Further development and adaptation of large area forest inventories and remote sensing applications to comprehensive data providers for international processes

Dissertation

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List of abbreviations

AD	Activity Data
AGB	Above Ground Biomass
AGB_{Tree}	Above Ground Biomass of Trees
AGC_{Tree}	Above Ground Carbon of Trees
ALUCCSA	Adaptation of Land-use to Climate Change in Sub-Saharan Africa
BMZ	German Federal Ministry for Economic Cooperation and Development
CGM	Chlorophyll Green Model
CRM	Chlorophyll Red Edge Model
CS	Circular Subplot
DEM	Digital Elevation Model
DLR	German Aerospace Center
EF	Emission Factors
EVI	Enhanced Vegetation Index
FAO	Food and Agriculture Organization of the United Nations
FRA	Forest Resource Assessment
GHG	Greenhouse Gas
GIZ	German Agency for International Cooperation
GLC 2000	Global Land Cover 2000
IPCC	Intergovernmental Panel on Climate Change
JRC	Joint Research Centre
LAI	Leave Area Index
LCCS	Land Cover Classification System
MDG	Mean Decrease Gini
MODIS	Moderate Resolution Imaging Spectroradiometer
MRT	Modis Reprojection Tool
MRV	Monitoring Reporting and Validation
NDVI	Normalized Difference Vegetation Index
NFI	National Forest Inventory
NFMA	National Forest Monitoring and Assessment
NIR	Near Infra-Red
OBB	Out-Of-Bag error estimate

OLWTC	Other Land With Tree Cover
OWL	Other Wooded Land
PSU	Primary Sampling Unit
RE	Red Edge
REDD	Reducing Emissions from Deforestation and Forest Degradation
RESA	Rapid Eye Science Archive
SPOT Vegetation	Satellite Pour l'Observation de la Terre
SRTM	Shuttle Radar Topographic Mission
SSU	Secondary Sampling Unit
SVM	Support Vector Machines
TOF	Trees outside forests
UTM	Universal Transverse Mercator

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1 Introduction

Since about one decade, with the adoption of the Kyoto-Protocol in 1997, climate change has become the focus of many scientific studies. Climate change in general, can be assigned to three major origins, 1) external, 2) internal and 3) human (McGregor and Nieuwolt, 1998). The external origin being the interaction of the sun and earth where fluctuations of the earth orbit, among others, causes climatic changes. Natural changes of the atmosphere and, land surface or volcano eruptions are considered as internal origins of climate change. The third origin, the so called human induced climate change, is mostly related to atmosphere pollution, deforestation and degradation of land surfaces.

Just as there are many unresolved questions with regards to the external and internal causes of climate change, there is still a lack of research when it comes to the human induced part of climate change. Here, one of the central questions is: How to assess deforestation, forest degradation and the related changes in carbon stocks? Considering that deforestation and forest degradation with a contribution of about 20% to the global greenhouse gas (GHG) emissions are the second largest emitters of GHG after the energy sector (UN-REDD 2011). It becomes apparent that the only chance to reduce the human influence on climate change is to reduce emissions, not only from the energy sector, among others, but also by reducing emissions from the forestry sector.

When we speak of forest, in particular in large area & global issues, one of the first questions that should be asked is: What is forest, or how can we define forest and other land uses? Here, many efforts are being undertaken to harmonize classification for the whole world. While researchers around the world have tried to harmonize competing classifications and definitions, so far no consensus has been achieved. One possibility for such a harmonized land use classification scheme is the classification scheme provided by the United Nations Food and Agriculture Organization (FAO), which proved to be applicable to most regions of the world.

The second question should be: How to correctly differentiate different land use classes on various scales, ranging from local level to country level or even the whole world? It has been

proven that terrestrial National Forest Inventories (NFI) or remote sensing based approaches are well suited tools for the assessment of such data.

Many temperate countries already have established NFI's, whereas most tropical, especially African countries still lack any means for a standardized reporting, data collection, analysis and of their natural resources; even though it has been stated by Working Group II of the Intergovernmental panel on climate change (IPCC)-2007-report: "New studies confirm that Africa is one of the most vulnerable continents to climate variability and change because of multiple stresses and low adaptive capacity" (Parry et al. 2008).

The above described existing uncertainty with regards to forest resources becomes even more important within the scope of new global market incentives like the United Nations collaborative programme on Reducing Emissions from Deforestation and Forest Degradation in Developing Countries (REDD), where industrialized countries can buy carbon credits from tropical, developing countries in order to reduce deforestation and forest degradation in the respective countries. For such a trading scheme to function, reliable, standardized, verifiable and cost effective data acquisition techniques are needed, in order to report on the current state and changes of land resources, especially forest and related carbon stocks.

The second approach for the assessment of data on land resources, which has been mentioned before, is the application of remote sensing technologies, where many different systems are available that operate with a worldwide coverage. Here, much debate is on-going about the harmonization of remote sensing based assessments and applications for the monitoring of forest resources. Especially within the frame of REDD, where large areas, which are difficult to access and measure on a terrestrial basis need to be assessed.

1.1 Project affiliation

The current study is part of a larger, international development research project. The project is being funded by the German Agency for International Cooperation (GIZ) and the Federal Ministry for Economic Cooperation and Development, Germany (BMZ). Within the research program "Adaptation of African Agriculture to Climate Change" nine projects were funded by GIZ/BMZ, each for a time period of three years (2008-2011). This study is part of

one of the nine projects, namely “ALUCCSA” which stands for Adaptation of Land-use to Climate Change in Sub-Saharan Africa.

The main objective of ALUCCSA is to develop scenarios and recommendations for agroforestry and silvopastoral land use systems in Burkina Faso. The developed scenarios and recommendations for the agricultural sector of Burkina Faso based on climate projections that are calculated for a time period between 1980 and 2050.

The climate scenario utilized, A1B, belongs to one of four groups of scenarios (IPCC 2007). A1 assumes a rapid economic growth and an introduction of new technologies where the population growth will peak in about 2050 (IPCC 2007). A1B is one of three directions the scenario A1 could develop to, based on the technological change; where A1B assumes a balanced technological development with an equal utilization of non-fossil and fossil energy sources (IPCC, 2007).The scenario A1B from the special Report on Climate Scenarios (IPCC 2000) is calculated from the coupled General Circulation Model ECHAM5-MPI-OM and used as input for the regional climate model “Mesoscale Model Version 5” (MM5) which downscales the climate projections from the global scale to the regional and local scale for Burkina Faso.

ALUCCSA implements an interdisciplinary approach and consists of several sub-projects (see Figure 1), reaching from regional climate modelling to the measurement of plant physiological parameters, to assess large and small scale vegetation structures (SP 4 and SP 5)to animal husbandry (SP 8), Soil-Vegetation-Atmosphere Transfer (SP 2 and SP 7) and radiative transfer models (SP 3).

The efficiency and sustainability of different land use types under conditions of climate projections is calculated by means of Soil-Vegetation-Atmosphere-Transfer- (SVAT)-Model WaNuLCAS (Water, Nutrient and Light Capture in Agroforestry Systems, Van Noordwijk and Lusiana 1999).

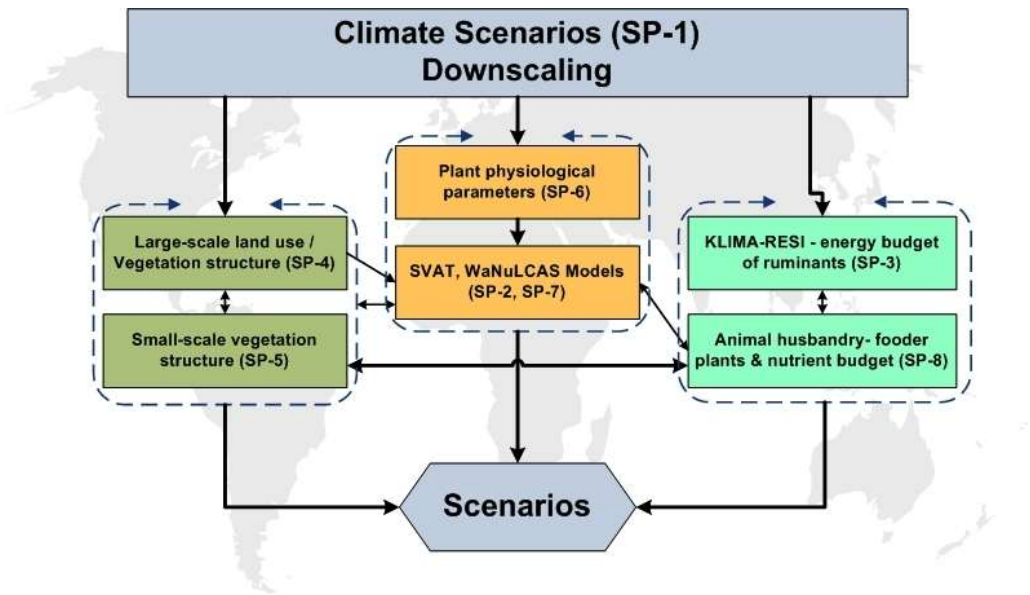

Figure 1: Schematic overview of the ALUCCSA project, where this study was conducted within SP 4, taken from project proposal.

The Objective of this study, within ALUCCSA, is to describe the distribution of vegetation and land use on regional as well as country scale by means of a national forest and land use inventory.

The data on vegetation distribution, its composition and spatial coverage can be used as input to the SVAT model, as impact models like WaNuLCAS, used for the analysis of the impacts of climate change on agricultural production are driven by climate and climate scenario data (Climate Local Model, Scenario A1B) and require small and large scale data on vegetation composition and structure, in particular on trees and forests, as input.

2 Goals, objectives and hypothesis

This study was conducted within the context of international processes and conventions focused on climate change. The two major goals of this study were to evaluate the potential of large area forest inventories based on reduced sample size for the assessment of land use, applying standardized land use definitions, on national scale for semi-arid environments. The second goal is to develop a remote sensing based land use classification scheme, on country level that applies standardized land use definitions. Within the study we analyse the suitability of such a sampling scheme, combined with remote sensing data, as data provider to international processes.

The given goals can be translated into the following research questions or hypothesis:

I. Large area forest inventories with reduced sample size are applicable in semi-arid environments and are able to deliver statistically sound estimates on various variables, including error estimates.
II. Current remote sensing based land use maps of Burkina Faso and other regions of the world do not apply standardized land use classification schemes and are insufficiently accurate.

We would like to show that the applied sampling approach delivers high quality results on land resources with the possibility to calculate the level of precision at reduced costs, compared to similar large scale inventories, which is of much importance for many developing countries. Further, we would like to show that such inventories deliver information that can be used as valuable information source, for international processes as the results are based on standardized definitions and statistical grounds.

With our remote sensing based approach for the generation of standardized land use maps we would like to contribute to the general discussion on up-scaling in remote sensing surveys, overcoming the problems of spatial resolution as well as establishing a standardized land use mapping scheme.

With regards to the above mentioned it should be remarked that, high costs are usually related to greenhouse gas (GHG) inventories. We hope to contribute to this discussion with our study, presenting a relatively cheap inventory approach, which could be extended to fulfil the requirements of a GHG inventory. Further, we would like to show that estimating above ground biomass or carbon is possible, with some limitations, with the applied sampling scheme.

3 Background and current state of science

3.1 Forest inventories

There is a strong need for sound data on forest and other land resources on national and global level, as these data are the basis for policy formulations and decision making on different levels. These data are also needed with regards to national reporting commitments to the respective international conventions.

National forest inventories are among the most important sources of information when it comes to the natural resources, especially, forest related large area information (Tomppo et al. 2010), their implementation are connected to high costs and depend on the local availability of technical expertise and suitable infrastructure within the country (Fischer et al. 2011). Many of the developing countries that have not implemented a national forest resource monitoring system face significant challenges in this framework (Fischer et al., 2011).

Large sample sizes which are a consequence of the mostly predefined precision requirements lead to the high costs which associated with national forest inventories (NFIs). Nevertheless, it is still unclear and seldom scientifically discussed to which extent the required precision of estimates of NFIs have influences on their actual support to political decision making (Fischer et al., 2011). It is rather arguable whether the stipulated precision and related necessary sample size is always planned based on considerations about the final usefulness and credibility of results (Kleinn et al. 2010). Most estimates on natural resource assessments that can be obtained are even presented without any appropriate statement of their precision. Following FAO (2010); Tomppo et al. (2010) many of the reported country estimates, for tropical countries, with regards to forest, should be considered with great care as many of the estimates are based on 'expert opinions', being best guesses, rather than actual measurements. Baccini et al. (2008) stated that for many African countries, forest inventories on national or other large scales are not available, or do not meet certain accuracy requirements. Following Baccini et al. (2008) Africa is host to the second largest part of tropical rain forest in the world, being second to the Amazon, which is, with regards to the above mentioned, to large extents not properly researched and assessed.

Fischer et al. (2011) state: “The planning of the monitoring design is sometimes driven rather by the availability of human and financial resources, technical feasibility, individual expertise, preferences and convention, than by careful optimization of design elements towards the scale-dependent statistical precision. This is an important consideration, as already marginal reductions of the targeted precision have a considerable effect on the required sample size and related costs.”

Much experience with low intensity sampling approaches has been gathered in the FAO program “Support to National Forest Assessment and Monitoring” (NFMA). In low intensity sampling sample size is much lower than in other NFIs approaches. Here, sample size is in the hundreds or even less ground plots, contrary to ten thousands of plots as used in many NFIs (e.g. (Thuresson 2002; Kleinn et al. 2005) (Fischer et al., 2011). The NFMA program focuses on helping developing countries to establish a baseline of their forest and other land resources by giving technical and financial help to conduct a national forest and land use inventory (Tomppo et al., 2010). Following Tomppo et al. (2010, chap. 38) there are three general standards that need to be fulfilled with in NFMA. 1.) NFMA is a demand driven program where the country requests help from FAO, well defining their assessment needs. 2.) NFMA is a participatory program where a wide range of stakeholders are encouraged to participate in order to strengthen the cooperation between capacities within the target country. 3.) NFMA uses harmonized terms and definitions, which are also used on international level leading to comparability between countries and serving as a basis for the reporting to international conventions.

3.2 Vegetation and climate

The current state of science suggests that climate change is, to large extents, human induced. Where, following Maniatis et al. (2011), human induced climate change is largely influenced by emissions from forest degradation and deforestation. Several studies have been undertaken to quantify the amount of CO2 emissions originating from the above mentioned human induced processes. It was concluded, that in 2007 about 20% of the total CO2 emissions worldwide derived from deforestation (Achard et al. 2007; IPCC 2007).

Following (FAO 2008a) Africa contributes with 17% to global greenhouse gas (GHG) emissions from deforestation and with 40% to global GHG emissions with fires. In a study conducted by Landmann et al. (2008), where satellite imagery of two different sensors, Moderate-resolution Imaging Spectroradiometer (MODIS) and Landsat, was classified following the Food and Agriculture (FAO) land cover classification system (LCCS), for two study areas, one in Ghana and one in Burkina Faso, it was assessed that population density and the increase of crop land are the main drivers for the conversion of forests and woodlands.

When reading such results the urgent need for action, concerning mitigation incentives becomes very clear. Thus, it was concluded by Gibbs et al. (2007) that one central issue with regards to combatting climate change is the reduction of emissions from deforestation and forest degradation (Gibbs et al., 2007). In order to achieve the above mentioned goals, harmonized monitoring systems have to be developed. It seems natural, that such monitoring systems usually need to provide information on many different topics, as various factors do influence GHG emissions. Thus, one could say that the demand for statistically sound information on the state and dynamics of forest resources is increasing with the current global challenges like mitigating climate change, conserving biodiversity, combating desertification and enhancing rural livelihoods.

Bonan (2008) assessed that various biological, chemical and physical processes exist, by which the global climate is influenced by vegetation. It is stated in Fischer et al. (2011): “The changes in vegetation cover influence climate also at regional scale due to changes in albedo, roughness, leaf area index etc. (Copeland et al. 1996), which can lead for instance to alteration in spatial and temporal patterns of precipitation (Sánchez et al., 2007). Therefore, when regional climate is to be modelled, correspondent information on the state and dynamic of regional vegetation structure is required. Detailed information on vegetation structure is also needed for high resolution modelling of wind and radiation regimes at local scale (Ross 1981; Knyazikhin 1997).”

3.3 Assessment of carbon stocks

With Africa being host to the world's second largest block of rainforest (Baccini et al. 2008) and also, with regards to carbon stocks in the poorly researched dry forest formations, it becomes apparent that assessing the carbon stocks in Africa within the frame of global climate change is an important task.

In many countries, National forest inventories are among the most sophisticated and most precise sources for data on carbon stocks, delivering high quality data (Böttcher et al., 2009).

Estimates on growing stock, based on diameter and height measurements, species composition, and the application of appropriate allometric models are available in relatively large number for most temperate forests. Allometric models, which are commonly used for the estimation of carbon stocks are based on destructive sampling measurements of tree diameter and tree height (Chave et al. 2005). The development of allometric models is very time consuming and thus expensive (Gibbs et al., 2007), as large numbers of trees have to be sampled. Many of the countries in the temperate zone have established permanent sample plots, allowing the monitoring of changes in carbon stocks over time (Böttcher et al. 2009).

For many tropical counties however, the above described situation is not reality. Following Byran et al. (2011), forest mensuration is not sufficient for accurate carbon stock estimates in many tropical countries. In addition very few allometric models are available for tropical species (Böttcher et al., 2009). Further, it was stated by Baccini et al. (2008) that carbon stocks and other related information is very scarce for African forests as they are the least researched until now. The lack of research has been attributed to various factors like political instability, limited infrastructure and a large ensemble of languages (Baccini et al. 2008), leading to a large lack of data.

It was assessed by Brown (2002) that using allometric models for forest types or ecological zones does work, generating results that are close to the measured results. The before mentioned result is of importance especially in regions, where either many unidentified species occur or, no allometric models are available for the species sampled. The reason,

why such general allometric models provide useful results is that, following Brown (2002), 95% of the variations of above ground carbon stocks are explained by the DBH. As mentioned above, large numbers of trees are needed for the calculation of allometric models; this is where the general approach based on e.g. ecosystems is useful, as these allometric models are usually based on large datasets, covering a larger diameter range (Chave et al. 2005). The above described circumstance was used by Chave et al. (2005) to develop general allometric models, covering many forest types allowing accurate carbon estimates. Nevertheless it should be considered that the allometric models presented by Chave et al. (2005) do not include any data from Africa, showing the great lack of data, when it comes to carbon estimates for the African continent.

3.4 Forest in the context of REDD

In order to implement the United Nations Collaborative Programme on Reducing Emissions from Deforestation and Forest Degradation in Developing Countries (REDD) reliable data on the current state and also on the changes of forest carbon stocks are needed (Maniatis et al. 2011), so called emission factors (EF). Thus, a standardized forest monitoring scheme has to be developed.

As the name REDD already suggests, tropical forests are targeted by this program (Byran et al. 2011). At the 16th Conference of the Parties in 2010 in Cancún Mexico, REDD+ was passed (Decision 1/CP.16 III C). REDD+ can be seen as an extended version of REDD, where conservation, sustainable management and the enhancement of forest carbon stocks are now included (UN-REDD 2011).

In the past, REDD has been criticized for its focus on carbon only; neglecting other important ecosystem functions like biodiversity conservation and for not considering social issues like poverty reduction (Brown et al. 2008). Usually ecosystem services are not object to global scale markets. Following Stickler et al. (2009), we agree that carbon, stored and sequested in forests might be the first ecosystem service which could be traded on the world market. The fact that such services can be traded on a worldwide market, producing revenues, could help mitigate the negative ecosystem impacts and improve lively hoods (Gibbs et al., 2007),

if the revenues from REDD are carefully reintegrated into society. Following the information provided in Stickler et al. (2009) the amount of money traded within carbon markets by 2008 already exceeded $100 billion, whereas it should be considered that an average of less than one billion $ were annually spent for the funding of international conservation in the 1990, with declining numbers (Wunder, 2006). With the above mentioned, we would like to show that the REDD process is about more than just about carbon.

Countries that participate, or want to participate at REDD will have to report on the changes of forest area and related changes in carbon stocks (Maniatis et al., 2011) and give evidence, that the government measures help reducing deforestation and forest degradation. Further, several carbon pools have to be assessed and reported, namely: above ground biomass, belowground biomass, dead wood, litter and soil organic matter (Eggleston and Intergovernmental Panel on Climate Change 2006). Such assessments are always connected to monitoring costs. It was assessed that one of the key points with regards to REDD is the discussion on monitoring costs, which will, to a great extend influence the overall success of REDD. Further, we agree with Olander et al. (2007) that in addition to the monitoring costs, the accuracy level to which forest degradation and deforestation GHG emissions can be measured, will also determine the success of REDD. Following Böttcher et al. (2009) costs of monitoring for REDD vary largely, depending on the required precision. In their study they showed that monitoring costs can vary from 0.5 – 550 $ per km². A comprehensive overview of remote sensing products including their coverage and related cots is given in Böttcher et al. (2009).

An underestimation of carbon stock as baseline, could lead to overestimations in carbon sequestration until a second phase assessment, leading to un-proportionally large payments, which could alter the functionality of the trading scheme.

In conclusion to the above identified, initialization costs as well as the unequal access to monitoring techniques have to be overcome for all participating countries, in order to establish an internationally harmonized monitoring scheme (Böttcher et al. 2009).

Before mitigation in any form can take place, a consistent, harmonized and transparent baseline for the monitoring of degradation and deforestation has to be established. Guidelines for such a greenhouse gas (GHG) monitoring system are provided by the

Intergovernmental Panel on Climate Change (IPCC) (Eggleston and Intergovernmental Panel on Climate Change 2006). With regards to the above mentioned it was stated in Maniatis et al. (2011) that until now most studies with regards to carbon stocks were carried out, either in the Amazon or in south-east Asia, while a great lack of data exists for Africa.

The simplest way to report on a GHG inventory is to assess the change in forest area, so called activity data (AD) and multiply the AD with a coefficient for the corresponding forest type emission factor, which can be found in the IPCC Emission Factor Database (IPCC-NGGIP 2011). The before described method corresponds to the accuracy level of tier 1, where there is a total of three tiers. Tier 2 is an improved version of tier 1, including higher demands on the accuracy estimates with regards to “AD” and “EF”, where “EF” needs to be calculated country specific. The tier which implements the strictest guidelines for the estimation of GHG emissions is tier 3, for detailed information please see (Eggleston and Intergovernmental Panel on Climate Change 2006). One of the advantages of implementing a flexible system, based on “tiers”, is that the technical abilities of countries can be taken into consideration as many countries have too limited capacities to provide REDD baselines on a higher tier level than level 1 (Olander et al., 2007).

GOFC-GOLD (2008) estimated, based on six study sites distributed over the globe, that estimates applying the coarse tier 1 approach can lead to large underestimations (up to 44%) as well as overestimations (up to 33%) of carbon stocks, compared to ground based measurements.

3.5 The role of remote sensing

With regards to the above described carbon trading scheme, it is important to monitor the forest area. For such monitoring the implementation and design of a standardized monitoring, reporting and validation (MRV) system is of utmost importance. The standardization of the MRV system has to result in replicable, consistent results, utilizing standardized methods. Benediktsson et al. (2007) state that remotely sensed data from various platforms has become the major source of information when it comes to earth observation.

We agree with Herold and Johns (2007), that remote sensing plays a crucial role in the success of REDD mechanisms. Remote sensing offers many possibilities when it comes to monitoring the earth surface in a continuous manner, for large areas, whereas terrestrial sampling can deliver precise data on smaller areas. According to DeFries et al. (2006) remote sensing is the only practical approach to monitor deforestation on a national level especially in regions with limited infrastructure.

As mentioned above, ground measurements can deliver data with high precision, giving information on variables which cannot be directly measured by remote sensing. However the two ways of measurement can very efficiently be combined, where ground data can serve as so called ground truthing for data that can be remotely measured. Nevertheless it should be considered that how to monitor the terrestrial carbon stocks is still not completely clear and research far from being completed, yet. The leitmotif under which this topic is debated is MRV which is also discussed in Achard et al. (2007). As stated by Chave et al. (2005), until now, there is no method available that allows direct measurement of carbon; neither terrestrial nor remote sensing based. Thus, methods or tools for the estimation of carbon in vegetation have to be developed, like allometric functions which were briefly described before.

A range of sensors is available at different costs. The costs of the imagery usually vary largely with the resolution, the spectral range, and technology of the sensor. Studies have been undertaken to evaluate the usefulness of different sensors for MRV systems (Achard et al. 2007; Gibbs et al. 2007). So far no conclusions were made, with regards to which sensor is the most suited, as each sensor has its strength and weakness, which is often determined by the goals set as well as the type of terrestrial sampling applied.

Some may conclude that high resolution sensors like Ikonos or Quickbird are the best choice as uncertainty is lower, with regards to classification accuracy, compared to low and medium resolution sensors like MODIS. Where sensors like MODIS can well be used for the detection of deforestation, but less so for the detection of forest degradation (Gibbs et al., 2007).

Within the scope of this discussion it should be regarded, which level of uncertainty is allowed, in the context of REDD, meaning to which tier should estimates be made. Another

very important, but often neglected point is that the high costs, related to high resolution imagery can be the limiting factor for many countries, if a wall-to-wall coverage of the country is wished for. Just as the costs of the imagery can be limiting, much expertise is needed with regards to the processing of remotely sensed imagery to useful data providers, which is often not existent in many countries.

Thus, it might be that for some countries it is more realistic to apply ground based measurements of carbon stocks, than remote sensing based studies, as labour costs are lower and expertise in field methods is more commonly available, compared to the costs and expertise related to remote sensing based approaches (Gibbs et al., 2007).

3.6 Classification methods for remote sensing

The above described REDD carbon trading scheme requires repeated measurements for the monitoring of change in forest area. Here remote sensing can play an important role within the framework of MRV, as most sensors have frequent revisiting rates and classification schemes can be developed for consecutive application.

In order to achieve consistent results from a remote sensing based decision support system, the remotely sensed data needs to be processed to derive the information needed for a defined application. The processing is done; either automatically, unsupervised, or half automatically, supervised (Richards and Jia, 2006). Just as various remote sensing products have become available in the last decades, many classification methods for the corresponding data have been developed. A comprehensive overview of different classification techniques is given in Richards and Jia (2006); Jensen (2005). It was remarked in Gislason et al. (2006) that many of the previously used model or regression based classifiers are parametric classifiers. A parametric classifier relies on certain distribution of the data and is not suited for the classification of many geographic data (Richards and Jia, 2006).

In order to solve the above described, non-parametric classifiers like neural networks (Benediktsson et al. 1990) or Support Vector Machines (SVM) (Boser et al. 1992), among others, were developed. One of the drawbacks of non-parametric classifiers like neural

networks or SVM is, that they are often described as a “black box” as no fixed classification rule is generated during classification, thus repeatability for a repeated monitoring is limited.

Classifiers that are able to deliver a fixed rule set, while being non-parametric are hierarchical decision tree methods. Hierarchical decision tree methods do not rely on an underlying model but apply a hierarchical splitting and are thus called “white box” (Tso and Mather 2009). In 2001 Breiman further developed the concept of decision trees by combining many decision trees into a ‘forest of decision trees’, naming this classification method RandomForest (Breiman, 2001).

Following Gislason et al. (2006), the RandomForest classifier is well suited for the classification of remote sensing and geographical data, which has been applied in various remote sensing studies (Benediktsson et al. 2007; Gislason et al. 2006; Pal and Mather 2003; Walton 2008).

4 Study site description

4.1 Study area Burkina Faso

Geographic location

The study area for this research is the whole country of Burkina Faso, where Burkina Faso is a land-locked West-African country with a total land area of 273,600 km² (FAO 2011). The country has six neighbouring countries, namely: Mali, Niger, Benin, Togo, Ghana and Ivory Coast. The size of Burkina Faso is smaller, than the other land locked neighbouring countries Mali and Niger, with sizes of 1,240,192 km² and 1,226,700 km² (CIA 2011), respectively. Considering the geographic location of the country and the absence of great natural resources, it becomes obvious, that Burkina Faso is strongly dependent on trade and serves as a transit country for transports between countries like Ivory Coast with its important port in Abidjan and e.g. Niger.

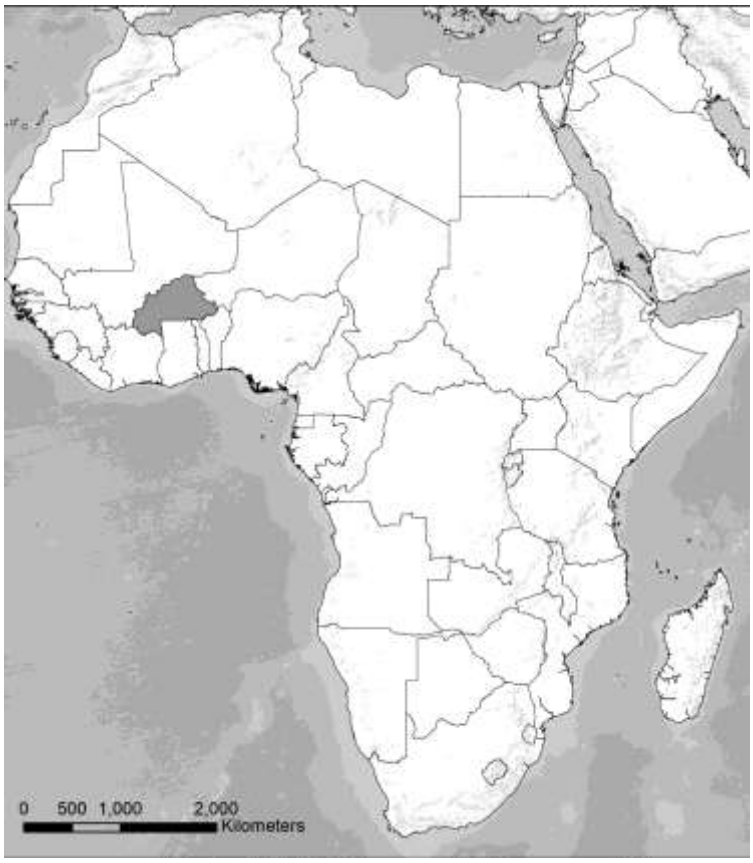

Figure 2: Map of continental Africa where Burkina Faso is marked in grey. Map source: ArcGIS online data base.

Climate

The climate in Burkina Faso has a strong seasonality, which is much dependent on the inner tropic convergence zone. The inner tropic convergence zone is the primary driving force for the seasonality of rainfall within the country, where one dry- and one wet season occur. The amount of yearly rainfall decreases with increasing distance from the equator (see Figure 3), which is also connected with longer dry seasons and increasing mean annual temperatures (Walter and Breckle 1999). Along the above described climatic gradient, climatic zones were defined. From north to south the climatic zones are defined as: Sahel, North and south Sudanian as well as Guinean zone (FAO 2000). The northern part of the country is dominated by a Sahelian climate (FAO 2000) with a rainfall of less than 500 mm yr^{-1} (Figure 3) and a pronounced dry period of up to nine month. In the mentioned climatic zone, vegetation is characterized by dry savannahs with sparse tree cover, where no perennial crops are being grown. The central part of Burkina Faso belongs to the transitional Sudano-Sahelian zone (FAO 2000) with an annual precipitation of about 500-900 mm, which covers large parts of Burkina Faso.

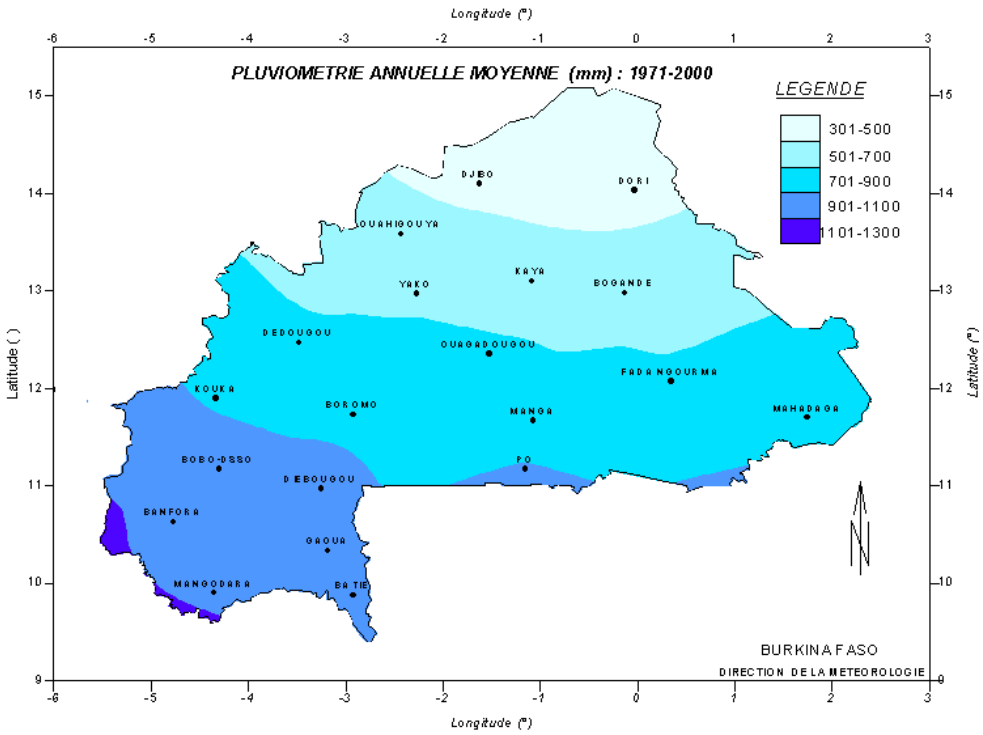

Figure 3: Precipitation pattern of Burkina Faso Meteo-Burkina (2011).

Agriculture

About 90% of the current 14 million inhabitants (INSD, 2010) in Burkina Faso depend on subsistence agriculture and livestock farming (CIA, 2011).

Agricultural production in Burkina Faso can be subdivided into two main products. The first agricultural product is livestock and the second is crops produced from subsistence agriculture. Subsistence agriculture is practiced in form of shifting cultivation by the sedentary part of the rural population, which constitutes the majority of the rural population (König 2006). With the practiced shifting cultivation soil fertility is supposed to regenerate during fallow. Fire is an integral part of the land management system, following Laris (2002) and Goldammer (2004) fire is being used to clear land for agriculture, but also to improve grazing grounds. Following König (2006) only small parts of the potential agricultural areas are under actual use, with a mean size of 1-5 ha. Due to the described practice, a heterogenic and patchy landscape where cultivated and fallow areas alternate, is very common for many areas in Burkina Faso.

In the northern Sahelian climate zone, the main crops being grown are millet and sorghum, having short growing cycles of about 90 days. Further to the south, rainfall increases to about 900-1100 mm yr^{-1}, defining the Sudanian Zone (FAO 2000). This zone is strongly cultivated and crops as cereals, corn and also root crops like potatoes and cassava are grown here. Further, this part of Burkina Faso is also used to grow important cash crops like, mangos, cashews, sugar cane and last but not least, cotton. Here, it should be remarked that Burkina Faso was the largest cotton producing country in Africa in 2008 (FAO 2011), being number ten in the world (FAO, 2011). A small portion of the south western parts of Burkina Faso belong to the Guinean Zone (FAO 2000), where annual rainfall exceeds 1100 mm (Figure 3) and dry seasons of about four month are present (Kagone, 2002). In this zone, agricultural production is focused on the same crops like in the Sudanian zone, but having a stronger focus on root crops.

Besides agricultural in form of crops, extensive livestock farming is practiced as an important source of income, where animals like goats, sheep and most importantly, cattle are kept. The regions in Burkina Faso, where livestock plays the most important role, are the regions where agricultural production is not profitable any more. Due to the climatic situation in

Burkina Faso these regions are the northern most regions, where yearly rainfall is very low. It is a common practice to undertake long distance (often crossing more than the whole country) migrations, so called transhumanz, with the livestock, where the livestock is normally given to the nomadic ethnic group of the Fulbe (König, 2006), thus about 90% of the cattle livestock is possessed by the Fulbe (König, 2006). These migrations are undertaken as the fodder supply in the northern parts of the country, is often not sufficient during the dry season; where the described migrations to southern parts of the country often led to conflicts with the sedentary farmers in the corresponding regions.

Vegetation and people

Vegetation in Burkina Faso and the whole of West Africa changes corresponding to the climatic gradients. Nevertheless extreme events like the drought period from 1966 - 2000 (Nicholson 2001) can happen and do not only severely affected livelihoods, but also lead to a significant loss in species diversity (Wezel and Lykke, 2006), leaving many introduced crop tree species in an unsuited environment.

Under 'normal' conditions, in Burkina Faso, species richness increases with a southward trend (Linder et al. 2005). The northern parts of the country are mostly covered by a species poor savannah where a closed grass cover prevails and scattered woody vegetation occurs. Following Schmidt (2006) trees constitute larger parts of the vegetation, the further south, where the southern most parts of Burkina Faso are covered with dry forest formations. To the Global Forest Resource Assessment (FRA) of FAO Burkina Faso reported a total forest area estimate of 56 490 km² (21% of the national territory) where, according to the FAO, forest and land cover classification are based on a national remote sensing study (FAO, 2009).

There has been a long and unresolved dispute whether savannahs are natural ecosystems or if they are human induced, following disturbance in the form of fire and herbivores. For areas with less than 650 mm of yearly rainfall Sankaran et al. (2004) established a relationship between tree cover and rainfall. In areas with more than 650 mm rainfall yr^{-1} the formation of forests is possible as trees would be more competitive than grasses.

Following Fischer et al. (2011) many new studies show that natural savannah dynamics are increasingly disturbed by agricultural land use. This human induced disturbance is

associated with the prevailing fragmented landscape with its embedded farm areas. Typical for large parts of Burkina Faso are agroforestry parklands (Figure 7) where multi-purpose tree species such as *Parkia biglobosa* or *Vittelaria paradoxa* are maintained (Basset and Crummney, 2003; Savadogo, 2007).

The observations above are further fortified by Landmann et al. (2008), where it was assessed that population density and the increase of crop land are the main drivers for the conversion of forests and woodlands. The conclusions of Landmann et al. (2008) were based on the evaluation of satellite imagery from two different sensors, 1) Moderate-resolution Imaging Spectroradiometer (MODIS) and 2) Landsat, that were classified following the Food and Agriculture (FAO) land cover classification system (LCCS), for two study areas, one in Ghana and one in Burkina Faso.

Further, Eva et al. (2006) assessed that human pressure on remaining natural resources is increasing because of the on-going population growth. Sub-Saharan population more than doubled from 1960 to 1990 (Eva et al. 2006). Here, Burkina Faso is no exception where the population is actually growing at an annual rate of 3.8% (CIA, 2011).

In general it can be concluded that the largest part of the population does strongly depend on goods provided by trees from forest, including timber, fuel wood, medicinal plants and animal fodder (Brännlund et al. 2009; Belem et al. 2007). DeBrie (1991) estimated that about 90% of the national energy supply originates from fuel wood. Burkina Faso ranges among the poorest countries in the world with a very low Human Development Index HDI, holding position 161 out of 196 countries in that list (UNDP, 2010) and natural renewable resource, including forest and tree resources outside forest (TOF) play, therefore, an superior role both for people´s livelihood and for the development of the national economy (Fischer et al., 2011). Due to this high level of dependency on these basic natural resources, changes in climate, with corresponding changes in vegetation have major impacts on livelihoods in Burkina Faso.

4.2 Study site description for four core study sites

Next to observing the whole of Burkina Faso during the field inventory conducted, we established four core study sites within the ALUCCSA project (for their location see Figure 11). The four core study sites were established to generate a common basis for all sub-projects, where measurements were undertaken by all sub-projects. Measurements ranged from cattle observation to the establishment of metrological stations, among others. The four study sites belong to two of the four climatic zones described above, namely: Sudano-Sahelian and Sudanian zone. Nevertheless it was assumed that the selected sites can be seen as representative for the four described climatic zones. Representative in this case, is meant as being covered by the according vegetation and land use. During the remote sensing part of this study the four core study sites were used as training sites for the development of a national land use classification method based only on remote sensing.

1.) Sokouraba is located at the south western part of Burkina Faso. It the study site with the highest annual rainfall. Where an annual rainfall of about 1000 mm yr-1 is common (rainfall data was obtained from Meteo-Burkina). The rainfall distribution is distinct, with a clear dry and rainy season, where the dry season has an average length of about four month, starting in November. The climate with a moderate annual mean temperature of ~ 28°C (min 22°C and max 35°C) of the study site is also influenced by the altitude of about 500 m above sea level, which is among the highest elevations within Burkina Faso. The study site is strongly influenced by agricultural use, where corn is one of the most important crops, being cultivated with an agroforestry system, mainly including the species Karité or shea butter tree (*Vittelaria paradoxa*). In contrast to the other three study sites, many cash crops are cultivated within the area. The main cash crops, which were also encountered during the field work, were mangos (*Mangifera indica*) and cashew (*Annacardium occidentale*). These crops are cultivated in small scale plantations of few hectares. Large parts of the produced mangos are directly sold to the only juice manufacturer of Burkina Faso (DAFANI S.A.) that has its factory close by. Within the patchy mosaic of cropped areas, there are many fallow areas, which will be re-cultivated at some point, therefore transforming now cultivated areas info fallow, if one assumes that the area of cultivated land will not increase. Further, forest patches of varying size are retained within the cultivated landscape.

2.) The study site of Nobéré is located at the south-central part of Burkina Faso, at the southern reaches of the central plateau where the topography is flat with an average altitude of 250 m. This study site belongs to the South-Sudanian climate zone (FAO, 2000), characterized by an annual rainfall of about 880 mm yr-1 (figures provided by Meteo-Burkina), where the dry season does not exceed a length of 5 month. The rainy season usually starts in early May and ends in October. Annual mean temperatures of 29°C were recorded with maximum temperatures of 38°C and minimum temperatures of 20°C. In contrast to the other three study sites, Nobéré is partly covered by a national park, the Kabore Tambi national park. Thus, this study site is subdivided into two main land uses; the northern and southern most parts are under Agricultural use, whereas the central part is covered by the national park. The national park is characterized by shrub land on its borders and forest in its core zone. Especially the shrub land on the outskirts of the national park are used as grazing grounds by sheep and cattle herders, even though it is prohibited by law. On the cultivated lands the main crops grown are Sorghum and Millet. Many agricultural areas are cultivated as agroforestry systems introducing the tree species Néré (*Parkia biglobosa*) and *Vittelaria paradoxa* into the agricultural areas. Fallow areas were not observed within the same frequency as in the study areas: Sokouraba and Safané, indicating an intensive and more permanent form of land use for agriculture.

3.) The study site of Safané is located at the mid-western part of Burkina Faso. The study site is characterized by a yearly rainfall of about 875 mm yr-1 (data obtained from Meteo-Burkina), where a distinct dry season of about four months on average is common. The dry season usually starts in October-November and extends until April-May. The climatic conditions present, assign this study site to the North-Sudanian zone (FAO, 2000). Maximum monthly temperatures reach 37°C in April and minimum temperatures of 18°C in January, and the mean temperature is 29°C were observed. Safané is an area of intensive agriculture. As assessed during the field inventory one of the main crops cultivated is cotton. Even though it is an area of intensive agriculture, with a long history of cultivation, which was perceived during field work, as some sample points were located on very old fallows; forested areas are still present. When comparing the study site of Safané with the study site

of Sokouraba, land use is less patchy, having larger homogeneous agricultural areas. In addition, it was observed that agroforestry systems are also applied to a lesser extent.

4.) Tougouri is located in the northern part of Burkina Faso, within the South-Sudanian climatic zone. The South-Sudanian climate is characterized by a very distinct dry season, with a length of about six to seven month. The rainy season usually starts in Mai and ends in September – October, where the annual rainfall is about 600 mm yr^{-1} (figures obtained from Meteo-Burkina). Where mean annual temperatures of ~29°C, maximum temperatures of 41°C and minimum temperatures of 18°C were measured, respectively Even though this study site belongs to the South-Sahelian (FAO, 2000) zone, agriculture is practiced. Two kinds of agricultural practices were observed, where the first is an agroforestry system, including *Vittelaria paradoxa* into the productions system, where millet was the dominating crop. The form of agriculture mentioned was mostly observed in depressions, where ground water is assumed to be available throughout the year. The second form of agriculture is the so called of "maraîchage", being practiced along the sides of the dam, located next to the city of Tougouri. In the maraîchage crops with high water demand like tomatoes and green beans, among others are produced, as these crops in these areas are not rain fed. Besides the agricultural production, animal husbandry is an important source of income. Fallow areas were not observed, leading to the conclusion that the fields cultivated are permanent. This observation was further supported by the fact that lands not cultivated were both barren and rocky or belonged to the vegetation form "Brusse tigrée", the "tiger bush". This vegetation form is, to large parts, constituted by the shrubby species *Combretum micranthum*, growing in dense conglomerations, forming stripes that alternate with bare soil, aligned perpendicular to the slope (Hiernaux and Gerard 1999). The name tiger bush might have developed from the fact that this vegetation form looks like the stripes of a tiger when looked upon from the air. Further, tiger bush was observed as a typical vegetation form in areas where vegetation could just survive, being on the border to barren lands.

Figure 4: Top and Bottom: Typical mixture of new agricultural fields with adjacent fallow and forest areas.

Figure 5: Top: central part of the national park with a mixture of trees and shrubs. Bottom: edge of national park, dominated by shrub species.

Figure 6: Top: Old fallow with shrubby regeneration and single trees. Bottom: Forest as often observed in the study region.

Figure 7: Top: Agroforestry system with Vittelaria paradoxa and millet found in depressions. Bottom: Barren lands often found within the study region.

5 Methods

5.1 Terrestrial sampling

Most parts of the methods for the terrestrial sampling section follow the methods described in: Fischer et al. 2011. A national level forest resource assessment for Burkina Faso - A field based forest inventory in a semi-arid environment combining small sample size with large observation plots. Forest Ecology and Management, doi:10.1016/j.foreco.2011.07.001.

5.1.1 Sampling and plot design

The vegetation type "forest" is the focus of the inventory conducted within this study. Following Fischer et al. (2011) trees outside forest (TOF) were also included because of their importance for modelling tasks of the overall project and to establish a baseline for the whole of the tree resource in Burkina Faso. In addition we were able to estimate the species composition for different land use classes and the corresponding above ground carbon stocks based on single tree measurements.

Fischer et al. (2011) mention: "The sampling design refers to the selection procedure for sampling locations inside a defined areal sampling frame, while the plot design is a rule-based framework that defines which elements are to be included into the sample at each location."

For the monitoring task at hand we chose to apply a systematic two-stage sampling design. It has been shown in several studies that two-stage sampling is an efficient sampling concept, especially if cost and the precision of estimates have to be optimized (Gregoire and Valentine 2007). For this study, one of the major cost factors to be considered were high the transport costs to reach the sample plots (Fischer et al., 2011). In order to optimize the efficiency of our sampling approach a maximum of information on the target variables were to be measured at each sample plot. As the costs for measuring an additional variable on the sample plot is inferior to the transport costs to reach a sampling location. Following Fischer et al. (2011) this is why large observation plots were defined. On the first stage of the sampling design, a systematic square sample grid of 72 km side length was laid out in

north-south orientation over the total area of Burkina Faso where a random starting point was predefined (Figure 8) (Fischer et al., 2011).

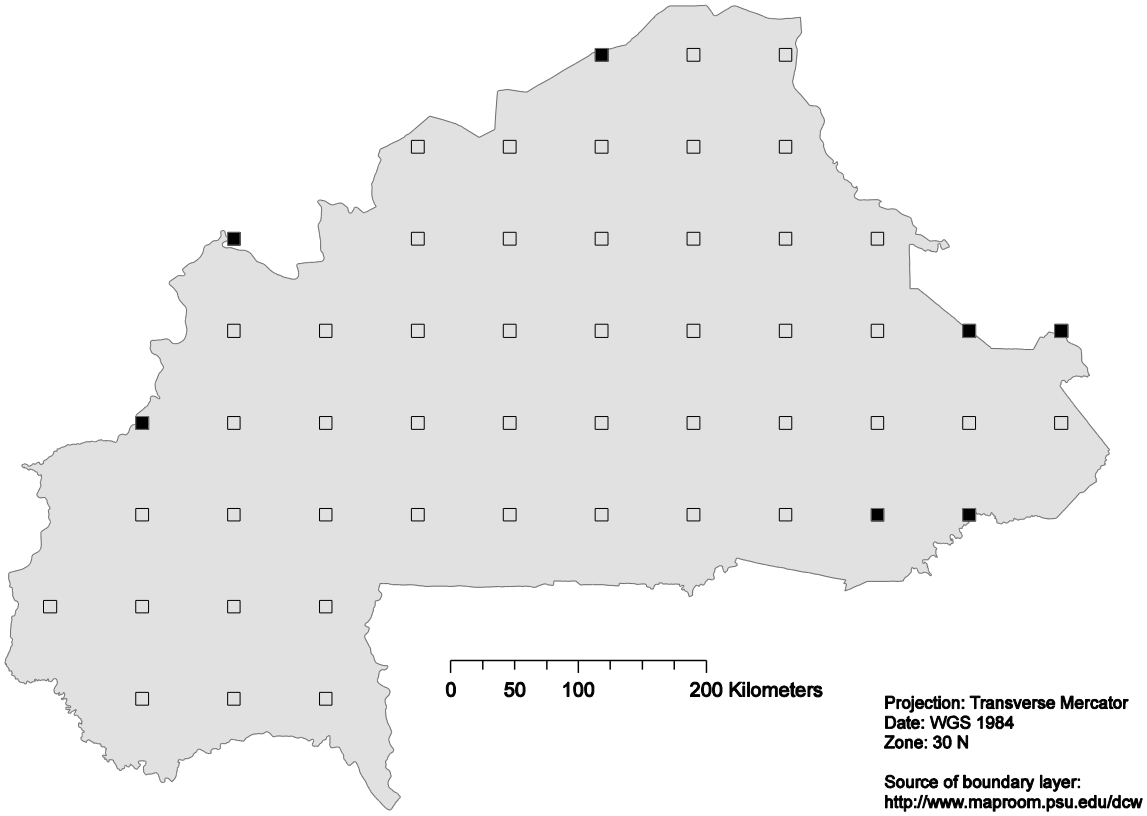

Figure 8: Map of Burkina Faso with the 72 km x 72 km sampling grid indicated by squares defining a sample size of *n* = 53 first stage plots (primary sampling units). The marked black squares are the seven primary sampling units for which field data could not be collected (see also text). Modified from Fischer et al. (2011).

One of the reasons why to choose systematic sampling is that at the first stage a fast and easy implementation is possible and an even coverage of all land-use types as well as environmental conditions proportional to their area is guaranteed by the so called self-stratification (Fischer et al., 2011). In addition this approach ensures that samples are drawn from a discrete population of non-overlapping sampling units. The decision on the grid size was based on the expected maximum number of field plots that were feasible to measure with regards to the available resources in terms of skilled labour, time and budget (Fischer et al., 2011). We decided to apply a sample size on the first stage of *n* = 53.

Each of the 53 primary sampling units (PSU) has a square shape with 10 km side length (100 km^2 area). Fischer et al. (2011) state that: “On seven of the selected PSUs, field assessments were not possible either because of limited access or due to security reasons, as they were partly overlapping or very close to the political boundary of Burkina Faso. Final sample size on the first stage was therefore reduced to *n* = 46 PSUs.” We came to the conclusion that there is reason why the existent non-response should lead to biased estimates on country level (Fischer et al., 2011). We did, therefore, not apply any imputation techniques or correction for non-response as suggested in McRoberts (2003). Following Fischer et al. (2011): “Each of the selected PSUs was subsequently subdivided into 25 secondary sampling units (SSU) based on a systematic square grid of 2 km side length. The second stage subsample consisted of selecting randomly two SSUs per PSU (Figure 9).”

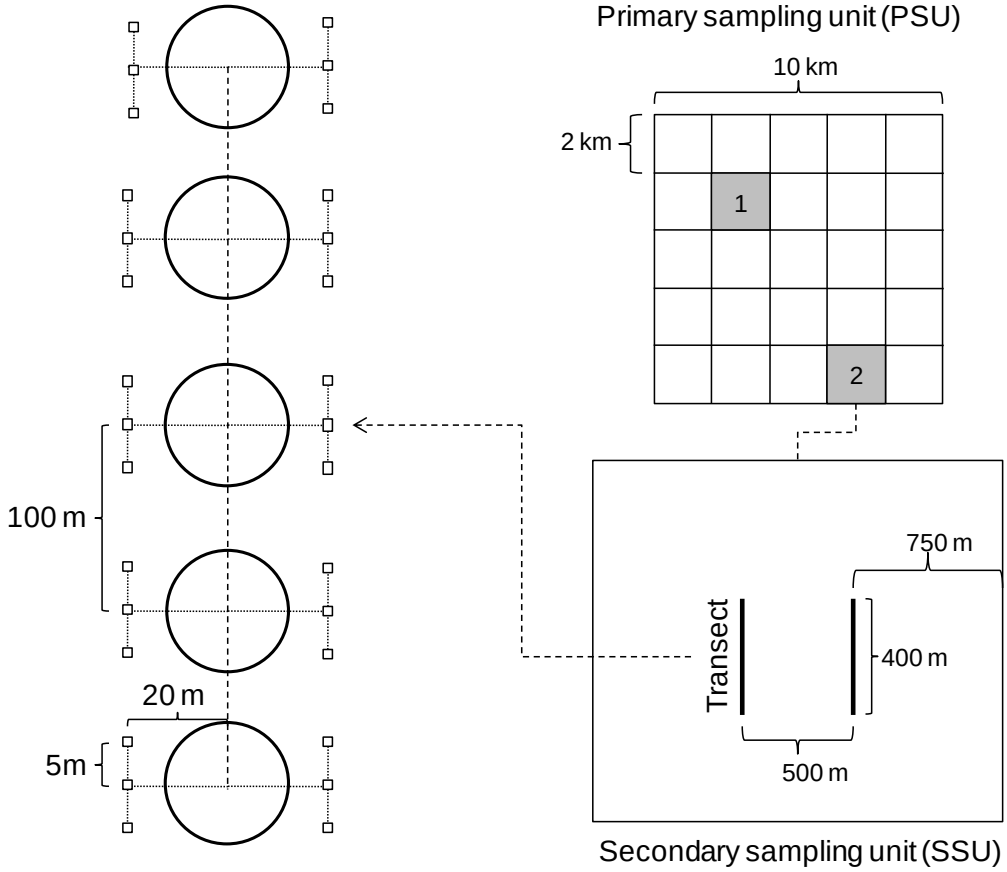

Figure 9: Schematic view of the inventory design (not to scale), including circular subplots (CS) with a radius of 15 m and quadratic regeneration plots of 1m² each from Fischer et al. (2011).

As described in Fischer et al. (2011): “In the selected SSUs two parallel transect lines of 400 m length were laid out at a distance of 500 m. The orientation (N-S or W-E) of these transects was alternating for the two SSUs: North-South and West-East. On each transect line the centre points of five fixed area circular subplots (CS) of 15 m radius were placed equidistantly (100 m between subplot centres). The cluster of 10 CS within each SSU constitute one second stage sample and were treated as one observation during data analysis. The total number of measured subplots was 905. At each subplot location six small quadratic regeneration plots of 1 m^2 were established systematically next to the circular subplots (Figure 9).” Various variables on the vegetation resources were assessed on the different plot design elements which are listed accordingly in Table 2. As we had no knowledge on the species in Burkina Faso, species identifiaction was condicetd by a very experienced botanist of the herbarium of the Institut de l’Environnement et de Recherches Agricoles (INERA), Burkina Faso. Species names and identification followed Arbonnier (2009). Following Fischer et al. (2011): “In each CS all trees with a minimum diameter at breast height (DBH) of 7 cm and shrubs with a diameter at ground level larger than 3 cm were included in the inventory. In case that multiple shrubs were growing tangly and forming one connected single crown, they were recorded as one individual. The crown projection area for trees and shrubs was asessed by two perpendicular crown diameter measurements. Regeneration of trees and shrubs (tree height ≤ 1.3 m and DBH < 7 cm, and shrub diameter < 3 cm at ground level) was counted seperately for species in the regeneration plots, while for grass, herbs and crops the ground coverage in per cent was estimated according to a specific key.”

The classification of land use types was done according to the definitions of the Food and Agriculture Organization of the United Nations (FAO, 2010) (see Table 1 and Figure 10).

Table 1: Land use classes with definitions as provided by the Food and Agriculture Organization (FAO).

Land use category	Definition
Forest	"Land spanning more than 0.5 hectares with trees higher than 5 meters and acanopy cover of more than 10 percent, or trees able to reach these thresholds in situ. It does not include land that is predominantly under agricultural or urban land use"(FAO, 2010).
Other wooded land	"Land not classified as "Forest", spanning more than 0.5 hectares; with trees higher than 5 meters and a canopy cover of 5–10 percent, or trees able to reach these thresholds in situ; or with a combined cover of shrubs, bushes and trees above 10 percent. It does not include land that is predominantly under agricultural or urban land use" (FAO, 2010).
Other land	"All land that is not classified as "Forest" or "Other wooded land" (FAO, 2010).
Other land with tree cover which is a subcategory of "Other land"	"Land classified as "Other land", spanning more than 0.5 hectares with a canopy cover of more than 10 per cent of trees able to reach a height of 5 meters at maturity" (FAO, 2010).
Inland water bodies	"Inland water bodies" generally include major rivers, lakes and water reservoirs (FAO 2010).

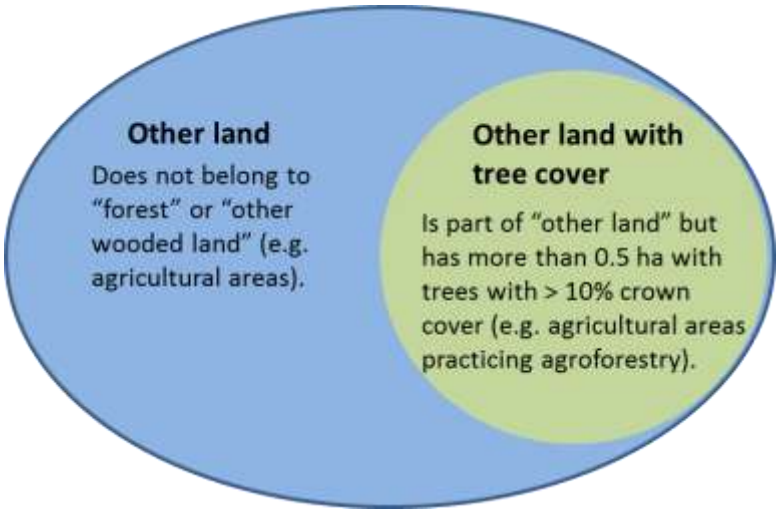

Figure 10: Schematic view of "other land" with subclass "other land with tree cover".

Based on measured criteria like crown cover, minimum height, land use, and life form (Table 2), each circular subplot assessed was assigned to one of the described land use classes. For each selected cluster plot an estimate of the relative share of land use types was calculated based on the number of subplots assigned to the different classes (Fischer et al., 2011). By multiplying the relative shares for each land use class with the total area of Burkina Faso we were able to calculate the total area covered by the correspondent land use class. An unbiased estimator for the relative share of land use classes over all PSUs is given with:

$$V\ y = \frac{N-n}{N}\ \frac{S_1^2}{n} + \frac{M-m}{M}\ \frac{S_2^2}{mn}$$

Following Cochran (1977), S_1^2 is the variance among PSUs and S_2^2 is the variance among SSUs within PSUs, N is the total amount of PSUs possible for the area of Burkina Faso, n is the number of PSUs in the sample, M is the total of SSUs in one PSU, m is the number of SSUs included in the sample for each PSU, respectively. Standard error and relative standard error calculations were made based on the variance of the estimates, following Cochran (1977). All statistical analyses were done in R (R Development Core Team 2011).

Table 2: Selected variables assessed on different subplot levels (CP= circular cluster subplots, RP= regeneration plots) (Fischer et al., 2011).

Life form	Variable	Plot types	
		CP	RP
	Land use class (*LU*)	X	
Living tree, standing dead tree, stump	species/genus	X	
	DBH> 7 cm	X	
	total height [m]	X	
	Crown diameter [m]	X	
Shrubs	species/genus	X	
	diameter of crown projection area [m]	X	
	total height [m]	X	
Tree/ Shrub regeneration	species/genus		X
	number		X
Grasses/ Crops	coverage [%]		X

5.1.2 Estimation of aboveground carbon stocks

We could estimate aboveground biomass and related carbon stocks only for trees, as reliable biomass models for shrubs are not available. We attributed the unavailability of biomass models for shrubs to the fact that most biomass studies focus on grasses or trees only, but ignore shrubs. To predict the aboveground biomass of trees (AGB_{Tree}) based on measurable single tree variables like DBH (cm) and tree height (m), we applied a general model for dry climates presented by Chave et al. (2005), as specific allometric models for particular tree species in the actual forest types were not available (Fischer et al., 2011):

$$AGB = 0.112\ (\rho * DBH * h)^{0.916} + e$$

With ρ being wood specific gravity in g cm^{-3}, *DBH* in cm, *h* in meter and AGB in kilo grams. The unavailability of wood density values for all identified species was treated by calculating an average value as median (D_s) for each land use class. Where D_s is based on the wood densities of the ten most abundant tree species (Brown 1997; Nygård and Elfving 2000; Ketterings 2001) (Fischer et al., 2011). Following Chave et al. (2006) mean wood density needs to be converted into wood specific gravity to fit the corresponding allometric models. This predcondition was consequently followed, applying Sallenave's relationship with: $\rho = 0.872 * D_s$ (Sallenave, 1971). For the conversion of AGB_{Tree} to carbon stocks (AGC_{Tree}) we applied a widely accepted approach based on the assumption that 50% of the biomass is carbon (Roy et al. 2001; Malhi et al. 2004), although it is known to us that Elias and Potvin (2003) showed that this relationship is not constant over tree species (Fischer et al., 2011).

5.2 Remote sensing

5.2.1 Regional scale land use classification

For the land use classification on regional scale we selected four study sites, each with a size of 2401 km².The Study sites are located within contrasting climatic regions of Burkina Faso (figure 11) in order to ensure a complete coverage of all five land use classes of interest. The land use classes in the remote sensing survey were defined as for the terrestrial sampling following FAO definitions, see Table 1.

We used Level 3A RapidEye imagery as basis for the land use classification on regional scale. The imagery was obtained from the German Aerospace Center (DLR). For scientific purposes the imagery could be obtained free of charge within the RapidEye Science Archive (RESA), as RapidEye was funded within a public private partnership.

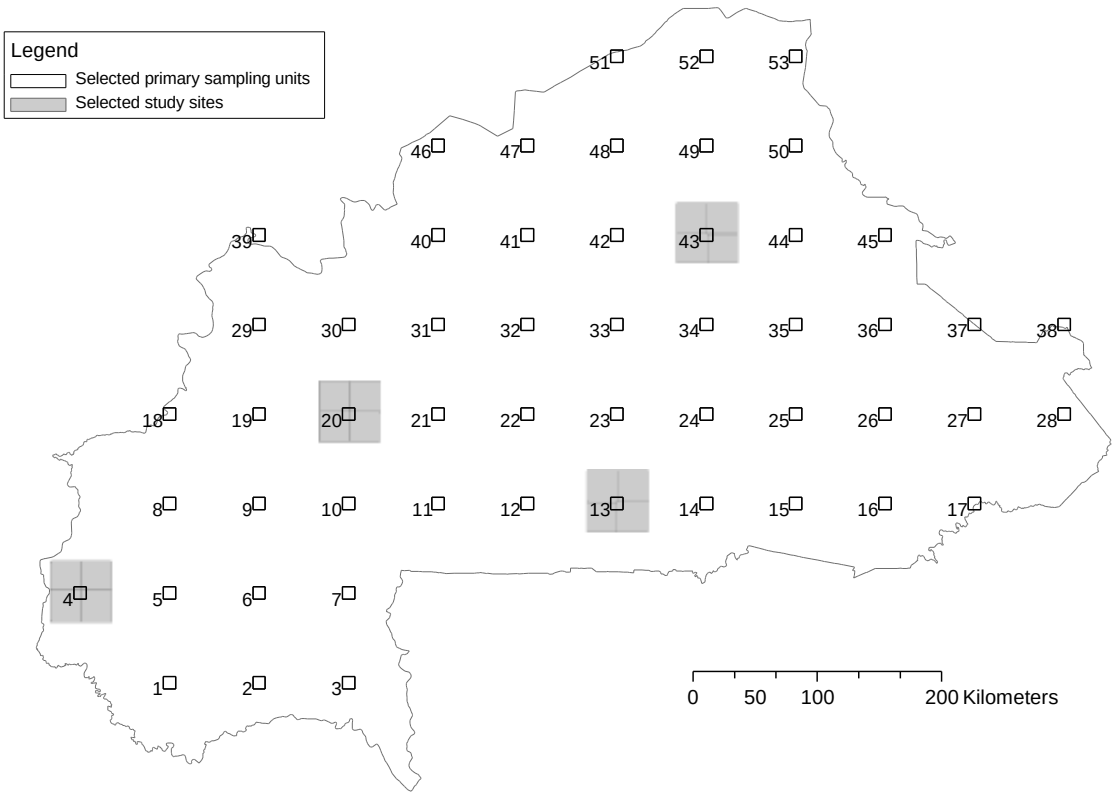

Figure 11: Location of the four study sites with corresponding primary sampling unit for the land use classification on regional scale.

RapidEye imagery is characterized by having five bands including a near-infrared (NIR) as well as a red edge channel (RE), in total covering a band width between 440-850 nm. The ground sampling distance is 6.5 m, which is then resampled to a pixel size of 5 m (RapidEye AG 2011). Each image tile covers an area of 25*25 km. For a full coverage of each study site four images are required, therefore the quality between the Level 3A products acquired differed. According to the RapidEye metadata, cloud coverage for all images was between 0-3 per cent even though clouds and especially haze were present in images 1, 2, 6, and 7 (Table 3), resulting in the mentioned quality dissimilarities.

Table 3: Acquisition details of the standard RapidEye Level 3A imagery products extracted from the metadata file (PSU= primary sampling unit).

ID	Study Site	Date	Time (UTC)	Cloud Coverage	Unusable Data	Satellite
1	PSU 4	2010-03-10	11:46:17	0%	0%	RE-1
2	PSU 4	2010-03-10	11:46:18	0%	15%	RE-1
3	PSU 4	2010-03-10	11:46:20	0%	0%	RE-1
4	PSU 4	2010-03-10	11:46:21	0%	1%	RE-1
5	PSU 13	2010-02-15	11:22:39	0%	0%	RE-3
6	PSU 13	2010-02-15	11:22:43	0%	0%	RE-3
7	PSU 13	2010-02-18	11:26:57	0%	0%	RE-1
8	PSU 13	2010-02-18	11:27:00	0%	0%	RE-1
9	PSU 20	2010-02-16	11:42:47	0%	0%	RE-3
10	PSU 20	2010-02-16	11:42:48	0%	0%	RE-3
11	PSU 20	2010-02-16	11:42:51	0%	0%	RE-3
12	PSU 20	2010-02-16	11:42:51	0%	0%	RE-3
13	PSU 43	2010-02-18	11:26:25	0%	0%	RE-1
14	PSU 43	2010-02-18	11:26:28	2%	2%	RE-1
15	PSU 43	2010-02-19	11:27:40	3%	3%	RE-2
16	PSU 43	2010-02-19	11:27:44	2%	2%	RE-2

5.2.2 Image preprocessing and enhancement – regional scale

All remote sensing platforms are influenced by the composition of the earth atmosphere as all energy that reaches the sensor, needs to pass at least parts of the atmosphere, where the wavelength of the incoming sunlight can be altered by aerosols or the gaseous composition of the atmosphere (Campbell 2008).

In our case, we used imagery with a bandwidth within the visible and near-infrared domain. Such data from a passive sensor is dependent on sun light thus is strongly affected by variations of the solar zenith angle and also the wavelength and the interaction of the atmosphere (Vermote et al., 1997). In order to minimize such negative influences on the imagery, which can lead to reductions in classification accuracy, we applied an atmospheric correction. Atmospheric correction aims at removing the atmospheric effects on the

imagery allowing the retrieval of the surface reflectance from the radiances measured at the sensor. Further, the application of atmospheric correction helps normalizing imagery taken at different times, improving comparison between images.

Next to the atmospheric corrections with regards to aerosol and gaseous composition of the atmosphere, cloud detection was applied. Cloud cover is often the limiting factor in passive remote sensing, especially for the moist tropics or regions with distinct rainy seasons; where the seasonal variation in cloud cover has to be taken into account when planning image acquisition. We implemented an automatic cloud detection algorithm based on a rule set of threshold values (Magdon, 2011), following the methodology proposed by Richter (2008). For the cloud detection we used top-of-atmosphere reflectance (Magdon, 2011) and three classes were differentiated: (i) cloud over land, (ii) cloud over water and (iii) water (Magdon, 2011).

For atmospheric correction various models are available, most of them are commercial and their source code is not publicly available, thus adaptations of the model are not possible. We implemented the Second Simulation of a Satellite Signal in the Solar Spectrum - Vector (6SV) model (Vermote et al., 1997) where the original code can be obtained. This model was further extended with a new subroutine defining specific filter transmission curves for the five RapidEye bands (Magdon, 2011). All image specific required input variables like the solar zenith angle, and these were derived from the metadata files of the input imagery. Additional information about the surface elevation for every scene was calculated from SRTM (Shuttle Radar Topographic Mission) digital elevation model (DEM) (Magdon, 2011). For the calculation of the atmospheric correction an ideal Lambertian surface reflection as well as a standard atmospheric profile for the gaseous components (US62) was applied, using a continental aerosol model (Magdon, 2011). The 6S model also includes information on the water vapour column, ozone concentration, and aerosol optical depth at 550 nm. Information on these can be obtained from the MODIS Atmosphere data collection (http://modis-atmos.gsfc.nasa.gov). The MODIS Terra data on the atmospheric composition utilized were taken on the same date as the RapidEye data with time offsets of less than one hour (Magdon, 2011).

To further improve classification results one can derive additional features (in our case additional bands) from the original image bands. We calculated a total of 15 additional features, belonging to two groups: 1.) Image ratios, and 2.) Image textures (Table 4).

Table 4: Artificial bands used in this study (Magdon et. al. 2011), where: NIR = near infra-red and RE = red edge.

Artificial Band	Formula	Reference
NDVI	$NDVI = \frac{NIR - red}{NIR + red}$	Haas et al. (1974)
Red Edge NDVI	$NDVI_{RE} = \frac{NIR - RE}{NIR + RE}$	Gitelson (1996)
Green NDVI	$NDVI_{green} = \frac{NIR - green}{NIR + green}$	Buschmann and Nagel (1993)
Ratio	$RATIO = \frac{NDVI_{RE}}{NDVI_{Green}}$	Marx (2010)
Chlorophyll Green Model (CGM)	$CGM = \frac{NIR}{Green} - 1$	Gitelson et al. (2005)
Chlorophyll Red Edge Model (CRM)	$CRM = \frac{NIR}{RE} - 1$	Gitelson et al. (2005)
Occurrence Mean	See reference given	Haralick et al. (1973)
Occurrence Standard deviation		
Occurrence Variation coefficient		
Co-Occurrence Angular second moment		
Co-Occurrence Contrast		
Co-Occurrence Entropy		
Co-Occurrence Inverse difference moment		
Co-Occurrence Correlation		
Co-Occurrence Dissimilarity		
Co-Occurrence Max. probability		
Co-Occurrence Mean		
Co-Occurrence Variance		
Co-Occurrence Cluster shade		
Co-Occurrence Cluster prominance		

We calculated a total of six ratios, which are calculated by dividing one image pixel from one band by the corresponding pixel of another band of the same image (Lillesand, 2008). The best known ratio in remote sensing of vegetation is the Normalized Vegetation Index (NDVI), which is one of five vegetation indices we implemented. The NDVI is calculated by the ratio of the sums and difference of the red and NIR bands. Vegetation indices like the NDVI are very efficient in segregating vegetation from non-vegetation or by making distinctions between vegetation cover as the NIR to red ratio is usually high for healthy vegetation and low where no vegetation occurs (Lillesand 2008).

Following Lillesand (2008), texture is defined as: "The frequency of tonal change on an image". Textures can increase classification when objects that need to be classified have similar brightness values but their structure differs, e.g. the distinction between conifer and broad leaf tree species. Calculations of texture are done by applying a moving window which passes over the whole image. We calculated a total of nine textures for band 2 of the RapidEye images (Table 4), which is the green band, applying a moving window with a size of 3 x 3 pixel (Magdon, 2011).

5.2.3 Image classification scheme – regional scale

Image classification followed the FAO land use classification scheme, segregating the five major FAO land cover classes: forest, other wooded land, other land, and other land with tree cover see (Table 1). For the classification we developed a multi-level classification scheme with three levels as shown in Figure 12. In a first step a level I classification with 14 classes was done based on the spectral and textural information from the image itself (Magdon 2011). Out of this classification the FAO land use classes were derived (Level II) and a forest /non-forest map (Level III) could be generated.

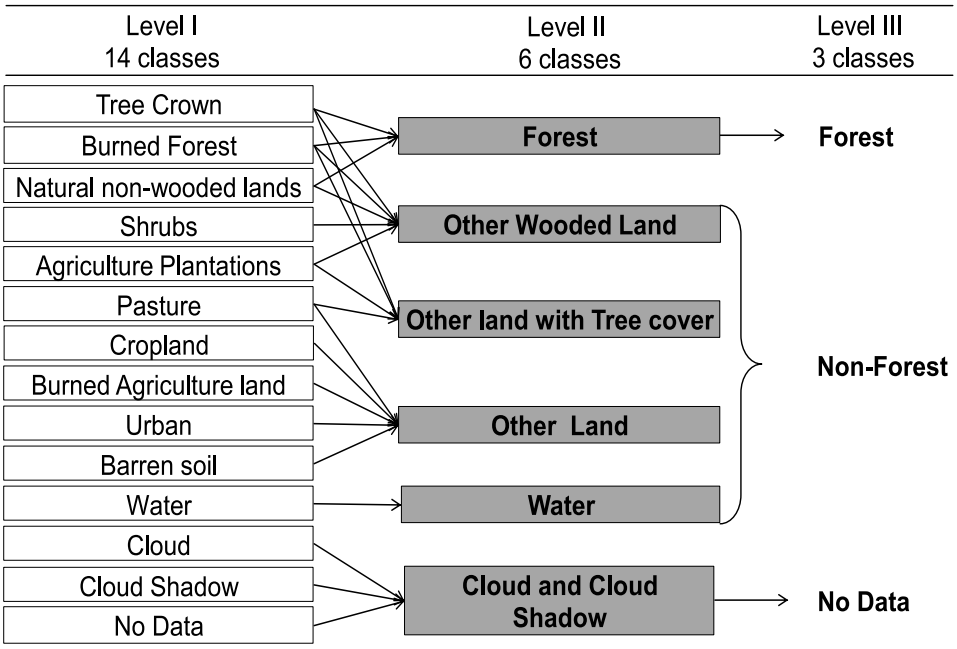

Figure 12: Classification scheme for forest cover mapping, taken from Magdon (2011).

As indicated in Figure 12, the transition from level I to level II is not injective, meaning that a rule set is needed to allocate level I classes to level II classes (Magdon 2011). The developed rule set, as shown in Figure 13, implements the FAO land use definitions, using both, quantitative and qualitative criteria (Magdon 2011).

In order to apply the rule set for the FAO conform land use classification in Figure 13, a reference area had to be defined for which the crown cover and the predominant land use was determined (Magdon 2011). In this context, we explain the term predominant as stated in the FAO land use definitions (FAO 2010) as the majority within the reference area. As reference area we choose a quadratic area of 625 m² (25 pixels). The next smaller reference area would have had a size of 225 m² (9 pixels), being the smallest possible reference area, whereas the next larger possible reference area would have had an area of 1225 m² (49 pixels). We chose the reference area with 625 m² in order to extensively harmonize our remote sensing survey with our field based observations, where one field plot had a size of 706 m². Our classification resulted in a FAO conform land use map which delivers the possibility to create a forest /non-forest map. The forest non-forest map was generated following the classification scheme in Figure 12, by reassigning the FAO land uses: other

wooded land, other land, other land with tree cover, and water to non-forest; cloud & cloud shadow to no data, whereas forest remains forest.

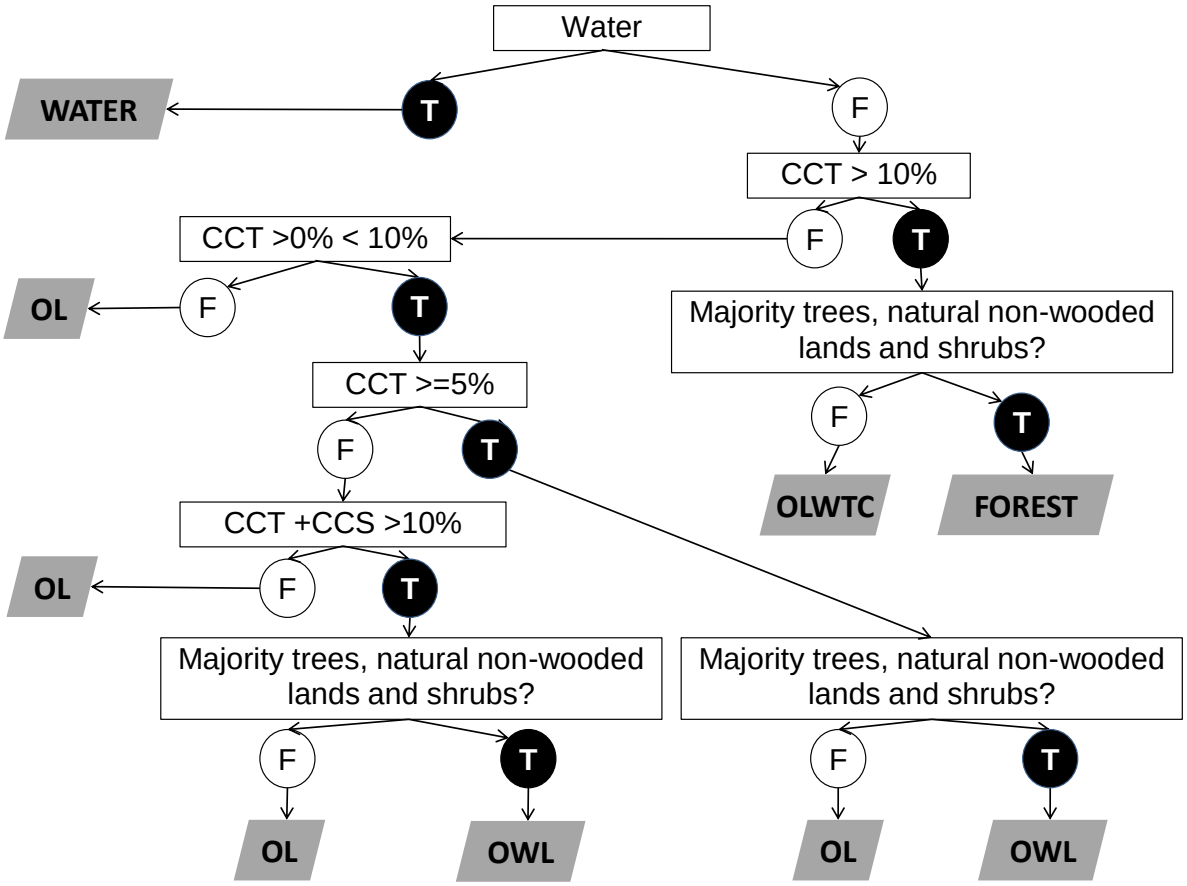

Figure 13: Hierarchical rule set (T=true, F=false) implementing the FAO land use definitions (OL = other land, OLWTC = other land with tree cover, OWL = other wooded land). With CCT = crown cover of trees and CCS = crown cover of shrubs. Modified following Magdon (2011).

5.2.4 Training- and validation data sets – regional scale

For consistent land use mapping the implementation of a common land use definition and a statistically sound accuracy assessment is needed. Further, training- and validation data need to be selected for the accuracy assessment. The selection of such data needs to be done in a randomized manner; leading to two independent data sets. Following Campbell (2008) training data should cover the spectral range of the images and must cover all classes of interest.

The training datasets were generated by overlaying the original images with a randomized systematic grid, defining *n* = 50 equidistant 200 m x 200 m plots following Magdon (2011). Within the established plots all image objects were mapped by an experienced image interpreter with local knowledge from field surveys; where mapping was done according to the level I classification key (Figure 12). After compiling the full test dataset all surface reflectance, vegetation indices, and texture measure pixel values were extracted from the train data (Magdon 2011).

Classification errors were computed using an error matrix as described in various text books (Jensen 2005; Jones and Vaughan 2010). In this study we used 1.) overall accuracy, 2.) user accuracy, 3.) producer accuracy, and 4.) kappa statistic, to describe the classification results. The overall accuracy is calculated by dividing the number of correctly classified pixels by the total number of pixels used in the classification (Jones and Vaughan, 2010). The user accuracy is a measure for the classification accuracy for each class. The user accuracy is calculated by dividing the number of correctly classified pixels by the total number of pixels in this category (Jones and Vaughan, 2010). Calculating the producer accuracy also gives an estimate of the classification accuracy for each class, but here, we divide the number of correctly classified pixels by the total number validation pixels in this class. The last measure of classification accuracy calculated is the kappa statistic, which gives the degree of divergence of the classification from a random distribution of classification results. Kappa quantifies whether the classification renders significantly better results than a random classification. Where kappa is given with:

$$\kappa = \frac{n \quad {}_{i=1}^{k} x_{ii} - \quad {}_{i=1}^{k} (x_{i+} * x_{+i})}{n^2 - \quad {}_{i=1}^{k} (x_{i+} * x_{+i})}$$

Where n represents the total number of elements in the matrix, x_{ii} are the diagonal cells of the error matrix, x_{i+} are the row marginal totals, and x_{+i} stands for the column marginal totals (Jones and Vaughan, 2010).

When computing the classification error we did not do so for each image individually, but for the four images covering one PSU. Accuracies were computed on the level of the four images as the population of interest is not each image but the region covered by the four images together. This procedure resulted in different extents for the train- and validation

data sets. Each validation dataset was generated following Magdon (2011), where a systematic grid with *n* = 100 validation points was overlaid over the study area and the level I classes were determined by image interpretation.

5.2.5 Classifier

Classification of the images was done using the RandomForest method developed by Breiman (2001). One of the advantages of using such a non-parametric classification method is that no assumptions need to be made concerning data distribution and independency (Im und Jensen 2005). Further, classification is based on a rule set which can easily be interpreted (Breiman, 2001). By convention, classifiers that are able to deliver a fixed rule set, at the same time being non-parametric are hierarchical decision tree methods (for a graphical view see Figure 15).

The RandomForest classifier is based on bagging, which is bootstrap aggregation (Gislason et al. 2006). Where the method of bagging was introduced by Breiman, a detailed description can be found in Breiman (1996). Bagging is a method that generates multiple versions of a predictor and combines them, to obtain an aggregated predictor. The multiple versions or trees of the predictor are generated by selecting a bootstrap sample from the training data set and using that as the training set during classification (Breiman, 1996). As a result each bootstrap sample, being a random sample with replacement, results in one version or tree of the predictor (Liaw and Wiener, 2002), where RandomForest grows a user defined number of decision trees and averages the results of all decision trees (Walton, 2008). The aggregation leads to a decrease of variance in the prediction (Gislason et al. 2006). Following Benediktsson et al. (2007) we could say that RandomForest uses an improved version of bagging.

On each node of one decision tree (the branches of the tree) a random number of variables are chosen (in our case a subset of all available image bands) and the best split is calculated from these (Liaw and Wiener, 2002). This randomization leads to marginally different results for each classification even for the same data set (Walton, 2008).

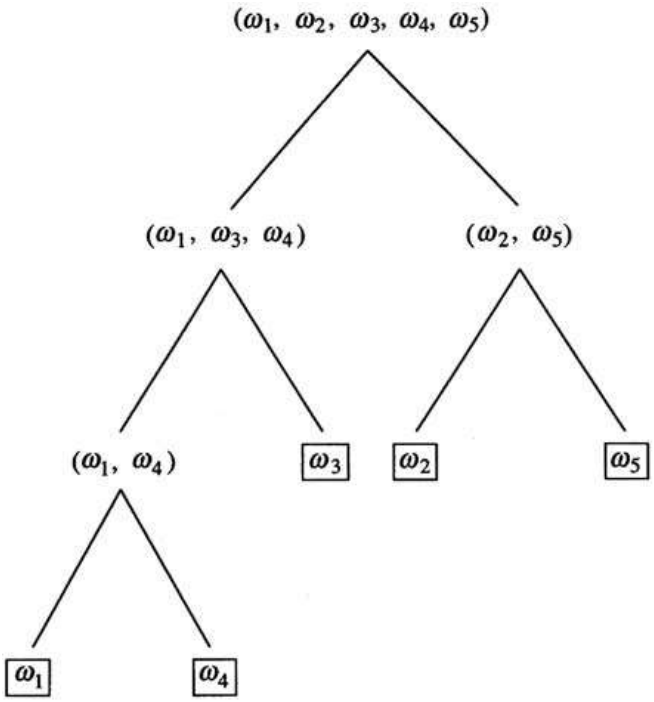

Figure 14: Schematic overview of a decision tree where five classes need to be classified. Modified from Richards and Jia (2006).

Due to the resampling method, which is not based on weighting, the RandomForest classifier is not sensitive to noise or over fitting (Gislason et al. 2006; Benediktsson et al. 2007) and does not need any guidance during computation. When classes, in our case, land use classes have to be classified with the RandomForest classifier, the final classification of one class is done by applying a majority vote over all versions or trees of the classifier for the class of interest.

With regards to new sensors, where the number of bands can range between just five and hundreds, it is important that a classifier is able to handle high dimensional data. It was assessed by Benediktsson et al. (2007) that RandomForest is able to handle high dimensional data. Not only the high level computing efficiency (Jensen 2005), but also the possibility to obtain an out-of-bag error estimation, without an additional dataset as well as variable importance calculation makes RandomForest an attractive classifier.

The out-of-bag error estimation for each tree is calculated by cross validating the classification result with original data that was not included in the sample chosen for the

calculation of the corresponding tree (Breiman, 2001). The overall out-of-bag error is calculated by averaging over all trees (Breiman, 2001).

An additional advantage of RandomForest is that the algorithm can estimate the importance of variables for the classification (Breiman, 1996), which can be of help to get insights into processes influencing classification. To determine the importance of a variable we used the Gini index as described by Breiman and Cutler (2011). Using the variable importance we were able to identify the variables with high value with regards to the classification result. By reducing the number of input variables (in our case the number of image bands) we were able to reduce computing time by about half without increasing classification errors to a greater extent (Table 10).

For each train set a RandomForest with n = 500 trees was grown and its feature importance calculated. For the final classification a subset consisting of the 5 features with the highest variable importance was used. We restricted the classification to five features and n = 100 trees as a compromise between accuracy and computational effort following Magdon (2011).

The entire workflow including preprocessing, image enhancement and classification was implemented as the ForestEye-Processor in the interactive data language using the software environment IDL 8.0 (ITT VIS). The RandomForest classification was integrated using the open source library *PARF* (Centre for Informatics and Computing of RuđerBošković Institute, Croatia, 2004) a parallelized implementation of the original RandomForest code developed by Breiman (2001) (Magdon 2011).

5.2.6 National scale land use classification

One of our objectives was to create a FAO conform land use map covering the whole of Burkina Faso. In order to achieve this we up scaled the existing regional scale FAO conform land use classification based on RapidEye imagery as described in 5.2.3. For the up scaling we used the daily MODIS Level 1 product MOD09GA. MOD09GA is delivered atmospherically corrected, applying the 6-S Model already described in 5.2.2 using a dynamic aerosol model. Further, the MODIS imagery used has 21 bands ranging between

0.620 - 2155 nm, bands 1 - 9 carry sensor information like Sensor Azimuth with a resolution of 1 km. Bands 10 - 21 have a resolution of 500 m, where bands 10 and 18 - 21 give general information on the solar reflective bands number 11 - 17. For the classification we used bands 11- 17 with a resolution of 500 m per pixel.

Table 5: MODIS MOD09GA band specifications where NIR = near-infrared and SWIR = short-wave length infrared.

MODIS (MOD09GA) Bands	Wavelength [nm]
Band 11 (Red)	620 - 670
Band 12 (NIR)	841 - 876
Band 13 (Blue)	459 - 479
Band 14 (Green)	545 - 565
Band 15 (NIR)	1230 - 1250
Band 16 (SWIR)	1628 - 1652
Band 17 (SWIR)	2105 - 2155

Three MODIS scenes are required to cover the whole of Burkina Faso, where one MODIS image tile covers an area of about 1140 x 1140 km. In order to ensure equal atmospheric as well as ground conditions all MODIS scenes used were taken at the same date (Table 6). All image tiles were of good quality with no cloud cover and homogenous illumination. The missing data areas (Table 6) were not within the boundary of Burkina Faso thus did not influence processing within our study. Further, in order to also ensure comparability with the imagery used for the land use classification on regional scale, the MODIS images were taken during the same season as the RapidEye imagery, which were used for the land use classification on regional scale (Table 3).

Table 6: Acquisition details of the standard MODIS imagery products (MOD09GA) extracted from the metadata file.

ID	Date	Time (UTC)	Cloud Coverage	Missing data	Tile ID
1	2010-02-08	10:20:00	0%	22%	51017007
2	2010-02-08	10:20:00	0%	0%	51018007
3	2010-02-08	10:25:00	0%	7%	51017008

5.2.7 Image preprocessing – national scale

As MODIS imagery is distributed in sinusoidal projection, the acquired imagery had to be reprojected to Universal Transverse Mercator (UTM) coordinates to fit the FAO land use maps on regional scale. As mentioned above, we needed three image tiles to cover the whole of Burkina Faso. To obtain one seamless image covering Burkina Faso we mosaicked the three image tiles using the nearest neighbour method. The image reprojection and mosaicking were done using the MODIS Reprojection Tool (MRT) Version 4.1 (Land Processes DAAC, USGS Earth Ressources Observation and Science (EROS) Center 2011). The mosaicked MODIS image was then cropped to only cover the area of Burkina Faso. The preprocessing resulted in one MOIDS MOD09GA image, covering only Burkina Faso having the same projection as the land use maps on regional scale.

5.2.8 Training and validation data sets – national scale

The training data set used to classify the MODIS imagery was created by spatially overlaying the MODIS mosaic with the FAO land use maps on regional scale. Thus, a direct allocation of the MODIS pixels to one of the FAO land use classes was done. As one MODIS pixel has an extension of 500 x 500 m and one RapidEye pixel, used for the FAO land use classification on regional scale has an extension of 5 x 5 m, 10 000 classified pixels were needed to cover one MODIS pixel. With the applied overlay method we were able to extract the fraction of cover of each land use in one MODIS pixel, meaning the per cent of one MODIS pixel covered by a RapidEye based land use class. By applying the threshold value of 100 to the fraction of

cover of each land use within one MODIS pixel, we were able to identify MODIS pixels that were covered by only one single FAO land use. By this method we obtained “clear” pixels as recommended for training data (Jones and Vaughan, 2010) in the remote sensing domain. The selected MODIS pixels were then used as training data during the classification.

In order to validate the remote sensing based classification results on the national scale; and to conduct a correct accuracy assessment we had to create a validation data set which is independent of the training data. Here, we used the data obtained during the field measurements, so called ground truthing data as validation data set. During validation we compared the FAO land use assigned to one MODIS pixel of the classified image to FAO land use class of the corresponding ground control point. For the validation we incorporated n = 905 ground control points, being the number of CP sampled during the inventory as described in 5.1.1.

5.2.9 Image classification scheme - national scale

The pixels selected as training data were extracted, including their original information contained in the seven reflective bands used (Figure 5). In the following we attached the corresponding FAO land use class assigned to each training pixel to the original information in form of an additional image band. The training data was then imported into the RandomForest classifier which is described in 5.2.5.. During the classification we grew 500 trees where two splits were possible at each nod. All preprocessing and classification steps for the land use classification on national scale were done with the software R (R Development Core Team 2011). The classification resulted in a FAO conform land use map for the whole of Burkina Faso.

6 Results

6.1 Terrestrial sampling

Most parts of the results for the terrestrial sampling section follow the results described in: Fischer et al. 2011. A national level forest resource assessment for Burkina Faso - A field based forest inventory in a semi-arid environment combining small sample size with large observation plots. Forest Ecology and Management, doi:10.1016/j.foreco.2011.07.001.

6.1.1 Land use

We estimated the cover of Burkina Faso by four land use classes: 1) forest, 2) other wooded land, 3) other land without tree cover, and 4) other land with tree cover, as defined by FAO. The results of our estimations are given in Table 7. The only source to compare our results to were the findings of the Global Forest Resource Assessment of FAO (FAO FRA), where were able to compare to findings from the years 1990, 2000, 2005 and 2010 (Fischer et al., 2011). The FAO FRA estimates we base our comparison on were taken FRA 2010 (FAO, 2010). The reason to use the estimates published in FRA 2010, even for estimates from earlier assessments, are that estimates vary between different FRA reports as the national correspondents recently made updated information available (Fischer et al., 2011). With the conducted inventory, applying the described methods, the forest area of Burkina Faso was estimated to be 116 847 km² (42.6%) of the land area, other wooded land 4 467 km² (1.6%), other land 146 729 km² (53.6%) of which 13 398 km² (9.1%) is with tree cover. We assessed that the relative standard error (SE%) of relative area proportions were substantially larger for the less frequent land use classes (e.g. wooded land SE%=41.4%). Whereas smaller SE%'s were calculated for the more frequent land use classes (e.g. forest SE%=9.9%, Table 7) (Fischer et al., 2011), which could be expected as SE and SE% strongly depend on the sample size.

Table 7: Comparison of area estimates from this study to others (all % values refer to the whole of Burkina Faso). Following Fischer et al. (2011).

FRA 2010 categories	FAO 1990	FAO 2000	FAO 2005	FAO 2010	This study	
	Cover [km^2 and %]				Cover [km^2 and %]	SE%
Forest	68 470	62 480	59 490	56 490	116 847	**9.9**
	24.9%	22.8%	21.7%	21.0%	**42.6%**	
Other wooded land	58 610	54 350	52 220	50 090	4 467	**41.4**
	21.4%	19.8%	19.1%	18.0%	**1.6%**	
Forest and other wooded land	127 080	116 830	111 710	106 580	121 315	**9.6**
	46.4%	42.6%	40.8%	39.0%	**44.2%**	
Other land	146 520	156 770	161 890	167 020	146 729	**8.5**
	53.5%	57.2%	59.1%	60.9%	**53.6%**	
... of which with tree cover	51 350	55 180	57 100	59 020	13 398	**17.4**
	18.7%	20.1%	20.8%	21.5%	**9.1%**	
Total land area	273 600	273 600	273 600	273 600	**270 060**	-
	99.9%	99.9%	99.9%	99.9%	**97.8%**	
Inland water bodies	400	400	400	400	5 957	**99.2**
	0.1%	0.1%	0.1%	0.1%	**2.2%**	
Total area of country	274 000	274 000	274 000	274 000	**274 000**	-
	100%	100%	100%	100%	**100%**	

6.1.2 Forest structure

Following Fischer et al. (2011) a total of 4631 life sample trees and 1879 life sample shrubs belonging to 104 tree and 41 shrub species were measured (see annex for a detailed species list). Out of the 104 tree species ten tree species co-occurred in all four land use types. Regarding all four land use classes, the inventory result revealed that *Vittelaria paradoxa* is with a share of 12% is by far the most abundant tree species among all observed trees. Its extraordinary high abundance becomes clearer when considering that the second most

abundant species accounts for 7% of all trees only (Figure 15), being about half the abundance of *Vittelaria paradoxa*. *Vittelaria paradoxa* is not only the most abundant tree species in Burkina Faso but probably also economically the most important tree species in Burkina Faso, not so much for its wood (which is illegally used for charcoal production), but for the production of "shea butter", extracted from the grains (Fischer et al., 2011). Fischer et al. (2011) conclude that the high abundance and wide distribution of *Vittelaria paradoxa*, in particular outside the forest, is an indicator for a landscape with a long history of human management where this tree species was favoured, forested and managed.

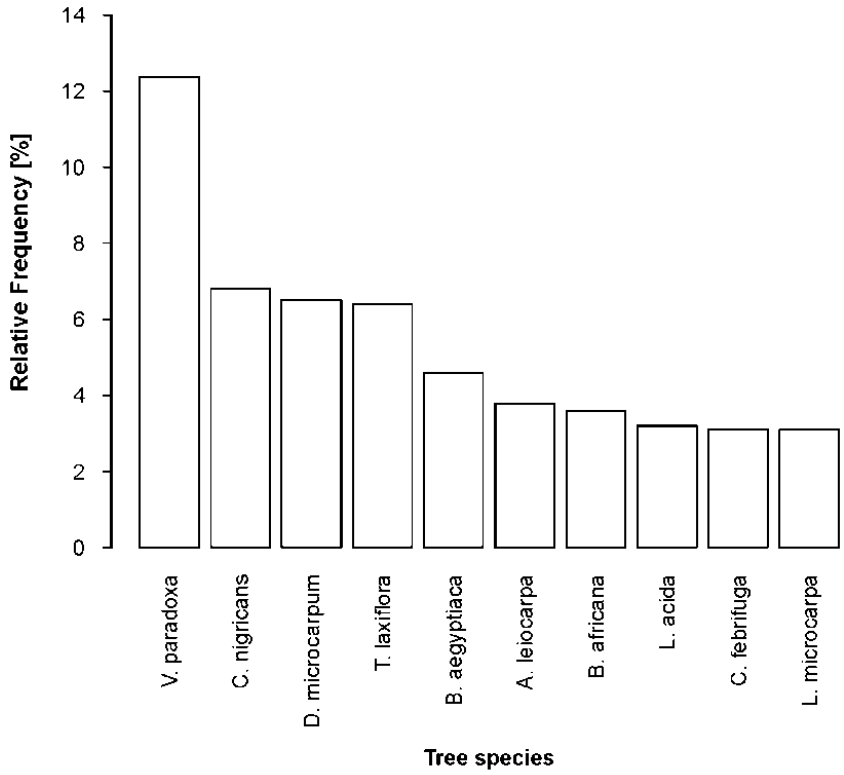

Figure 15: Frequency distribution of ten most abundant tree species of all sampled life trees.

Not only the high abundance of a single tree species was used as indicator for the anthropogenic influence on the landscape, but also the relative frequency of stumps, compared to remaining trees for all land uses. The relative frequency of cut trees was 3.6%, 2.6%, 14.3% and 24.2% for forest, other wooded land, other land and other land with tree cover, respectively (Fischer et al., 2011).

Figure 16 illustrates the relative frequency of the ten most common species for the four land use types where the most common species are similar for all land use types. A major difference in species composition can only be found for “other wooded land” where shrub species are considered by definition, contrasting the other land use class definitions (Fischer et al., 2011).

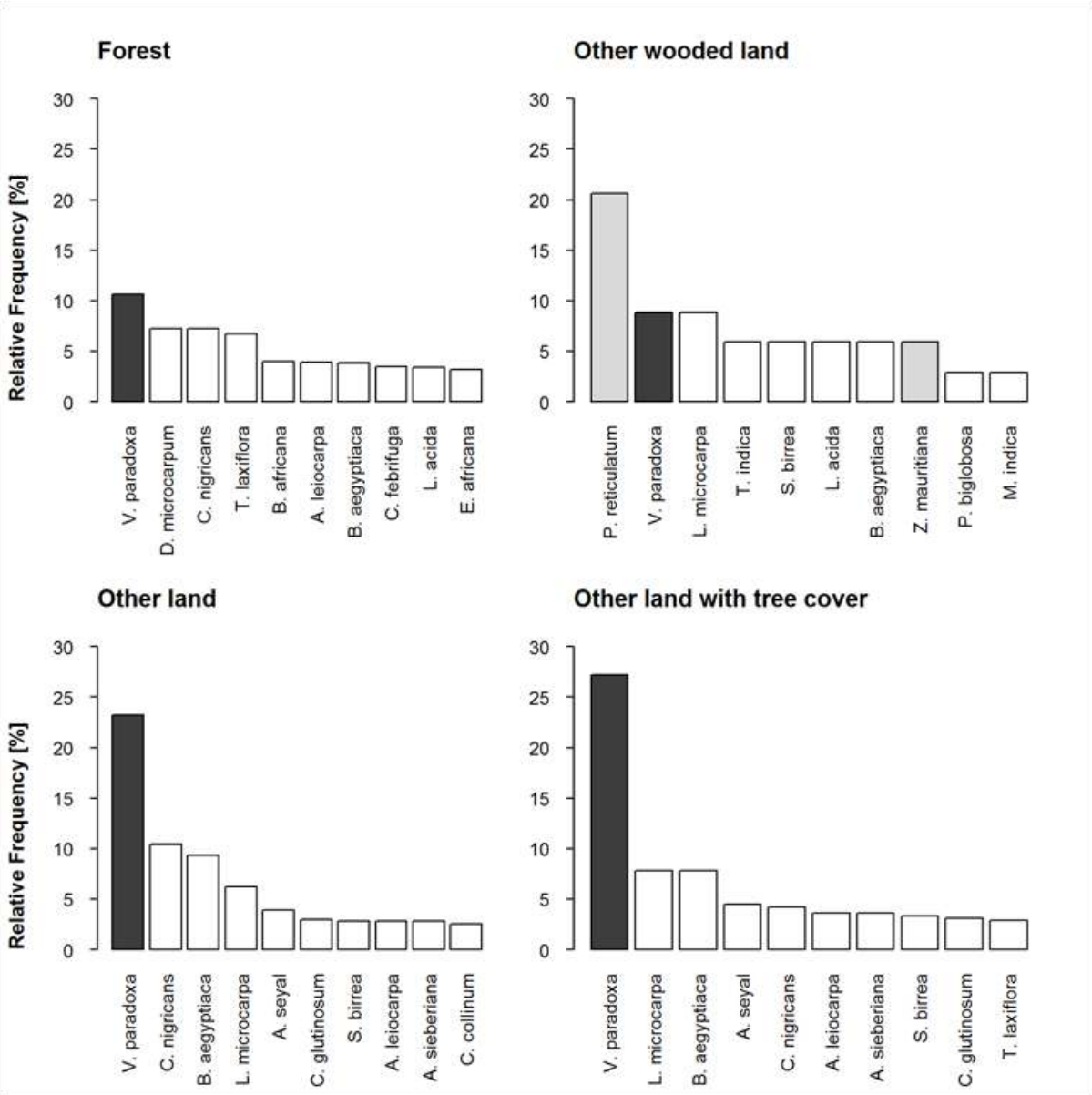

Figure 16: Frequency of the ten most abundant species for the four land use types. The overall most frequent species (*Vittelaria paradoxa*) is marked in black. For “other wooded land” also shrub species are included - marked in light grey. Following Fischer et al. (2011).

Following Fischer et al. (2011): “The “shea butter tree” *Vittelaria paradoxa* is by far the most frequent tree species in “other land” (with an estimated 23.2%) and “other land with tree cover” (27.2%). “Other wooded land” is dominated by shrub species where *Piliostigma reticulatum* is by far the most frequent species with an estimated share of 20.6%.” In accordance to the observations made with the proportion of cut vs. uncut trees, which lead to an unnatural species distribution, in forest the species distribution is much more uniform. In “forest” *Vittelaria paradoxa* is still the most abundant tree species, but the proportion is just 10.6% (Fischer et al., 2011).

In addition to species composition we observed the structure of the land use classes where Table 8 gives an overview of the DBH range of observed trees, height and crown size. In order to illustrate the symmetry and skewness of the underlying distributions, median and mean values are given as measures of central tendency (Fischer et al. 2011). A correlation (Pearson) of r_p = 0.59 between total height and DBH over all observed trees was estimated. The correlation can be considered typical for dry forest formations as diameter dynamics are more prominent than height dynamics under this climatic condition (Fischer et al., 2011). The described relationship expresses itself in different coefficients of variation, for forest DBH (around 71.2%) and forest tree height (40.4%). “For all sampled trees the correlation between crown size, calculated from two measured crown diameters, and DBH was estimated as r_p= 0.68, despite the common practice of pruning for fodder and other uses” as stated by Fischer et al. (2011).

It should be noticed that Table 8 does not include the variable *DBH* for the land use class “other wooded land” as DBH was not measured for shrubs which, nevertheless dominate this land use class. We perceived that the range of DBH measurements is quite large for all land cover types with trees, which is due to some huge trees (e.g. *Baobab* (*Adansonia digitata*)), which contribute to the asymmetry of the DBH distribution (Fischer et al., 2011). Additionally Fischer et al. (2011) state: “Mean and median DBH are clearly lower in “forest” than on “other land” and “other land with tree cover”, pointing to the fact that regeneration and smaller trees are found only in forests and trees on non-forest land usually remain uncut serving specific utilization purposes.” Land use class “other wooded land” exhibits a markedly smaller average total height where we attribute this result to the high abundance of shrub species attaining lower heights compared to trees. As a direct result, a high

variability of height is apparent in these classes as trees, which are higher, and shrubs, which are lower, are mixed, whereas crown areas exhibit relatively small variations in "other wooded lands" (Fischer et al., 2011).

Table 8: Estimates for variables of forest and tree cover, following Fischer et al. (2011).

Variables/ Land use	Minimum	Median	Maximum	Mean	CV%
Diameter at breast height [cm]					
Forest	7.0	12.0	320.0	15.0	71.3
Other wooded land (trees only)	7.0	12.0	132.2	24.9	67.4
Other land	7.0	18.1	155.0	24.3	78.2
Other land with tree cover	7.0	19.9	116.0	25.6	72.9
Total height [m]					
Forest	1.5	5.8	24.0	6.3	40.4
Other wooded land	0.5	4.7	14.0	5.7	70.3
Other land	2.0	6.5	26.3	7.0	45.6
Other land with tree cover	2.0	6.7	26.3	7.3	43.8
Crown size [m²]					
Forest	0.4	44.1	2402.0	66.8	138.1
Other wooded land	7.1	60.3	1072.0	141.7	152.5
Other land	0.2	76.7	1385.0	137.4	122.8
Other land with tree cover	0.2	94.1	1385.0	150.1	116.6

6.1.3 Above ground carbon stocks of tree resources (AGC_{Tree})

We were able to calculate AGC_{Tree} stocks for the land use classes which consider trees only within their definition. Namely "forest", "other land", and "other land with tree cover", where the estimates are given in Table 9. The estimates range between 5.580 and 7.222 Mg ha^{-1} with about the same relative standard errors of around 18% (Fischer et al., 2011). Unexpectedly, the estimate for AGC_{Tree} is highest for "other land with tree cover", although not statistically significantly different from forest AGC_{Tree}, where the significance was tested with a simple T-test. We explain the higher value of AGC_{Tree} on "other land with tree cover"

by the high frequency of large solitary multi-purpose trees (see also Table 8, where "other land with tree cover" has the largest average DBH) (Fischer et al., 2011).

Table 9: Above ground carbon (AGC_{Tree}) estimates for trees in Mg ha-1 and relative standard errors (SE%), following Fischer et al. (2011).

Forest		Other land		Other land with tree cover	
Mg ha^{-1}	**SE%**	**Mg ha^{-1}**	**SE%**	**Mg ha^{-1}**	**SE%**
6.640	18.25	5.580	17.88	7.222	17.37

6.2 Remote Sensing

6.2.1 Regional scale land use classification

In general the classification based on the RandomForest classifier proved to be time efficient and the classifier proved to be able to handle varying, sometimes very complex, vegetation compositions present in the study sites. It can be concluded that the classification resulted in high classification accuracies for all training sets (table 10), even though a high variation in accuracies was present between the four considered study regions: 1.) Sokouraba, 2.) Nobéré, 3.) Safané, and 4.) Tougouri. Hereafter, we will name the four study regions corresponding to the PSUs located at their centre, namely: 1.) PSU 4, 2.) PSU 13, 3.) PSU 20, and 4.) PSU 43.

Mean accuracies of the classification were higher when all variables were used. Overall, an increase in accuracy could be observed for n = 24 features of 6.1% compared to n = 5 features. This indicates that using more explanatory variables increases classification accuracy while computing time and related computing power needed increases largely.
Mean accuracies between the four PSUs varied with 14.2%, the lowest accuracy for n = 24 was found in PSU 20 with a mean value of 79.1%. Whereas the highest accuracy for n = 24 was achieved in PSU 43 with 93.3%. There are several reasons for the difference in classification accuracy. First there is the number of land use classes present in the corresponding PSU, as well as the spatial distribution of the land use classes. Another reason is the presence of haze, clouds, cloud shadow, burned areas, and very bright areas of bare

soil. The RandomForest classifier often misclassifies areas where haze is present, or classifies burned forest areas as cloud shadow. Another difficulty in classification is the difference in the degree to which areas are burned. Some burned areas are black, but others, belonging to the same land use class, are rather a mixture between blue and black. This difference in reflection makes the same land use class very heterogeneous, which also holds true for other land use classes than "burned forest". The last major source of misclassification on the regional scale is the confusion of clouds and haze with bright bare soils.

Table 10: Average overall accuracies for level I classification from the cross-validation of the RandomForest classification with 100 trees per forest for the full test set (*n* = 24) or the selected test set with five features with the highest Gini-index (*n* = 5), PSU = Primary sampling unit.

ID	Study Site	*n* = 5	*n* = 5	*n* = 24	*n* = 24
		Overall Accuracy	Cohen's kappa	Overall Accuracy	Cohen's kappa
1	PSU 4	80.68	0.64	87.02	0.76
2	PSU 4	72.89	0.58	80.02	0.69
3	PSU 4	77.28	0.59	82.14	0.68
4	PSU 4	74.29	0.62	81.92	0.73
5	PSU 13	88.61	0.82	92.01	0.87
6	PSU 13	85.06	0.62	91.30	0.78
7	PSU 13	86.31	0.80	91.63	0.88
8	PSU 13	67.31	0.53	82.80	0.75
9	PSU 20	73.52	0.62	77.97	0.69
10	PSU 20	70.32	0.55	76.72	0.64
11	PSU 20	76.83	0.63	81.08	0.70
12	PSU 20	75.26	0.61	80.50	0.70
13	PSU 43	85.55	0.73	91.64	0.84
14	PSU 43	92.59	0.87	96.19	0.93
15	PSU 43	84.77	0.72	91.42	0.84
16	PSU 43	88.77	0.80	93.94	0.89
	Mean	80.00	0.67	86.14	0.77

By reducing the number of input features for the RandomForest, the variation of classification accuracy between the PSUs decreased only marginally by 0.3%, to a variation of 13.9%. Thus, the same trends in classification present for the whole feature space holds true for the reduced feature space with *n* = 5. The lowest accuracy for *n* = 5 features was attained in PSU 20 with 74.0% whereas the highest accuracy for *n* = 5 features was realized in PSU 43 with 87.9%, reflecting the same trend observed above, where the reasons for misclassification are thought to be the same as described above.

When observing the calculated kappa values the same trends are present as for the overall accuracies. Mean kappa values were higher when using the whole test set with *n* = 24 in the classification, where a kappa value of 0.77 vas obtained. Whereas for *n* = 5 features a mean kappa of 0.67 was calculated. Thus, the reduction of features led to a decrease of kappa by 0.1.

When observing the differences in kappa between the PSUs, for the whole feature space kappa varied by 0.2. PSU 43 attaining the highest mean kappa value and PSU 20 incorporating the lowest mean kappa with 0.68. This trend can be explained by the decrease of classification accuracy between PSU 43 and PSU 20, where not only the overall accuracy, but also the user- and producer accuracy are lower for PSU 20.

Compared to the whole feature space, variation of kappa was lower for the reduced feature space, with a reduction of kappa by 0.18. Again, PSU 43 showed the highest kappa with 0.78 and PSU 20 highlighted the lowest mean kappa with 0.60 for the reduced feature space. Thus, as for the accuracies, a reduction of features led to a very small decrease (0.03) in variation between PSUs for kappa.

6.2.2 Feature selection for the classification with RandomForest

As stated before, one of the advantages of the RandomForest classifier is the possibility to gain insights into the importance of single features, used as predictive variables during the classification. The Index used for the ranking of the features is the Gini index. When analysing our results we observed a variation in selection frequency for each feature, which is depicted in Figure 17. It was assessed that the RandomForest classifier utilized all original bands and vegetation indices, at least once during classification. Surprisingly, only two of

the 14 texture measures were selected by the classifier, one occurrence texture "Occurrence Mean", and one co-occurrence texture "Co-occurrence Mean". The selection of only two textures showed us that the spectral range of the RapidEye sensor, as well as vegetation indices, derived from the original bands are well suited for the classification we implemented. Further, it showed that most variations in texture are not large enough, in our case, to be of importance for the classification with the RandomForest classifier.

It was assessed that NIR had the highest relative selection frequency with 18.75%, followed by the green NDVI with 13.75%. The features with the lowest selection frequency, of the selected features, were the chlorophyll Red Edge Model with 1.25% selection frequency and the original green band with 2.5% selection frequency (Figure 17).

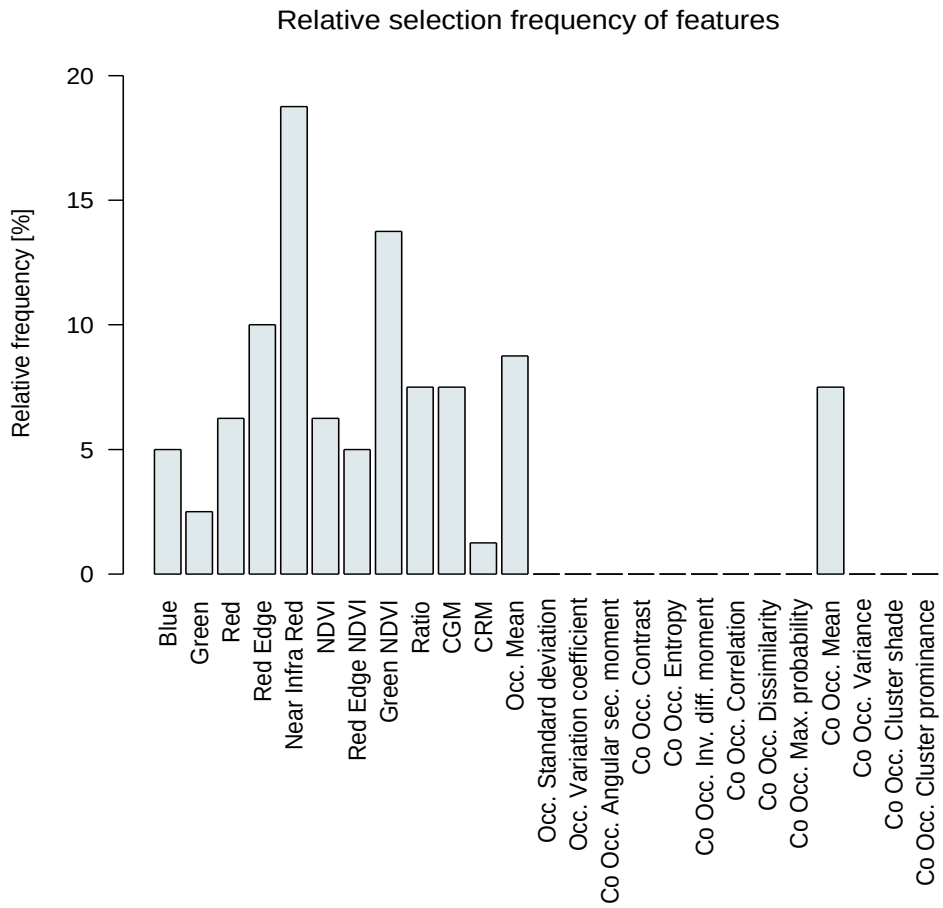

Figure 17: Relative selection frequency of features based on the out-of-bag cross-validation if *n* = 5 features with the highest Gini-index are selected. Abbreviations of the features are given in table 4.

For the final land cover classification, RandomForests built with the reduced feature space of n = 5 features were used. We decided to use the reduced feature space, changing dimensionality from 24 to 5 features, as this clearly outperformed the slight loss of classification accuracy (see Table 10). More specific, the reduction of the feature space lead to a reduction of computation time by more than half. An additional argument for the reduction of the feature space was that even with a reduced feature space all land cover types were detected during the classification. The results of the different classification levels (level 0, level I, level II, and level III) are depicted in Figure 18, Figure 19, Figure 20 and Figure 21, where the preprocessed images of the four PSUs and the corresponding three land cover/ use classification levels are shown.

The study site of Sokouraba (PSU 4) is the south-western most study site, having the highest annual rainfall of the four study sites considered. This study site is under strong human influence and is intensively cultivated. Barren soils are seldom encountered, thus only one validation point was on barren soil, resulting in a patchy mosaic of land uses, where crop lands are often intermitted by forest areas and burned forest areas, as well as shrubby vegetation, respectively (Figure 18). In total 26 validation points were on crop land with a user accuracy of 1.00 (Table 11). Tree crown and burned forest were both assessed with thirteen validation points each and user accuracies of 0.63 and 0.92, respectively. In the upper right part of the study site clouds and cloud shadows are present in the original imagery, with two and three validation points (Table 11). Clouds and cloud shadows were classified with fewer errors than in other study sites (e.g. Nobéré (PSU 13)). User accuracies of 0.43 for class “cloud” and one for “cloud shadow” were achieved. The improved performance of the RandomForest classifier in this case of imagery with cloud cover, can possibly be attributed to the fact that the clouds present in the imagery were clearly delineated (see Figure 18) and cloud shadows were also very dark and homogeneous. The overall accuracy for PSU 4 was 0.83 with a kappa value of 0.78, meeting our expectations with regards to classification accuracy. As all images were classified independently the image mosaic in Figure 18 Level III shows distinct lines between the image tiles. The lines are present as atmospheric conditions, cloud & haze cover, training datasets and decision tress for the classification differ between the imagery.

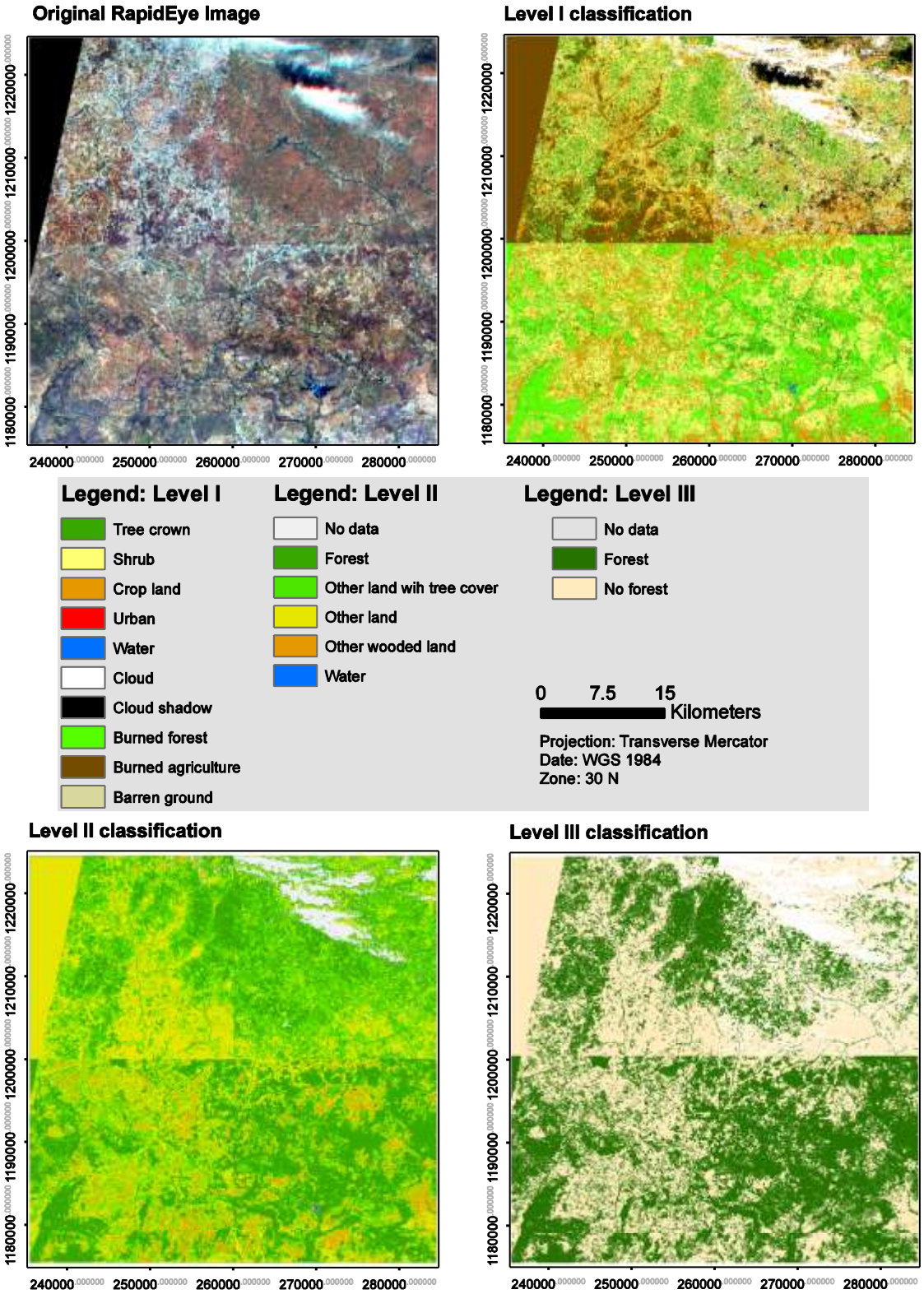

Figure 18: Original RapidEye image and resulting land cover and FAO accordant land use classification levels I-III for study site Sokouraba (PSU 4). Scale of imagery 1:550.000.

The study site of Nobéré (PSU 13) is located at the south-central part of Burkina Faso. The region is strongly influenced by agricultural use in the northern half of the study site (see Figure 19), whereas the southern half of the study site is covered by a national park. Some parts of the national park are former agricultural areas, which can be seen by the high shrub cover within the clearly delineated boundaries of the national park (Figure 19). In the study region of Nobéré greater areas covered by tree crowns that are not burned, can only be found along the sparse rivers and natural non-wooded vegetation is nearly not present. This observation gives insights into the land use practices, where fire plays an important role for land preparation and for increasing sight for hunting purposes, among others. Further it shows the high human pressure on vegetation, among others. As a result only two points of the validation dataset are covered by tree crowns and one by natural non-wooded vegetation, leading to low user accuracies (Table 11). On the other hand, shrubs and burned forest areas are very common, with 41 and 24 validation points and user accuracies of more than 90%. The border of the National Park, which is, as stated before, clearly visible in the upper left preprocessed image as a sharp line is also evident in the level III and use map. Large areas of the southern half of the study area are classified as “cloud”, as cloud and much haze are evident in the original images (see Figure 19). The presence of cloud and haze in the original images leads to large no-data areas in the level II land use map, and do account for the lowest overall accuracy with 0.67 and the lowest kappa value with 0.56, compared to the other three study regions (see Table 11). As many features are still visible through the clouds but the validation points were not classified as “cloud” during the image interpretation, low user accuracy for clouds as shown in table 11 were achieved. The overall conclusion for PSU 13 is that clouds and especially haze were identified as the largest impediment during the classification, deteriorating the classification results.

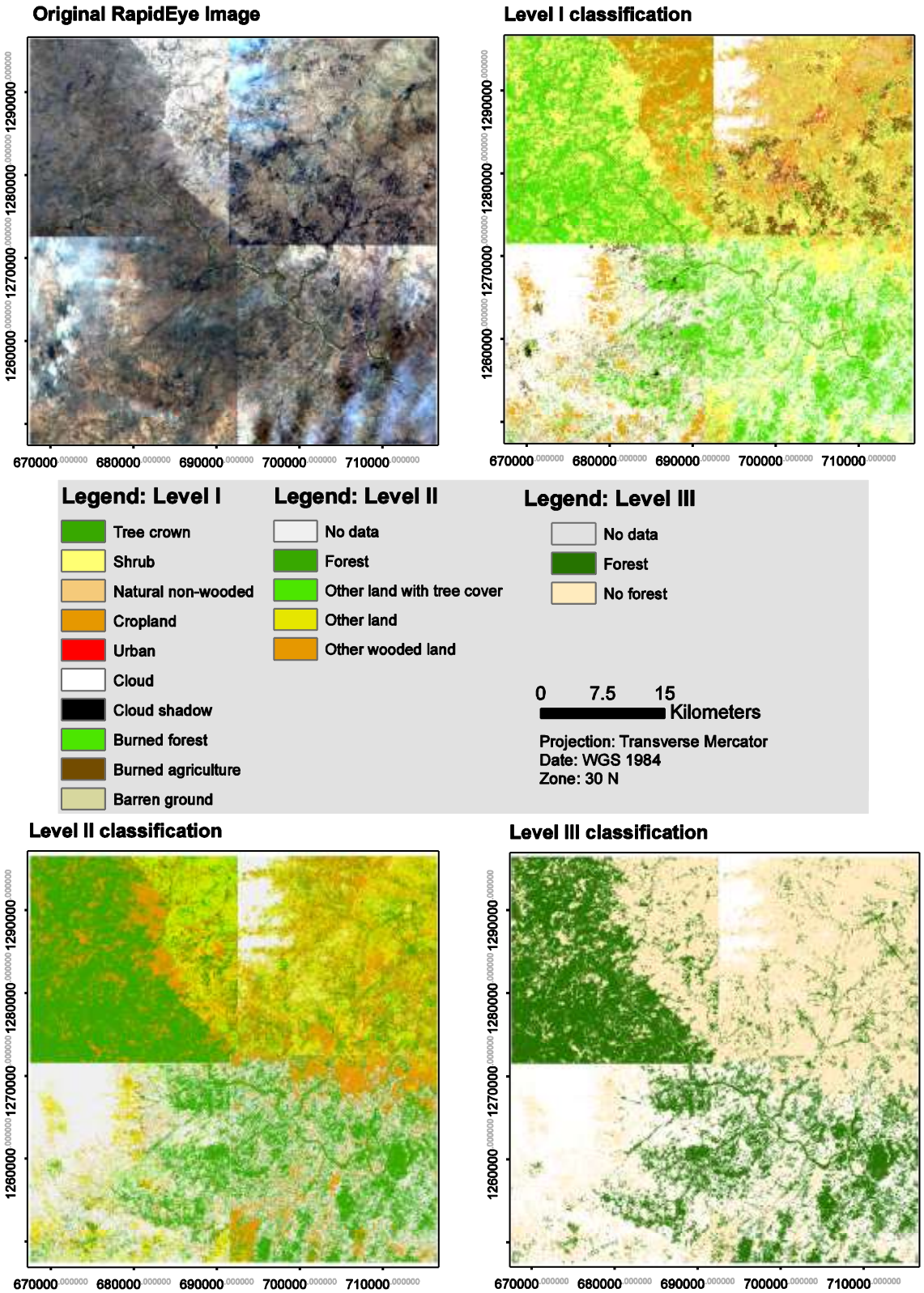

Figure 19: Original RapidEye image and resulting land cover and FAO accordant land use classification levels I-III for study site Nobéré (PSU 13). Scale of imagery 1:550.000.

PSU 20 is an area of intensive agricultural use, located at the mid-western part of Burkina Faso, being on the western edge of the central plateau, where we had 30 validation points for class crop land and nine for class burned agriculture (Table 11). As fire is extensively used, not only for land preparation, but also for land clearing, we observed 24 validation points for the class “burned forest” and only five for the class “tree crown”, showing the high importance of fire. The class “tree crown” had an user accuracy of 0.5, whereas “burned forest” resulted in high user accuracy with 0.88. Shrubs, constituting an important part of the vegetation especially in fallow areas, were represented by 16 validation points and an user accuracy of 0.80. The reasons why PSU 20 is the study site with the second lowest overall accuracy of the four considered study sites can partly be attributed to the presence of clouds and haze in the original imagery. Nine validation points were assessed as “cloud”; the user accuracy for the class “cloud” is low with 0.25. The misclassification of clouds in this region can be associated with the fact that the clouds present were haze (see Figure 20) thus the reflectance of the vegetation underneath the clouds was visible and thus falsely interpreted by the RandomForest classifier. It can be concluded that an overall accuracy of 0.82 with a corresponding kappa value of 0.77 (Table 11) for PSU 20 is within the frame of our expectations with regards to classification accuracy, but higher accuracies could be achieved in cloud and haze free imagery.

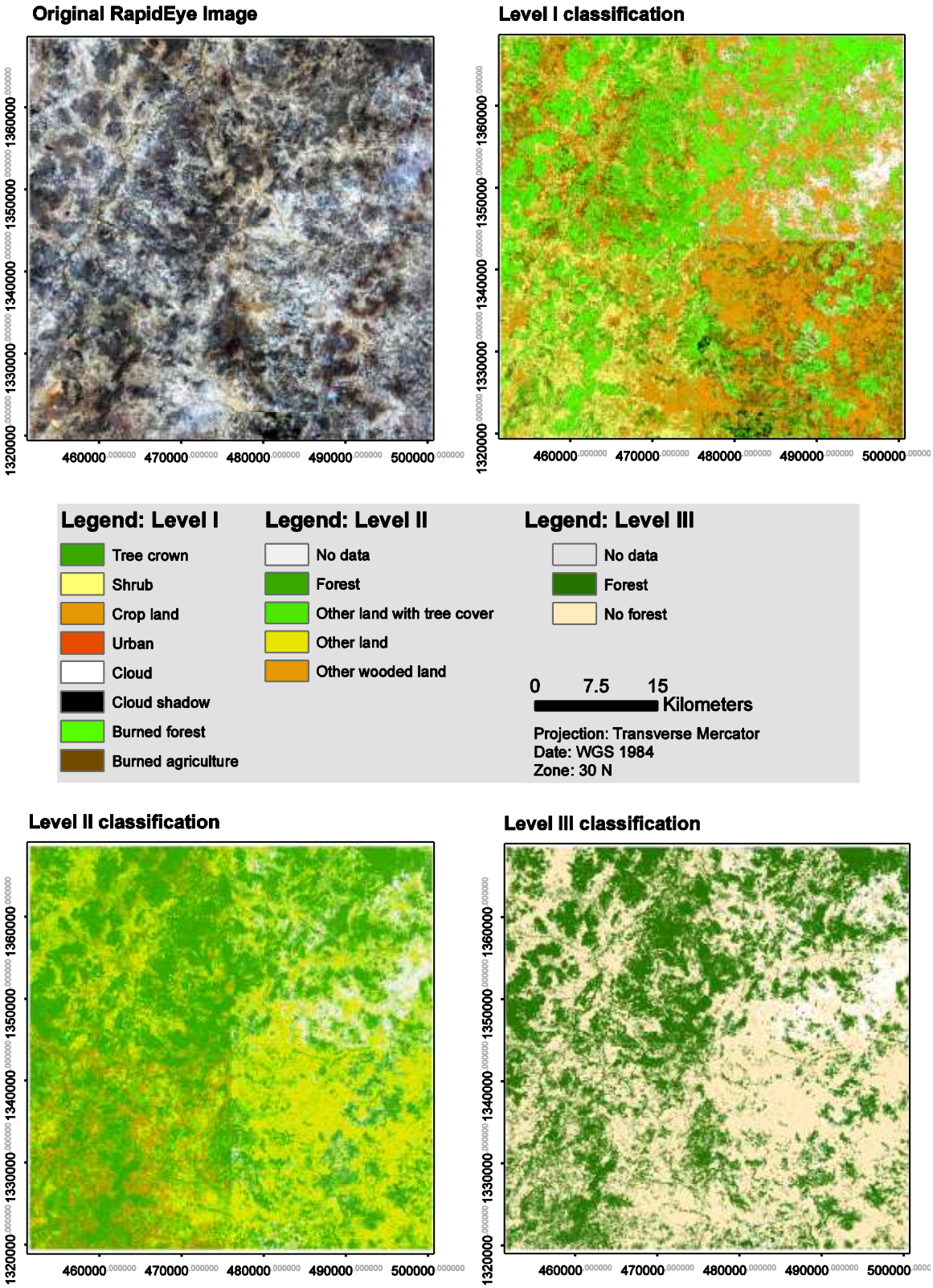

Figure 20: Original RapidEye image and resulting land cover and FAO accordant land use classification levels I-III for study site Safané (PSU 20). Scale of imagery 1:550.000.

The study site of Tougouri (PSU 43) is the northern most study region considered for the regional scale land use classification, exhibiting the lowest annual rainfall of the four study sites included in the remote sensing based land use classification on regional scale. Large areas of uncultivated barren soils are present, which are represented by 31 validation points (Table 11) with a user accuracy of 0.96. The dominating vegetation class in this area is the class “natural non-wooded land” with 41 validation points and 0.81 as user accuracy. Scattered trees or groups of trees along rivers and dams are also present in the landscape (see Figure 21). Shrubs are a very common life form in this region; nevertheless, we only assessed two validation points for this class, with user accuracy of 0.93 (Table 11). The study site of Tougouri is the only study site where inland water bodies are present. We assessed one validation point for class “water”, which was misclassified leading to a user accuracy of 0.00 (see Figure 21, Level I classification). As already observed for other study sites the presence of clouds and haze led to confusion with bright barren soils. Nevertheless, PSU 43 had the overall accuracy with 0.87 and the highest kappa value with 0.81. The higher overall accuracy compared to the other three study sites is probably attributed to the reduced patchiness of land use within this study site as well as high contrast between the classes present and considered for classification.

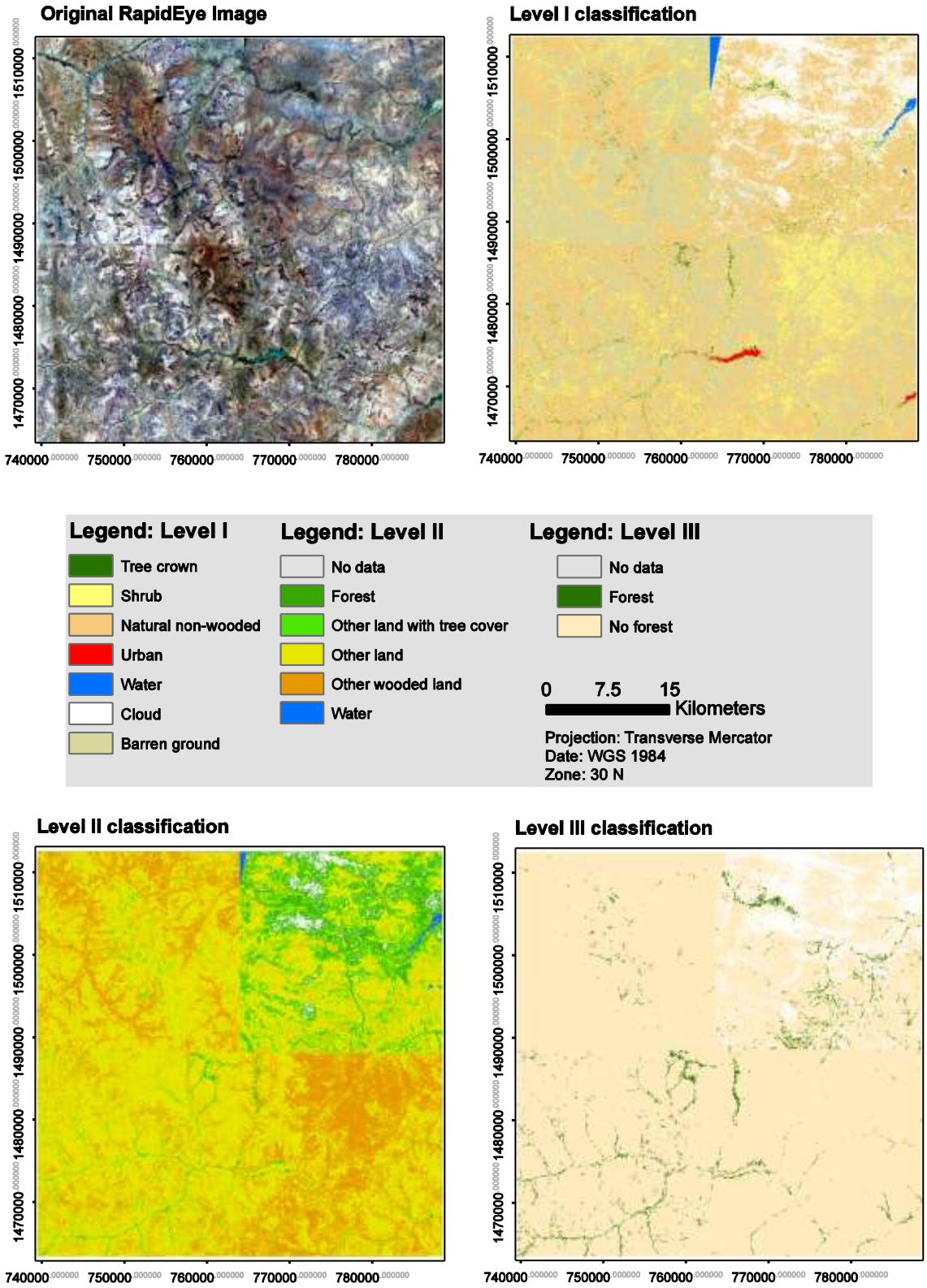

Figure 21: Original RapidEye image and resulting land cover and FAO accordant land use classification levels I-III for study site Tougouri (PSU 43). Scale of imagery 1:550.000.

Table 11: Validation results for all four study sites.

Study site	Sokouraba			Safané			Nobéré			Tougouri		
Level–I Class	Number of validation points	Producer accuracy	User accuracy	Number of validation points	Producer accuracy	User accuracy	Number of validation points	Producer accuracy	User accuracy	Number of validation points	Producer accuracy	User accuracy
Tree Crown	13	0.77	0.63	5	1.00	0.50	2	1.00	0.50	4	1.00	1.00
Shrub	31	0.94	0.85	16	0.75	0.80	41	0.63	0.93	2	0.82	0.93
Natural Non-wooded	0	-	-	0	-	-	1	0.00	0.00	41	0.95	0.81
Agriculture Plantation	0	-	-	0	-	-	0	-	-	0	-	-
Pasture	0	-	-	0	-	-	0	-	-	0	-	-
Crop Land	26	0.77	1.00	30	0.87	0.96	6	0.67	0.57	0	-	-
Urban	0	-	-	0	-	-	0	0.00	0.00	0	-	-
Water	0	-	-	0	-	-	0	-	-	1	0.00	0.00
Cloud	3	1.00	0.43	9	0.50	0.25	9	1.00	0.32	6	0.83	0.83
Shadow	2	0.50	1.00	0	-	-	0	-	-	0	-	-
Burned Forest	13	0.85	0.92	24	0.88	0.88	24	0.67	0.94	0	-	-
Burned Agriculture	9	0.67	0.86	21	0.76	0.84	7	0.43	1.00	0	-	-
Barren Soils	1	1.00	1.00	1	0.00	-	0	-	-	31	0.81	0.96
Overall Accuracy			**0.83**			**0.82**			**0.67**			**0.87**
Cohen's kappa			**0.78**			**0.77**			**0.56**			**0.81**

When comparing the out-of-bag (OBB) accuracy estimates provided by the RandomForest classifier to the assessed cross validation results, one cannot observe a clear trend. Meaning we did not observe that the OBB estimates are always lower or higher than the cross validation results (Table 12). This observation leads us to the conclusion that the RandomForest classifier does not introduce a bias in this form, nor does over fitting occur following the observation of (Breiman 2001). This result further convinced us of the advantages of the RandomForest classifier, delivering conservative realistic classification results.

Table 12: Comparison of out-of-bag (OBB) accuracy provided by the RandomForest classifier with results of cross validation from Table 11.

	OBB estimates (5 features)		Cross validation	
	Accuracy	Kappa	Accuracy	Kappa
PSU 4	0.76	0.61	0.83	0.78
PSU 13	0.82	0.69	0.67	0.56
PSU 20	0.74	0.60	0.82	0.77
PSU 43	0.88	0.78	0.87	0.81

6.2.3 National scale land use classification

We overlaid the original MODIS MOD09GA image mosaic, covering the whole of Burkina Faso, with the RapidEye based FAO conform land use classification to derive the training data needed for the national scale classification based on the MODIS imagery (see 5.2.8). The RapidEye based land use classification at regional scale had a resolution of 5 x 5 m per pixel, while each of the MODIS pixel overlaid had a size of 500 x 500 m. As described before, we included four study sites into the up scaling approach. Each of the four regional scale study sites constituted 100,000,000 classified pixels. Each of the four study sites were covered by 10,000 pixels, leading to 40,000 MODIS pixels included in the overlay. We were able to identify n = 491 MODIS pixels that were completely covered by forest, a pure pixel for land use class “forest”. Further, we assessed n = 215 pure pixels for class “other land”, n = 4 pixels were completely covered by “other wooded land”, and n = 2 pixels were assigned to class “water” (see Table 13).

We used the *n* = 712 pure pixels to calculate a RandomForest (for further descriptions see 5.2.5) with *n* = 500 trees, for the final land use classification on national scale. With the given input the RandomForest classifier calculated an out-of-bag classification error of 0.84% (Table 13).

The confusion matrix in Table 13 shows that most uncertainty occurs in the two classes “OWL” and “water”, which are represented with only four and two pixels, respectively. Two out of four OWL pixels were correctly classified, leading to a classification error of 0.5 (Table 13). The falsely assigned pixels, actually belonging to class “other wooded land” were assigned to class “forest”. For the class “water”, the classification results were very poor, as the two pixels belonging to this class, were confused, leading to a classification error of 1. The total misclassification of “water” is also visible in (Figure 23), where no “water” pixels are present, assigning pixel of class “water” to class “other land”. The misclassification of “water” is most probably due to the fact that the water bodies identified were coloured green (see Figure 21 Original RapidEye image), due to high algae concentrations. High algae concentrations do occur during the dry season, when the water level is low and water temperatures are high. The other two major land use classes included in the classification were “forest” and “other land”, where classification errors were very low with 0.002, and 0.005, respectively. Confusion of forest pixel occurred only with class “OWL”, whereas pixels belonging to class “other land” were falsely assigned to class “forest” (Table 13).

Overall it can be concluded that the OBB error estimate is very low, implying a very high classification accuracy. Classes including more training pixels such as “forest” and “other land” had much lower classification errors compared to classes with small training data sets. The higher classification accuracy can be attributed to the coverage of more inter-land use class variability by a higher number of training data. Further, we concluded that a low OBB error estimate showed that using the seven original reflective bands (Table 5) is sufficient as input to the classification.

Table 13: Confusion matrix of the RandomForest (500 trees) based on MODIS imagery (OWL = other wooded land).

		Predicted				
		Forest	OWL	Other land	Water	Class. error
Observed	Forest	**490**	1	0	0	0.002
	OWL	2	**2**	0	0	0.500
	Other land	1	0	**214**	0	0.005
	Water	0	0	2	**0**	1.000

Out-of-bag estimate of error rate: **0.84%**

In Table 14 we listed the respective mean decrease of Gini (MDG) for each band, used in the building of the RandomForest, for the national level land use classification. The MDG is an indicator for the variable importance during classification, which can be used for variable ranking, as described in (5.2.5). Following Calle and Urrea (2010), a high MDG stands for the reduction of uncertainty when selecting this variable to form a split in the RandomForest, for further information (see 5.2.5). Thus, variables with a high MDG are more important while calculating the RandomForest, carrying relevant information, than variables with a low MDG.

It was assessed that the three most important image bands for the classification were band 14 (green), followed by bands 13 (blue) and 11 (red), respectively (Table 14). Further, it was observed that band 15 (NIR) incorporated a much lower mean MDG value than all other image bands (Table 14). Where a value of 2.26 is about seven times smaller than the second smallest MDG value with 16.64 for band two (Table 14). The above stated observations lead us to the conclusion that the two NIR bands (bands 14 and 15) of the MODIS image product MOD09GA did not carry much information, in addition to what was already provided by the other five bands, thus did not play an important role in land use classification within this study.

Table 14: Variable importance for the MODIS imagery (MOD09GA) classification, calculated by the RandomForest using 500 trees.

Original MODIS band	Mean decrease Gini (MDG)
Band 11	54.80
Band 12	16.64
Band 13	65.42
Band 14	72.84
Band 15	2.26
Band 16	54.77
Band 17	41.60

The cross validation of the MODIS classification was carried out by comparing the results of the terrestrial sampling described in 5.1 with the remote sensing based classification. Thus the results of the field based inventory were used as ground truthing data as recommended in the various literature (Jensen 2005; Campbell 2008; Lillesand 2008). The cross validation was implemented by comparing the results of each circular plot (CP) assessed in the field with the corresponding MODIS pixel classification value. Here, it should be considered that each CP was a circle with 15 m radius, while one MODIS pixel was a square with a side length of 500 m, resulting in large differences in the reference area used for comparison. The results of the cross validation are presented in Table 16. It was assessed that the MODIS classification led to an overall accuracy of 64% with a kappa value of 0.31. Further, we were able to calculate estimates of land use class proportions for Burkina Faso. From the cross validation in Table 16 we calculated the following land use proportions 1.) forest = 30.76%, 2.) other wooded land = 2.82%, and 3.) other land = 66.41% (see Table 15).

Table 15: Area estimates of FAO land use classes on country level, where OLWTC is "other land with tree cover.

FAO land use class	Source and coverage in of Burkina Faso [%]		
	FRA 2010	This study: terrestrial with (SE%)	This study: remote sensing
Forest	21.0	42.6 (9.9)	30.8
Other wooded land	18.0	1.6 (41.4)	2.8
Other land	60.9	53.6 (8.5)	66.4
OLWTC	21.5	9.1 (17.4)	-
Inland water bodies	0.1	2.2 (99.9)	-

When analysing the confusion matrix in Table 16, one can see that land use class "OLWTC" was not predicted at all. This is due to the fact that no MODIS pixel was covered by only OLWTC, when applying the spatial overlay described in 5.2.8. Accordingly OLWTC was not included in the MODIS based remote sensing classification on national scale. Thus, no conclusion can be drawn with regards to the area covered by OLWTC in Burkina Faso, using MODIS imagery. Most of the areas covered by OLWTC, following ground data, were assigned to class "forest" and "other land" (see Table 16). Further, nearly half of all n = 393 CP assigned to class "forest", were falsely assigned to class "other land" (Table 16), whereas the largest misclassification for class "other land" with n = 442 sample points was done with class "forest". The previously described result leads us to the conclusion, that there are still major issues to solve with regards to the clear separation of these two named land use classes. A clear distinction of the two main land use classes in Burkina is needed to improve remote sensing based land use classification. As a consequence of the results presented in Table 13, where "water" had a classification error of one, class "water" showed an user accuracy of zero. The user accuracy of zero for class "water" is due to the fact that all n = 10 CP of class "water" were assigned to class "other land" during the MODIS classification (Table 16). Classification results for class "OWL" were weak, as of the actual n = 15 CP covered by OWL zero were correctly classified. Nearly all of the falsely classified "OWL" pixels were assigned to class "other land", leading to a producer accuracy of zero for class "OWL". Nevertheless, the user accuracy for class "OWL" is quite high with 0.91. A total of n = 12 pixels were falsely assigned to class "OWL", eleven "forest" pixels and one "OLWTC" pixel, respectively. This observation leads to the conclusion that the area estimate for class "OWL"

in the final land use map (Figure 23) is in accordance with the field sampling based area estimate for this land use class. However, one should keep in mind that the map in Figure 23 is not free of errors, where the accuracy assessment is given in Table 16. Nevertheless, the accuracy assessment does not provide information on the spatially explicit distribution of the classification error.

Table 16: Error matrix for the MODIS based FAO conform land use classification of Burkina Faso (OWL = other wooded land, OLWTC = other land with tree cover).

		Observed					
		Forest	OWL	Other land	OLWTC	Water	
Predicted	Forest	**193**	2	53	31	0	279
	OWL	11	**0**	0	1	0	12
	Other land	189	13	**389**	13	10	614
	OLWTC	0	0	**0**	0	0	0
	Water	0	0	0	0	0	0
		393	15	442	45	10	**905**
	User acc.	0.69	0.91	0.31	-	-	
	Producer acc.	0.49	0.00	0.88	0.00	0.00	
	Overall acc.	**0.64**					
	Cohen's kappa	**0.31**					

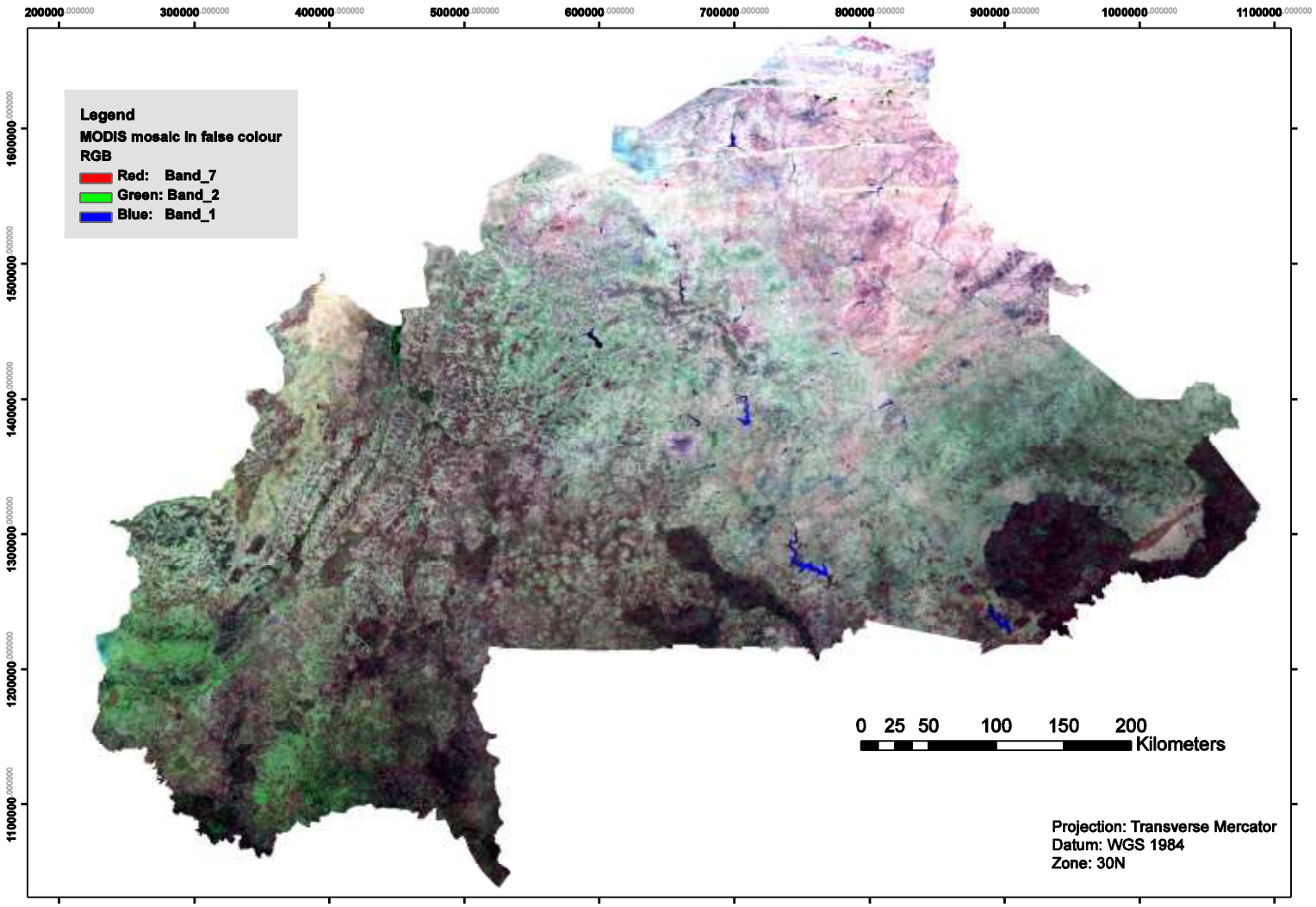

Figure 22: MODIS (MOD09GA) mosaic of Burkina Faso used as basis for FAO conform land use classification.

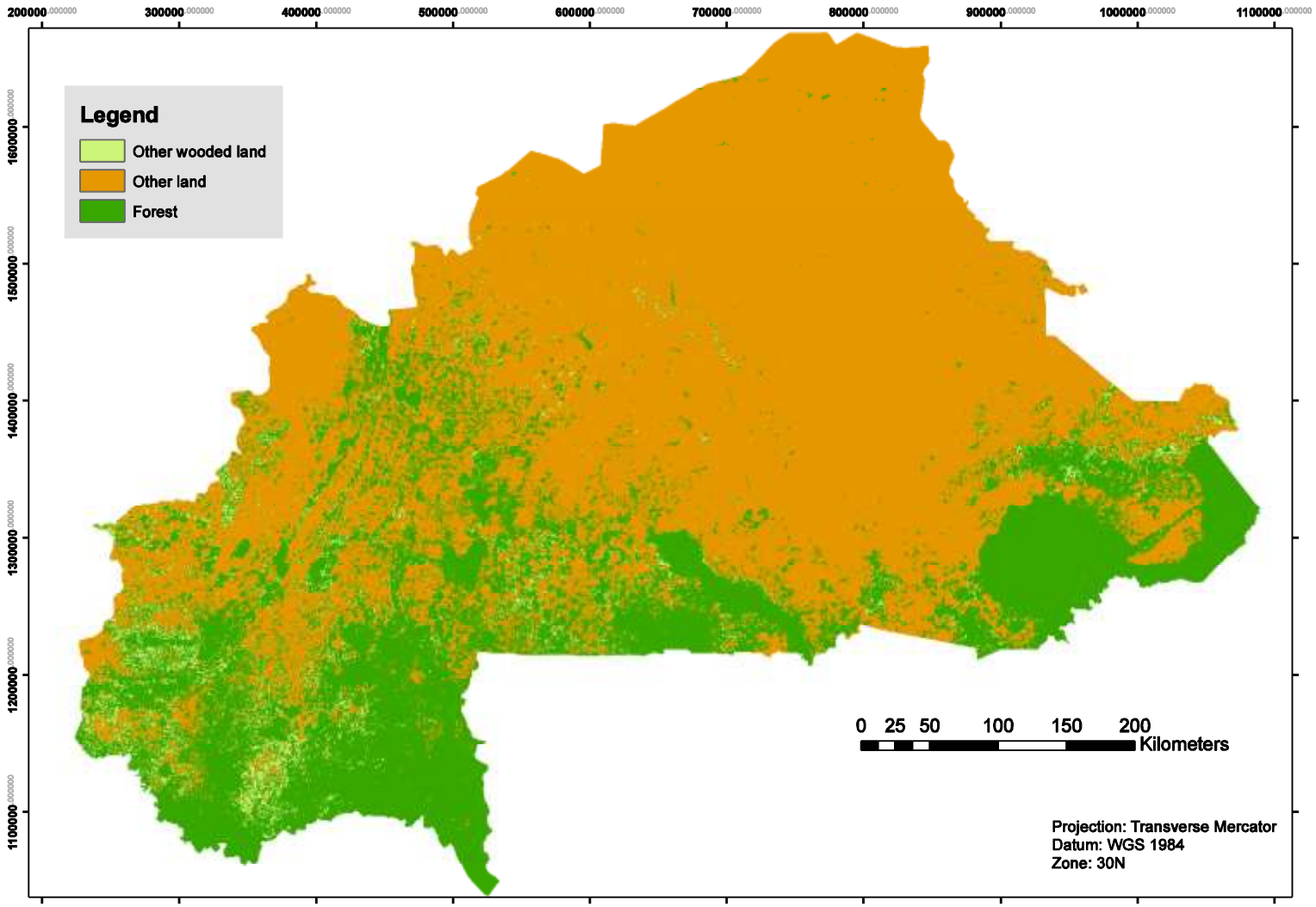

Figure 23: MODIS based map of Burkina Faso with land use classes following FAO definitions.

7 Discussion

Most parts of the discussion for the terrestrial sampling follow the discussion described in: Fischer et al. 2011. A national level forest resource assessment for Burkina Faso - A field based forest inventory in a semi-arid environment combining small sample size with large observation plots. Forest Ecology and Management, doi:10.1016/j.foreco.2011.07.001.

7.1 Terrestrial sampling

7.1.1 Sampling approach and estimates of land use classes

We applied a sampling design where we adopted a low sample size combined with large sample plots. Even though sample size is can be considered low, the number of measured field cluster subplots is quite large (n = 905). Here it is important to consider the difference between sample size and sample plot. As sample size is the number of samples that were statistically independently selected, which is n = 53 and that was further reduced to n = 46 because of non-response (Fischer et al., 2011). We consider the conducted inventory the first field based sampling approach, covering the whole of Burkina Faso, which permits the calculation of estimates on land use classes based on statistical grounds (Fischer et al., 2011). We were also able to estimate confidence intervals for our estimates. Fischer et al. (2011) state: "The results show that the methods applied are suitable for the conditions encountered in Burkina Faso and for the inclusion of the tree resource on other lands than forest. The estimated errors of estimation, though, were in the order of magnitude of 9%, owing to the small sample size. Comparison to other error estimates on land use area was not possible due to unavailability of such data."

Errors within the magnitude of 9% are commonly accepted in small area forest management inventories. Whereas large area forest inventories like the German national forest inventory allows error estimates within the order of magnitude of 1%, contrasting our sampling scheme, these inventories as commonly characterized much higher sample size (e.g. twenty thousand). Experiences with large area inventories based on small sample size were made in a FAO study conducted in Costa Rica where the relative standard error varied between 9.3%

and 32% for different land use classes, depending in their cover, thus samples within the class (Kleinn et al. 2005).

Following Fischer et al. (2011) it was identified that it is mostly unclear to which precision level estimates should be made when it comes to large area forest assessments. “Based on the inventory design implemented in this study, one can easily estimate the required sample size if an area estimation with a precision level of, for example 5%, is targeted. Given a SE% of 9.9% for a sample size of $n_{9.9\%}$ = 46 observed field plots and assuming simple random sampling with the common error probability of $\alpha = 0.05$ (setting t = 2), one would estimate a needed sample size by the factor $(9.9/5)^2 = 3.9$ times larger than in our study, that is about $n_{5\%} = 3.9*46 = 179$” Fischer et al. (2011).

One of the central questions, especially within the context of development research is whether the government of a developing country would be willing to make expenses 3.9 times higher for a 2 times higher precision (Fischer et al., 2011). Following Kleinn et al. (2010) we put emphasis on the point that a great need of research is needed within this context as the link between the precision of estimation of data and its usefulness in political processes is largely unknown.

Following Fischer et al. (2011): “It should be noted here that the area estimates mentioned above are based exclusively on field sampling with a relatively small sample size.” A general assumption is that full cover high resolution remote sensing imagery, which is very costly, or high resolution remote sensing support of field sampling would have allowed increasing the precision of estimation of land use areas (Fischer et al., 2011). When combining field based observations with remote sensing based observations, next to the standard error, also the error of observation is of importance. A good example can be found in the distinction between land use classes in dry areas where closed crown surfaces are not common, making distinction challenging. Here, field observations are supreme as they are based on direct observations for variables like crown cover or tree and shrub height (one criterion in the FAO definition of “forest” and “other wooded land”) (Fischer et al., 2011). Furthermore the distinction between trees and shrubs is much better possible from a ground based study. We consider the named uncertainties related to the application of the FAO definitions in remote sensing studies as the major reason for the enormous divergences between our field based estimates and FAO estimates for forest area (about the factor 2 higher in our study) and the

area of other wooded lands (about the factor 12 lower in our study) (see Table 7) (Fischer et al., 2011). We base this assumption on the observation that the sum of the two area estimates is more within the range of our estimates, with about 12% when compared to the standard error of estimation. Following Fischer et al. (2011): "The discrepancies in land classification between field based and remote sensing based studies following criteria of minimum tree crown cover appear to be insufficiently researched so far. This point is of importance also for all carbon accounting approaches where area estimates (so called "activity data") are of critical relevance."

7.1.2 Forest structure and land use

The multi-purpose "shea butter tree" *Vittelaria paradoxa* is the most abundant and most important tree species in Burkina Faso, in particular in agroforestry systems which is promoted by legal regulations for the protection of this species (Fischer et al., 2011). Our observations made with *Vittelaria paradoxa* are in line with the observations from several authors who came to the conclusion that species spatial distribution in general is largely affected by human intervention (Augusseau et al. 2006). Maranz and Wiesman (2003) analysed paleobotanical and recent data on *Vittelaria paradoxa* and come to the conclusion that its distribution is exclusively defined by human involvement. Furthermore our observations fortify the results of Boffa (1999) & Maranz and Wiesman (2003) who assessed that it is common for African semi-arid regions with a long land use history, that single multipurpose species are kept during land clearing. This practice leads to high abundances of multipurpose tree species within the land scape. Fischer et al. (2011) agree with the named observations, where the human influence on vegetation was assessed by measuring the tree stumps. Here, we assessed a highly significantly difference ($p < 0.001$) in proportions of cut trees between land use classes (3.6% for forest and 24.2% for other land with tree cover), which points to the importance of logging for land preparation and other uses following the results of Maranz and Wiesman (2003).

Abandoned agricultural land mostly falls into the land use category "other wooded land" which is dominated by the shrub species *Piliostigma reticulatum.* Whereas the second and third most abundant species in "other wooded land" are the tree species *Vittelaria paradoxa*

and *Lannea microcarpa* which are the two most abundant species in “other land with tree cover”. We observed that “other wooded land” is an important land use class for herders as no direct ownership is valid, thus access is permitted to them, and the shrub species are an important fodder resource for the animals. Furthermore, we came to the conclusion that “other wooded land” can be seen as the source of tree species regeneration as we measured more regeneration from different species within this land use class than in any other, pointing to its ecological importance.

7.1.3 Above ground carbon

As one of the variables considered biomass calculations is wood density, which varies with species, it was proposed by Nygård and Elfving (2000) to take species composition into account when calculating woody biomass. Moreover Nygård and Elfving (2000) assessed that species composition varies for different forest sites in Burkina Faso and thus recommended to take species frequencies into account for the estimations of woody biomass. Following Fischer et al. (2011), we calculated a median wood density for the 10 most abundant tree species in each land use for biomass and carbon estimations. We were surprised that the estimates of above ground tree carbon AGC_{Tree} stocks do not vary much between the included land use classes. We were even more surprised that "other land with tree cover" stored more biomass than "forest". Our interpretation of this result is that farmers conserve and favour large, productive agroforestry trees that are known to highly contribute to biomass (e.g. a Baobab with a diameter of 3 m), this was also observed by Chave et al. (2003) and Chave et al. (2004).

A common impediment for the comparison of data on biomass is the difference in methods used. We encountered similar challenges not only due to methodological issues like the minimum diameter to consider or where to measure the diameter or differences in land use definitions, but also due to the plain unavailability of other studies for the region. All studies we could find are small area case studies (Nygård and Elfving 2000; Woomer et al. 2004b) that do not need to cope with the issue of large area variability (Fischer et al., 2011). Based on our experiences we fully agree with Lewis et al. (2009) who state that carbon storage of about one-third of the world’s tropical forests, which is located in Africa, are to large parts

unknown simply because of the lack of spatially extensive observation networks and suitable biomass models, especially so for the dry tropics.

As mentioned above, all comparisons made with other studies should be treated with care. Nevertheless we would like to compare our results with the some available, published estimates (Fischer et al., 2011): For land use classes or plant communities, ranging from degraded grasslands to degraded shrub lands with scattered trees Woomer et al. (2004b) estimated AGC_{Tree} stocks in the Sahel zone of Senegal. Here, AGC_{Tree} stock estimates were estimated to range between 0.419 - 6.543 Mg ha^{-1}. In addition, Woomer et al. (2004b) observed a significant correlation between crown cover and total carbon stocks. Following Fischer et al. (2011) "They found that an increase of canopy cover to about 16% would lead to stocks of about 12 Mg ha^{-1}; this, however, is far above the AGC_{Tree} of 6.640 Mg ha^{-1} that we estimated for forest area with a crown cover of more than 10% in Burkina Faso." The second study we compare to by Touré et al. (2003) estimated about 1.8-5.8 Mg ha^{-1} of carbon for protected woodland in Central Senegal, being much more within the range of our estimates. Woomer et al. (2004a) conducted a second study where they assessed carbon stocks for cultivated tree parklands in Senegal. Here, Woomer et al. (2004a) calculated AGC_{Tree} stocks of 32 Mg ha^{-1}; this is far above our estimates of 7.222 Mg ha^{-1} Fischer et al. (2011) and the findings of Tschakert (2004) with AGC_{Tree} stocks of 6.3 Mg ha^{-1}. With these few comparisons, based on published estimates for the region give insights to the wide range of AGC_{Tree} stock estimates for semi-arid environments and show the urgent need for harmonized measurement protocols as well as land use definitions (Fischer et al., 2011).

With our study we were able to show that both, area estimates ("activity data" in IPCC terminology) and estimates of carbon per hectare so called "carbon density" and "emission factors" for semiarid areas with tree and/or shrub cover pose manifold challenges that are insufficiently researched (Fischer et al., 2011). In addition Fischer et al. (2011) perceived that: "Large lacks of data concerning allometric functions for trees and especially shrubs exist, for tropical Africa. We are convinced that significant research is needed also beyond the current mainstream of remote sensing oriented research to achieve significant improvements of carbon estimates for semiarid regions like in Burkina Faso."

7.2 Remote Sensing

7.2.1 Regional scale land use classification

With the developed classification method we were able to produce FAO conform land use maps for the study regions considered, based on RapidEye imagery. In addition to the classification, we were able to report statistically sound accuracy estimates for the classification.

The developed classification method is based on the RandomForest classifier, which proved to be able to handle multidimensional data. The classification accuracies were high and within the range of other studies (e.g. Gislason et al. (2006)).

We were able to calculate statistically sound error estimated with the applied sampling strategy for train- and validation datasets. With the applied approach, using a systematic grid, covering the whole image of interest we guaranteed an equal coverage of the whole scene. It should be considered that this approach does not guarantee an equal amount of training data; due to the self-stratification implied by systematic sampling, where each class is sampled proportional to its size. As a result of the before described, rare land use classes (e.g. inland water bodies) were covered by few training points. As the validation points were also assessed using systematic sampling, the same precautions have to be taken as for the training data, as further research is needed with regards to the effect of sampling scheme on classification and validation results.

Classification errors for the regional land use maps were in the range of 13 - 33% for the Level I classification. With the spatial resolution of the RapidEye sensor we were able to detect large single trees and trees along rivers with high accuracies, contributing to the estimation of tree resources outside the forest.

It can be assumed that aggregation of classes would lead to smaller classification errors, as described in Walker et al. (2010), where an aggregation of classes leads to reductions in confusion probability between classes. We observed very similar trends when comparing classification results of study site Nobéré with ten classes in Level I, to classification results of study site Tougouri with seven classes. Thus we conclude that classification accuracy results for Level II are higher than the given cross validation results for Level I. Even higher

classification results can be expected for the Level III classification results, considering the fact that trees and shrubs had high classification accuracies and these classes are essential for the forest, non- forest classification.

In addition to the number of features and land use classes considered during the classification, land use spatial patchiness has to be considered as an additional factor influencing classification accuracy. We observed that classification accuracy results for the study site Tougouri were higher than for the other three study sites, as it is a more homogeneous area. Thus, the classification accuracy is also be influenced by the landscape structure. This observation is in line with the findings of Moody and Woodcock (1995), where a negative influence on classification results was observed with decreasing patch size i.e. more heterogeneity.

As mentioned in the methods section (5.2.5), the RandomForest classifier provides the possibility to assess the importance of each feature for the classification (Breiman, 2001). We used the Gini index to rank features corresponding to their importance, even though other measures like the chi-square method (Mingers, 1989) are available. This procedure was based on the findings of Breiman (1984) where it was assessed that the classification level does not depend on the choice of selection measure.

It was observed that during regional scale classification with the RandomForest classifier, all original image bands were chosen for the classification, where NIR was the band with the highest selection probability with 18.25%. Further, all vegetation indices were selected as well, where NDVI green was chosen with a probability of 13.75%, being the band with the second highest selection probability. In a study by Marx (2010), NDVI green also proved useful for a rule based classification when distinguishing different levels of beetle attack, based on RapidEye imagery. When the NDVI green was introduced by Gitelson (1996), it was assessed that NDVI green is on average five times more sensitive to chlorophyll concentration than the NDVI. We conclude that the improved sensitivity of NDVI green helped distinguishing vegetation, which shows very similar reflective properties and was helpful in the detection of vegetation, even during the dry season, where imagery was acquired.

In addition to the above mentioned factors influencing classification accuracy, Achard et al. (2007) mentioned clouds to be one of the main obstacles for remote sensing in the tropics;

whereas Burkina Faso is not fully part of the humid tropics, where clouds pose a constant hindrance. We agree with the mentioned finding, in our study especially haze was identified as a major hindrance during classification, as can be seen in Figure 19. Haze does not incorporate a sharp border between cloud and non-cloud, making distinction difficult, her further research is needed. Never the less it should be noted that we did achieve good classification results for clouds with clear outlines.

7.2.2 National scale land use classification

With the applied method for up scaling, applying the RandomForest classifier we were able to produce FAO conform land use maps for the whole of Burkina Faso.

Following Moody and Woodcock (1995), we think that the relationships between the spatial pattern of land use classes, the scale of observation and the corresponding classification error have to be considered, when it comes to the ranking of classification accuracy. With regards to the above mentioned, it should be noted that not all land use classes that could be classified on the regional scale could be up scaled using 500 m resolution MODIS imagery. The classes affected by this were “other land with tree cover” and “inland water bodies”. The reasons for the above described could lie in the fact that OLWTC is a land use class that is very patchy, meaning that it did not obtain a size of 500 x 500 m, within the regional scale land use classification, without enclosing other land uses. For the land use class “inland water body” the situation is different, here the reason lays in the misclassification during up scaling. Thus, we agree on the general findings of Moody and Woodcock (1994), who assessed that large classification errors can occur with increasing sensor resolution. The results described above, with regards to the land use classes “OLWTC” and “Inland water bodies” are similar to the findings of Turner et al. (1989) who describes that rare land use classes can disappear during up-scaling. Further it was also assessed by Moody and Woodcock (1994) and Turner et al. (1989) that the interaction between the scale of aggregation , the spatial pattern of the landscape and the initial proportion of the element of interest (in our case the land use classes) will constitute in the coarser resolution land cover map.

Among others, Walton (2008) described that many classification techniques, so called hard classifiers, cannot work with in situations were mixed pixels occur. In our case mixed pixels are often present, as our target variable, land use class, is often smaller than one pixel. This situation is often the case for sensors of moderate resolution like MODIS. Huang and Townshend (2003) state that non-parametric methods, like decision tree and thus also RandomForest, are well suited to cope with such data, resulting in more reliable results than results from parametric classifiers. Decision tree methods do not imply normal distribution of data (Breiman, 2001) and are ranked as one of the most efficient expert systems (Im and Jensen 2005).

Further, it was assessed that supervised classifiers strongly depend of the data used for the training of the classifier (Campbell 1981). We think that the approach applied by us is well suited to deliver high quality data as input to the classifier, excluding mixed pixels.

Before using the MODIS data as input for the RandomForest classifier, we did not undertake any image enhancement measures like calculating additional image bands e.g. NDVI, among others. We used that approach as it was assessed by Pal and Mather (2003) that increasing the number of bands does not always increase classification accuracy. Our observation is in the same direction as we achieved an OBB error estimate of 0.84 which is very good, without calculating additional bands. Another reason for not calculating any additional bands before the classification was based on the experiences made by Baccini et al. (2008) where carbon stocks were estimated with a combination of MODIS imagery and ground data using the RandomForest classifier. Within their study it was assessed that including ratio bands like the NDVI, Enhanced Vegetation Index (EVI) or the Leave Area Index (LAI) did not result in a large increase of classification accuracy, sometimes even having negative effects on the classification. Thus, in their study it was also concluded that using the original seven MODIS bands, which were designed to monitor landscapes would be the best approach.

We did assess that the MODIS image product we used was well suited for the classification and observed that the green band was the most important band during classification, which is not astonishing when classifying vegetation.

When comparing our results to a study conducted by Borak and Strahler (1999) where a decision tree method was applied to classify a MODIS (1 km resolution) land cover product for a semiarid environment with similar land use classes as the ones encountered in Burkina

Faso, with an achieved overall accuracy of 42%, we achieved a considerably higher accuracy. Further, we do not think that the classification result with 64% is related to the quality of the training data, but is much rather an effect of the amount of training data. In a study by Pal and Mather (2003), it was assessed that the classification accuracy of decision tree based classification methods does improve with the size of the training set, accumulating at a certain stage. Nevertheless it was also assessed that decision tree based do not require large training sets to be effective (Pal and Mather 2003). When observing the above mentioned findings we come to the conclusion that one of the reasons for our classification result is the low amount of training data e.g. for class “OWL”. A possible solution to that would be to include more regional scale study sites in the study, by this increasing the amount of training data available for the classifier. An optimal solution would be to use the field based inventory results, using these in a two phase sampling approach, where the remote sensing imagery is acquired based on the field observation information. Thus, image acquisition could be optimized by focusing on the coverage of all land use classes in the remotely sensed data.

As mentioned above, our classification accuracy results achieved during cross validation are, with 65%, perhaps considered low. However, it could be shown that the up-scaling approach developed is applicable and suggestions for the improvement of classification accuracy were developed. With regards to the estimates of “forest”, “other wooded land” and “other land” area, where we estimated covers of 30.8%, 2.8%, and 66.4%, respectively, we observed that these estimates are more in line with our terrestrial sampling based estimates, than with estimates of FAO FRA 2010. During terrestrial sampling we estimated 42.6% with SE% of 9.9 for Forest, 1.6% with SE% of 41.4 for OWL, and 53% with SE% of 8.5 for land use class “other land”. Whereas following FRA 2010 Forest area was estimated to be 21.0%, OWL 18.9% and other land 60.9%, respectively (see Table 15). Here we conclude that our remote sensing based approach delivers more realistic results than the FAO FRA remote sensing based approach, especially when it comes to the distinction of land use classes where shrubs are included (e.g. OWL).

Further we compared our forest area findings with the results presented in (Xiao et al. 2009), where different land cover products like Global land cover 2000 (GLC 2000) and the MODIS land cover product (MOD12Q1) were compared. The GLC 2000 is based on one km

resolution imagery, obtained from the platform “Satellite Pour l’Observation de la Terre (SPOT) VEGETATION”, and was developed by the Joint Research Centre (JRC) of the European Commission, together with more than 30 other partner institutions around the world (Fritz et al. 2003). The MODIS land cover product was developed by the Boston University, based on one km resolution MODIS imagery (Friedl et al., 2002).

The comparison showed that GLC 2000 estimated 4.1% of “deciduous woodland” for Burkina Faso, if we would add land use class “deciduous shrub land with sparse trees” to “deciduous woodland” we would obtain a total of 21.5% coverage (see annex for map, Figure 24). Following MOD12Q1 an estimated 2.2% of Burkina Faso is covered with “deciduous broad leave trees”, if we would sum up classes “evergreen needle leave trees”, evergreen broad leave trees”, “deciduous broad leave trees” and “mixed forest” we would obtain a coverage of 2.4%, respectively (see annex for map, Figure 25). The estimates given by GLC 2000 for a land cover class similar to “OWL” with 21.5% for Burkina Faso are within the range of the findings provided by FAO FRA with 18.9%. Compared to our findings they underestimate this land cover, both, to our terrestrial and remote sensing based approaches, where we estimated “Forest” to be within the range of 42.6% and 30.8%. This result of GLC 2000 could be due to the confusion of shrubs with trees as already perceived for the findings of FAO FRA. For forest-like land cover classes MOD12Q1 underestimates the actual “Forest” cover of Burkina Faso about 17-fold, compared to our terrestrial sampling, and about 12-fold compared to our remote sensing approach indicating weaknesses within their classification.

It should be considered that the comparison with the global land cover data sets (GLC 2000 and MOD12Q1) should be done with care, as complete comparability is not always clear, due to different image sources, classifiers and training sets, and forest definitions used (Xiao et al. 2009; Giri, Zhu, and Reed 2005). Nevertheless we can observe that data sets that are the most comparable datasets, with regards to spectral and spatial resolution, to our dataset, very much underestimate the forest cover of Burkina Faso.

When observing our classification results, one comes to the conclusion that the accuracy in terms of geographic location is not as high as in other studies, but the area totals are within expected margins. The observation previously described, has also been observed by Nelson et al. (2009), where they spatially aggregated a dataset and the total area estimates were not deteriorated by this approach. The observations described by Nelson et al. (2009) seem

to be analogue for our up scaling approach. Thus, we conclude that spatial accuracy decreased within the applied up-scaling approach, whereas area estimates were not so strongly affected by the up scaling applied.

8 Conclusion

Most parts of the conclusion for the terrestrial sampling follow the conclusion described in: Fischer et al. 2011. A national level forest resource assessment for Burkina Faso - A field based forest inventory in a semi-arid environment combining small sample size with large observation plots. Forest Ecology and Management, doi:10.1016/j.foreco.2011.07.001.

8.1 Terrestrial sampling

With the conducted study we demonstrated that estimates on a wide range of forest related variables is possible on a national scale, applying a sampling approach based on small sample size combined with large observation plots. Furthermore we showed that estimates are possible at a realistic level of precision. Even though the study was part of an international development research project which focused on the adaptation of agriculture in Sub-Saharan Africa to climate change where the data on vegetation, especially on forest as well as trees and shrubs outside forest, was needed for impact modelling, the study has many similarities to a national forest inventory (Fischer et al., 2011). The exact estimation of the costs connected to inventory as a whole can only be estimated as the inventory was conducted within the frame of a larger collaborative project. We estimated a total of only just about Euro 400 per planned field plot (n = 53) (Fischer et al., 2011)! If we compare to other inventories in the tropics, where low sample size approaches were applied, the cost effectiveness of our study becomes apparent. FAO (2008b) estimated average costs for other tropical country national inventories to be in the order of magnitude of about 2300 Euro per PSU where one of the large cost factors in FAO supported inventories are the expenditures for consultants.

It is clear that an increase in sample size would lead to an increase in precision accordingly (Fischer et al., 2011). We were able to show that not only an increase in sample size is needed to improve estimates in biomass and carbon stocks. Neither will modern remote sensing technologies be able to extensively deliver better-quality data on carbon stocks as developments need to be made in various other fields. Here, we follow Lewis et al. (2009) & Fischer et al. (2011) who concludes that much more research and development efforts need to be directed towards the improvement of locally specific biomass and carbon models; for semiarid environments like in Burkina Faso. Especially in dry regions of young secondary

forests it is of much importance to include shrubs which we were not able to include in our carbon stock estimate of “other wooded land”, although shrubs are the dominant life form within this land use class. We are aware that the described lack of sufficiently accurate carbon models for above ground stocks also is valid for all other carbon pools like belowground carbon stocks that were not considered in this study (Fischer et al., 2011). We conclude that methodologically harmonized and more sophisticated field carbon estimates are needed otherwise all higher order models are likely to fail. Furthermore we agree with Fischer et al. (2011) that: “Compared to image analysis of new remote sensing instruments, collecting data to improve such field biomass models is tedious and time consuming field work and these efforts will exhibit significant progress only after years when results of various biomass modelling studies can be merged.”

8.2 Remote sensing at regional scale

Our study showed that the classification method developed is able to deliver estimates on FAO land use classes, based on remote sensing only.

Further it was shown that the classifier chosen was able to handle the multidimensional data at hand, delivering unbiased estimates. Needs for further research, with regards to training and validation data were identified. For a future study we would recommend to research into the possibilities of image pre-stratification based on the spectral composition, as basis for the generation of training data. After all, we conclude that the RapidEye sensor is well suited for land use classification and mapping, based on its spectral range and high visiting time, which could result in cloud and haze free imagery, which is of high importance for land use classification in the tropics.

The possibility to obtain a feature importance ranking helped improving the classification efficiency, by reducing the number of variables needed during classification. This resulted in reductions of computing time and computing power need without reducing the classification accuracies too much. It should be considered that our classification accuracies were still very high, using a reduced feature space for the final classification.

We observed that some features were of no importance for the classification, whereas others were of importance, giving insights into general questions with regards to vegetation

classification in a semiarid environment and giving hints towards the development of adapted vegetation indices and spectral resolution of future remote sensing platforms.

8.3 Remote sensing at national scale

We were able to show that the method developed for the national scale, FAO conform land use classification, is applicable, delivering sound estimates on land use classes.

Further, the classification approach is very transparent and intuitive, meaning that replication is well possible.

In addition, it was shown that the classifier chosen was able to handle the multidimensional data needed for the national level classification conducted. Further, it was assessed that the RandomForest classifier is able to deliver sound estimates even if the amount of training data is much reduced.

Based on the land use classification results presented, we come to the conclusion, that the MODIS MOD09GA product used for the classification is well suited for the classification applied. Where its spectral range, which proved well suited for the classification of vegetation, paired with its daily revisiting time, increasing the chance of a cloud free image seems to be optimal. With regards to its spatial resolution it was assessed that not all land use classes could be detected. Here, we come to the conclusion that either an increase of spatial resolution, using a different MODIS product e.g. MOD09GQ with a spatial resolution of 250 m but only two spectral bands, or data from another platform; or an increase of training data, would improve our estimates.

Nevertheless, to our knowledge, we were able to produce the first land use map for Burkina Faso, based on FAO definitions, also supplying error estimates.

We were able to show that our classification method yields, for the land use classes we could detect, estimates that are more within the range of the estimates we assessed during out terrestrial inventory, as was assessed during the FAO FRA 2010 or GCL 2000, which is also remote sensing based. Thus we conclude that our classification approach is superior, for the classes we assessed, to the method applied by FAO, especially so, if the suggested

improvements, above all, increasing training data or pre-stratifying training data to cover all land use classes existent were implemented.

8.4 National forest inventories as data providers for international processes

Within the frame of climate change and other related global issues, information on the natural resources of a country, at national level became the focus of scientific and market related interest.

Here, we focused on the possibility to provide input to the REDD market incentive which focuses on carbon trading (see 3.4) at global level, by means of a national forest and land use inventory, as the REDD mechanism is strongly dependent on reliable and standardized information on forest. Countries that want to participate at REDD will first of all need to report their current forest extents and later, the changes in forest area and the related carbon stocks. It is clear that a monitoring system for such a task generates high costs, which for many developing countries, can be the limiting factor for its implementation. For the monitoring scheme there exist three levels of accuracy (see 3.4), tiers 1-3, where tier three delivers the most accurate carbon estimates.

Within this study we were able to conduct a national forest inventory for Burkina Faso at much reduced costs, which is able to deliver reliable information on the extend of forest and other land use classes, following standardized definitions. With the applied sampling scheme we were able to calculate the level of precision achieved for the estimation of the area of each land use class. Further, we were able to measure the species composition as well as structure of the vegetation for each land use, which allowed, with the use of allometric models, to calculate the aboveground carbon stocks including error estimates. Our sampling approach more than fulfils the requirements for the calculation of carbon stocks at Tier 1 level and could be further extended to fulfil at least the tier 2 requirements by including additional carbon stock measurements like litter, dead wood and species specific carbon measurements into the sampling scheme.

In the REDD+ carbon trading scheme described in 3.4 remote sensing techniques play an important part in the monitoring requirements. We were able to develop a consistent,

standardized and transparent remote sensing based land use classification scheme covering the whole of Burkina Faso. With the developed classification scheme we are able to classify forest and other land use classes and deliver the possibility for a consecutive forest cover monitoring system for Burkina Faso as demanded by the REDD+ requirements.

By combining the information from the terrestrial and remote sensing based approaches developed, we are confident to deliver a useful tool to increase the REDD+ readiness of Burkina Faso and other countries that would like to utilize the developed methods.

9 Summary

In this study we present a forest inventory approach on national level for Burkina Faso where a relatively small sample size is combined with relatively large sample plots. To our knowledge, we present here the first sample based inventory of forest and tree resources for Burkina Faso, providing national level information based upon a uniform and statistically consistent methodology. We hope the results of this study can contribute to the discussion on land-use dynamics and further planning of a more detailed national wide monitoring system on the tree resource.

The inventory conducted here is one of the central components of a research project aiming at modelling the expected future changes in climate, vegetation and land-use on country-level. Low sampling intensity was stipulated mainly due to limited resources in terms of time, budget and labour, but also because the expected precision of baseline information on land cover classes and their major characteristics, like species distribution or aboveground carbon stocks of the tree compartment (AGC_{Tree}), was found to be sufficient for the regional modelling goals of this study.

With the applied inventory we were able to estimate land use, based on FAO definitions, where we estimated that a total of 42.6%, 1.6%, 53.6%, 9.1% and 2.2% of Burkina Faso are covered by “forest”, “other wooded land”, “other land”, “other land with tree cover” and “inland water bodies”, respectively. Further we were able to estimate precision for all land use proportions.

In addition we were able to assess the vegetation structure and species composition for different land use classes. The results on vegetation structure could successfully be used by the climatological group within the project, where a model on radiation within forest stands is being developed.

The assessed species data was used to derive land use specific information on wood density, which was further used in the calculation of above ground carbon stocks for different land use classes. We were also able to define urgent needs for research, especially with regards to carbon estimates. It was assessed that we were not able to calculate carbon stocks for shrubs, which are part of land use class “other wooded land”, as no suitable allometric models were available.

With the applications developed in the remote sensing part of our study, we were able to produce a land use map for Burkina Faso, based on FAO definitions, which is for the first time also supplying error estimates for the cover estimates and information on classification accuracy. For the above mentioned we developed a standardized classification scheme following FAO land use definitions based on the new RapidEye sensor. In a second step we showed the possibility to up-scale the results based on local scale land use maps, derived from the RapidEye imagery to country level using MODIS imagery. Herewith we established a cost effective monitoring system for the whole of Burkina Faso, which is based on remote sensing only.

With our study we were able to show that RapidEye imagery is well suited for land use classification based on FAO definitions, where limited study sites were worked on. Classification of different vegetation forms under different climatic conditions was possible, achieving good classification accuracies. Thus, we proved that not only the imagery, but also the classification scheme applied is well suited for different vegetation as well as climatic conditions.

With the developed processing chain, we achieved estimates that were much more within the range of our ground based study for land use class “Forest”, in Burkina Faso, than in any other remote sensing based study we know of. Based on the MODIS imagery we estimated a total of 30.8% of “forest” for Burkina Faso. Additionally we identified further needs for research to improve classification accuracy as well as the detection of all land use classes of interest.

10 References

Achard, F., DeFries, R., Eva, H., Hansen, M., Mayaux, P., Stibig, H.-J., 2007. Pan-tropical monitoring of deforestation. Environ. Res. Lett. 2, 045022.

Arbonnier, M., 2009. Arbres, arbustes et lianes des zones sèches d'Afrique de l'Ouest. Quae éditions, Versailles.

Augusseau, X., Nikiéma, P., Torquebiau, E., 2006. Tree biodiversity, land dynamics and farmers' strategies on the agricultural frontier of southwestern Burkina Faso. Biodiversity and Conservation 15, 613–630.

Baccini, A., Laporte, N., Goetz, S.J., Sun, M., Dong, H., 2008. A first map of tropical Africa's above-ground biomass derived from satellite imagery. Environmental Research Letters 3, 045011.

Basset, T.J., Crummney, D., 2003. African Savannas: Global Narratives and Local Knowledge of Environmental Change. James Currey.

Belem, B., Nacoulma, B.M.I., Gbangou, R., Kambou, S., Hansen, H.H., Gausset, Q., Lund, S., Raebild, A., Lompo, D., Ouedraogo, M., others, 2007. Use of Non Wood Forest Products by local people bordering the" Parc National Kaboré Tambi", Burkina Faso. Journal for Transdisciplinary Environmental Studies 6.

Benediktsson, J.A., Swain, P.H., Ersoy, O.K., 1990. Neural Network Approaches Versus Statistical Methods In Classification Of Multisource Remote Sensing Data. IEEE Trans. Geosci. Remote Sensing 28, 540-552.

Benediktsson, J.A., Chanussot, J., Fauvel, M., 2007. Multiple Classifier Systems in Remote Sensing: From Basics to Recent Developments, in: Haindl, M., Kittler, J., Roli, F. (Eds.), Multiple Classifier Systems. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 501-512.

Boffa, J.M., 1999. Agroforestry parklands in sub-Saharan Africa. Food & Agriculture Org.

Bonan, G.B., 2008. Forests and Climate Change: Forcings, Feedbacks, and the Climate Benefits of Forests. Science 320, 1444-1449.

Borak, J.S., Strahler, 1999. Feature selection and land cover classification of a MODIS-like data set for a semiarid environment. Int. J. of Remote Sensing 20, 919-938.

Boser, B.E., Guyon, I.M., Vapnik, V.N., 1992. A training algorithm for optimal margin classifiers, in: Proceedings of the Fifth Annual Workshop on Computational Learning Theory - COLT '92. Presented at the the fifth annual workshop, Pittsburgh, Pennsylvania, United States, pp. 144-152.

Böttcher, H., Eisbrenner, K., Fritz, S., Kindermann, G., Kraxner, F., McCallum, I., Obersteiner, M., 2009. An assessment of monitoring requirements and costs of "Reduced Emissions from Deforestation and Degradation". Carbon Balance Managegement 4, 7.

Brännlund, R., Sidibe, A., Gong, P., 2009. Participation to forest conservation in National Kabore Tambi Park in Southern Burkina Faso. Forest Policy and Economics 11, 468-474.

Breiman, L., 1984. Classification and regression trees. Wadsworth, Belmont, California.

Breiman, L., 1996. Bagging predictors. Machine Learning 24, 123-140.

Breiman, L., 2001. Random Forests. Machine Learning 45, 5-32.

Breiman, L., Cutler, A., 2011. Random forests - classification description [WWW Document, Accessed: 21.10.2011]. URL http://www.stat.berkeley.edu/~breiman/RandomForests/cc_home.htm

Brown, S., 1997. Estimating Biomass and Biomass Change of Tropical Forests: a Primer. (FAO Forestry Paper - 134) [WWW Document, Accessed 21.10.2011]. URL http://www.fao.org/docrep/W4095E/W4095E00.htm

Brown, S., 2002. Measuring carbon in forests: current status and future challenges. Environmental Pollution 116, 363-372.

Brown, D., Seymour, F., Peskett, L., 2008. How do we achieve REDD co-benefits and avoid doing harm?, in: Moving Ahead with REDD. CIFOR, Bogor, pp. 107-118.

Buschmann, C., Nagel, E., 1993. In vivo spectroscopy and internal optics of leaves as basis for remote sensing of vegetation. International Journal of Remote Sensing 14.

Byran, J., Kirkpatrick, J.B., Shearman, L., Ash, J., 2011. On estimating tropical forest carbon dynamics in Papua New Guinea. Annals of Forest Science 68, 213-216.

Calle, M.L., Urrea, V., 2010. Letter to the Editor: Stability of Random Forest importance measures. Briefings in Bioinformatics 12, 86-89.

Campbell, J.B., 1981. Spatial correlation effects upon accuracy of supervised classification of land cover. Photogrammetric Engineering and Remote Sensing 47.

Campbell, J., 2008. Introduction to remote sensing, 4th ed. Guildford Press, New York.

Chave, J., Condit, R., Lao, S., Caspersen, J.P., Foster, R.B., Hubbell, S.P., 2003. Spatial and temporal variation of biomass in a tropical forest: results from a large census plot in Panama. Journal of Ecology 91, 240-252.

Chave, J., Condit, R., Aguilar, S., Hernandez, A., Lao, S., Perez, R., 2004. Error propagation and scaling for tropical forest biomass estimates. Philosophical Transactions of the Royal Society B: Biological Sciences 359, 409-420.

Chave, J., Andalo, and C., Brown, S., Cairns, M.A., Chambers, J.Q., Eamus, D., Fölster, H., Fromard, F., Higuchi, N., Kira, T., others, 2005. Tree allometry and improved estimation of carbon stocks and balance in tropical forests. Oecologia 145, 87–99.

Chave, J., Muller-Landau, H.C., Baker, T.R., Easdale, T.A., Steege, H., Webb, C.O., 2006. Regional and phylogenetic variation of wood density across 2456 neotropical tree species. Ecological Applications 16, 2356–2367.

CIA, 2011. CIA - The World Factbook [WWW Document, Accessed 20.10.2011]. URL https://www.cia.gov/library/publications/the-world-factbook/index.html

Cochran, W.G., 1977. Sampling Techniques (Wiley Series in Probability and Mathematical Statistics), 3rd ed. John Wiley & Sons.

Copeland, J.H., Pielke, R.A., Kittel, T.G.F., 1996. Potential climatic impacts of vegetation change: A regional modeling study. J. Geophys. Res. 101, 7409-7418.

DeBrie, S., 1991. Wildlife Resources of the West African Savannah. Vageningen Agricultural University Papers 91.

DeFries, R., Achard, F., Brown, S., Herold, M., Murdiyarso, D., Schlamadinger, B., de Souza Jr., C., 2006. Reducing Greenhouse Gas emissions from Deforestation in Developing Countries: Considerations for Monitoring and Measuring (GOFC-GOLD report No. 26). Rome.

Eggleston, H., Intergovernmental Panel on Climate Change., 2006. 2006 IPCC guidelines for national greenhouse gas inventories. Institute for Global Environmental Strategies,, Hayama, Japan.

Elias, M., Potvin, C., 2003. Assessing inter-and intra-specific variation in trunk carbon concentration for 32 neotropical tree species. Canadian Journal of Forest Research 33, 1039–1045.

European Commission, Joint Research Centre, 2003. Global Land Cover 2000 database [WWW Document, Accessed 20.10.2011]. URL http://bioval.jrc.ec.europa.eu/products/glc2000/data_access.php

Eva, H.D., Brink, A., D.Simonetti, 2006. Monitoring Land Cover Dynamics in Sub-Saharan Africa - A pilot study using Earth observing satellite data from 1975 and 2000. Institute for Environment and Sustainability, Joint Research Centre of the European Commission.

FAO, 2000. FAO/GIEWS Sahel Report No.4, 11 September 2000 [WWW Document, Accessed 21.06.2011]. FAO corporate document repository. URL http://www.fao.org/docrep/004/x8210e/x8210e00.htm

FAO, 2008a. FAO Media Centre: Africa could reduce greenhouse gases [WWW Document, Accessed 21.10.2011]. URL http://www.fao.org/news/story/en/item/8664/icode/

FAO, 2008b. NFMA approach and process: an analysis of Cost and Time.

FAO, 2009. The FRA 2010 remote sensing survey. [WWW Document, Accessed 21.10.2011]. URL http://www.fao.org/forestry/fra/remotesensingsurvey/en/

FAO, 2010. Global Forest Resources Assessment 2010. Food and Agriculture Organisation of the United Nations.

FAO, 2011. FAOSTAT [WWW Document, Accessed 27.06.2011]. URL http://faostat.fao.org/site/339/default.aspx

Fischer, C., Kleinn, C., Fehrmann, L., Fuchs, H., Panferov, O., 2011. A national level forest resource assessment for Burkina Faso – A field based forest inventory in a semiarid environment combining small sample size with large observation plots. Forest Ecology and Management.

Friedl, M., McIver, D.K., Hodges, J.C.F., Zhang, X.Y., Muchoney, D., Strahler, A.H., Woodcock, C.E., Gopal, S., Schneider, A., Cooper, A., Baccini, A., Gao, F., Schaaf, C., 2002. Global land cover mapping from MODIS: algorithms and early results. Remote Sensing of Environment 83, 287-302.

Fritz, S., Bartholome, E., Hartley, A., Stibig, H.-J., Eva, H.D., Mayaux, P., Bartalev, S., Latifovic, R., Kolmert, S., Sarathí Roy, P., Aggarwal, S., Bingfang, S., Wenting, X., Ledwith, M., Pekel, J.F., Giri, C., Mucher, S., De Badts, E., Tateishi, R., Champeax, J.I., Defourny, P., 2003. Harmonisation, Mosaicing and Production of the Global Land Cover 2000 Database. European Commission.

Gibbs, H.K., Brown, S., Niles, J.O., Foley, J.A., 2007. Monitoring and estimating tropical forest carbon stocks: making REDD a reality. Environ. Res. Lett. 2, 045023.

Giri, C., Zhu, Z., Reed, B., 2005. A comparative analysis of the Global Land Cover 2000 and MODIS land cover data sets. Remote Sensing of Environment 94, 123-132.

Gislason, P., Benediktsson, J., Sveinsson, J., 2006. Random Forests for land cover classification. Pattern Recognition Letters 27, 294-300.

Gitelson, A., 1996. Use of a green channel in remote sensing of global vegetation from EOS-MODIS. Remote Sensing of Environment 58, 289-298.

Gitelson, A.A., Vina, A., Ciganda, V., Rundquist, D., Arkebauer, T.J., 2005. Remote estimation of canopy chlorophyll content in crops. Geophys. Res. Lett. 32.

GOFC-GOLD, 2008. Reducing greenhouse gas emissions from deforestation and degradation in developing countries: a sourcebook of methods and procedures for monitoring, measuring and reporting. (No. GOFC-GOLD Report version COP 13-2). GOFC-GOLD Project Office, Natural Resources Canada, Alberta, Canada.

Goldammer, J., 2004. Wildland fire management handbook for Sub-Sahara Africa. Global Fire Monitoring Center(GFMC), [S.l.].

Gregoire, T.G., Valentine, H.T., 2007. Sampling Strategies for Natural Resources and the Environment (Applied Environmental Statistics). Chapman & Hall.

Haas, R.H., Deering, D.W., Schell, J.A., Harlan, J.C., 1974. Monitoring the Vernal Advancement and Retrogradation (Green Wave Effect) of Natural Vegetation. NASA.

Haralick, R.M., Shanmugam, K., Dinstein, I., 1973. Textural Features for Image Classification. IEEE Trans. Syst., Man, Cybern. 3, 610-621.

Herold, M., Johns, T., 2007. Linking requirements with capabilities for deforestation monitoring in the context of the UNFCCC-REDD process. Environ. Res. Lett. 2, 045025.

Hiernaux, P., Gerard, B., 1999. The influence of vegetation pattern on the productivity, diversity and stability of vegetation: The case of `brousse tigree' in the Sahel. International Journal of Ecology 20, 147-158.

Huang, C., Townshend, J.R.G., 2003. A stepwise regression tree for nonlinear approximation: Applications to estimating subpixel land cover. Int. J. of Remote Sensing 24, 75-90.

Im, J., Jensen, 2005. A change detection model based on neighborhood correlation image analysis and decision tree classification. Remote Sensing of Environment 99, 326–340.

INSD, 2010. Institut National de la Statistique et de la Démographie (INSD) [WWW Document, Accessed 20.10.2011]. URL http://www.insd.bf/fr/

IPCC, 2000. IPCC Special Reports on Climate Change - Complete online versions | UNEP/GRID-Arendal - Publications - Other [WWW Document, Accessed 20.10.2011]. URL http://www.grida.no/publications/other/ipcc_sr/

IPCC, 2007. Climate Change 2007: Synthesis Report.

IPCC-NGGIP, 2011. EFDB - Main Page [WWW Document, Accessed 20.10.2011]. URL http://www.ipcc-nggip.iges.or.jp/EFDB/main.php

Jensen, J., 2005. Introductory digital image processing: a remote sensing perspective, 3rd ed. Prentice Hall, Upper Saddle River N.J.

Jones, H., Vaughan, R., 2010. Remote sensing of vegetation : principles, techniques, and applications. Oxford University Press, Oxford ;;New York.

Kagone, H., 2002. Burkina Faso [WWW Document, Accessed 20.10.2011]. URL http://www.fao.org/ag/AGP/AGPC/doc/Counprof/BurkinaFeng.htm

Ketterings, Q., 2001. Reducing uncertainty in the use of allometric biomass equations for predicting above-ground tree biomass in mixed secondary forests. Forest Ecology and Management 146, 199-209.

Kleinn, C., Ramírez, C., Holmgren, P., Valverde, S.L., Chavez, G., 2005. A national forest resources assessment for Costa Rica based on low intensity sampling. Forest Ecology and Management 210, 9 - 23.

Kleinn, C., Ståhl, G., Fehrmann, L., Kangas, A., 2010. Issues in forest inventories as an input to planning and decision processes. Allgemeine Forst und Jagt Zeitschrift 181, 205-210.

Knyazikhin, Y., 1997. Small-scale study of three-dimensional distribution of photosynthetically active radiation in a forest. Agricultural and Forest Meteorology 88, 215-239.

König, K., 2006. Der Beitrag von Fernerkundungsdaten zur Analyse von räumlichen und zeitlichen Phytodiversitätsmustern in Savannengebieten Westafrikas.

Land Processes DAAC, USGS Earth Resources Observation and Science (EROS) Center, 2011. MODIS Reprojection Tool | Tools | LP DAAC: ASTER and MODIS Land Data Products and Services [WWW Document, Accessed 14.06.2011]. URL https://lpdaac.usgs.gov/lpdaac/tools/modis_reprojection_tool

Landmann, T., Machwitz, M., Le, Q.B., Desta, L.T., Vlek, P., Dech, S., Schmidt, M., 2008. A Land Cover Change Synthesis Study for the GLOWA Volta Basin in West Africa using Time Trajectory Satellite Observations and Cellular Automata Models, in: IGARSS 2008 - 2008 IEEE International Geoscience and Remote Sensing Symposium. Presented at the IGARSS 2008 - 2008 IEEE International Geoscience and Remote Sensing Symposium, Boston, MA, USA, p. III - 640-III - 643.

Laris, P., 2002. Burning the Seasonal Mosaic: Preventative Burning Strategies in the Wooded Savanna of Southern Mali. Human Ecology 30, 155-186.

Lewis, S.L, Lopez-Gonzalez, G, Sonké, B, Affum-Baffoe, K, Baker, T.R, Ojo, L.O, Phillips, O.L, Reitsma, J.M, White, L, Comiskey, J.A, others, 2009. Increasing carbon storage in intact African tropical forests. Nature 457, 1003–1006.

Liaw, A., Wiener, M., 2002. Classification and Regression by randomForest. R News 2, 18-22.

Lillesand, T., 2008. Remote sensing and image interpretation, 6th ed. John Wiley & Sons, Hoboken NJ.

Linder, H.P., Lovett, J., Mutke, J.M., Barthlott, W., Jürgens, N., Rebelo, T., Küper, W., 2005. A numerical re-evaluation of the sub-Saharan phytochoria of mainland Africa. Biologiske Skrifter 55, 229-252.

Magdon, P., 2011 (personal communication). Manuscript: Standardized Forest Cover mapping in the Tropics using RapidEye: A Case study from Costa Rica and Burkina Faso.

Malhi, Y., Baker, T.R., Phillips, O.L., Almeida, S., Alvarez, E., Arroyo, L., Chave, J., Czimczik, C.I., Fiore, A.D., Higuchi, N., 2004. The above ground coarse wood productivity of 104 Neotropical forest plots. Global Change Biology 10, 563–591.

Maniatis, D., Malhi, Y., Saint André, L., Mollicone, D., Barbier, N., Saatchi, S., Henry, M., Tellier, L., Schwartzenberg, M., White, L., 2011. Evaluating the Potential of Commercial Forest Inventory Data to Report on Forest Carbon Stock and Forest Carbon Stock Changes for REDD+ under the UNFCCC. International Journal of Forestry Research 2011, 1-13.

Maranz, S., Wiesman, Z., 2003. Evidence for indigenous selection and distribution of the shea tree, Vitellaria paradoxa, and its potential significance to prevailing parkland savanna tree patterns in sub-Saharan Africa north of the equator. Journal of Biogeography 30, 1505-1516.

Marx, A., 2010. Detection and Classification of Bark Beetle Infestation in Pure Norway Spruce Stands with Multi-temporal RapidEye Imagery and Data Mining Techniques. Photogrammetrie - Fernerkundung - Geoinformation 2010, 243-252.

McGregor, G.R., Nieuwolt, S., 1998. Tropical Climatology: An Introduction to the Climates of the Low Latitudes, 2nd ed. John Wiley & Sons Inc, Chinchester, England.

McRoberts, R.E., 2003. Compensating for missing plot observations in forest inventory estimation. Canadian Journal of Forest Research 33, 1990–1997.

Meteo-Burkina, 2011. MOY_7100.GIF (GIF Image, 746×554 pixels) [WWW Document, Accessed 27.06.2011]. URL http://www.meteo-burkina.net/CARTES/MOY_7100/MOY_7100.GIF

Mingers, J., 1989. An Empirical Comparison of Pruning Methods for Decision Tree Induction. Machine Learning 4, 227-243.

Moody, A., Woodcock, C.E., 1994. Scale-dependent errors in the estimation of land-cover proportions: implications for global land-cover datasets. Photogrammetric Engineering and Remote Sensing 60, 585-594.

Moody, A., Woodcock, C.E., 1995. The influence of scale and the spatial characteristics of landscapes on land-cover mapping using remote sensing. Landscape Ecol 10, 363-379.

Nelson, M.D., McRoberts, R.E., Holden, G.R., Bauer, M.E., 2009. Effects of satellite image spatial aggregation and resolution on estimates of forest land area. International Journal of Remote Sensing 30, 1913–1940.

Nicholson, S.E., 2001. Climatic and environmental change in Africa during the last two centuries. Climate Research 17, 123–144.

Van Noordwijk, M., Lusiana, B., 1999. WaNuLCAS, a model of water, nutrient and light capture in agroforestry systems. Agroforestry Systems 43, 217-242.

Nygård, R., Elfving, B., 2000. Stem basic density and bark proportion of 45 woody species in young savanna coppice forests in Burkina Faso. Annals of Forest Science 57, 143–153.

Olander, L.P., Gibbs, H.K., Steininger, M., Swenson, J., 2007. Data and Methods to Estimate National Historical Deforestation Baselines in Support of UNFCCC REDD.

Pal, M., Mather, P.M., 2003. An assessment of the effectiveness of decision tree methods for land cover classification. Remote Sensing of Environment 86, 554-565.

Parry, M.L., Canziani, O.F., Palutikov, J.P., van der Linden, P.J., Hanson, C.E., 2008. Climate Change 2007: Impacts, Adaptation and Vulnerability. Cambridge University Press, Cambridge, UK.

Platnick, S., 2011. MODIS Atmosphere [WWW Document, Accessed 27.05.2011]. URL http://modis-atmos.gsfc.nasa.gov

R Development Core Team, 2011. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.

RapidEye AG, 2011. Satellite Imagery Product Specifications Version 3.2.

Richards, J.A., Jia, X., 2006. Remote Sensing Digital Image Analysis - An Introduction, 4th ed. Springer Berlin Heidelberg.

Richter, R., 2008. Classification Metrics for Improved Atmospheric Correction of Multispectral VNIR Imagery. Sensors 8, 6999-7011.

Ross, J., 1981. Radiation Regime and Architecture of Plant Stands (Tasks for Vegetation Science), 1st ed. Kluwer Academic Publishers.

Roy, J., Saugier, B., Mooney, H.A., 2001. Hierarchy and Productivity of MediterraneanType Ecosystems, in: Terrestrial Global Productivity. Academic Press, p. 573.

Sallenave, P., 1971. Propietes physiques et mecaniques des bois tropicaux. Deuxieme supplement.

Sánchez, E., Gaertner, M.A., Gallardo, C., Padorno, E., Arribas, A., Castro, M., 2007. Impacts of a change in vegetation description on simulated European summer present-day and future climates. Clim Dyn 29, 319-332.

Sankaran, M., Ratnam, J., Hanan, N.P., 2004. Tree-grass coexistence in savannas revisited - insights from an examination of assumptions and mechanisms invoked in existing models. Ecol Letters 7, 480-490.

Savadogo, P., 2007. Dynamics of Sudanian savanna-woodland ecosystem in response to disturbances.

Schmidt, M., 2006. Pflanzenvielfalt in Burkina Faso - Analyse, Modellierung und Dokumentation.

Stickler, C.M., Nepstad, D.C., Coe, M.T., McGrath, D.G., Rodrigues, H.O., Walker, W.S., Soares-Filho, B.S., Davidson, E.A., 2009. The potential ecological costs and cobenefits of REDD: a critical review and case study from the Amazon region. Global Change Biology 15, 2803-2824.

Thuresson, T., 2002. Feasibility of low intensity samplingapproach for national inventories, including cases. Background paper to the UN-ECE/FAO Expert Consutation Kotka IV. Kotka, Finnland.

Tomppo, E., Gschwantner, T., Lawrence, M., McRoberts, R.E. (Eds.), 2010. National Forest Inventories. Springer Netherlands, Dordrecht.

Touré, A., Rasmussen, K., Diallo, O., Diouf, A., 2003. Actual and potential carbon stocks in the north-sudanian zone. A case study: The forests of Delbi and Paniates in Senegal. Geografisk Tidsskrift, Danish Journal of Geography 103, 63.

Tschakert, P., 2004. Carbon for farmers: assessing the potential for soil carbon sequestration in the old peanut basin of Senegal. Climatic Change 67, 273–290.

Tso, B., Mather, P., 2009. Classification methods for remotely sensed data, 2nd ed. CRC Press, Boca Raton.

Turner, M.G., O'Neill, R.V., Gardner, R.H., Milne, B.T., 1989. Effects of changing spatial scale on the analysis of landscape pattern. Landscape Ecol 3, 153-162.

UNDP, 2010. Indices & Data | Human Development Reports (HDR) | United Nations Development Programme (UNDP) [WWW Document, Accessed 21.10.2011]. URL http://hdr.undp.org/en/statistics/index.html#hdirank

UN-REDD, 2011. -- UN-Redd Programme - About REDD -- [WWW Document, Accessed 20.10.2011]. URL http://www.un-redd.org/AboutREDD/tabid/582/Default.aspx

USGS - U.S. geological survey, 2004. MOD12Q1 | Yearly L3 Global 1km | Land Cover | MODIS Products Table | Products | LP DAAC: ASTER and MODIS Land Data Products and Services [WWW Document, Accessed 21.10.2011]. URL https://lpdaac.usgs.gov/lpdaac/products/modis_products_table/land_cover/yearly_l3_global_1km2/mod12q1

Vermote, E.F., El Saleous, N., Justice, C.O., Kaufman, Y.J., Privette, J.L., Remer, L., Roger, J.C., Tanré, D., 1997. Atmospheric correction of visible to middle-infrared EOS-MODIS data over land surfaces: Background, operational algorithm and validation. J. Geophys. Res. 102, 17131-17141.

Walker, W.S., Stickler, C.M., Kellndorfer, J.M., Kirsch, K.M., Nepstad, D.C., 2010. Large-Area Classification and Mapping of Forest and Land Cover in the Brazilian Amazon: A Comparative Analysis of ALOS/PALSAR and Landsat Data Sources. IEEE J. Sel. Top. Appl. Earth Observations Remote Sensing 3, 594-604.

Walter, H., Breckle, S.-W., 1999. Vegetation und Klimazonen, 7th ed. Ulmer, Stuttgart.

Walton, J.T., 2008. Subpixel urban land cover estimation: Comparing Cubist, Random Forests, and support vector regression. Photogrammetric Engineering and Remote Sensing 74, 1213-1222.

Wezel, A., Lykke, A.M., 2006. Woody vegetation change in Sahelian West Africa: evidence from local knowledge. Environment, Development and Sustainability 8, 553–567.

Woomer, P.L., Tieszen, L.L., Tappan, G., Toure, A., Sall, M., 2004a. Land use change and terrestrial carbon stocks in Senegal. Journal of Arid Environments 59, 625-642.

Woomer, P.L., Touré, A., Sall, M., 2004b. Carbon stocks in Senegal's Sahel Transition Zone. Journal of Arid Environments 59, 499 - 510.

Wunder, S., 2006. Are Direct Payments for environmental Services Spelling Doom for Sustainable Forest Management in the Tropics? Ecology and Society 11.

Xiao, X., Biradar, C.M., Czarnecki, C., Alabi, T., Keller, M., 2009. A Simple Algorithm for Large-Scale Mapping of Evergreen Forests in Tropical America, Africa and Asia. Remote Sensing 1, 355-374.

11 Annex

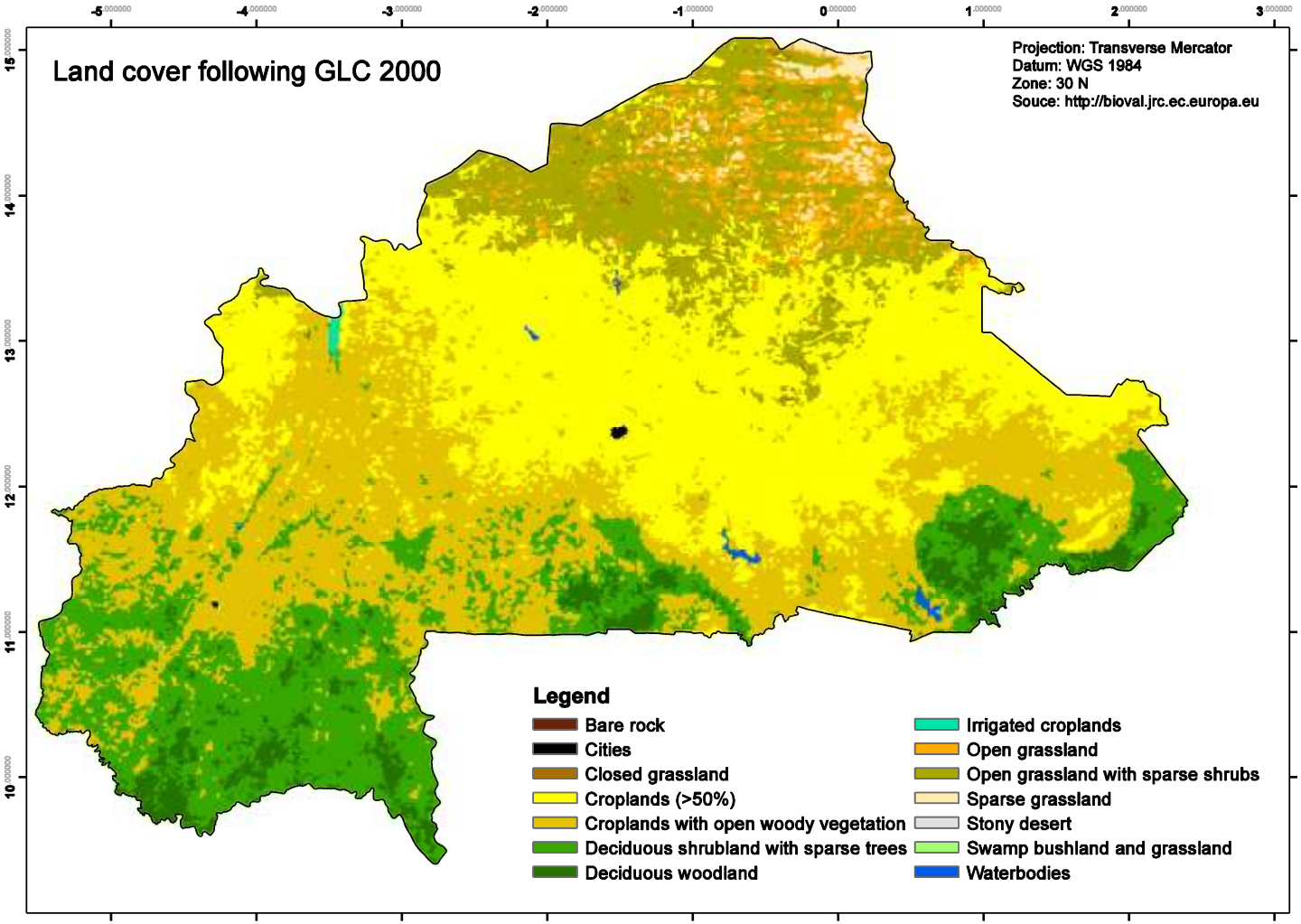

Figure 24: Land cover classification following Global Land Cover 2000 (European Commission, Joint Research Centre, 2003).

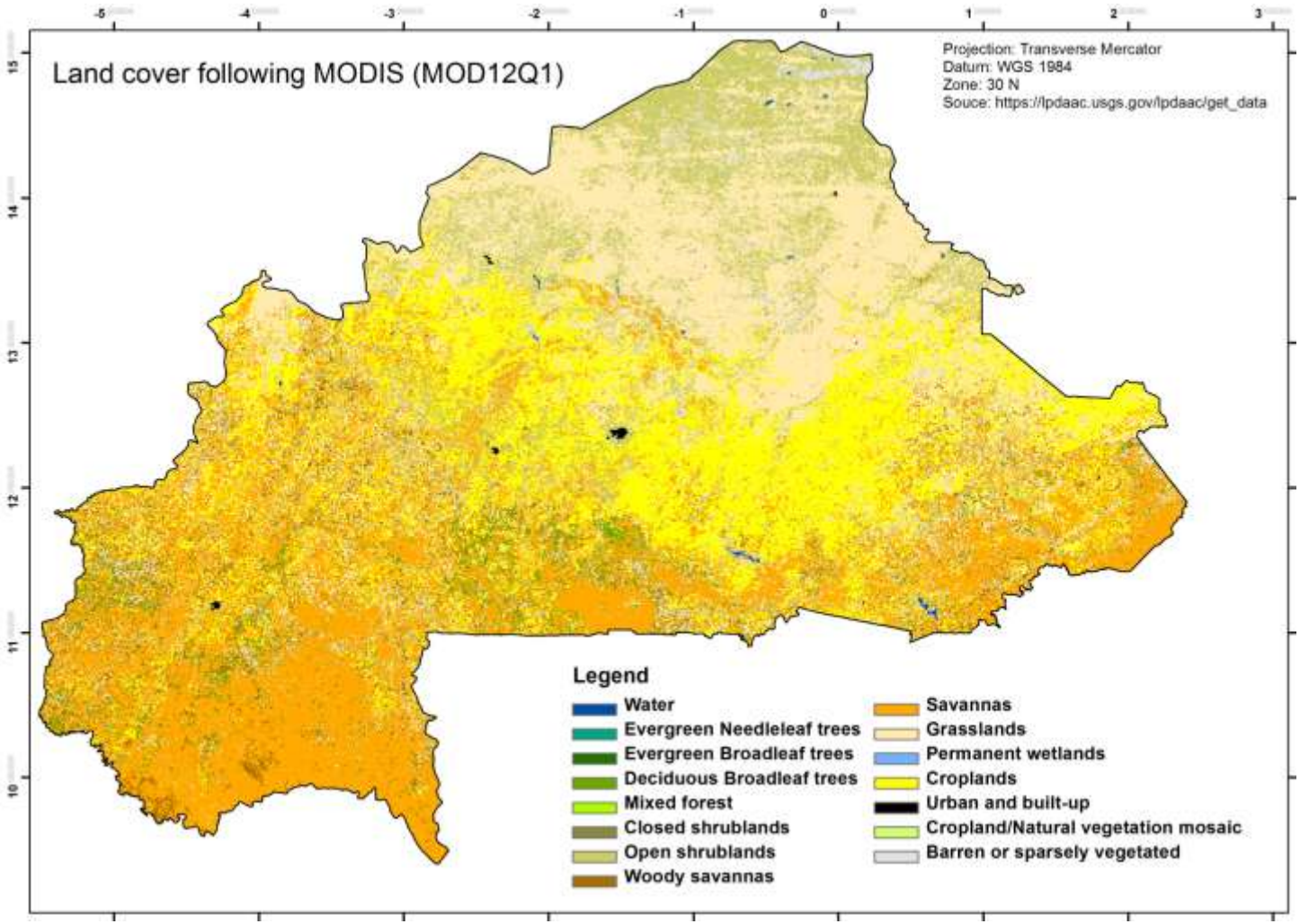

Figure 25: Land cover classification following MODIS (MOD12Q1) IGBP global vegetation classification scheme (USGS - U.S. geological survey).

Species list:

	Scientific name
1.	Acacia albida
2.	Acacia ataxacantha
3.	Acacia brunaiensis
4.	Acacia dudgeonii
5.	Acacia gourmaensis
6.	Acacia hockii
7.	Acacia laeta
8.	Acacia macrostachya
9.	Acacia nilotica
10.	Acacia pennata
11.	Acacia polyacantha
12.	Acacia raddiana
13.	Acacia senegal
14.	Acacia seyal
15.	Acacia sieberiana
16.	Adansonia digitata
17.	Afzelia africana
18.	Albizia chevalieri
19.	Anacardium occidentale
20.	Annona senegalensis
21.	Anogeissus leiocarpa
22.	Azadirachta indica
23.	Baissea multiflora
24.	Balanites aegyptiaca
25.	Bauhinia rufescens
26.	Berlinia grandiflora
27.	Bombax costatum
28.	Borassus aethiopum
29.	Boscia angustifolia
30.	Boscia senegalensis
31.	Boswellia dalzielii
32.	Bridela ferruginea
33.	Burkea africana
34.	Cadaba farinosa
35.	Calotropis procera
36.	Capparis corymbosa
37.	Cassia albida
38.	Cassia brunaiensis
39.	Cassia machrostachya
40.	Cassia sieberiana
41.	Cassia singueana
42.	Cedrocedrella cotchii
43.	Celtis integrifolia
44.	Cissus quadrangularis
45.	Combretum aculeatum
46.	Combretum collinum
47.	Combretum fragrans
48.	Combretum glutinosum
49.	Combretum micranthum
50.	Combretum molle
51.	Combretum nigricans
52.	Combretum paniculatum
53.	Commiphora africana
54.	Cordia myxa
55.	Crossopteryx febrifuga
56.	Dalbergia melanoxylon
57.	Daniellia oliveri
58.	Detarium microcarpum
59.	Dichrostachys cinerea
60.	Diospyros mespiliformis
61.	Elaeis guineensis
62.	Entada abyssinica
63.	Entada africana
64.	Eucalyptus camaldulensis
65.	Faidherbia albida
66.	Feretia apodanthera
67.	Ficus capensis
68.	Ficus glanphalocarpa
69.	Ficus ingens
70.	Ficus platiphylla
71.	Ficus sp.
72.	Ficus sycomorus
73.	Gardenia erubescens
74.	Gardenia sokotensis
75.	Gardenia ternifolia
76.	Gardenia triacantha
77.	Grewia bicolor
78.	Grewia flavescens
79.	Grewia villosa
80.	Grewiia mollis
81.	Guiera senegalensis
82.	Hannoa undulata
83.	Hexalobus monopetalus
84.	Holarrhena floribunda
85.	Hopilia curatelifolia
86.	Hopilia seltidifolia
87.	Hymenocardia acida
88.	Hyphaene thebaica
89.	Isoberlinia dalzielii
90.	Isoberlinia doka
91.	Isoberlinia tomentosa

92. Khaya senegalensis
93. Lannea acida
94. Lannea barteri
95. Lannea kerstengi
96. Lannea microcarpa
97. Lannea velutina
98. Leptadenia hastata
99. Leptadenia pyrotechnica
100. Lonchocarpus laxiflorus
101. Lophira lanceolota
102. Maerua angolensis
103. Maerua crassifolia
104. Maerua oblongifolia
105. Mangifera indica
106. Manilkara multinervis
107. Maranthes polyandra
108. Maytenus senegalensis
109. Mitragyna inermis
110. Monotes kerstengii
111. Nauclea latifolia
112. Oncoba spinosa
113. Ozoroa insignis
114. Parinari curatellifolia
115. Parkia biglobosa
116. Pericopsis laxiflora
117. Philenoptera laxiflora
118. Piliostigma reticulatum
119. Piliostigma thonningii
120. Prosopis africana
121. Pseudocedrela kotschyi
122. Pteleopsis suberosa
123. Pterocarpus erinaceus
124. Pterocarpus lucens
125. Saba senegalensis
126. Sarcocephalus latifolius
127. Sclerocarya birrea
128. Securidaca longipedunculata
129. Securinega virosa
130. Sterculia setigera
131. Stereospermum kunthianum
132. Strychnos spinosa
133. Swartzia madagascariensis
134. Syzygium guineense
135. Tamarindus indica
136. Tectona grandis
137. Terminalia avicennioides
138. Terminalia febrifuga
139. Terminalia glaucescens
140. Terminalia laxiflora
141. Terminalia macroptera
142. Terminalia mollis
143. Thevetia neriifolia
144. Trichilia emetica
145. Uapaca togoensis
146. Unknown
147. Vitellaria paradoxa
148. Vitex doniana
149. Vitex simplicifolia
150. Xerroderris stulhmanii
151. Ximenia americana
152. Ziziphus mauritiana
153. Ziziphus mucronata

12 Curriculum Vitae

Personal data

Name	Christoph Fischer
Date of birth	31.05.1982
Place of birth	Offenbach a.M.

Education

Oct. 2008 – Oct. 2011	Research Associate (PhD Student) at Burckhardt Institute, Chair of Forest Inventory and Remote Sensing at Universität Göttingen, Germany.
Oct. 2006 Aug. 2008	Master of Science in Tropical and International Forestry, Universität Göttingen, Germany.
Okt. 2003 Okt. 2006	Bachelor of Science in Forstwissenschaften und Waldökologie, Universität Göttingen, Germany.