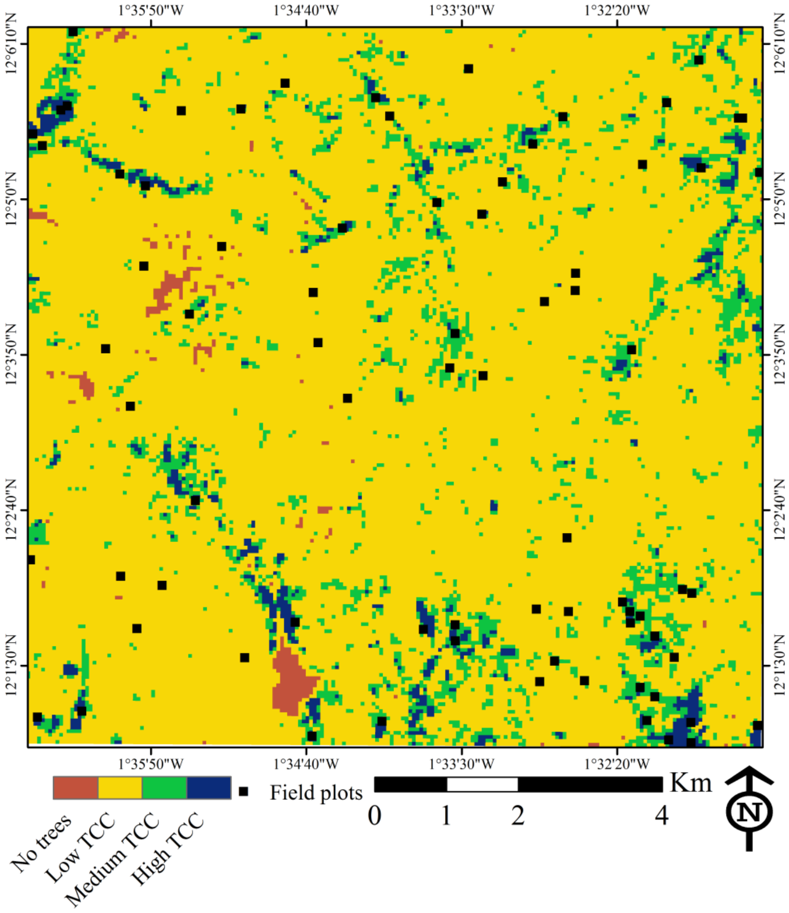

Figure 5. Location of field plots overlaid on WorldView-2 NDVI based stratification.

Measurements were made on all trees with a diameter ≥ 5 cm at breast height (DBH), which is the standard size limit for tree inventories (Ravindranath and Ostwald 2008). The surveyed attributes include the stem diameter at 20 cm (D^{20cm}), DBH, tree height, crown diameters, species and location. D^{20cm} and DBH were derived from the stem circumference assuming a circular stem shape. D^{20cm} and DBH for trees with multiple stems were calculated by taking the square root of the sum of all squared stem diameters (Swiecki and Bernhardt 2015). Tree height was measured using a Haglofs electronic clinometer. Tree species were determined with assistance from a local botanist and tree position was recorded using GPS. Two crown diameters per tree were measured from the ground, including the largest axis and the axis perpendicular to it (Mueller-Dombois and Ellenberg 1974). The crown area (CA) of individual trees was then calculated by assuming an elliptical crown shape using Equation 2, where D1 and D2 represent the largest axis and the perpendicular axis, respectively.

$$CA = (D1 / D2) \times (D2 / 2) \times \pi \qquad \text{Equation 2}$$

D^{20cm}, DBH, height and species specific wood density were used to calculate the aboveground biomass (AGB) on individual tree and per hectare basis through species specific allometric equations (Henry et al. 2011), when such were available (Table 5). A generalized allometric equation for tropical trees was used when species specific equations were not available (Chave et al. 2014). Species specific wood densities (WD) used in the generalized equation were derived from the Global Wood Density Database (Zanne et al. 2009, Chave et al. 2009).

Table 5. Description of allometric equations used for deriving tree level aboveground biomass. Diameter at breast height (DBH); diameter at 20 cm (D20); height (H); wood density (WD).

Tree Species	Input Variables	Location	References
Balanites aegyptiaca	DBH	Senegal	(Poupon 1980)
Eucalyptus camadulensis	DBH	Kenya	(Kuyah et al. 2013)
Guierra senegalensis	DBH	Burkina Faso	(Neya et al. 1998)
Acacia dudgeon, Anogeiosus leiocarpus, Combretom fragrance, Combretum collinum, Detarium microcarpum, Entada africana, Piliostigma thonninghii	D20, DBH, H	Burkina Faso	(Sawadogo et al. 2010)
Sclerocarya birrea	DBH, H, WD	South Africa	(Colgan, Asner, and Swemmer 2013)
Tectona grandis	DBH	Indonesia	(Siregar 2011)
Vitellaria paradoxa	DBH, H	Burkina Faso	(Koala 2015)
Other	DBH, H, WD	Pan-tropical	(Chave et al. 2014)

3.4 Satellite data and pre-processing

3.4.1 WorldView-2

WorldView-2 data from July and October 2012 were purchased from Digital Globe Inc. and used in Papers II-IV. WorldView-2 was launched in October 2009 and provides data in one panchromatic band and eight multispectral bands with a pixel size of 0.5 m and 2 m, respectively (Table 6). Due to pointing capabilities of the sensor, WorldView-2 can collect data with a revisit period between 1 and 4 days. The WorldView-2 data were acquired on dates that represented the wet season and the early dry season (Table 7; Figure 6), and was delivered in product level LV2A, which means that it had been corrected for radiometric, geometric, sensor and terrain distortions.

Digital numbers of the WorldView-2 images were converted to top-of-atmosphere reflectance using the absolute radiometric calibration factors and effective bandwidths for each band, according to the specifications provided by the data provider (Digital Globe 2010a). This step was mainly done to enable calculation of vegetation indices (Glenn et al. 2008) and to transform the data into a common scale (i.e., percent reflectance).

Table 6. Technical specifications of the WorldView-2 sensor (Digital Globe 2010b).

Band	Width (nm)	Region
Pan	450-800	Panchromatic
1	400-450	Coastal blue
2	0.450-510	Blue
3	510-580	Green
4	585-625	Yellow
5	630-690	Red
6	705-745	Red edge
7	770-895	Near infrared (NIR) 1
8	860-1040	NIR 2

Table 7. Properties of the WorldView-2 data used in Papers II-IV.

Sensor	WorldView-2	WorldView-2
Acquisition date	2012-07-18	2012-10-21
Acquisition time	2.19 p.m.	1.55 p.m.
Mean in-track view angle	18	12.9
Mean cross-track view angle	-5.9	-0.9
Mean sun azimuth	58	153.4
Mean sun elevation angle	72.1	64.5
Season in Burkina Faso	Wet	Dry

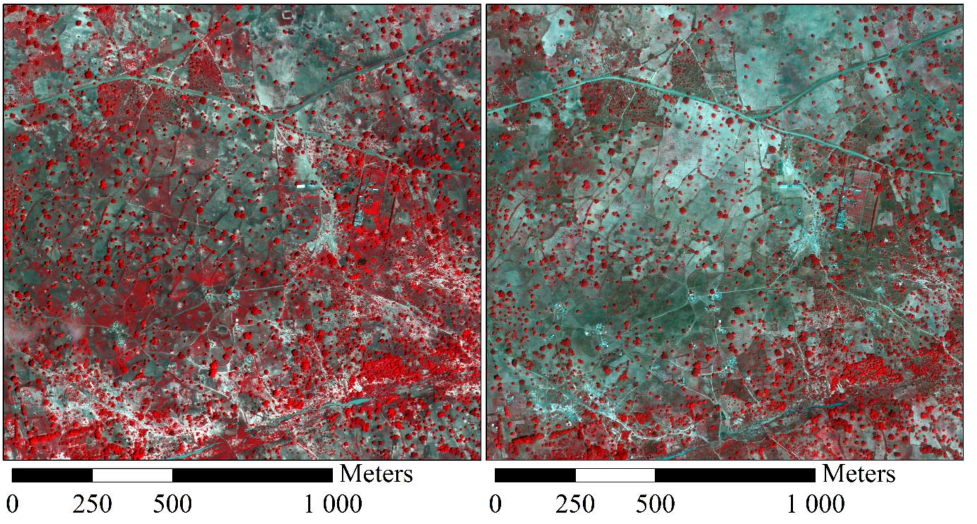

Figure 6. Subsets of pan-sharpened WorldView-2 data (false color composite; red: band 7, green: band 5, blue; band 3). July 2012 image (wet season) to the left and October 2012 image (dry season) to the right.

The multispectral bands were merged with the panchromatic band through a processes referred to as pan-sharpening (Vrabel 1996, Zhang 2010) to facilitate the detection of individual trees (Bunting and Lucas 2006, Rasmussen et al. 2011). The Hyperspherical Color Space (HCS) algorithm and a 7 × 7 pixel smoothing filter was used to create 8-band 0.5 m multispectral images for July and October (Padwick et al. 2010). The HCS algorithm was developed specifically for use with WorldView-2 data and is implemented in ERDAS Imagine 2013 software suit.

After pan-sharpening, the images were rectified to the UTM coordinate system (zone 30N) using 35 ground control points collected in the field and third order polynomials. This resulted in a root mean square error of 0.5 m. Figure 6 provides an example of the pan-sharpened WorldView-2 imagery.

3.4.2 Landsat 8

The Landsat series of satellites have collected multi-spectral data since 1972 and represent the most widely used system for terrestrial RS (DeFries 2008). The launch of Landsat 8 in February 2013 had long been anticipated by the scientific community since both Landsat 5 and 7 have experienced technical problems in recent years. Furthermore, Landsat 8 has more advanced sensing capabilities, in particular it collects data in more spectral bands (11 compared to 8 of Landsat 7) at a higher dynamic range (12 bits compared to 8 bits of Landsat 7), which theoretically increases the resolving power of the imagery. Landsat 8 became operational in May 2013 and provides open access data in one panchromatic (15 m), eight multispectral bands (30 m) and two thermal bands (100 m) with a swath width of 185 km (Table 8).

Table 8. Technical specifications of the Landsat 8 sensor (USGS 2013).

Band	Width (nm)	Region
1	433-453	Coast/aerosol
2	450-515	Blue
3	525-600	Green
4	630-680	Red
5	845-885	NIR
6	1560-1660	Short wave infrared (SWIR) 1
7	2100-2300	SWIR 2
8	500-680	Panchromatic
9	1360-1390	SWIR/cirrus
10	10600-11190	Thermal IR 1
11	11500-12510	Thermal IR 2

Cloud free Landsat 8 data (path 195, row 52) from the early wet season and from the dry season in 2013 and 2014 (Figure 7) were obtained from the United States Geological Survey (USGS) Earth Resources Observation and Science repository (http://earthexplorer.usgs.gov/) for use in Paper IV (Table 9). The Landsat 8 data were delivered in the L1T format, which means that ground control points and digital elevation models have been used to produce an ortho-rectified product free of geodetic and geometric distortions (USGS 2013). The geo-referenced WorldView-2 image (see Section 3.4.1) was used to evaluate the geo-location accuracy of the Landsat imagery. The close correspondence between the two images confirmed that no further correction was necessary. Digital numbers of the Landsat imagery were converted to top-of-atmosphere reflectance according to the instructions provided by USGS (2013).

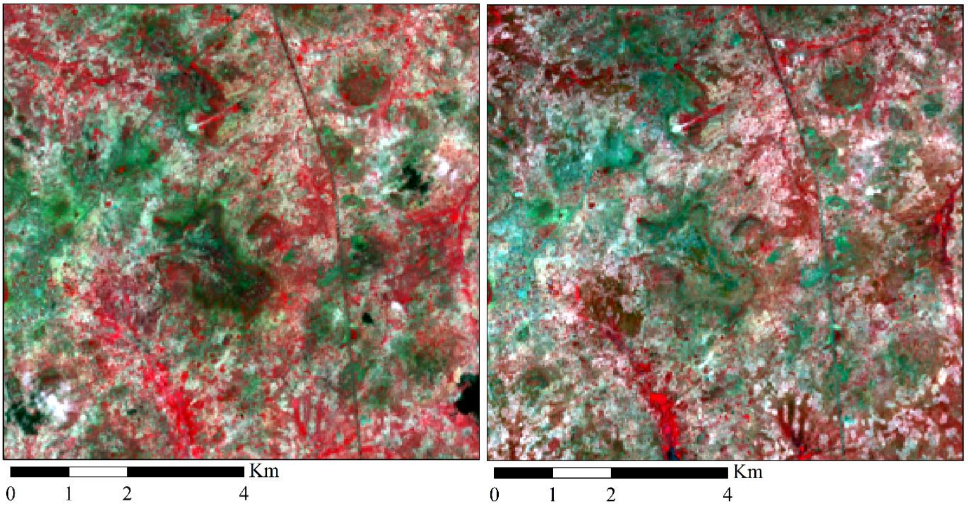

Figure 7. Subsets of false color composite (red: Band 5; green: Band 4; blue: Band 3) Landsat 8 data. July 2013 data (wet season; left) and November 2013 data (dry season; right).

Table 9. Landsat 8 data used in Paper IV. MS - multispectral, PAN – panchromatic.

Sensor	Date	Season	Pixel Size
Landsat 8	27 October 2013 28 November 2013 30 December 2013 31 January 2014 16 February 2014 4 March 2014	Dry season	MS: 30 m
	8 June 2014	Wet season	MS: 30 m PAN: 15 m

3.5 Integration of multi-resolution reference data

Calibration and validation of empirically based RS models require an accurate geographic registration between the reference data and the imagery. Different approaches were used to integrate the field reference data and the satellite data in Papers II-IV. Field data were used for reference for individual tree crown delineation (Paper II) and tree species classification (Paper III). A combination of WorldView-2 and field data were used for calibration and validation of the Landsat 8 based mapping of TCC and AGB (Paper IV).

The reference data used in Papers II and III included individual geo-referenced trees that were also manually identified in the WorldView-2 data using information on crown dimensions, height and species as additional guidance. Each tree was represented as a point in a geographic information system (GIS) layer that contained data surveyed during the field campaign (see Section 3.3).

For Paper IV, the reference data consisted of both the field data and tree crown polygons delineated in the WorldView-2 imagery. Using the method described in Paper II, tree crown delineation was performed using the dry season WorldView-2 data. The delineation was performed in 150 m × 150 m areas centered on the field plots to extend the spatial coverage of the field data and to facilitate registration to Landsat pixels (Paper IV). Some manual editing of the resulting tree crown polygon layer was done to correct for false detection and crown overlaps using the field data for guidance. The areas of the delineated individual tree crown polygons served as input to an allometric equation that relates the tree crown area of *Vitellaria paradoxa* trees to AGB (Koala 2015). Considering that *Vitellaria paradoxa* is the dominant species in the study area and that allometric equations that relate crown area and AGB are practically absent in the literature, the Koala (2015) equation was used for all delineated tree crowns. TCC and AGB from the field data and from the tree crown delineation were aggregated using a raster with 30 m × 30 m grid cells (matching the Landsat pixel size). In areas where TCC and AGB were inventoried in the field, the aggregation was based on the field data instead of the delineated tree crown polygons.

3.6 Methods for satellite data analysis

3.6.1 Paper II – Tree crown delineation

Paper II describes how well a semi-automated method for tree crown delineation (Bunting and Lucas 2006) performed when it was applied in the parkland landscape. The method is based on geographic object-based image analysis (GEOBIA), and was implemented in the eCognition® Developer 8.8 software. Individual tree crowns (ITC) were delineated in WorldView-2 imagery acquired during the early dry season and the results were evaluated using field reference data. The dry season WorldView-2 data was selected because a visual assessment suggested that it provided better contrast between the tree crowns and the background component compared to the wet season data. Furthermore, clouds obscured some of the field plots in the wet season image. Since this study focused specifically on the parkland landscape type, 13 field plots representing tree plantations, gallery forest and sacred groves were excluded from the analysis. Thus, 64 of the field plots were used, including 29 plots in active fields and 35 plots in fallows. Seventeen of these field plots, manually chosen to capture the environmental complexity of the landscape, were used to guide the adaptation of the delineation method.

The adaptation of the delineation method required significant manual and time consuming work following a trial and error process. Field data and visual assessment of the WorldView-2 image were used to optimize the six main steps of the method (Figure 8). These six steps are applied and iterated according to Figure 8 in order to delineate tree crowns in the WorldView-2 data.

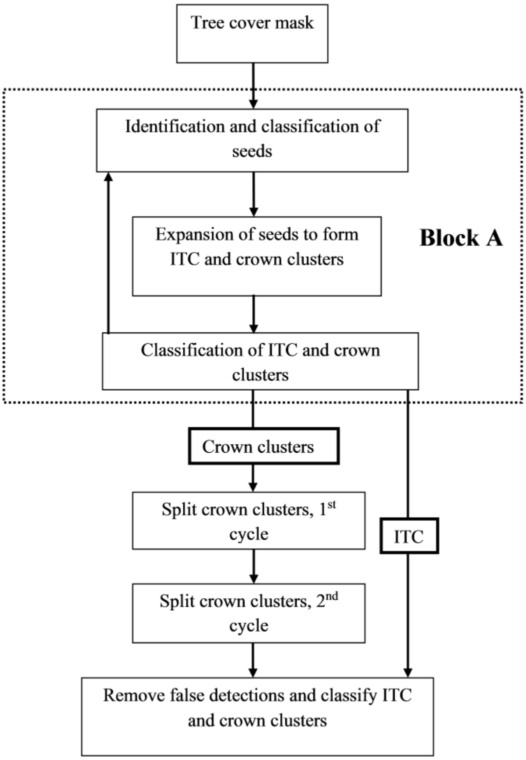

Figure 8. Flowchart showing the different steps in the tree crown delineation method.

The first step involves masking out non-tree cover landscape components, including water, soil, built up areas, crops, grass and shrubs. In the next step (Block A), the NDVI maximum of each remaining tree mask object is identified and serve as the starting point, or seed, for region-growing segmentation (Culvenor 2002, Bunting and Lucas 2006). These so-called seeds are assumed to represent individual tree tops. The objects that result from the region-growing segmentation are then classified as ITC or crown clusters by the shape and size characteristics of the objects (Paper II; Table 4). Crown clusters are further processed in order to delineate individual tree crowns. Firstly, region-growing segmentation is applied with an iteratively decreasing spectral threshold used for defining the tree crown edge (1^{st} cycle). Secondly, objects classified as crown clusters after the previous step are further split into ITC using morphological watershed segmentation (Doughtery 1992) which is based on shape characteristics rather than spectral gradients (2^{nd} cycle). This step is particularly useful in cases when tree crowns overlap and the space between the trees is obscured. In the last step, false detections are removed and the remaining objects are classified as either ITC or crown clusters.

3.6.2 Paper III - Tree species classification

Paper III assesses the capability of multi-temporal WorldView-2 to distinguish common West African agroforestry tree species. Individual tree crown objects derived using the method presented in Paper II was used as the mapping unit. The Random Forest (RF) algorithm was used for classifying the objects and for determining the relative importance of the predictor variables derived from the wet and dry season WorldView-2 data. Both WorldView-2 images were pan-sharpened using the HCS algorithm (Section 3.4.1).

Individual tree crowns (n = 202) of the six most common species in the test site were selected from the field data (Section 3.3) to form the reference dataset (Table 10). These six tree species constituted 80% of the field dataset. Only free standing trees (i.e., non-interlocking crowns) with a crown diameter greater than 6 m were included to ensure high confidence in the reference dataset (Cho et al. 2012).

Table 10. Description of the reference dataset.

Scientific name	Common name	Frequency (%)
Eucalyptus camadulensis	Red River Gum	9
Lannea microcarpa [2]	African Grape	13
Lannea acida [2]	Sabaga	4
Mangifera indica	Mango	9
Parkia biglobosa	African Locust Bean	7
Vitellaria paradoxa	Shea Tree	38

An area of interest mask was created using NDVI and NIR thresholds to exclude pixels within the delineated tree crowns that contained soil and shadow (Colgan et al. 2012). The thresholds for NDVI ($\leq$ 0.5) and NIR ($\leq$ 25%) were determined empirically, and the mask was used to extract spectral data from the WorldView-2 data. Wet and dry season spectral libraries were then created for the six tree species. Due to their similar spectral profiles, the tree crowns of *L. acida* and *L. microcarpa* were aggregated to the class *Lannea spp*.

The predictor variables presented in Table 11 were used as input to the RF classification models. The selection of suitable vegetation indices was informed by previous research (Waser et al. 2014, Naidoo et al. 2012). Both the mean and maximum value was derived from the mask objects, which resulted in a total of 56 predictor variables for the multi-temporal dataset. Separate classifications were conducted using wet season, dry season and multi-temporal predictor datasets, and the results were compared. The predictor variables of the three datasets were also ranked based on their individual contribution to the classification success using the decrease in Gini criterion (Section 2.4.3; Naidoo et al. 2012). Initial tests revealed that variable selection did not improve the RF classification accuracies, as has been suggested by several studies (Ismail and Mutanga 2010, Karlson et al. 2015, Mutanga, Adam, and Cho 2012, Naidoo et al. 2012). Variable selection was therefore not considered further in Paper III, and the classification models were constructed using the full predictor datasets. The

[2] *Lannea acida* and *Lannea microcarpa* were combined into the class *Lannea spp.*

ranking of the predictor variables was mainly done to increase the transparency of the classification procedure.

Table 11. Predictor variables used for tree species classification.

Predictor variables	**Description**	**Formula**	**Reference**
WorldView-2 bands	coastal blue, blue, green, yellow, red, red edge		
Vegetation indices	NDVI	(NIR1 – red) / (NIR1 + red)	(Rouse et al. 1974)
	RENDVI 1	(NIR1 – red edge) / (NIR1 + red edge)	(Gitelson and Merzlyak 1994)
	RENDVI 2	(NIR2 – red edge) / (NIR2 + red edge)	
	Blue ratio (BR)	(red / blue) × (green / blue) × (red edge / blue) × (NIR1 / blue)	(Waser et al. 2014)
	Green ratio (GR)	green / red	
	Red Ratio (RR)	(NIR1 / red) × (green /red) × (NIR1 / red edge)	

3.6.3 Paper IV - Tree canopy cover and aboveground biomass mapping

Paper IV describes how Landsat 8 data can be used for generating maps of TCC and AGB in woodland landscapes. RF regression was used as the modeling framework and TCC and AGB was predicted at pixel-level. The reference dataset used for model training and validation consisted of a combination of field data and tree crown polygons that were produced using the method described in Paper II. Section 3.5 described the procedure for assembling the reference data of Paper IV.

Three types of predictor variables derived from Landsat 8 imagery were used as input to the RF model (Table 12). The spectral variables included top of atmosphere reflectance values of the Landsat 8 bands, vegetation indices and Tasseled Cap components. Texture variables were calculated using the grey level co-occurrence matrix (GLCM) approach implemented on the panchromatic band. Spectral and texture predictor variables were derived from an image acquired in the early wet season (June). This period has been suggested to provide favorable spectral contrast between trees and background components in the Sahel (Couteron, Deshayes, and Roches 2001). Phenology predictor variables were derived from a dry season NDVI time series. RF regression (Breiman 2001, Liaw and Wiener 2002), was used for three undertakings, including i) predictor variable selection, ii) to build models between predictor variables and tree attributes (TCC and AGB), and iii) to map TCC and AGB in the study area.

Table 12. List of the predictor variables used in Paper IV.

Predictor variables	Formula	Reference
Landsat 8 bands 2-8		
Vegetation indices		
NDVI	(NIR – red) / (NIR + red)	(Rouse et al. 1974)
Simple Ratio	NIR / red	(Birth and McVey 1968)
Specific Leaf Area Vegetation Index	NIR / (red + SWIR 2)	(Lymburner, Beggs, and Jacobson 2000)
Enhanced vegetation index	$\mathrm{EVI} = 2.5 \times \frac{\mathrm{NIR} - \mathrm{red}}{NIR + (6 \times red - 7.5 \times B) + 1}$	(Huete et al. 2002)
Generalized Difference Vegetation Index	(NIR^2 – red^2) / (NIR^2 – red^2)	(Wu 2014)
Normalized Difference Water Index	(NIR – SWIR 2) / (NIR + SWIR 2)	(Gao 1996)
Tasseled cap transformations		
Brightness		(Crist and Cicone 1984, Baig et al. 2014)
Greenness		
Wetness		
GLCM Texture (window sizes: 3 × 3, 5 × 5, 7 × 7 pixels)		
Homogeneity		(Haralick, Shanmugam, and Dinstein 1973)
Mean		
Variance		
Phenology (dry season NDVI)		
Maximum		(Gessner et al. 2013)
Mean		
Median		
Minimum		
Product		
Standard deviation		

Variable selection was done to assess whether the use of a reduced predictor variable dataset could improve model performance (Mutanga, Adam, and Cho 2012, Beguet et al. 2014). All predictor variables were first ranked based on the mean decrease in accuracy variable importance measure (Breiman 2001). This initial ranking was used throughout an iterative backward elimination, where the least important predictor variables were successively removed (Diaz-Uriarte and de Andres 2006). The smallest number of predictor variables resulting in the lowest OOB mean square error was used to construct “reduced” models for TCC and AGB. Separate models were constructed using single date and multi-temporal (i.e., including phenology variables) Landsat 8 data.

3.6.4 Accuracy assessment

An accuracy assessment needs to be conducted to ensure that the method used for mapping tree attributes by RS data is robust. Specifically, the reproducibility and the generalization performance of a method, or model, is estimated under realistic conditions by applying the method on an independent dataset (Richter et al. 2012). Overfitting is a critical issue in this context and refers to a situation when a method performs perfectly on training data, whereas it fails when used with independent data. Three different strategies for accuracy assessment were used in Papers II-IV.

In Paper II the reference data was sufficiently large to allow a split-sample approach to be used. The reference data were divided into two subsets; 18 field plots were used for training the tree crown delineation method and 46 plots were used for validation. The validation dataset is therefore effectively independent, but similar to the training dataset since it was collected in the same area. Two aspects of accuracy were considered in Paper II, including tree detection accuracy and crown delineation accuracy. Tree detection accuracy was assessed by recording the number of field trees that were clearly associated with a single crown object (individual tree detection) and the cases when multiple trees were associated with a single crown object (crown cluster detection). In addition, errors of omission and errors of commission were recorded. The overall detection accuracy was assessed using the accuracy index (Pouliot et al. 2002) described in Equation 3, where *n* is the total number of trees in the validation dataset, and *O* and *C* represent the errors of omission and commission, respectively.

$$Accuracy\ index\ (\%) = \frac{(n-(O+C))}{n} \times 100 \qquad \text{Equation 3}$$

Delineation accuracy was assessed by comparing the crown area (CA) of field trees with the area of the delineated crown objects, for both individual trees and crown clusters. Four measures of delineation accuracy were computed from the validation data, including the Spearman’s Rho correlation coefficient, the mean absolute error (MAE), the mean relative error (averaged ratio of the absolute error to field crown area; MRE), and the mean bias error (difference between the mean delineated crown area and the mean field CA; MBE), which indicates the degree of over- or under-estimation (Willmott and Matsuura 2005). Both detection and delineation accuracy were assessed with respect to the size of the trees, the tree species and land use (i.e., active field or fallow).

An alternative to using the split-sample approach is cross-validation, which was used in Papers III-IV. In cross-validation the reference dataset is randomly divided into training and validation subsets multiple time. Statistical measures of accuracy are derived from the mean or median values of all iterations. Cross-validation can provide a more realistic estimation of model performance when the available dataset is limited in size or if the data distribution is imbalanced (Richter et al. 2012, Fassnacht et al. 2014). There are several versions of the cross-validation approach, where the most common is leave-one-out cross-validation: all reference samples but one are used for training, whereas the remaining sample is used for validation. While popular in the literature, leave-one-out cross-validation tends to yield overoptimistic estimates of accuracy, especially in cases when the reference dataset is large (Richter et al. 2012). In Paper III, repeated random sub-sampling cross validation was used to assess tree species classification accuracy. In this version of cross-validation, the reference dataset is randomly partitioned into a training set (e.g., 70%) and validation set (e.g., 30%) an arbitrary number of times; 100 times was used in Paper III. Confusion matrices were created from the sum of the values of the 100 iterations (Congalton 1991). Four measures of classification accuracy were then calculated using the confusion matrices, including producer's and user's accuracy, overall accuracy and Cohen's Kappa coefficient (Cohen 1960).

In Paper IV, *k*-fold cross-validation was used. In this approach, the reference dataset is randomly partitioned into *k* subsamples (i.e., folds) of equal size (Picard and Cook 1984). Models are trained using *k*-1 of the folds, whereas the remaining fold is used for validation. This process is repeated *k* number of times so that each fold is used once for validation. In Paper IV, *k* was set to 10 and each fold therefore contained 15 pixels. Four statistical measures of model performance were derived from each fold, including the coefficient of determination (R^2), root mean square error (RMSE), relative RMSE (relRMSE) and MBE. The statistical measures were then averaged over all validation folds to produce an overall estimation of model performance.

4. Results and Discussion

This chapter presents the main results from the Papers included in the thesis. Further details and discussions about the individual studies are provided in the appended Papers I-IV.

4.1 Literature review

The material of Paper I encompassed 268 peer-reviewed articles that present research where remote sensing (RS) has been used to study vegetation in the Sudano-Sahelian zone (SSZ). The focus of the analysis was on four main aspects of the material that together describe how the use of remote sensing has advanced in this area over the last four decades (1975-2014). The present section describes the main outcomes of the literature review and discusses the results in relation to information needs and environmental problems in the SSZ.

The use of RS for vegetation analysis has a long tradition in the SSZ and the number of articles has increased consistently since the first publication in 1977. The end of the 1980s saw a sharp increase in publication activity in the SSZ. There are several possible explanations for this pattern. The potential of using the meteorological satellite the Advanced Very High Resolution Radiometer (AVHRR) for wide scale observation of vegetation productivity was increasingly being recognized in the SSZ during the late 1980s (Tucker et al. 1983, Tucker et al. 1985), and the accessibility of such data increased considerably with the installation of local ground receiving stations, for example the AGRHYMET Regional Centre in Niamey, Niger (Prince et al. 1995). At this time, AVHRR time series also began to become reasonably long (~10 years) to enable analysis of vegetation changes (Tucker, Dregne, and Newcomb 1991). Additionally, the scientific interest in desertification and land degradation was reinvigorated following the severe drought that hit the area in the mid-1980s, and the imminent 1992 Rio Earth Summit where desertification was one of the main subjects for discussion (Hutchinson 1996, Nicholson, Tucker, and Ba 1998). RS was seen as a key tool to monitor desertification and to understand the underlying factors. However, the sharpest increase in publication activity has occurred during the last seven years. Explanations for this are more speculative, but could include the recent trend in free RS data distribution policies (Roy et al. 2010), and the rapid development of internet access and bandwidths, including in Africa (Internet World Stats 2015), which enables easier access of RS data.

In the SSZ, RS has been used to address three main research topics in the SSZ, including i) to map vegetation properties, ii) to analyze relationships between vegetation and environmental factors, and iii) to study vegetation changes resulting from different disturbances. Research about vegetation change was the largest category amounting to 50% of the articles, followed by vegetation mapping (38%) and vegetation and environmental factors (12%). This uneven distribution of the articles suggests that the main use of RS has been used to map and monitor vegetation properties and changes. On the other hand, the use of RS study interactions between vegetation and environmental factors, such as soil properties, groundwater and climate, has been relatively limited in the SSZ.

The largest proportion of articles within the vegetation mapping category focused on primary production. Other vegetation variables that has received limited attention in this category include tree cover properties, vegetation types, transpiration and water content, leaf area index (LAI) and phenology. Research in the category vegetation and environmental factors mainly used RS data to study relationships between vegetation and rainfall. The understanding of this relationship is highly relevant for different applications of RS data in the SSZ, including primary production modeling, drought monitoring and famine early warning systems, and to interpret observations of long term vegetation changes (Nicholson, Davenport, and Malo 1990, Fensholt et al. 2006, Huber, Fensholt, and Rasmussen 2011). Specifically, a prerequisite, as well as a main source of controversy, for vegetation change analysis in the SSZ have been to remove the effect of short term climate variability on vegetation productivity in order to enable the detection of long term trends (Hein and de Ridder 2006, Prince et al. 2007, Herrmann, Anyamba, and Tucker 2005, Fensholt et al. 2013). A few studies has also used RS to analyze relationships between vegetation and soil properties and global sea surface temperature patterns. Furthermore, the factors causing self-organization of vegetation have been clarified using RS data (Couteron 2001). Both exogenous (e.g., slope of terrain, availability of resources) and endogenous (facilitation and inhibition between plants) factors have been shown to cause the characteristic banded or spotted vegetation patterns found in parts of the Sahel (Couteron and Lejeune 2001). Vegetation change analysis in the SSZ has mainly studied changes in vegetation productivity or vegetation types. Considerably less research has analyzed changes in tree cover variables and phenology.

This review shows that the main progress in the use of RS has been made in the mapping of vegetation productivity and vegetation types. These two vegetation variables have been the most widely used in the applied research categories, i.e., vegetation and environmental factors and vegetation change. These variables have two main benefits for analyzing vegetation in the SSZ: (1) well established methods for transforming RS data into tangible information is available and (2) they enable wide spatiotemporal coverage in the analysis. However, vegetation productivity and vegetation types are not optimal for characterizing the heterogeneous landscapes in the SSZ or to detect subtle vegetation changes. Additional properties of the vegetation cover need to be mapped with RS in order to develop a comprehensive understanding of vegetation changes and their environmental impacts in the SSZ. For example, changes in tree cover properties and species composition are considered to represent critical aspects of future environmental change in the SSZ (Maranz 2009, Gonzalez, Tucker, and Sy 2012). Results from the review also suggest that there may be a gap between the present capabilities of RS and the vegetation data requirements of research concerned with interactions between vegetation and environmental factors. Specifically, vegetation variables need to be mapped at a higher level of detail and at relevant spatial scales to increase the contribution of RS to research about interactions between vegetation and environmental factors (Ustin and Gamon 2010).

About half of the RS based vegetation research in the SSZ has been published in journals with a specific focus on RS applications. The remaining articles have been published in journals oriented towards interdisciplinary research, geography, ecology and land management. The most interesting observation is that the distribution of articles has changed considerably from the 1970s to present day. Specifically, between 1988 and 2011 the proportion of articles published in RS journals was reduced, whereas other types of journals were more frequently used as channels for publishing RS based vegetation research. This pattern is augmented during the most recent time period (2002-2014) where the number of articles published in ecological, geographical, interdisciplinary, and land management oriented journals has increased considerably. This indicates that RS has become more widely used as a scientific tool for vegetation analysis by an increasing number of scientific disciplines. Thus, it appears that the users of RS in the SSZ have diversified in terms of disciplinary belonging, whereas the application focus on similar topics, such as vegetation change and vegetation productivity.

Lastly, the review scrutinized the affiliations of the articles´ lead- and co- authors to establish the degree to which RS has been used by scientists based in the region. The outcome provides an indication of the local scientific capacity to use RS for vegetation analysis in the SSZ. The results show that only a small portion (14%) of the lead authors were affiliated with African institutions. The proportion for African co-authors were slightly higher: 29% of the total number of articles had one or more co-author affiliated with an African institution, and 17% of the total number of co-authors in the review material were affiliated with an institution based in Africa. The relatively low contribution of African authors is not surprising since the access to and use of RS data in Africa has been hampered by bureaucratic, financial and technical constraints (Abiodun 2000). However, these results reinforce the importance of a continued, and preferably increased, transfer of both knowledge and technology to developing countries (Achard et al. 2007), including those in the SSZ.

4.2 Individual tree crown delineation

This study presents and evaluates a semi-automated method for detecting and delineating individual tree crowns in WorldView-2 imagery. The method is adapted to the parkland landscape and consists of several steps that are designed to account for the heterogeneous tree cover structure (Figure 7), which is manifested by highly variable tree sizes, densities, species diversity and field layer conditions.

When a correct detection was defined as a 1:1 correspondence between field trees and single delineated crown objects, the detection accuracy was relatively low: 48% of trees ≥ 5 cm diameter at breast height (DBH) and 54% of trees ≥ 10 cm DBH were associated with a single object (Table 13). The detection accuracy increased to 86% for trees ≥ 5 cm DBH when the definition of a correct detection was relaxed to also include crown clusters. Specifically, a detection was considered correct when a field tree was contained by a delineated object. The use of crown cluster as a mapping unit is a reasonable compromise in situations when tree cover structure is patchy and the crowns often interlock, and when the resolving power of the RS imagery is limited (Culvenor 2002, Bunting and Lucas 2006). The omission error rate (i.e., missed trees) is low in relation to previous research (Ardila et al. 2012, Bunting and Lucas 2006), and mainly comprise small trees. The commission error (i.e., false detections) mostly consisted of small objects (≤ 20 m^2). Elevated commission errors is a common problem for tree crown detection in high resolution imagery, but statistics about its magnitude are seldom reported in the literature (Ke and Quackenbush 2011). In this study, the detection accuracy was not related to tree species, which suggests that the early dry season is a suitable period for image acquisition. None of the present tree species appear to have undergone substantial leaf senescence that may limit the detection accuracy (Ke and Quackenbush 2011). The detection accuracy was significantly lower in fallows compared to active fields. There are two main reasons for this difference. Firstly, trees in fallows are generally smaller compared to trees in active fields, which increases the likelihood of omission errors. Secondly, the field layer in the fallows consists of small shrubs and coppice regrowth with a spectral response similar to tree crowns that can lead to higher commission errors. These small trees and shrubs were not sampled in the field and some commission errors may in fact represent correct detections.

Table 13. Results of crown detection accuracy assessment.

Land use	Field trees	Detection rate % (ITC)	Detection rate % (crown clusters)	Omission error %	Commission error %	Accuracy index %
Active field	189	55 [1]/60.7 [2]	88.4 [1]	11.6 [1]/5.3 [2]	12.7	76 [1]/79 [2]
Fallow	308	43.8 [1]/48.4 [2]	87.7 [1]	12.3 [1]/9.3 [2]	21.7	66 [1]/64.5 [2]
Total	497	48.4 [1]/53.8 [2]	85.7 [1]	14.3 [1]/6.6 [2]	18.3	67.4 [1]/69.7 [2]

[1] Trees with DBH > 5 cm; [2] Trees with DBH > 10 cm.

The results in Table 14 show that delineation accuracy is a function of tree crown size, with higher errors for small trees, compared to medium sized and large trees. The crown area (CA) of small trees was overestimated, whereas the CAs of medium and large trees were underestimated. One explanation to the lower accuracy for small trees is that they do not cause a distinct shadow, which obstructs the crown edge detection. Furthermore, small trees are more frequent in fallows where the complex field layer reduces the spectral contrast with the crown edges. Nevertheless, the overall delineation accuracy of individual tree crowns in this study is in the same range as to those reported in studies where the field layer is less complex. For example, Ardila et al. (2012) reported mean relative error (MRE) of 40% in an urban setting, and Brandtberg and Walter (1998) reported MRE of 46% in a boreal forest area.

Table 14. Results of crown delineation accuracy assessment showing Spearman's Rho correlation coefficient (r_s), mean absolute error (MAE), mean relative error (MRE), and mean bias error (MBE).

Level of Aggregation	Category	r_s	MAE (m^2)	MRE (%)	MBE (m^2)	n
ITC	Small CA (< 35 m^2)	0.42	8.5	65.0	4.0	122
	Medium CA (35–100 m^2)	0.61	15.2	26.8	−6.9	85
	Large CA (≥ 100 m^2)	0.90	44.5	21.3	−41.8	31
	All (active field)	0.88	16.5	30.0	−12.5	107
	All (fallow)	0.80	14.8	58.0	−0.5	131
	All (fallow + active field)	0.84	15.6	45.6	−5.8	238
Crown clusters	Active field	0.86	27.2	32.7	−7.1	21
	Fallow	0.74	35.0	77.0	24.3	39
	All	0.80	32.3	61.5	13.3	60
ITC and crown clusters	Active field	0.89	18.2	30.7	−11.7	128
	Fallow	0.81	19.5	62.5	5.2	170
	All	0.84	18.9	48.8	−2.0	298

Crown clusters proved more difficult to delineate compared to individual tree crowns (ITC; Table 14). It is likely that this is an effect of the field reference dataset where the CAs of individual trees were aggregated to represent crown cluster area without taking into account possible crown overlaps. Furthermore, large trees within a cluster may obscure smaller trees from the view of the satellite sensor, which means that the crown cluster areas in the reference dataset will tend to be positively biased.

Individual tree crown and crown cluster areas were also aggregated to percent tree canopy cover (TCC) at the plot level. The remotely sensed TCC agreed well with the field reference data (r_s = 0.86; MAE = 2.4%), with considerably better agreement for plots in active fields as compared to fallow. These results are similar or better when compared to related research where high resolution satellite data and GEOBIA has been used for mapping TCC (Rasmussen et al. 2011, Morales, Miura, and Idol 2008). For example, Rasmussen et al. (2011) reported a moderate agreement (R^2 = 0.51) between field data and TCC derived from Quickbird data for an area in northern Senegal. Morales et al. (2008) reported R^2 = 0.86 and MAE = 2% when using Ikonos data in a Hawaiian dry forest.

The tree crown delineation method was adapted to the characteristics of a limited yet structurally complex test site. The method requires that a large number of geometrical and spectral thresholds are optimized in order to produce accurate results. These thresholds need specific attention when the method is applied in another area or during another vegetation season. Furthermore, the thresholds need to be adapted to account for potential differences in RS data characteristics, including the spectral properties of the sensor and sun-sensor geometry (Leckie, Gougeon, et al. 2005, Asner 1998). In this study, the use of near nadir imagery and the generally flat landscape were probably important factors for the relatively high delineation accuracies. If this method were to be applied over a hillier area then topographic correction of the RS data would likely be needed. In addition, the delineation method is quite demanding in terms of data processing. Image tiling is therefore recommended in cases when the area of interest is large. The most accurate results were produced when the method was applied in areas with a sparse tree cover. Such conditions can be found over large areas in the SSZ, in particular in the agroforestry parklands.

4.3 Tree species classification

In Paper III, WorldView-2 data were used to classify five tree species/groups common to the West African parklands. The tree crown objects derived from Paper II were used as the mapping unit and the classification results from three predictor variable datasets (wet season, dry season and multi-temporal) were compared. Object-based classification was chosen over a pixel based classification because it is more suitable to handle high spatial resolution RS data (Blaschke 2010, Benz et al. 2004), and it has produced higher tree species classification accuracies (Immitzer, Atzberger, and Koukal 2012). This study is novel in the sense that no previous research has attempted to map tree species using RS in the SSZ, nor has multi-temporal WorldView-2 data been used for this task.

The main results of Paper III are presented in Figure 9, which shows that relatively high overall classification accuracies were achieved, in particular when the multi-temporal dataset was used as input to the RF classification. The dry season dataset also produced a reasonably high classification accuracy. The latter is a promising result seen from an application perspective because acquisition of optical satellite data is highly problematic in the SSZ during the wet season due to the high occurrence of clouds (Romijn et al. 2012). The overall classification accuracies in Paper III (dry season = 76.3%; multi-temporal = 82.4%) are in good standing when compared to previous studies, both in Africa and elsewhere. Tree species classification accuracies in African savannas using different RS data have ranged between 76% and 89% (Adelabu and Dube 2014, Cho et al. 2012, Colgan et al. 2012, Naidoo et al. 2012). WorldView-2 based tree species classification accuracies have ranged between 62.9% and 83% in temperate mixed forests (Immitzer, Atzberger, and Koukal 2012, Verlic et al. 2014, Waser et al. 2014) and urban forests (Pu and Landry 2012). However, comparisons between studies should be interpreted with caution because many factors influence the classification accuracies, including the total number of tree species, the type of ecosystem (e.g., broad-leaved, conifer or urban forest), the amount and quality of reference data, and the method used for accuracy assessment (Immitzer, Atzberger, and Koukal 2012).

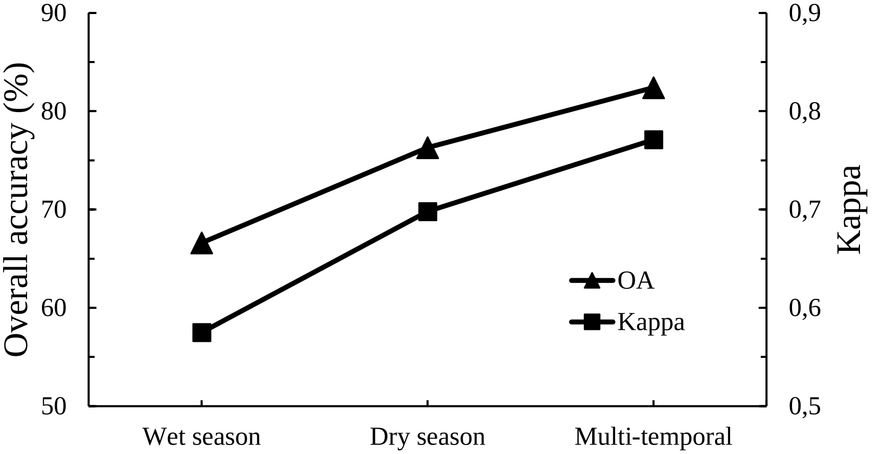

Figure 9. Graph showing the overall classification accuracy and Kappa coefficient for the three predictor variable datasets.

The use of the multi-temporal dataset also substantially increased the classification accuracies for the individual tree species, in particular for *Lannea spp.*, *P. biglobosa* and *V. paradoxa*. The producer's accuracies were above 70% for four of the five tree species when the dry season dataset were used, and above 80% when the multi-temporal dataset was used. The user´s accuracies were marginally higher than the producer's accuracies. The most problematic tree species was *Lannea spp.*, which was frequently misclassified as *V. paradoxa*. Confusion in the classification also occurred between *M. indica* and *V. paradoxa*. An important factor for relatively low classification accuracy for *Lannea spp*. was probably the aggregation of two tree species in this group. The leaves of *L. acida* and *L. microcarpa* are highly similar, but differences in the timing of senescence may have increased the spectral variability within this group to a point where the classification accuracy was negatively affected. In addition, Cho et al. (2012) identified a positive relationship between classification accuracy and tree crown size in a South African savanna. This relationship was also observed in Paper III where the species with the smallest mean CA, *Lannea spp.* and *V. paradoxa*, were associated with lower classification accuracies.

Higher accuracies were obtained for the dry season classification compared to the wet season classification. This difference indicates that phenology is an important factor that modifies the spectral signatures of parkland trees, and consequently affects the classification accuracies. The wet season dataset was acquired at a time when the productivity of parkland trees is at its peak in terms of leaf development. The lower classification accuracies suggest that the difference between the spectral signatures of parkland tree species is smaller during this period of time. On the other hand, some of the tree species (*Lannea spp*. and *E. camadulensis*) were undergoing senescence and leaf shedding during the time when the dry season dataset was acquired, which coincided with the field work in 2012. Other parkland tree species, in particular *M. indica* and *V. paradoxa,* change leaves progressively (Arbonnier 2004). These species had begun developing new leaves that have rather divergent colors. Consequently, it appears as if the leaf shedding and the development of new leaves produces more distinct spectral signatures in the dry season that facilitates RS based classification.

The difference in spectral properties of trees between the wet and the dry season was also apparent in the predictor variable ranking. The importance of the different predictor variables diverged noticeably between the wet and dry season classifications. Specifically, visible WorldView-2 bands (e.g., green, and yellow) were amongst the most important predictor variables in the wet season dataset. In the dry season dataset, vegetation indices were more important than the visible bands. Overall, the red edge band was identified as the most important predictor variable for both datasets. Previous research has shown that the spectral configuration of the WorldView-2 sensor is suitable for classifying tree species in a range of ecosystem, including African savannas (Cho et al. 2012, Verlic et al. 2014, Immitzer, Atzberger, and Koukal 2012, Pu and Landry 2012, Peerbhay, Mutanga, and Ismail 2014). The results from Paper III reassert this conclusion and provide evidence of the suitability of WorldView-2 for classifying parkland tree species.

4.4 Tree cover mapping

The objective of Paper IV was to assess the utility of Landsat 8 for mapping tree canopy cover (TCC; %) and aboveground biomass (AGB; tons ha^{-1}) in the woodland landscape setting. Three types of predictor variables (spectral, texture and phenology) were obtained from Landsat 8 data and constituted input to RF regression models. The spectral and texture variables were based on an early wet season image acquired in June and a dry season time series consisting of monthly images from October to March were used for the calculation of the phenology variables. Separate RF models based on single date and multi-temporal imagery were constructed to assess the influence of including phenology variables. The effect of reducing the total number of predictor variables in the models through variable selection was also assessed.

The results in Table 15 clearly show that Landsat 8 is more suitable for mapping TCC compared to AGB. The relative RMSE was rather high for AGB (66%), but lower for TCC

(40.6%). However, it is important to consider that the mean values of TCC and AGB are low in the study area, which inevitably leads to higher relative RMSE. Furthermore, the accuracy of the maps was assessed at pixel level. If TCC and AGB estimates were to be aggregated over larger areas, the errors would be lower. The prediction accuracies of the best models in this study are similar or better than results reported in related literature where Landsat data have been used to map tree cover attributes in comparable ecosystems (Zheng et al. 2004, Carreiras, Pereira, and Pereira 2006, Armston et al. 2009, Huang et al. 2004, Stojanova et al. 2010, Tian et al. 2014, Lu 2005).

Table 15. Main results from Paper IV.

Variable	Variable Selection	Predictor Dataset	R^2	relRMSE (%)	RMSE	MBE
Tree canopy cover (%)	Full	Single date	0.49	60.0	13.1	0.04
		Phenology included	0.54	57.0	12.5	0.08
	Reduced	Single date	0.65	49.7	10.9	0.02
		Phenology included	0.77	40.6	8.9	0.08
Aboveground biomass (tons ha^{-1})	Full	Single date	0.34	83.0	22.2	0.06
		Phenology included	0.46	75.0	20	−0.66
	Reduced	Single date	0.44	75.0	20	0.44
		Phenology included	0.57	66.0	17.6	0.22

The better performance of Landsat 8 for mapping TCC compared to AGB was quite expected since optical sensor measurements are mainly controlled by properties of the canopy layer, whereas the influence from height related tree attributes, such as AGB, is smaller (Lefsky and Cohen 2003). Predictor variables based on image texture were included in the models because they are sensitive to spatial features in the data, including tree crown size and shadow structures, which may contribute information on height related attributes (Lu 2005, Eckert 2012). This succeeded to some extent because several texture variables were identified as particularly important for predicting AGB. The relatively strong relationship between texture predictor variables and tree cover attributes found in this study further add to the evidence showing that image texture calculation is a particularly useful technique in areas where the tree canopy is relatively open (Eckert 2012, Lu 2005, Sarker and Nichol 2011).

Variable selection generally improved the predictions of TCC and AGB, which suggests that many of the included predictor variables were redundant. The reduced models for TCC included four predictor variables when single date imagery was used, and five predictor variables when phenology variables were considered (see Paper IV: Figure 5-6). For AGB, both models included four predictor variables. A key result in Paper IV is that the reduced models for both TCC and AGB included all three types of predictor variables (i.e., spectral, texture, and phenology). This shows that the three types of predictor variables bear partially independent information about the trees that is complimentary in the context of woodland tree cover mapping. In this study, the panchromatic band of Landsat 8 showed the strongest relationship to both TCC and AGB according to the RF variable importance ranking, followed by the homogeneity texture features calculated from the panchromatic band (see Paper IV: Figure 1-4). The other Landsat 8 bands (bands 2-7) were ranked low for both TCC and AGB.

The highest ranked vegetation indices were the tasseled cap greenness for TCC and wetness for AGB.

A dense understory vegetation layer makes the relationship between tree cover attributes and optical RS data less predictable, as the two vegetation layers can be spectrally similar (Lu 2006, Wu, De Pauw, and Helldén 2013). The ambition in Paper IV was to reduce this effect by using imagery from periods when the phenological differences between trees, grasses and crops are most prevalent. In the SSZ, these periods occur in the early wet season and during the dry season (Seghieri et al. 2012, Seghieri, Floret, and Pontanier 1995, Couteron, Deshayes, and Roches 2001). The relatively accurate results suggest that this approach succeeded to some extent. However, a sizeable proportion of the error in the predictions may be attributed to limitations in the reference dataset. Specifically, the understory vegetation in the study area included a large component of shrubs and tree coppice whose phenology is similar to that of the trees. This component was not well represented in the reference dataset: only trees with DBH ≥ 5 cm were sampled in the field and the tree crown delineation in the WorldView-2 imagery has a higher likelihood of omitting small trees (Paper II). An additional source of uncertainty in the reference dataset is the use of allometric equations to obtain AGB from individual tree attributes. Species specific equations were used to derive AGB from the field data when such were available (~60% of field data), whereas the pan-tropical equation by Chave et al. (2014) was used for the remaining part. Furthermore, an allometric equation that related CA to AGB developed for *Vitellaria paradoxa* (Koala 2015) was used for the tree crown objects delineated in the WorldView-2 data. The uncertainty introduced by these allometric equations may be an important factor for the lower performance of the AGB models in Paper IV.

To accurately co-locate RS data of medium spatial resolution with field reference data is a challenging task. A common approach to limit the potential effect of an incorrect geographic co-location is to average the RS data within several pixels (e.g., 3 × 3 pixel window) that unequivocally cover the field plots (Lu 2005, Lu 2006, Dube and Mutanga 2015). However, the spatial variation in tree cover attributes can be very high in the Sudano-Sahelian woodlands and it is unlikely that an averaged RS measurement or an up-scaled field measurement is representative of the situation of the ground. In Paper IV, WorldView-2 imagery was used to extend the coverage of the field reference data, which facilitated the accurate alignment between RS data and reference data on the pixel-level. This approach is dependent on the availability of high resolution data over the area of interest, in particular over the field plots. High resolution data is expensive relative to data of coarser resolution. However, this cost is low when compared to those associated with field data collection. High resolution satellite data therefore represents an economically sound alternative that can limit the need for extensive field surveys. This was demonstrated by Wu et al. (2013) who used Google Earth imagery to create a reference dataset used for MODIS based mapping of AGB throughout the Sudan. The main drawback with Google Earth imagery, however, is that the possibility to automate the image processing, as was done in Paper IV, is limited.

RF regression is generally considered a well suited modeling technique for predicting tree cover attributes from optical RS data (Fassnacht et al. 2014, Armston et al. 2009, Breiman

2001). However, the RF models in Paper IV were less accurate at the extremes of the TCC and AGB ranges, where low values were overestimated and high values were underestimated. This effect was stronger for AGB compared to TCC, which suggests that the influence of AGB on the Landsat data saturates when the tree canopy approaches full closure. The overestimation of low TCC and AGB values was likely due to the prevalence of dense understory vegetation that was poorly represented in the reference dataset. On the other hand, the models did produce more accurate predictions in the mid-ranges of TCC (10-60%) and AGB (10-50 tons ha^{-1}), in which the main proportion of the Sudano-Sahelian woodlands and parklands falls (Chidumayo and Gumbo 2010). Consequently, the approaches presented in Paper IV for mapping TCC and AGB using Landsat 8 are well suited for application in the SSZ.

5. Conclusions

This thesis has investigated the applicability of remote sensing (RS) as a scientific tool for mapping and analyzing vegetation in the Sudano-Sahelian zone (SSZ) of Africa. A literature review was first conducted to provide a detailed description of the development of this scientific field, and to identify important research gaps. The remaining parts of the thesis focused on filling some of these research gaps. Specifically, the capabilities of two new satellite sensors and novel RS data processing methods for mapping tree attributes in the Sudano-Sahelian woodland landscape were assessed. Four tree attributes were in focus, including individual tree crown area, tree species, tree canopy cover (TCC) and aboveground biomass (AGB). These tree attributes all relate to important aspects of sustainable development in the region, including land management and climate change (Chidumayo and Gumbo 2010). The main conclusions of the thesis are presented below.

1) The scientific use of remote sensing for analyzing vegetation has increased consistently in the SSZ since the mid-1970s, with a peak during the last decade, and the technology has been adopted by a diversifying group of scientific disciplines. The main application area for RS in this region has been vegetation change analysis, while its use to study interactions between vegetation and environmental factors has been relatively limited. RS has mainly provided information on two vegetation variables (i.e., vegetation productivity and vegetation types), which have spatial and thematic limitations to characterize the heterogeneous landscapes in the SSZ.

2) RS research in the SSZ has mainly been conducted by foreign actors and the geographical clustering of research activities suggests that local scientific capacities are uneven within the region. Transfer of technology and knowledge to enhance local capacities for RS utilization therefore represents an important area to improve preconditions for sustainable land management and environmental research in the SSZ.

3) Detection and delineation of parkland tree crowns and crown clusters in WorldView-2 data can be automated using geographic object-based image analysis (GEOBIA), but the accuracy is dependent on the size of trees, the degree of crown closure, and on the composition and density of the undergrowth vegetation. Delineation of individual tree crowns in high resolution satellite data may not be feasible when trees are arranged in compact clusters. In such cases, crown cluster delineation represents a more appropriate and useful approach.

4) GEOBIA provides a useful tool for designing crown delineation algorithms for use in areas with a complex landscape composition. GEOBIA enabled the inclusion of mechanisms that account for the variability in spectral and spatial properties of trees and understory vegetation. Substantial increases in detection and delineation accuracy may be achieved by constructing a tree cover mask from height information, which excludes shrubs and tree coppices and thereby reduces commission errors.

5) The WorldView-2 sensor is well suited for classifying five main agroforestry tree species commonly found throughout the Sudano-Sahelian woodlands. The spectral configuration of the sensor was an important factor for the relatively high classification accuracies.

6) Phenology is an important factor for RS based tree species classification in the Sudano-Sahelian woodland. The dry season is better suited for image acquisition compared to the wet season in the *Vitellaria paradoxa* dominated landscape type. However, multi-temporal imagery improves classification accuracy considerably over that achieved with single date data.

7) Landsat 8 has higher utility for mapping TCC compared to AGB in the woodland landscape type. The poorer accuracy of the AGB models was anticipated, and can be explained by the difficulty to resolve features related to the three dimensional structure of trees in the Landsat 8 data. Furthermore, the application of allometric equations to obtain AGB introduces higher uncertainty in the reference data and may negatively affect the relationship modeling.

8) The combined use of spectral, spatial and temporal information derived from Landsat 8 generally improved prediction of TCC and AGB, which suggests that these three types of predictor variables contribute partly independent information about the tree cover. Image texture variables have previously shown promise as predictor variables for TCC and AGB mapping in areas with on open tree canopy, but the use of phenology variables is novel in this type of environment. The use of variable selection to reduce model complexity resulted in improved predictions of TCC and AGB suggesting that many predictor variables were redundant.

9) The combination of field data and high resolution WorldView-2 data represents a novel approach for integrating TCC and AGB reference data with Landsat 8 data at pixel level. This approach limits the need to average the Landsat 8 data over a larger area to reduce effects of spatial misregistration, and is less sensitive to mixed pixels caused by the heterogeneous woodland landscape composition. It also represents a cost-efficient complement to field data collection.

10) The timing for data acquisition is a critical factor for RS of trees in the SSZ. Early dry season acquisition of WorldView-2 proved to be suitable both for tree crown delineation and tree species classification. However, inclusion of wet season data provided independent information that improved the tree species classification accuracies. Landsat 8 acquired in the early wet season was suitable for mapping of TCC and AGB, but the inclusion of phenological information from a dry season NDVI time series further improved the prediction accuracies. Ecological theory suggests that the early wet season is the optimal timing for Landsat 8 based mapping because trees develop leaves before the herbaceous vegetation in the SSZ, but RS data acquisition is hindered by clouds during this period.

6. Future Outlook

Almost four decades have passed since remote sensing (RS) was first introduced as a tool to study vegetation in the Sudano-Sahelian zone (SSZ). During this time, the capability of RS has developed substantially in many ways, as was shown in Paper I. The use of RS has opened up new spatial and temporal perspectives and has thereby enabled the acquisition of new knowledge about the condition and functioning of the vegetation cover in the SSZ. However, the potential for further development of RS is obvious given the current rapid advances in sensor technology, computer power and RS data access. Seen from my perspective, the future development of RS involves two main issues, including i) advances in sensor capabilities and data processing techniques for accurate information retrieval, and ii) scientific application of remotely sensed information. This thesis has mainly focused on the first of these two issues, in particular techniques for RS data processing. Research on this topic is important because it produces efficient techniques for transforming RS data into tangible information about the vegetation cover in different types of ecosystems. Such information needs to be sufficiently accurate in order to be of value for undertakings in the scientific application of remotely sensed information. It is this second issue that will advance knowledge about the vegetation cover in the SSZ. Adequate vegetation cover data are essential for making informed decisions towards sustainable management of the vegetation resources, which are currently under pressure from climate change and intensified land use. Based on the results from this thesis work, some key research priorities that can contribute to advancing the utility of RS in the SSZ have been identified.

There is a need to continue the development of techniques for transforming RS data into relevant vegetation information. Methods for continental scale analyses of vegetation productivity are well established and their limitations are well understood (Fensholt et al. 2013). Using coarse resolution RS data, in particular AVHRR and MODIS, these methods enable observation of vegetation productivity dynamics and identification of areas where large changes have occurred (Seaquist et al. 2009). Correlations with long term datasets on different climate variables have revealed the main drivers of vegetation dynamics and changes in the SSZ (Hickler et al. 2005, Seaquist et al. 2009). Over the last decade there has been a trend where more detailed vegetation information has been obtained from coarse resolution RS data, including variables such as net primary productivity, phenology and tree cover (Horion et al. 2014, Seaquist et al. 2006, Heumann et al. 2007). A similar trend cannot be seen for medium and high resolution RS data, which have the main advantage of enabling observation at higher levels of spatial detail. In the SSZ, such RS data has mainly been used to create categorical, or thematic, maps where the land may be represented by a limited number of broad vegetation and land use classes. Time series of thematic maps created from RS data have been the backbone for land cover change analyses on the landscape scale. Such time series have also been useful for producing regional scale estimates of agricultural expansion and tree cover changes (Vittek et al. 2014, Bodart et al. 2013, Brink and Eva 2011). However, vegetation information in the format of thematic maps with broad classes may not be compatible with the requirements of other types of research (Xie, Sha, and Yu 2008), including research that studies the interactions between vegetation and environmental factors (e.g., soil properties, water resources and bushfire) and changes in floristic composition. An important task for remote sensing research in the SSZ is therefore to research the potential of mapping of more relevant vegetation variables, including categorical maps with a higher level of thematic detail. Papers II-IV contribute to this task by evaluating data sources and processing methods for mapping of tree canopy cover (TCC), aboveground biomass (AGB) and individual trees, including tree species. Other important vegetation variables that have received limited attention by remote sensing research in the SSZ include herbaceous species types (e.g., annual or perennial), vegetation height and biochemical properties (e.g., chlorophyll and nitrogen).

Several RS systems with improved data characteristics suited for vegetation mapping will become operational in the coming years. The most anticipated addition is arguably the Sentinel-2 system, which will consist of two satellites phased at 180° to each other (Drusch et al. 2012). Sentinel-2 multispectral data will be freely available with a spatial resolution between 10 m and 60 m (depending on the band), a revisit time of 5 days and a swath width of 290km. These are considerable improvements compared to the data provided by Landsat 8, where Sentinel-2 may be particularly suitable for mapping vegetation in the fragmented landscapes of the SSZ. For example, the higher spatial and temporal resolution of Sentinel-2 can help reduce the uncertainties of the TCC and AGB predictions achieved in this thesis (Paper IV). In addition, the high temporal resolution enables improved observation of tree and grass phenology, which can facilitate species classification and reduce problems with cloud contamination.

Another interesting satellite system is WorldView-3, which became operational in February 2015. Compared to its predecessor, WorldView-3 offers considerably improved data characteristics in terms of spatial and spectral resolution. Specifically, the pixel sizes have been reduced to 0.31 m and 1.24 m for the panchromatic and multispectral bands, respectively. The band configuration is similar to WorldView-2, but additional shortwave infrared bands have been included. The use of WorldView-3 data may therefore enable improved tree crown delineation (Paper II) and tree species classification (Paper III) compared to the results reported in this thesis. Furthermore, WorldView-3 data can be acquired in stereo mode and image matching can be used to create canopy height models (Straub et al. 2013). It is possible that WorldView-3 represents a flexible and low cost alternative (e.g., as compared to LiDAR) for mapping tree height, but further research is needed to assess this potential capacity. Tree height information can improve both individual tree crown delineation (Cho et al. 2012), tree species classification (Naidoo et al. 2012) and AGB estimation. Moreover, many efforts have been made to study interactions between trees and other components of the landscape, for example grasses, soil properties, groundwater, livestock and crops (Bayala et al. 2015, Bargués Tobella et al. 2014, Scholes and Archer 1997). These studies have primarily been conducted on the plot scale, while the landscape scale effect of trees thus remains elusive (Bayala et al. 2015). The possibility of deriving highly detailed and accurate datasets of individual trees over large areas may increase the utility of RS for research concerned with such ecosystem interactions.

There is also a need to further improve RS methods for detecting and analysing vegetation change in the SSZ. RS based research about vegetation change has often focused on a single vegetation attribute, for example, vegetation productivity or vegetation type. This research has obviously contributed key knowledge about many aspects of vegetation change in the SSZ. However, a more comprehensive understanding would be possible if additional vegetation attributes were integrated in the analysis, or if vegetation change was observed simultaneously at multiple spatial scales (Li, Xu, and Guo 2014). For example, AVHRR data could initially be used to detect areas where changes in vegetation productivity and/or phenology have occurred. Landsat data would then make it possible to quantify the contribution of the tree cover to the observed change, and WorldView data would enable a detailed description of the tree cover, including tree sizes and tree species composition. In addition, WorldView data could be used to quantify grass species diversity (Dalmayne et al. 2013) and thereby provide additional important insights to vegetation change in the SSZ (Mbow et al. 2013).

There is great potential of RS to enable efficient collection of vegetation data, and thereby to improve the preconditions for research and natural resource management in the SSZ. There are no signs that the technological development of RS systems and data processing tools is stagnating. At the same time, the accessibility of RS data is increasing globally due to relaxed distribution policies, free or reduced-cost data, and improved internet connections. A key to allow the people of the SSZ to benefit from these developments will be to further improve local capacity for making use of RS data and technology.

7. References

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Papers