LANDSCAPE CARBON MEASUREMENT IN SYSTEMS OF TREES OUTSIDE OF FORESTS: THE CASE OF AGROFORESTRY SYSTEMS IN RURAL SAVANNAS OF SENEGAL

By

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ABSTRACT

LANDSCAPE CARBON MEASUREMENT IN SYSTEMS OF TREES OUTSIDE OF FORESTS: THE CASE OF AGROFORESTRY SYSTEMS IN RURAL SAVANNAS OF SENEGAL

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Monitoring forest cover changes and carbon content at regional and global level by using remote sensing has advanced significantly for closed humid tropical forests, and several methods have been developed. On the other hand monitoring of cover and carbon for semi-arid savannas and woodlands has been under-studied, and more methods are needed. Further, for systems of Trees Outside of Forests in semi-arid regions, monitoring of cover and carbon has not advanced at all, and new methods are needed.

In this dissertation, I developed methods for remote sensing-assisted carbon measurement and monitoring in semi-arid landscapes of Trees Outside of Forests (TOF) which include:

- Plantation and Agroforestry systems
- Other trees on farms: planted trees
- Other trees on farms: remnant savanna trees

In this study, remote sensing satellite techniques were used to estimate carbon at a landscape level in savanna systems. Remote sensing tree crown projection area (CPA) was used as a proxy to predict tree diameter at breast height (DBH).

A relationship was established between remote sensing based crown projection area (CPA) and the field-based DBH. Both simple linear and non-linear regression analysis were applied to the Sokone and Karang sites in Senegal.

The linear function presents a higher coefficient of determination (R^2) in both sites with respectively R^2= 0.71 and R^2= 0.79 for Sokone and Karang sites. The non-linear model shows R-squared values ranged between 0.61 and 0.77 for Sokone and Karang sites respectively.

The regression equations derived from the relationship between remote sensing-based crown projection area (CPA) and the field-based DBH are used to predict the DBH of all trees within the study area knowing their crown projection area from remote sensing.

A general allometric equation that uses DBH as a parameter to calculate biomass and carbon per tree was used in this study. My findings show that:

(1) A model that uses remote-sensing assisted landscape-scale carbon stock measurement has promise;

(2) The relationship between CPA detected from remote sensing and allometric scaling is something that can be refined but seems to be a workable approach and these refinements would include an improved relationship model using non-linear relationships, developing a local allometric equation using destructive sampling, and specific parameters for the savanna or tree type/species and explore the use of automated detection.

This study's findings will be useful for the Senegalese government and others with savanna systems. With 1,043,000 ha of savanna systems and trees outside of forests (TOF), my findings could be an important step for integrating TOF into the natural resource management scheme for carbon stock estimation and the reduction of greenhouse gas emissions in the forestry sector. The use of remote sensing will lower the costs of field sampling based methods in highly patchy woodland and TOF landscapes and increase the opportunity for small holders and communities of small holders to be engaged in carbon mitigation projects. My findings show that, with a minimum training, they will be able to do the tree measurements in their own farms.

This dissertation is dedicated to the loving memory of my mother Khady Faye who did not live to see the accomplishment that built the foundation and reap the fruits of her sacrifice.
This work is most deservedly dedicated to Fatou, my "super-woman" wife, for her love, support, patience, endurance and tolerance.
Finally I also dedicate this work to my two kids Mouhamadou and Khadidiatou, who often times were told “Daddy is at his office” when they asked for me and had to do without.

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KEY TO ABBREVIATIONS

AGB	Above Ground Biomass
AF	Agroforestry
A/R	Afforestation/ Reforestation
CCX	Chicago Climate Exchange.
CDM	Clean Development Mechanism
C2M	Carbon2Markets
CPA	Crown Projection Area
DAC	Diameter at 20 cm Above the root Collar
DBH	Diameter at breast height
FAO	Food and Agriculture Organization
FM DBH	Field measured diameter at breast height
GIS	Geographic Information System
GPS	Global Positioning System
GOES	Global Observatory for Ecosystem Services
HCS	Hyperspherical Color Space
ICRAF	World Agroforestry Center
IPCC	Intergovernmental Panel on Climate Change
KTGAL	Kyoto: Think Global, Act Local
LDP	Local Development Plan
MRV	Measurement, Reporting and Verification
NFI	National Forest Inventory

PASA	Projet Agroforestier Senegalo-Allemand
REDD	Reducing Emissions from Deforestation and forest Degradation
RS CPA	Remote Sensing Crown Projection Area
SPSS	Statistical Package for the Social Sciences
TOF	Trees Outside of Forests
UNDP	United Nations Development Programme
UNFCCC	United Nations Framework Convention on Climate Change
USDA	U.S. Department of Agriculture
UTM	Universal Transverse Mercator
VCS	Voluntary Carbon Standard
WGS	World Geodetic System

CHAPTER 1 . GENERAL INTRODUCTION

1.1. BACKGROUND AND RESEARCH CONTEXT

Climate change has been an emerging global environmental problem and policy concern, and is now a key economic development challenge in developing countries in Sub-Saharan Africa (Mbow *et al.* 2012; Collier *et al*., 2008) whose consequences include the adverse effects on livelihoods of farmers. Climate change is the result of increased levels of greenhouse gases in the atmosphere caused in part by fossil fuel combustion and land conversion, the latter is due primarily to tropical deforestation. The trend to-date has been toward significant greenhouse gas emissions with few land based sinks. Trends in land use change have been predominantly conversion of high biomass ecosystems to low biomass agricultural systems that have significantly lower carbon stocks. The emissions contribution of land-use conversion is estimated to be 10 to 30% of the current total anthropogenic emissions of CO_2 (IPCC, 2001 Houghton *et al*., 1985). In Senegal, the current terrestrial carbon stock of the landscape is affected by both land use change and land degradation. There has been a loss of 292 MtC from 1965 to 2000 (Woomer *et al.*, 2004). One estimate for southern Senegal indicates that from 1900 to 2000 there has been a landscape-wide decline of carbon stocks in vegetation and soils of 37% (Liu *et al*., 2004).

One interesting characteristic of the land use component of the carbon cycle is that land management can reduce emissions *and* remove carbon from the atmosphere. This dual source-sink characteristic of land use change makes it an important focal point for land management interventions in ways that are not available with energy strategies. Thus, there has been a growing interest in developing modalities for creating carbon sinks in both forest and non forest landscapes, which include, among other forms of intervention: reforestation, afforestation, assisted natural regeneration, plantation management, and agro-forestry and other uses of trees outside of forests.

As one of these forms of intervention, agro-forestry combines a multitude of environmental, social and economic benefits to rural land owners in addition to carbon sequestration. The use of woody perennials on farms in rural Africa can provide high-value products and increased incomes over traditional annual crop production systems. However, it is not widely adopted because the *delayed benefits* obstacle of agro-forestry may be too significant for farmers to adopt these systems by replacing existing annual cropping systems[1]. For example, the long period (5-8 years) to full tree maturity and production may be too long for farmers to feel secure in removing from production cropland that is already producing annual revenues, even if their existing yields and economic returns are meager. As carbon markets have been growing, there has been an increasing emphasis on activities that enable carbon sequestration in tree systems, mostly with large-scale commercial plantation systems. Smallholder agro-forestry presents another option for carbon

[1] The specific role for carbon payments may not lie in its direct sale value, but as a trigger or catalyst that removes the barriers to adoption. Key among these barriers is the so-called "delayed benefits" barrier. Farmers engaged in annual production systems usually have no "excess" land capacity to install agro-forestry. Since an agro-forestry system takes years before it begins to produce, farmers are often reluctant to make this long term investment in tree establishment on annual cropland. For example, it might take three to six years for an agro-forestry system before fully realizing benefits compared to the only few months needed to harvest annual crops (Franzel and Scherr, 2002). Studies in the GOES lab at MSU suggest that while carbon income might only be 15-20% of total farm product income, that is enough to push some farmers into adoption, if the carbon credits can be accrued from the initial planting year. Similarly, those farmers that do engage in adoption of agro-forestry often finance their investment with loans, which immediately places an economic exposure or financial risk on the household. Conceivably carbon finance can be used in the place of capital finance with considerably less (albeit different) risk. Dewees (1995) also suggests that "investments in tree planting are most favorable when they involve low costs and low risks". Also, some studies have shown that the time delay between the planting and the harvesting of trees put farmers in rural areas in a position where they are less likely to adopt agroforestry (Scherr, 1995).

sequestration that can also provide environmental co-benefits (increased soil fertility and lower erosion rates) and at the same time a potential source of income for poor smallholders through carbon sequestration credits.

The model developed under the Michigan State University program, Carbon2Markets, provides a mechanism that creates “year-one” value chains from carbon sequestration for smallholders who adopt agro-forestry, and can alleviate the *delayed benefits* problem by providing early value-chain income from carbon sequestration. Thus, carbon sequestration in agro-forestry and other Trees Outside of Forests (TOF) has the potential to provide increased incomes and provide environmental and agronomic co-benefits such as climate change mitigation.

The challenge, however, is that before agro-forestry carbon value chains can be established there must be rigorous and accurate protocols for measuring, reporting and verifying carbon sequestration in agro-forestry systems and other TOF. These protocols and methods must be acceptable to the international climate change mitigation community and at the same time be acceptable “technologies” for community level implementation and participation. International standards for carbon measurement are being developed and promoted through international conventions, carbon financial markets, and both regulatory and voluntary regimes and institutions.

As such, scientific and technical rigor for international carbon measurement is extremely high, and involves exact reporting and verification standards and best practices. This is particularly true for new modalities of carbon measurement. Currently the common practice for carbon measurement in tree-based sequestration systems is based in large-scale plantations or reforestation in large tracts of closed canopy forests. There is less credibility and "trust" placed in small-scale systems involving agroforestry or small-scale reforestation systems that are managed by local land owners, particularly in savanna and woodland landscapes.

1.2. RATIONALE AND RESEARCH OBJECTIVE

Regional and global monitoring of forest cover changes and carbon content using remote sensing has advanced significantly for closed humid tropical forests, and several methods have been developed. At the meantime, for semi-arid savannas and woodlands, monitoring of cover and carbon has been under-studied, and more methods are needed. Further, monitoring of cover and carbon for systems of Trees Outside of Forests in semi-arid regions has not advanced at all, and new methods are needed. Also, most remote sensing methods for monitoring cover and carbon stocks have used moderate resolution optical sensors such as Landsat. Most of these methods have been either statistical classification or end-member analyses based on spectral characteristics. Consequently, these approaches are inaccurate or inappropriate in landscapes with sparse tree cover; most of the land looks bare to optical spectral signature models. Therefore, we need a new methodology to monitor Woodlands and TOF.

Monitoring is needed on two "fronts" of the problem of carbon accounting of emissions and removals:

- Measurements of changes in forest or tree cover over time, deforestation, reforestation, degradation (also known as Activity Data in IPCC)
- Measurements of stocks and stock changes in carbon content of live biomass (also known as Emission Factors)

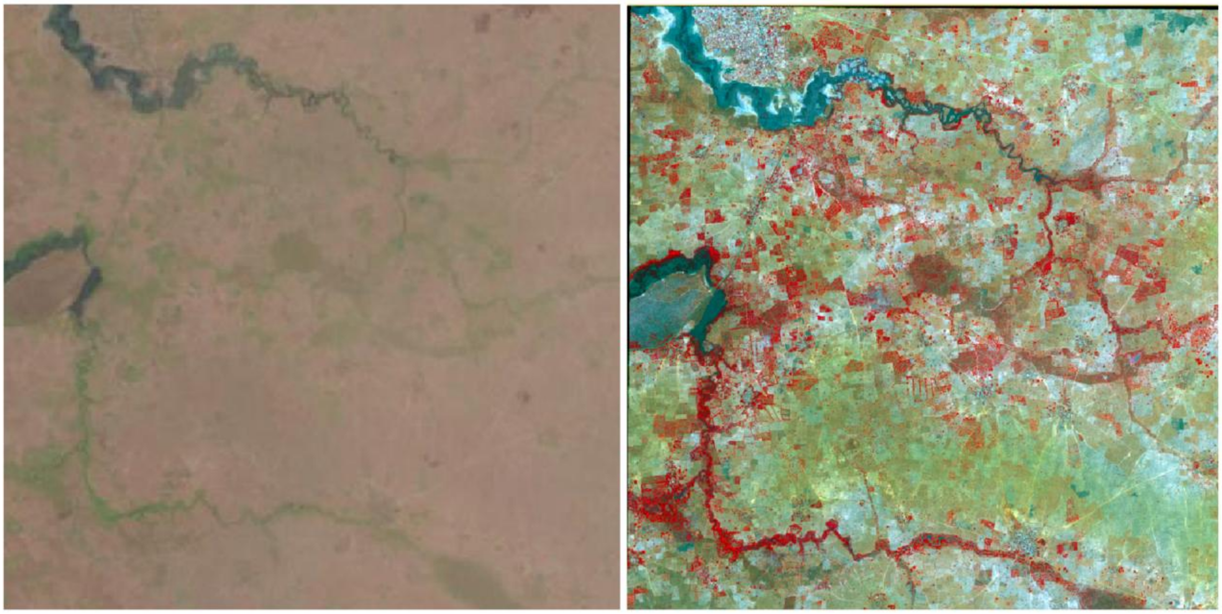
Where convention in IPCC is stated as:

$$ER = AD * EF$$

These measurements lay the foundation for nearly all carbon accounting of emissions and removals associated projects, interventions, investments, and policy actions. They are also fundamental for both sequestration activities and REDD activities, in baselines and reference emission levels, whether project based or national in scope.

There are opportunities on better investigating this area of research because new technologies are emerging that allow very high spatial resolution earth observations: for example, 10 years ago, remote sensors had a 1-2 meters resolution compared to the .46 cm resolution today. This may create opportunities for monitoring landscapes in which tree cover is sparse or widely spaced and where individual trees, as objects, can be detected. If methods exist, remote sensing allows for large area monitoring – at the landscape scale. This could reduce costs of field sampling based methods in highly patchy woodland and TOF landscapes and increase in opportunity for small holders and communities of small holders to be engaged in carbon mitigation projects.

Figure 1.1 Comparison between Landsat 5 and Worldview Image taken the same day (April 16, 2010) in the Sokone study area



Landsat Image **Worldview 2 Image**

In this research, I aim at addressing these problems of small-scale TOF systems as potentially important sequestration systems, and the necessary measurement requirements for enabling these systems in the international system of carbon management and regulation. The major question posed to frame such research is:

- Can protocols be developed that allow for landscape scale measurements of trees outside of forests with the accuracy and rigor that is acceptable to the international community?

This research examines this question through an analysis of potential landscape level carbon measurement, reporting and verification (MRV) methods in rural Senegal. And if we want to sustain these methods, local communities have a role to play. Therefore, I will assess the ability of those communities to accomplish tree carbon measurements on their own farms, which is different from community participation in its richest and fullest extent, a full treatise beyond the rather narrow measurement scope of this study.

The focus of this study specifically is to develop methods for remote sensing-assisted carbon measurement and monitoring in semi-arid landscapes of Trees Outside of Forests (TOF) which include:

- Plantation and Agroforestry systems
- Other trees on farms: planted trees
- Other trees on farms: remnant savanna trees

The method uses a combination of advanced remote sensing and basic allometry in systems of “trees outside of forests” in the semi-arid savanna ecosystems of West Africa, especially in Senegalese semi arid woodland and agricultural landscapes. While doing so, I will assess the local communities' skills on making accurate ground measurements of critical tree parameters, such as tree stem diameter, tree height, and tree canopy projected area to be used to compute carbon stock and stock changes, and thereby be active participants in, and co-owners of, the MRV process.

1.3. FOCAL POINTS FOR THIS STUDY

1.3.1. Climate Change Mitigation Potentials for Agro-Forestry

To mitigate climate change, massive forest protection and reforestation have been promoted as one way to stabilize the concentration of carbon dioxide in the atmosphere through Afforestation/Reforestation (A/R) activities in the Clean Development Mechanism (CDM) or REDD+ activities. However, while these efforts to reduce large scale deforestation or create large-scale reforestation projects provide new land uses for significant climate mitigation (FAO, 2010), they also can conflict with the growing need for expansion of the agricultural land base (Mbow, 2012). Smallholder forest agroforestry on the other hand could be a compromise solution to the apparent land use conflict between forest conservation, reforestation and agricultural land use, because it increases the storage of carbon and at the same time provide opportunities for agriculture. Moreover, the agroforestry option may in fact *enhance* agricultural production (Unruh, 1993).

Currently, there is a growing interest in investing in agroforestry systems for this dual benefits of climate mitigation and livelihoods enhancements (ICRAF, 2008) and also as a set of innovative practices that strengthen the farming system's ability to cope with, or adapt to, adverse impacts of changing climate conditions (Verchot, 2007). In this context it is possible to view agroforestry as both a mitigation and an adaptation option for smallholders. Agroforestry practices can be implemented in a variety of forms and range of intensities depending on local conditions to provide a locally relevant approach to sustainable agriculture production and soil fertility management. Agroforestry might become a key component of the African farmers' household portfolio of farming practices, and provide an important role in meeting farmers' food and non-food subsistence needs through the ecosystem services it provides (Jonsson, 1999). There is also some evidence suggesting that the high production levels and economic values of agroforestry value chains may actually facilitate the production of financial capital beyond subsistence levels alone, thereby aiding in capital accumulation and re-investment at the farm level (Jonsson, 1999).

1.3.2. Advantages of Agro-forestry Carbon Sequestration beyond Climate Change Mitigation

In Africa a critical characteristic of the rural landscape is the preponderance of many smallholder farming systems that are operating on the environmental and economic margins, where any newly introduced practice will be adopted only if it improves food security as well as generates income on a sustainable basis. Under such conditions, climate mitigation interventions, such as increased carbon stocking with trees on farms will need to not only contribute to improve food production but also generate income (Smith, 2012). In this context, climate mitigation becomes a co-benefit of a primarily food-focused enterprise. Hence, there are practices that are keys to sustaining agricultural productivity and they include those that minimize the rate of soil degradation, improve soil fertility, increase crop yields and raise farm income by using the "right tree at the right place". In turn, this will provide better conditions for climate adaptation in many of the poor rural communities that might be most adversely affected by climate change and variability (Neupane, 2001), and then also provide added benefits for climate mitigation through increased greenhouse gas removals from the atmosphere. Agroforestry – as a system of "trees outside of forests" – readily bundles both mitigation and adaptation strategies and provides several pathways to a range of environmental and social co-benefits and outcomes, including food security, increased farm income, restoration and maintenance of above-ground and below-ground biomass and biodiversity, reestablishment of biological corridors between protected forests, maintenance of watershed hydrology, improved soil conservation, availability of timber and fuel wood, and ultimately a reduction of pressure on natural forests outside the farming domain (Pandey, 2002).

1.3.3. Carbon Sequestration as Part of a Value Chain or Production Strategy

Agroforestry is a promising option to sustain agricultural productivity and livelihoods of farmers (Syampungani *et al*., 2010), and a low-cost method to sequester carbon. In the context of emerging carbon markets and ecosystem payment schemes, and where extreme poverty is a crucial problem in many parts of tropical countries, especially in rural areas, carbon benefits of specific farming systems may be a means to encourage and incentivize sustainable agriculture and natural resource management systems. Some studies have shown the value of increasing tree cover through tree planting by households as a solution to the problem of deforestation (Carle *et al*., 2002; Medugu, *et al*., 2010). In a country like Senegal, where farmers represent more than 70% of the population and depend on land to develop their activities, agro-forestry presents a real opportunity with potential pay offs for livelihoods, land productivity and environmental integrity. It has also the added benefit of creating options at the household and community level for climate change mitigation and adaptation.

Farmers ordinarily don't include, nor often even comprehend, the carbon dimension of their farming system when considering or engaging new land management practices such as agro-forestry. For example, evidence from the Nhambita Project in Mozambique has shown a “lack of deeper understanding of the concept and its mechanisms” (Campesina Africa, 2012). And “even though farmers know that their income from planting trees comes from carbon, they do not understand what carbon is (Campesina Africa, 2012).

Rather, farmers focus more on the direct economic return of the new alternative and the benefit of improving the land management system; altogether contributing to increase annual crop productivity, sustainability and cost effectiveness. One challenge is to determine how and if, carbon can be another commodity value chain that provides economic returns to land managers and can be integrated into farmers’ own strategies.

One way of assessing the value of carbon sequestration is to measure carbon using more accurate techniques so that it can be sold and benefit those people whose activities contribute to the sequestration. Also, engaging the communities in carbon measurement activities could lower the cost of carbon sequestration and increase the benefits. It is also important to investigate the role of carbon in agroforestry adoption.

1.3.4. The Need for a New "Bundle of Methods" for Carbon Measurement and Reporting

A logic model has been developed and briefly laid out below:

1. In land-scarce areas, agroforestry can provide an alternative to dedicating land solely to reforestation to reduce pressure on forests;
2. Agroforestry as a carbon sequestration system and a production system might provide a means for both climate change mitigation and an enhanced agricultural production;
3. One major obstacle is that delayed benefits prevent widespread adoption of agroforestry;
4. Carbon value chains may offer a way to overcome these barriers to AF adoption.

However, before agroforestry as a carbon sequestration strategy and value chain will be necessary, it requires that its carbon be quantified and measured accurately, be reportable, and verifiable.

Many accepted methods for carbon measurement in programs or projects that are based on sequestration (as opposed to avoiding emissions from deforestation) have been defined at a project scale with specified boundaries of the project, often on land parcels with a single owner. When trying to develop methods for rural poor farmers, experience suggests that a landscape approach is needed (Estrada-Carmona *et al*., 2014), whereby many farmers can be bundled into a single project, even if the parcels are not contiguous.

The landscape approach offers new opportunities for a greater participation of the rural poor in carbon markets. However, the means for landscape-scale measurement need to be developed. Remote sensing offers a means to do landscape scale measurement and monitoring, but most advanced methods in recent years have focused on closed forests, rather than open woodlands and savannas or, to be sure, systems of trees outside of forests.

Thus, the current study focuses on the need to develop rural community-focused, landscape-wide measurement methods for systems of trees outside of forests (cf. agro-forestry and related systems) in the savannas of Africa. This measurement and monitoring approach provides a bundle of methods (landscape wide, trees outside of forests, community-scale).

1.3.5. Remote Sensing

In recent years there has been substantial progress by the research community in developing ways to detect land cover change in tropical forests with remote sensing analysis. Initially the focus was on measuring the conversion of tropical forests to non-forest land (Skole and Tucker 1993). However, recent advances have made it possible to increase the variety of disturbances that can be detected for closed tropical forests to include deforestation, degradation, logging, fragmentation, reforestation, and fire (Matricardi *et al.* 2013, Matricardi *et al.* 2010; Matricardi *et al.* 2007; Wang and Cochrane 2005). Thus, there are now methods available to remotely detect a full range of disturbance intensities, from outright clearing to low levels of degradation, over large areas.

But these approaches have been applied only in very dense closed tropical forests, and in particular in key regions of the Amazon Basin, Central Africa, and South East Asia. There has been very little advancement of detection methods for two important other forms of land cover change: 1) deforestation and degradation of open woodlands such as the *cerrado* and the *chaco* ecosystems in South America, woodlands of East Africa, Savannas of West Africa, and other open forest ecosystems in the tropics and sub tropics, and 2) regeneration systems on managed landscapes where biomass recovery occurs as plantations, orchards, agroforestry, and widely-spaced tree complexes associated with agriculture.

Some studies have suggested that disturbance in open forest systems is quantitatively as important as in closed forests systems (Erickson *et al.* 2002; Murphy and Lugo 1995; Serca *et al.* 1998), especially because disturbances in these systems may have longer term degradation effects with lower probabilities of recovery than in closed forest systems. Observations of reforestation and biomass accumulation in trees on agricultural land is important because these data are needed to understand the global magnitude and capacity for carbon sequestration, and to inform decision makers and policy makers on options for carbon management practices that can remove carbon from the global atmosphere. There is also considerable uncertainty on the current land area in woody perennials on farms in developing countries and the global potential for managing carbon sequestration in tree-based agriculture. Some estimates from international organizations suggest a large amount of carbon sequestration already occurring in these managed landscapes (Verchot and Singh 2009).

Although frequently treated as a secondary priority to monitoring of the much higher biomass forests of the humid tropics, the dry and open forests of the world are more abundant than closed forests and usually are more prone to occupation and disturbance by humans. Although these low density forests contain as little as 25% of the total carbon stock of humid tropical closed forests, the global area is more than 30% greater and rates of disturbance are suspected to be equal to or greater than the closed forests, and less likely to recover lost carbon. Thus, it is vitally important to begin to assess the global magnitude of open forest disturbances.

What is often unrecognized is that while forested area is declining in developing countries, tree cover on farms is increasing, as farmers substitute annual cropland for the tree products which were formerly available in local forests. Farmers are also increasingly seizing specific market opportunities to sell higher-value tree products (e.g. natural rubber, bio-fuels, bio-chemicals, timber). For example, remote sensing in 64 rural locations in Uganda revealed that between 1960 and 1995, forested area declined 50%, agricultural area increased 23%, and the proportion of agricultural land under tree cover increased 22% (Place 2001). Agricultural land now accounts for over double the area of forested land in Africa (FAO 2006), giving justification to the slogan that, "the future of trees is on farms."

Increasing woody biomass on farms in developing countries is seen as a possible global climate and carbon mitigation option that deserves serious attention. Montagnini and Nair (2004) have estimated that a vigorous program to introduce agro-forestry on farms in tropical Africa and Asia has the potential to sequester 3.5 Mg C ha^{-1} yr^{-1}. However, for this to be a successful strategy it will be necessary to have sound detection and monitoring systems in place.

1.3.6. Linking Remote Sensing to Ground Measurement

A significant challenge for efficient, timely and cost-effective automated monitoring of A/R/AF is the accurate measurement of woody biomass in the landscape. Detecting and measuring individual tree objects that are sparsely planted on farms, along roadways, or in backyards cannot be done accurately with low or moderate resolution satellite imagery where a single tree may represent only a small proportion of a single pixel. Although pixel unmixing techniques (Keshava 2003) can provide an estimate of the proportion of different land cover types represented in a single pixel, in general, these techniques are not amenable for accurate estimation of tree size, number of trees or other measurements required for accurate assessment forest cover change in sparsely planted landscapes. Also they do not work well for savanna and TOF landscapes. However, recent technological advancements in satellite image acquisition provide access to hyper-resolution imagery of the Earth and its land uses. For instance, the Worldview 2/3 satellite acquires 4 bands of multispectral data at 2.4m resolution and a panchromatic band at 60 centimeters or finer. Other sensors now can detect resolutions of objects at 0.5 m in size. Very high-resolution imagery enables the detection of objects in the landscape using remote sensing. Subsequent processing can be used to associate attributes, such as size or texture, with detected objects. Therefore, it may be possible to count trees, estimate size and evaluate change remotely, which is a focal point for this study.

If one can detect individual trees and tree crowns, there is a potential to develop a crown-based allometry for individual trees. This would require the development of methods for ground measurements that could support the remote sensing analysis. Most reforestation projects use small sample plots in a sampling frame for forest inventory. This ground measurement protocol must be re-defined for systems of individually planted or growing trees, and then also extended to the woodland or savanna landscape. The landscape approach allows one to inventory both land in forests (in this case savanna) and land with trees outside of forests (in this case agroforestry on farms).

1.3.7. Community Outreach and Engagement for Joint Measurements

Although there is considerable concern and interest in involving local communities in the various international carbon programs, there is also some uncertainty over whether they can participate in the basic measurement process (Evans and Guariguata, 2008). This has made it difficult to include smallholder systems in the international agenda, and thus forgoes the potential of systems like agroforestry from being a low-cost and local system for carbon and climate mitigation.

However, work in Southeast Asia by Samek *et al*. (2014) shows that the measurement process could readily engage local communities, at least as partners who are trained to implement the standard forest inventory measurements on the ground. Ground measurements are expensive and time consuming, especially when done by external project developers or verifiers, and it is not likely that local community members can readily participate in, and share the benefits of a project that relies on outsiders doing the measurements of their own lands. The first step in the process of claiming ownership of the benefits of carbon sequestration begins with measurements and reporting. So it is important that community-based abilities must contribute to measurements. Yet, community level understanding of carbon as a service or commodity, and their willingness to participate can be difficult. Obstacles, such as land and labor availability may hinder willing participants, according to Tschakert (2004). However at the most fundamental and basic level, there is a need to know how well collaborative measurements with the project specialists and the local people could produce accurate measures - a simple but important issue is whether or not traditional and local communities can make accurate measurements, that can withstand the scrutiny of international protocols, and thereby enable the deployment of the Carbon2Markets model.

The Global Observatory for Ecosystem Services (GOES) laboratory at Michigan State University has been working with communities in Africa, South Asia and Southeast Asia on joint measurement campaigns for assessing carbon stocks in smallholder plantation and community forest systems for more than five years, mostly in small locally-owned stands of teak (*Tectona grandis*), but also with native species in community forests (Samek *et al.* (2011), Samek *et al.* (2013). In early work in Thai communities of the Inpang Network, a sufficiency economy organization in Northeast Thailand (Krongkaew 2003; Chalapati 2008), this project produced a new protocol that engaged collaborative teams of local people and university specialists from both Thai and American universities. This protocol was accepted by the Chicago Climate Exchange (CCX, 2009).

There are a number of other existing C mitigation projects that include smallholders and agroforestry in developing countries, e.g., the Plan Vivo C mitigation projects in Tanzania, Mexico, Mozambique, and Uganda (Plan 2010). These projects, however, include other forest C mitigation components than agro-forestry, such as afforestation/reforestation, forest conservation, and avoided deforestation – the typical complement of REDD+ activities. Moreover, Plan Vivo is a "standard" rather than a protocol. The Plan Vivo standard is a set of best practices to ensure that a forest C mitigation project provides equitable distribution of benefits, ensures livelihood needs are met, includes local people in the development and management of the project, and supports biodiversity and environmental services (Ruiz-De-Oña-Plaza *et al.* 2011). Plan Vivo projects emphasize capacity-building, long term C benefits, diversifying livelihoods, and protecting biodiversity (Plan Vivo, 2010). The Inpang Carbon Bank activities also follow the same principles. Two main differences between the GOES approach to agroforestry C offsets and the Plan Vivo standard are the use of an Internet-enabled content management application, which uses GIS and remote sensing data analysis, and a focus on developing a new Chicago Climate Exchange (CCX) market approved agroforestry C offset protocol.

In order for agroforestry C to be developed as a commodity it must, however, be economically viable; thus most forestry projects have been large-scale enterprises. For smallholders there are market, institutional, and social barriers that all yield costs. The GOES Lab's work has focused on addressing the social barriers through capacity building and training local people in the Inpang Network, the institutional barriers through partnering with provincial and national organizations representing the national commitments to the UNFCCC, and the market barriers through technological innovations in managing C offset projects. One piece of this dissertation, centered in Senegal, focuses only on a narrow slice of the first, social barrier in terms of accuracy assessment.

The Carbon2Markets internet-based C offset management system is truly in a software R&D phase. The proposed advantage of the Carbon2Markets system for smallholder C offsets is in lowering the transaction costs associated with field-level measurements and verification. The fully developed on-line C management system will allow a farmer's agroforestry C offset field to be enrolled through on-line tools that will register the field boundaries, calculate the baseline C, estimate leakage from on-farm management practices and report future amounts of C sequestration (*ex ante* projections).

The on-line tools require input data uploaded to the database. Field boundaries are either delineated using a hand held GPS receiver, uploaded via the Internet, entered as coordinates on-line, or drawn on-screen using hyper-resolution satellite imagery (1 m or less) and Internet-GIS tools.

An important question related to this approach is "Can smallholder agroforestry C offset projects be scaled up?" With an on-line Internet-GIS management application, such as Carbon2Markets, and the potential to use satellite remote sensing data to directly measure and monitor C sequestration in biomass, the proposition is that it is feasible. Aggregating individual farm parcels is a key function of the Carbon2Markets software application that allows scaling and lowers scale-up costs. The smallholder teak plantation studies in Thailand demonstrate how farms spread across five provinces can be managed as a single project and scaled up to national levels. Ground-based measurements are essential components of this method and will be a requirement for project validation and verification against rigorous international standards for all projects in the foreseeable future. The coupling of satellite remote sensing measurements with ground measurements of C in biomass means larger areas can be assessed with fewer field data requirements.

While progress has been made with the Inpang Carbon Bank project the GOES Lab is cautiously optimistic about realizing agroforestry C offset transactions and the potential economic benefits to rural farmers in the near term. Follow-on studies have been developed in other smallholder plantation systems and community forests in Thailand, Laos and Vietnam. This work has expanded the experience of the GOES Lab in the context of REDD+ forests as well. One could imagine that these new projects in Asia have been developed against a backdrop of views, perceptions and arguments over the pros and cons of REDD+ at the community level. Indeed there is a resonating view among those skeptical about REDD+ implementation that identifies the risk that REDD+ may marginalize local people, hinder their access and rights to forest and forest resources, and negatively impact local livelihoods. These are legitimate concerns, even in light of discussions about safeguards working to ensure “the full and effective participation of relevant stakeholders, in particular indigenous peoples and local communities” (UNFCCC CP 16 2010). Ribot and Larson have reviewed some of these concerns (Ribot and Larson, 2012). These Asian projects and the proposed Senegal site are not focused on analyzing the various forest policies and implementation of these policies in the three countries, which can indeed impact how local people benefit or are marginalized in such activities as REDD+. Rather, our research is targeting the practical implementation of engaging communities in the tasks of measuring biomass in forested areas and the collection of field data that could be integrated with satellite remote and GIS analysis in a Carbon2Markets MRV system.

From preliminary results of Asian projects, the GOES Lab has identified several important elements that affect community-based field measurements with GIS and remote sensing for a REDD+ MRV (Samek *et al.* 2013). Forest biometric data collection can be done using simple or hi-tech tools. The diameter at breast height of a tree can be measured with a DBH tape or a simple tailor's tape and the measurement converted to diameter. GPS devises are now common in University labs and with local agencies in the field. The management of data measurements, however, must be systematic and uniform across biomass plots within a project location. Common print outs of spreadsheets, or data field forms in data loggers are important. Tools to manage all project data are also very important. Ideally, with web-based service becoming more and more common, data management can be developed as a set of tools for REDD+ implementation that include basic description and management, document and file management, plot level data management and carbon stock calculations, geo-spatial data management and even emissions reporting.

Measurement and monitoring for REDD+ can effectively combine local, community data collection with expert analysis using remote sensing and GIS. National-level forest measurements often are conducted under National Forest Inventory (NFI) programs in which permanent sample plots are established and repeated measurements are taken every few years. Unfortunately, not all countries have adequate NFI programs in place. Forest monitoring, to assess areas and rates of change, is most often conducted using satellite remote sensing. The combination of ground based plot biomass measurements and satellite remote sensing analyses is powerful for measuring and monitoring REDD+ carbon stock and carbon stock changes. This is because, measurement and monitoring of REDD+ carbon is not dependent on ground only or remote sensing only techniques, but a combination of the two. Integrating community level plot measurement data with geo-spatial analysis (GIS and remote sensing) supports REDD+ measurement and monitoring requirements for an MRV system. The combination captures or utilizes the opportunity to integrate community level abilities with professional, expert analysis.

The limitation of the aforementioned work of the GOES Lab is that all these projects deal with forests or forest stands – smallholder plantations, community forests, or REDD forests – and do not address the application of the Carbon2Markets MRV in systems of *trees outside of forests* nor agroforestry systems in predominantly agricultural landscapes. There is a need to explore the effectiveness, accuracy and precision of joint measurement campaigns in savanna landscapes and agroforestry systems outside forests.

1.4. DEFINITION OF CONCEPTS

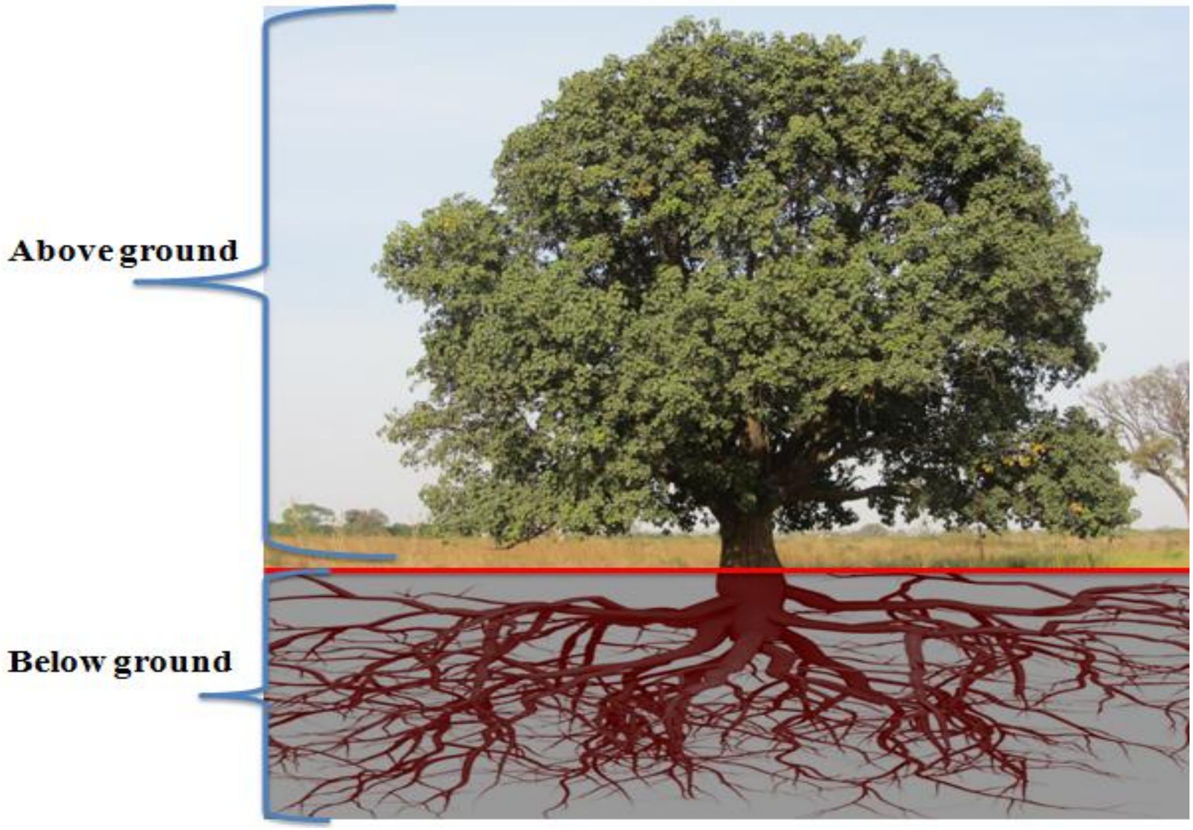
The following terms are used throughout this study, and the definitions given here are used to clarify those terms.

1.4.1. Biomass

Biomass is a vegetation attribute that refers to the dry weight of a plant material within a given area. It includes living and dead above and below ground biomass (Figure

1.2) as well as soil organic matter (IPCC, 2007). However, only above and below ground biomass is considered in this study.

Figure 1.2 Above and below ground biomass of a tree



1.4.2. Cropland

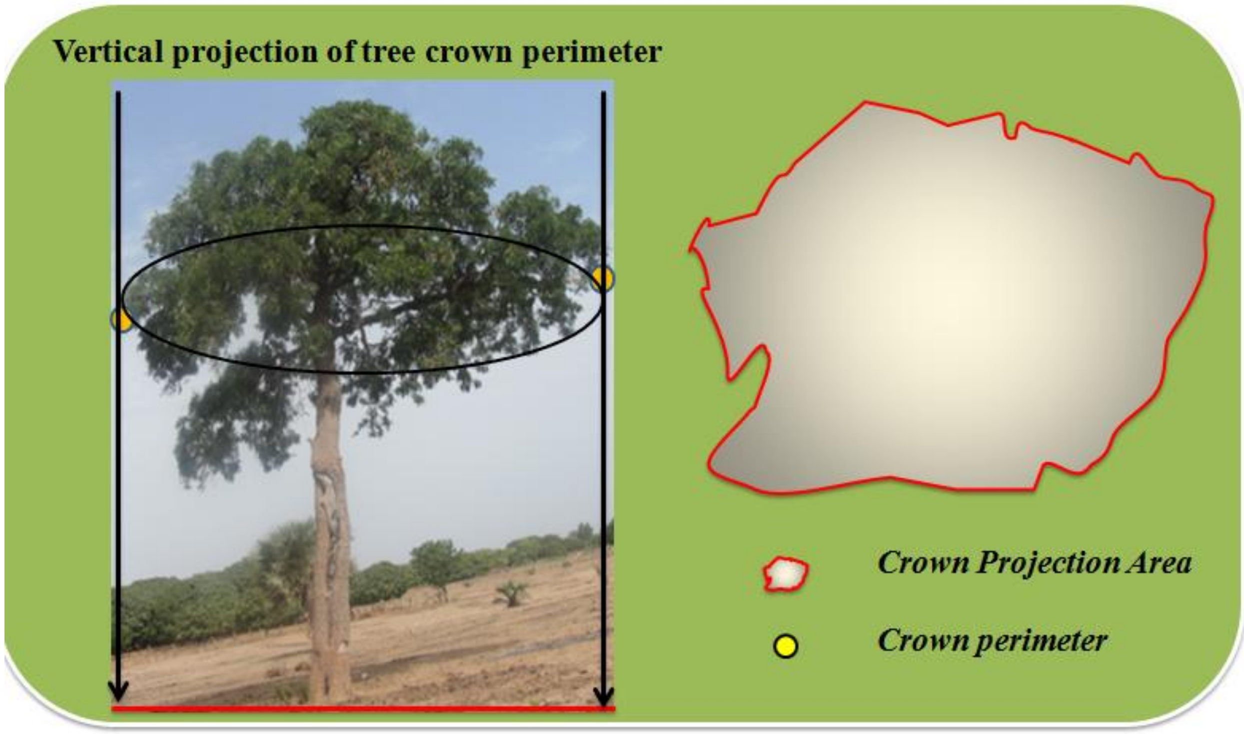
There are many components of cropland as classified by the USDA based on the major uses. Cropland includes land planted for crops, crop failure, cropland used only for pasture and idle cropland (USDA/NASS, 2011). However, in this study, the concept is used to refer to only land on which agricultural crops are grown.

1.4.3. Crown Projection Area

The crown projection area of a tree is the area of the vertical projection of the outermost perimeter of the crown on the horizontal plane (Gschwantner *et. al*, 2009). We determined the CPA by using the formula for the area of an ellipse which is

CPA = π * 1/2 of the maximum diameter * 1/2 of the diameter at 90^{o}

Figure 1.3 Crown perimeter and crown projection area of a tree (adapted from Gschwantner *et. al*, 2009)



1.4.4. Forest

The FAO define forest as a land with a minimum area of 0.5 ha occupied by trees with more than 5 m height and more than 10 % tree cover and agricultural lands are excluded in this definition (FAO, 2010). According to the definition, the potential of trees outside of forests, especially in agricultural lands and more importantly, in the case of agroforestry based systems and crop lands might be neglected in terms of providing benefits within the framework of the carbon market. In this study, forest is defined as "a land with a minimum area of 0.5 ha and occupied by trees with at least 30% tree cover and can reach a minimum height of 2 meters" as stated by the national definition adopted by Senegal.

1.4.5. Savanna

It is defined as grassland with scattered trees or shrubs. The tropical savannas occur between the tropical dry forests and the deserts. These savannas are warm and have low precipitation that is highly seasonal (Chapin *et al*., 2002).

1.4.6. Trees Outside of Forest (TOF)

According to the FAO (2002), these categories of trees are growing in areas not belonging to the category of forest, forest land, or other wooded land. In this study, the concept of trees outside of forest includes all trees in agricultural land, agroforestry systems, trees growing inside the settlements and along the roads. Regarding the size, only trees that attained a diameter at breast height (DBH) of 10 cm or more are included in this definition.

1.4.7. Rural Community

A Rural Community is the smallest unit of local government in Senegal composed of several villages. However, since 2013, all of the rural communities are now Communes after the new law No. 2013-10 of December 28, 2013, which established the General Code of Local Government.

1.4.8. Arrondissement

It is the next highest level after the Rural Community and is composed by 2 or more Rural Communities.

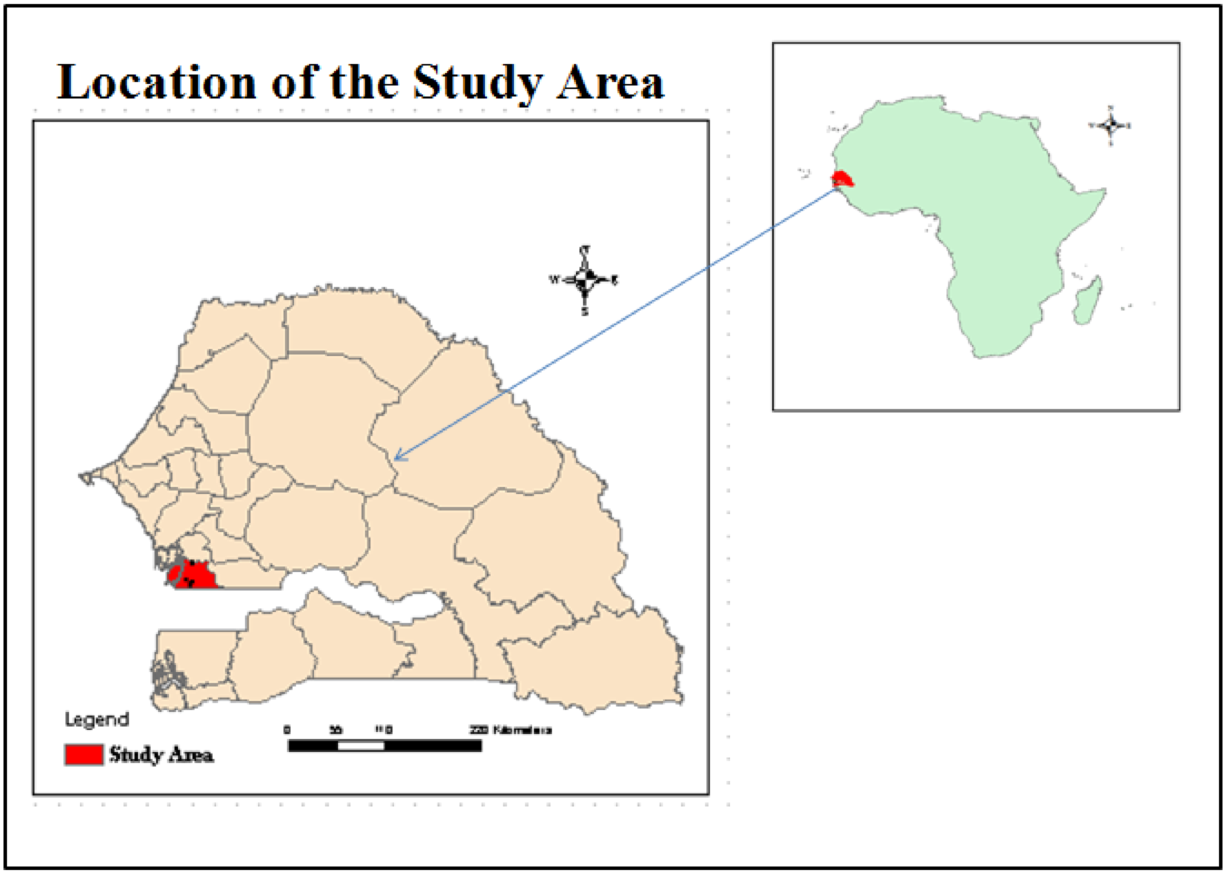
1.4.9. Sous Préfet

The *Sous-Préfet* is the State Representative at the Arrondissement level.

1.5. GEOGRAPHY OF THE STUDY AREA

The research is located in Senegal, in a semi-arid environment that is dominated by savanna ecosystems, and marginal arable lands. The study is carried out in the Fatick Region, located 190 km from the capital of Dakar.

Figure 1.4 Location of the study area



The region is in the southern part of the so-called peanut basin, part of the *Sudanian* zone characterized by savanna landscapes. This region is poorly developed economically, and suffers from low vegetation and crop productivity. Agriculture in Senegal and in this region of Senegal is dominated by peanut production and is now undergoing severe productivity and production declines. Peanut production has been steadily declining over the past decades for historical, political, economic and environmental reasons. After playing a prominent part in the economic and social history of Senegal (Bonnefond and Couty, 1991) in the 1970s and 1980s, overall peanut production and commodity prices are now declining, leading to a reduction of peanut exports and loss of farmer incomes. Several factors have caused peanut yield to fall and consequently reduce farmers' income, including soil fertility decline (Tappan *et al.* 2004) due to the reduction of fertilizer use, reduction of fallow periods (Kelly *et al.*, 1996), and the concomitant shortening of the soil regeneration period (Reinwald, 1997). To this, must be added the rapid population growth of the country and the intensive use of land which has also contributed to agricultural land degradation and soil fertility depletion.

Figure 1.5 Selected photos of the study area

Photo 1: Cashew plantation intercropped with groundnuts in Kouatine Village

Photo 2: TOF *(Prosopis africana)* with cashew plantation on the background Keur Samba Gueye Village

Photo 3: Scattered individual trees in Senghor village's landscape

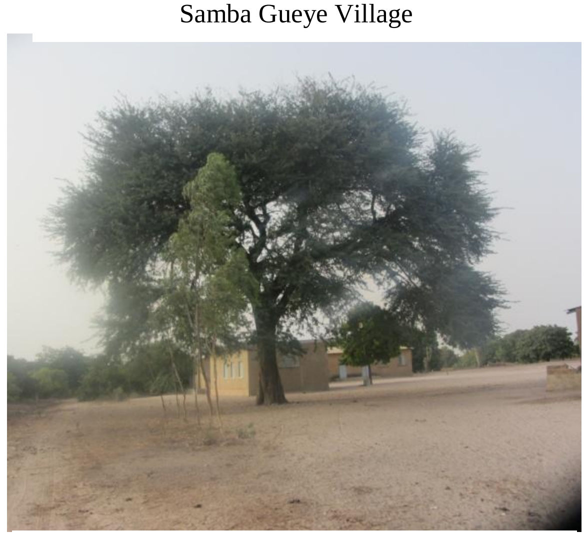


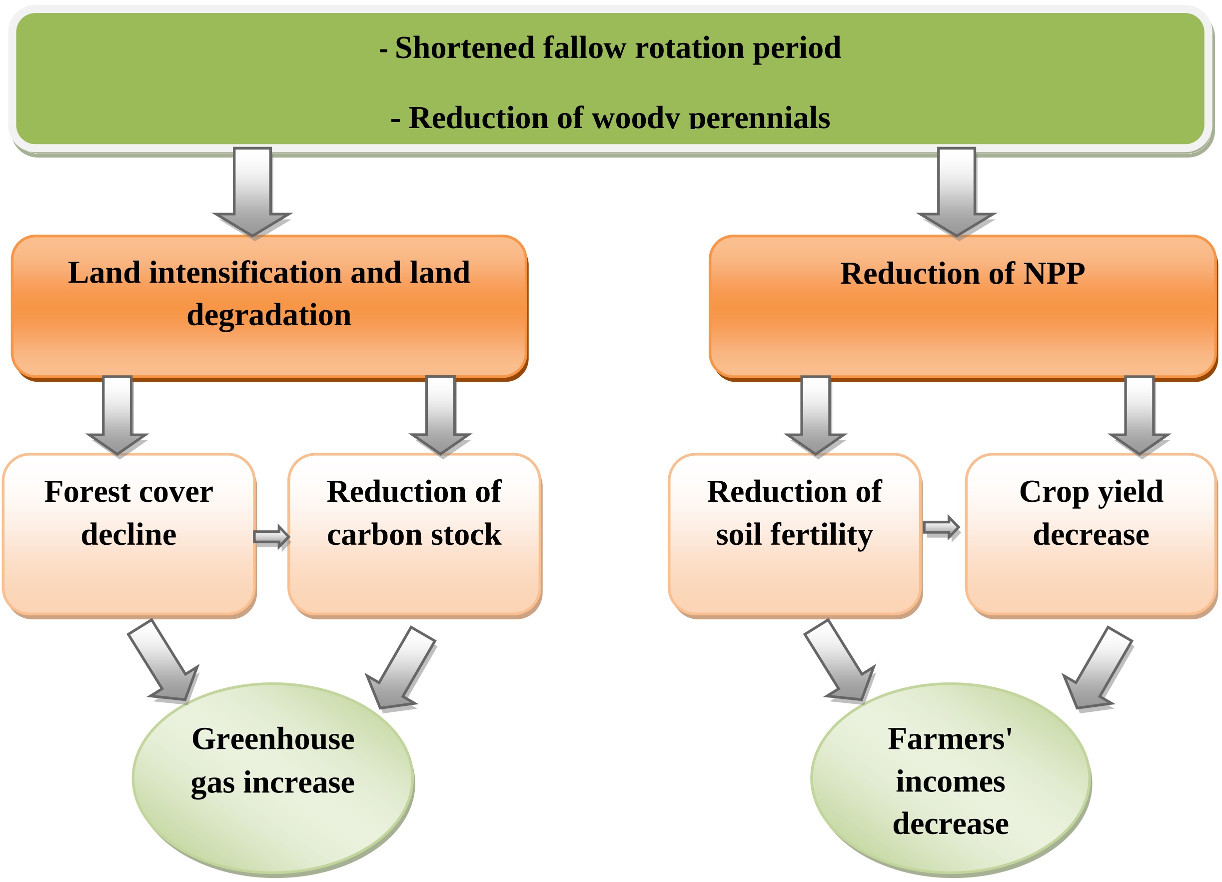
Photo 4: Big TOF *(Acacia albida)* in Senghor village

With increased population densities and associated reduction in fallow periods, soil fertility decline is becoming acute, not only in Senegal but throughout the tropics (FAO, 2005). This has been leading to a situation where soil and land degradation are an emerging threat to food security in developing countries (Scherr, 1999), which will at the same time increase the vulnerability of these places to climate change and reduce the range of options that farmers have for adaptation. Land degradation leads to lower water holding capacity, loss of soil organic matter, and increased loss of soil nutrients which leave farmers vulnerable to drought and increased temperatures. With little access to remediation resources such as irrigation, fertilizers, and new drought tolerant varieties of crops, farmers in the tropics and Senegal are likely to be disproportionately and adversely affected by climate change. These aforementioned factors have social and economic consequences for farmers and seriously affect their livelihood systems beyond income loss alone – e.g. food security, health, nutrition, and sanitation.

As land use intensification is reducing or eliminating fallow rotation periods, trees that are used in the agricultural landscape are being removed to expand the land under cultivation or as a source of fuel wood. Wood and charcoal are the main source of primary cooking energy and fuel for at least half of the country's 13-million people (Media Club South Africa, 2009). Firewood and charcoal are used by 55.5 % and 11% of Senegalese households respectively (Senegal, 2010).

The combined influence of shortened fallow period and the reduction of woody perennials are contributing to increased land degradation. With the additional land degradation and land scarcity, forest land is increasingly being brought under cultivation (Figure 1.6).

Figure 1.6 Changes in land use and their environmental and economic consequences



Like many developing countries, Senegal is facing major problems in the forestry sector and on forest lands generally from deforestation and forest degradation. Forest cover has been declining over the past twenty years from 9, 348,153 ha in 1990 to 8,473,153 ha in 2010 (FAO, 2010). The rate of forest loss, estimated to be 45,000 ha per year in 2005, has been reduced to 40 000 ha per year due to national reforestation initiatives but this loss rate remains high and requires government intervention. The main causes of forest loss are clearing for agriculture (38 %), illegal production of charcoal (25%), fire (25%), other causes such as mining accounting for 12% (FAO, 2010). While the factors that we mentioned are still causing negative consequences for both the environment and the social and economic conditions of communities, mitigation strategies exist that may contribute to reduce the effects. Carbon sequestration is among these strategies and agro-forestry is also among the mitigation activities that can benefit both the environment and the communities that practice these activities. As a sustainable practice, it "helps to achieve both mitigation and adaptation objectives while remaining relevant to the livelihoods of the poor smallholder farmers in Africa" (Mbow *et al*., 2014). However, measuring the carbon sequestered by these practices is a big challenge, especially in savanna systems.

1.6. ORGANIZATION OF THE DISSERTATION

This dissertation is organized in five chapters including the introduction (Chapter 1). In Chapter 2 a model is developed to predict tree DBH from crown projection area using remote sensing high resolution satellite imagery. High resolution data and ground data are combined to develop this model for trees outside forests. Chapter 3 focuses on the role of Remote Sensing in measuring biomass and carbon at landscape level in savanna systems. A regression analysis between field measured DBH as dependent variable and remote sensing crown projection area as independent variable is developed. The regression equation is used to predict tree DBH and an allometric equation used to calculate the biomass and carbon for all trees. Chapter 4 is dedicated to apply the model at the landscape level and to produce carbon map of the study area. Finally, chapter 5 presents a summary of the results and discusses their implications, limits and recommendations for further research.

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CHAPTER 2 . MODEL DEVELOPMENT TO PREDICT TREE DBH FROM CROWN PROJECTION AREA USING REMOTE SENSING

2.1. INTRODUCTION

Carbon sequestration in agro-forestry has the potential of providing increased income and livelihood support, several environmental and agronomic co-benefits, and potential for climate change mitigation. At the same time, it can reduce the barriers to widespread adoption of these high carbon stock agro-forestry systems. For example, in the Nhambita Project in Mozambique, results have shown that systems that combine sequestration and cash crop production have higher benefits compared with sequestration only, although they have less-carbon sequestration potential (Palmer and Silber, 2011). In addition to direct ecosystem uses carbon appears to be a top-up benefit for farmers as it can provide additional incomes. Accounting for the market value of carbon in these systems cannot be achieved without a proper assessment of their performance for sequestering carbon (i.e. carbon sequestration rates), hence the need for cost effective methods suited to estimate carbon stocking potential of trees in farming landscapes.

The international climate change mitigation community recognizes the need for rigorous and accurate protocols for measuring, reporting and verifying carbon sequestration in agro-forestry systems. Such protocols must have acceptable “technologies” for community level implementation and participation. International standards for carbon measurement are being developed and promoted through the international conventions, carbon financial markets, and both regulatory and voluntary regimes and institutions. As such, scientific and technical requirements for international carbon measurements are extremely high, and involves high reporting and verification standards. Currently the common use of carbon measurement in tree-based sequestration systems is in large-scale plantations, or reforestation in large tracts of closed canopy forests. Less certainty and "trust" are accorded to small-scale systems involving agroforestry or small-scale reforestation systems that are managed by local land owners, particularly in savanna landscapes.

There are numerous landscape-wide deforestation and carbon measurement protocols for forests, particularly closed forests (Matricardi *et al.*, 2012). The Voluntary Carbon Standard (VCS) is also used in forest carbon accounting to lead a greenhouse gas reduction program across the world (VCS, 2014) and has developed several methods for forests. However, few methods are available for sparsely wooded systems, such as savannas. The Voluntary Carbon Standard (VCS) protocol for the Kasigau Corridor REDD Project in Kenya (VCS, 2011) is among those methods although it uses plot-level measures and not remote sensing. There has not been much progress on developing a method for assessing tree biomass over large areas in these non-forested landscapes. The current methods for landscape-level carbon measurement are particularly challenging and are unlikely to meet scientific and rigorous standards (for example the requirements of the CDM Executive Board) and potential carbon project investors. Therefore, there is a lack of confidence in existing measurement systems with implications that go beyond the measurement of carbon credits, and create doubts about the project viability. New advances in remote sensing of canopies and individual tree crown detection offer great promise.

It is also important to note that most of the forestry methods used to estimate biomass are based on diameter at breast height or 1.3 m from tree-stem base (DBH). In this study, we explore the role of crown projection area(CPA) as an allometric measure that can be obtained from high resolution remote sensing images, and investigate the possibility of using remote sensing CPA to predict DBH. Thus, the research goal of this study is to determine whether or not protocols can be developed to allow landscape scale measurements of trees outside of forests with the accuracy and precision that is acceptable to the international standards. To respond to this question I suggest basic measurement tools for monitoring carbon stocks in systems of trees outside of forests using remote sensing, ground measurements and GIS because there is a need for a new "bundle of methods" for carbon measurement and reporting that requires linking remote sensing to ground measurement.

A significant challenge for efficient, timely and cost-effective automated monitoring of A/R/AF is the accurate measurement of woody aboveground biomass in the landscape. Detecting and measuring individual tree objects that are natural trees or sparsely planted on farms, along roadways, or in backyards cannot be done accurately with low or moderate resolution satellite imagery where a single tree may represent only a small proportion of a single pixel. While pixel unmixing techniques (Keshava 2003) can provide an estimate of the proportion of different land cover types represented by a single pixel, in general, these techniques are not amenable for accurate estimation of tree size, number or other measurements required for accurate assessment of forest cover change in sparsely planted landscapes. However, recent technological advancements in satellite image acquisition provide access to hyper-resolution imagery of the Earth and its land-uses. Very high-resolution imagery enables the detection of objects in the landscape using remote sensing. The Worldview 2 satellite acquires 4 bands of multispectral data at 2.4 m spatial resolution and a panchromatic band at 46 centimeters. Subsequent processing can be used to associate attributes, such as size or texture, with detected objects. Therefore, it is possible to count trees, estimate size, and evaluate change remotely.

Mbow *et al.* (2013) used the close relationship between DBH and tree height to build a biomass estimation model, but they did not include the crown diameter in their research because "it was not exploited further at this stage". Additionally, the relatively low density of trees outside forests makes the assessment by conventional methods costly and time-consuming (Singh and Chand, 2012).

If one can detect individual trees and tree crowns, there may be a potential to develop a crown-based allometry for individual trees. This requires the development of methods for ground measurements. Most reforestation projects use small sample plots in a sampling frame for forest inventory. This ground measurement protocol must be re-defined for systems of individually planted trees, and then also extended to the woodland or savanna landscape. The landscape approach allows one to inventory both land in forests (in this case savannas) and land on trees outside of forests (in this case agroforestry landscapes).

Another reason for combining remote sensing and ground data is that biomass is mostly determined by classical allometries from measurements of either diameter at breast height or height, and currently none of these measurements can be obtained from remote sensing. However, it may be possible to use high resolution satellite imagery to measure tree crown projection area and use it as an independent variable to predict tree DBH.

In this study, I developed a regression model to predict tree diameter at breast height (DBH) from tree crown projection area (CPA) for trees outside forests in savanna agroforestry systems. This relationship could then be used with remote sensing if it were possible to accurately measure CPA using remote sensing. In my model, field measures of crown projection areas of individual trees, are used to determine the relationship between diameter at breast height (DBH) and CPA. After establishing the relationship, the DBH of trees can be predicted from satellite observations of tree crowns and then used as the independent variable in standard allometric equations to estimate biomass and carbon based on DBH.

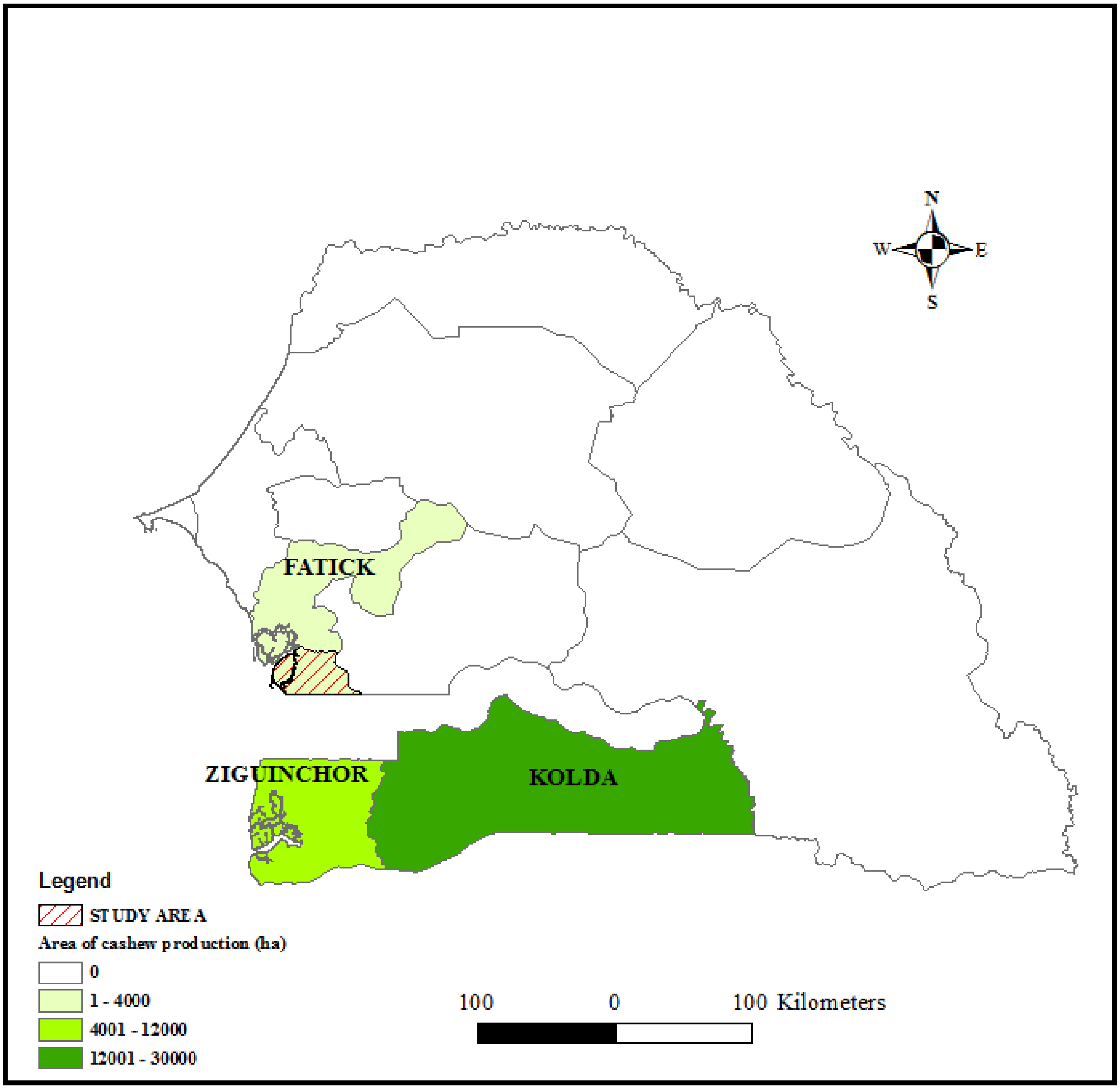
2.2. MATERIALS AND METHODS

2.2.1. The Study Sites

The study area for this work is in the Southern part of the so-called peanut basin of Senegal, and is part of the Sudanian zone characterized by savanna landscapes. The ground measurements and model development focused on villages in three *Rural Communities* of southern Senegal: Toubacouta, Keur Samba Gueye, and Nioro Alassane Tall**.** A *Rural Community* is the smallest unit of local government in Senegal composed of several villages[2]. These communities—dominated by a largely rural population—are some of the most important production zones for *Anacardium* agro-forestry in Senegal and are also parts of the former Senegalese-German Anacardium Project (PASA). As shown in Figure 2.1, Fatick, Ziguinchor and Kolda are the three major cashew production zones in the country.

[2] Following the recent local elections that passed law No. 2013-10 of December 28, 2013, which established the General Code of Local Government, all of the *Rural Communities* became C*ommunes*.

Figure 2.1 Area of cashew production in Senegal and the study area



The climate is semi-arid and the annual rainfall ranges from 400 to 1000 mm. The rainy season usually lasts 3 months from July to September (Toubacouta), but can last 5 months (from June to October) in the Rural Community of Keur Samba Gueye. The annual rainfall here can reach up to 1845 mm, as was the case in 2003 (LDP, 2009). Rainfall can vary significantly from year-to-year in quantity, timing, and duration.

The most common tree species that dominate the vegetation in the rural community of Toubacouta are *Cordyla pinata*, *Cola cordifolia*, *Mangifera indica*, and block plantations of planted trees, including eucalyptus and the large areas of *Anacardium occidentale*. In the southern where is located the *Rural Community* of Keur Samba Gueye, the vegetation is dominated by *Combretum glutinosum, Cordila pinata, Pterocarpus erinaceus, Adansonia digitata, Zizyphus mauritiana, Diospyros mespiliformis, Prosopis africana* and *Parkia biglobosa*.

Regarding the *Rural Community* of Nioro Alassane Tall, the vegetation is very sparse due to overexploitation and the forest cover is deteriorating gradually. It is dominated by species such as *Cordyla pinata* and *Adonsonia digitata* in its tree layer, *Combretum glutinosum* and *Guiera senegalensis* in the shrub layer and some popular grass for fodder at the herbaceous layer (LDP, 2009).

The main types of soil are locally called *Dior* and *Deck*. *Dior* soils, containing > 95% sand and few nutrients (< 2% organic carbon), are usually associated with former dune slopes. *Deck* soils are hydromorphic, occasionally flooded, contain 85-90% sand, and have 0.2% organic carbon (Badiane *et al.,* 2000).

2.2.2. Field and remote sensing data collected

Most of the data collected in this study are extensive field data that were collected during two field campaigns on May and June 2013. I also used remote sensing data from high resolution satellite imagery. In the next section I will discuss the acquisition and use of these data.

For the ground data, a field inventory was conducted throughout the non-forest land cover area of the study sites, which included measurements in plantations of *Anacardium* *occidentale* and other trees on agricultural lands. The primary focus of the field work was to collect individual tree allometric tree data to estimate biomass and carbon stocks. All ground data were collected during a field campaign in May and June 2013 using the following field parameters and associated equipment (Table 2.1.)

Table 2.1 Variables measured in the field and equipment used

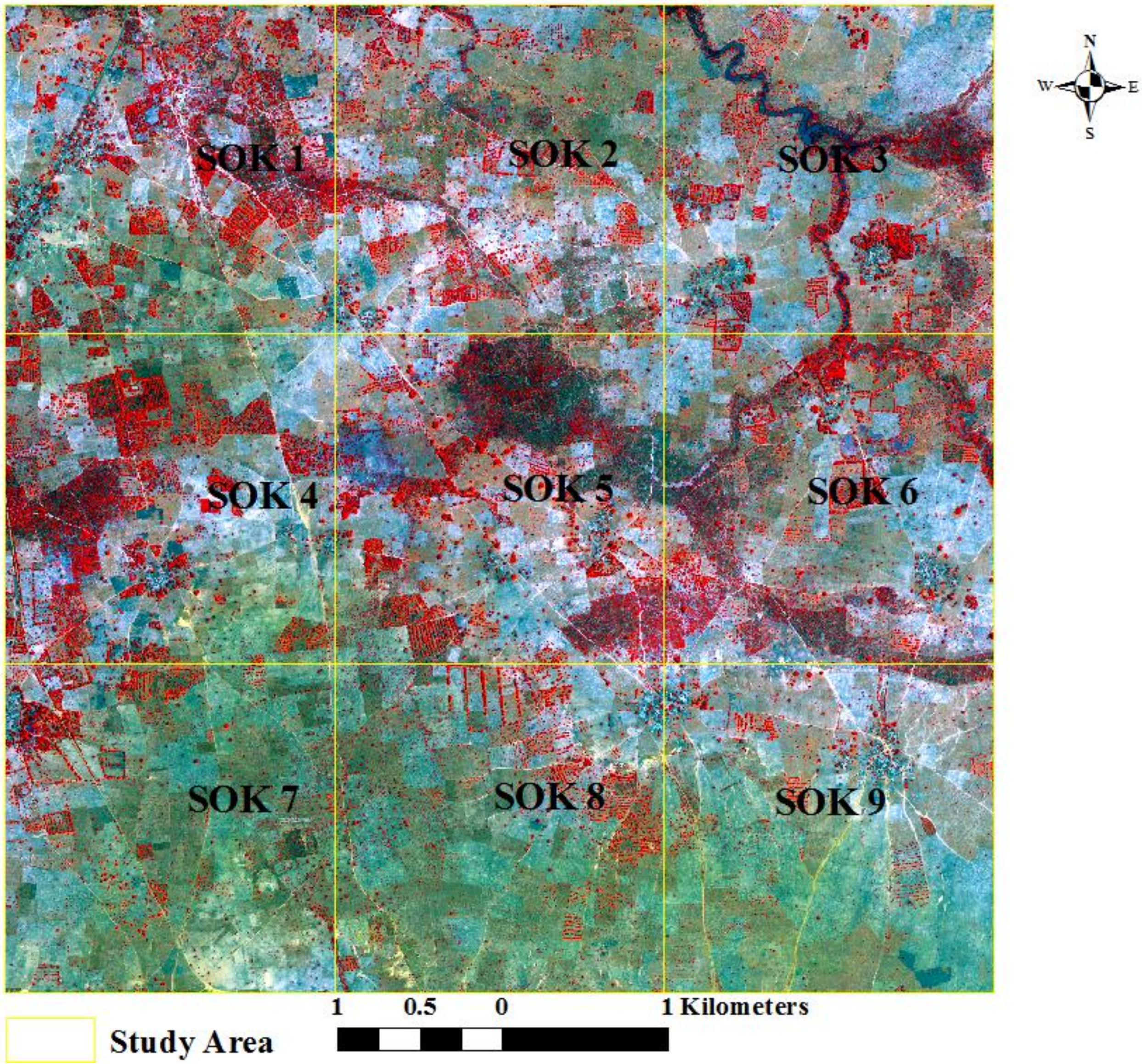
Variables	Description	Instrument
Plot dimensions	Plot area and determination of trees "in" plot	Tape measure
Coordinates and altitude	X and Y location of the centre of plot and each sampled tree	Trimble GPS
Tree Diameter at breast height (DBH)	Diameter at breast height	Diameter tape and data collection sheet
Tree Diameter above the root collar	Diameter measured at 20 cm above the root collar for dwarf *Anacardium*	Diameter tape and data collection sheet
Tree crown diameter	Two perpendicular crown diameters	Diameter tape
Tree characteristics	Genus and species of each individual tree	Trimble GPS and data collection sheet
Pictures	Taking pictures of trees and field activities	Nikon Photo Camera

The measurement of tree DBH is used to estimate tree biomass using standard allometric equations. The DBH (cm) was measured for all sampled trees at 1.30 m above the ground with a standard DBH tape. For dwarf *Anacardium* trees, the diameter at 20 cm above the root collar (DAC) was measured as an alternative measure for DBH because of the tendency of *Anacardium* trees to subdivide into several small trunks below the level of breast height.

To measure the tree crown projection area (CPA), a method that consists of measuring at least two crown diameters (m) was used for each tree. The first crown diameter measured is the longest crown diameter as determined by visual inspection of the tree. The second crown diameter is measured at the right angle (90°) to the longest crown diameter.

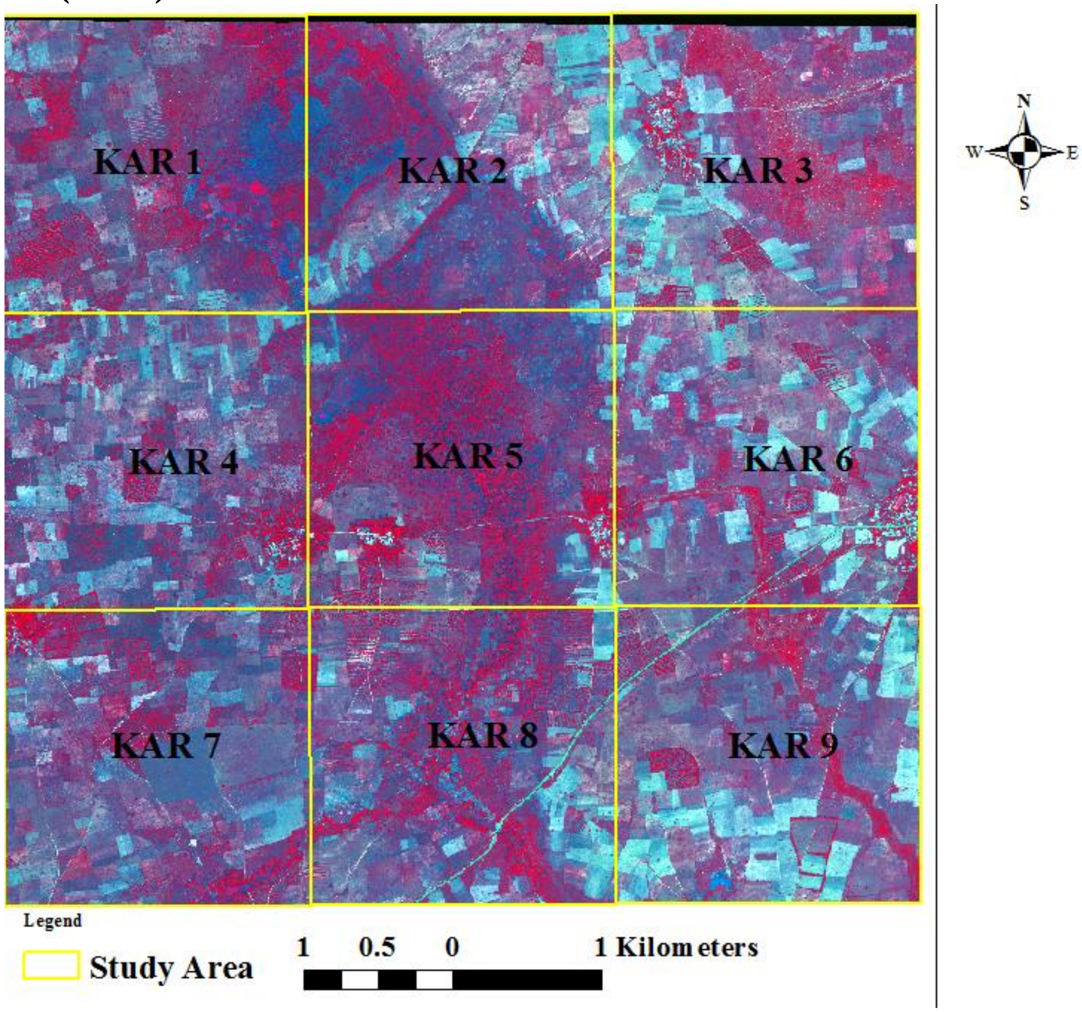
Regarding the remote sensing data, it should be mentioned that high resolution satellite remote sensing techniques are very useful in detecting individual tree crowns but "the accurate monitoring of forest carbon has not been fully demonstrated" (Gonzalez *et al*., 2010). The method used by Gonzalez *et al*. (2010) to validate Quickbird crown diameters against field measurements in forest areas showed a significant correlation between Quickbird-estimated and field measured crown diameters. However, the use of high resolution remote sensing techniques in tropical trees outside of forests areas continues to need more study.

Figure 2.2 Selected blocks in the Sokone (a) and Karang (b) sites from the Worldview 2 satellite image in 432 band combination



a)

Figure 2.2. (cont'd)



b)

To estimate carbon in trees outside forests, I apply a method that combines remote sensing and field data. This method requires fine resolution remote sensing data, in particular using Worldview 2 data (Table 2.2.).

Table 2.2 Spectral, spatial and temporal characteristics of Worldview 2

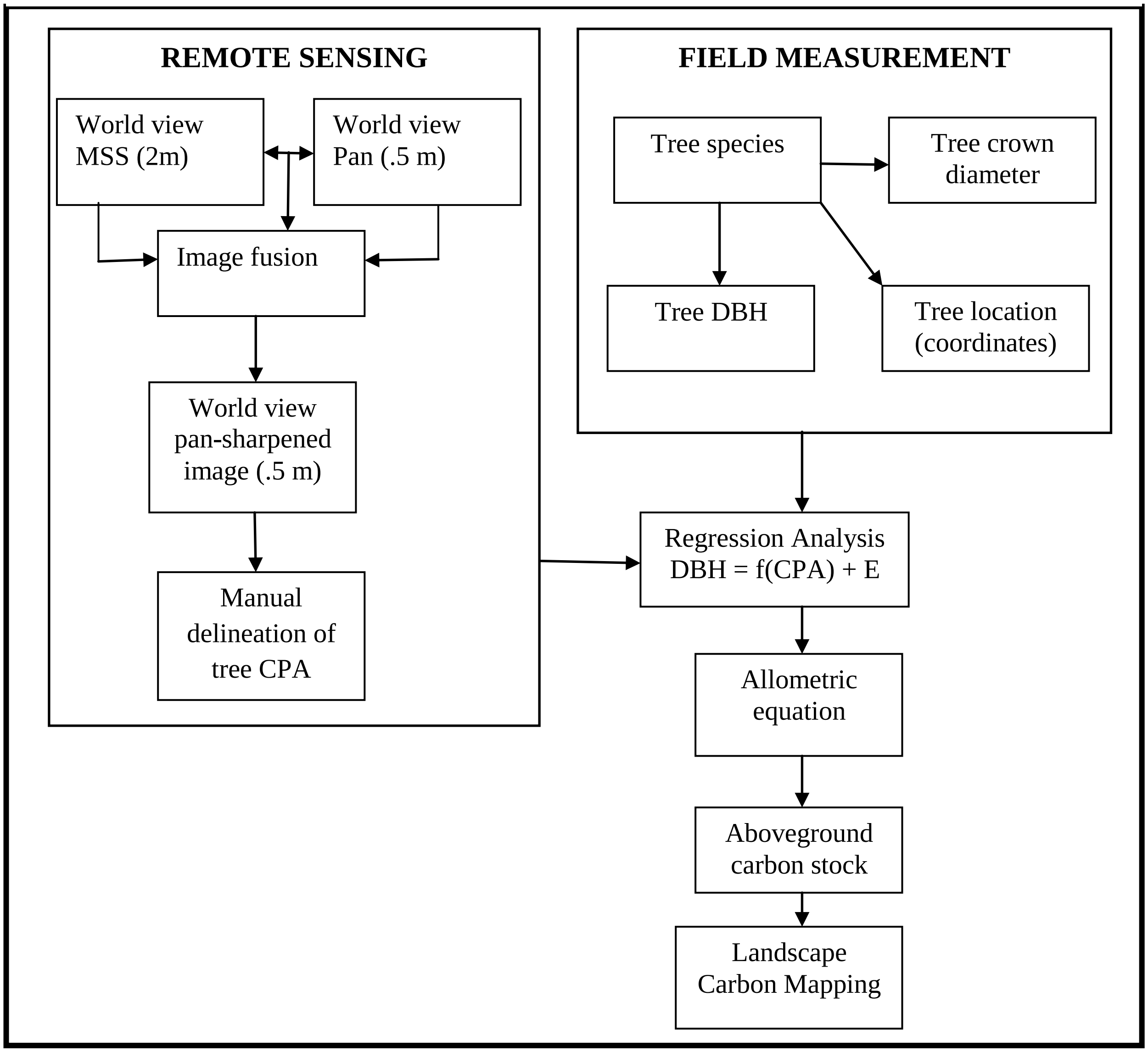
Spectral, spatial and temporal characteristics	Quantities
Number of bands	8 bands
Resolution	0.5 m (Pan) and 2 m (MSS)
Period	100 minutes
Orbital velocity	200 km/ 10 seconds
Swath width	16.4 km at nadir
Collection capacity	Up to 1 million km^2/ day
Average revisit	1.1 days at 1 m GSD
Date collected	April 16, 2010

The Worldview 2 Satellite sensor is capable of acquiring image data at 0.5 meter panchromatic (B&W) and 2 meters multispectral resolution. It also features a revisit time of less than three days, as well as the ability to precisely locate an object within just three meters of its true geographic location. Two Worldview 2 satellite images were acquired for the two zones in overall study area (around cities of Sokone and Karang) as they cover all villages in the three *rural communities* of the study: Toubacouta, Keur Samba Gueye and Nioro Alassane Tall. All imagery were acquired during the dry season (April 16, 2010) which helps reduce the problem of cloud cover. The image projection is UTM Zone 28 N, WGS 84 datum. To work at the higher spatial resolution, the panchromatic and multispectral images were merged through a pan-sharpening process using the Hyperspherical Color Space (HCS) resolution merge tool in ERDAS Imagine. The single high resolution color image created through that process is used and displayed in Arc Map to perform the digitizing and the other remote sensing processing and analysis.

2.2.3. Method

The method deployed in this part of the study supports a technical investigation of carbon stock measurement in agroforestry systems and trees outside forests (TOF) over large landscapes and for multiple farms/households in multiple communities. With satellite imagery of 1 meter spatial resolution or finer it is possible to remotely detect and measure individual tree crowns and crown projected area (CPA). With a relationship developed in this study between remote sensing-based crown area and ground-measured DBH, I could develop individual tree allometry based on CPA and DBH. This method involves several steps described in the following flow diagram (Figure 2.3) and text that follows:

Figure 2.3 Flow diagram of biomass estimation and carbon mapping method



The method is divided into two components:

The first component focuses on ground data measurements, where tree CPA and DBH are measured in the field and a correlation is established. With a strong correlation between CPA and DBH, it is then possible to use crown measurements in a schema from a DBH-based allometric equation to estimate aboveground live biomass in individual trees. Such DBH allometric equations are usually available as standard equations, and are also published in the IPCC guidance documents. Thus the aim of the model developed here is to represent a relationship between CPA, which could be defined using remote sensing as well as field measures, and DBH. If such a model is specified, then it is highly likely possible to use remote sensing as a surrogate for ground measures, which are usually made by foresters and other specialists working in the field but only in a few limited locations in the landscape due to the work effort that is required. The premise is that by substituting remote sensing for field data collection, a much larger area of the landscape can be captured and measured for carbon stocks. If an entire landscape can be measured, then discontinuous households can be bundled into a single project. The transaction costs could be lowered enough to allow their inclusion in carbon credit schemes.

The second component involves the use of remote sensing to detect and digitize tree crown projected area (CPA) using hyperspectral imagery of 1 meter spatial resolution or finer and then predict tree DBH using a model that relates CPA to DBH. In this way, I use a remotely sensed CPA to predict tree DBH in order to then apply a standard allometric equation to compute aboveground live biomass from the imagery observations, on a tree-by-tree basis. The CPA is estimated from field measurements by using the formula for the area of an ellipse which is as follows and requires two field or remote sensing measures of diameter:

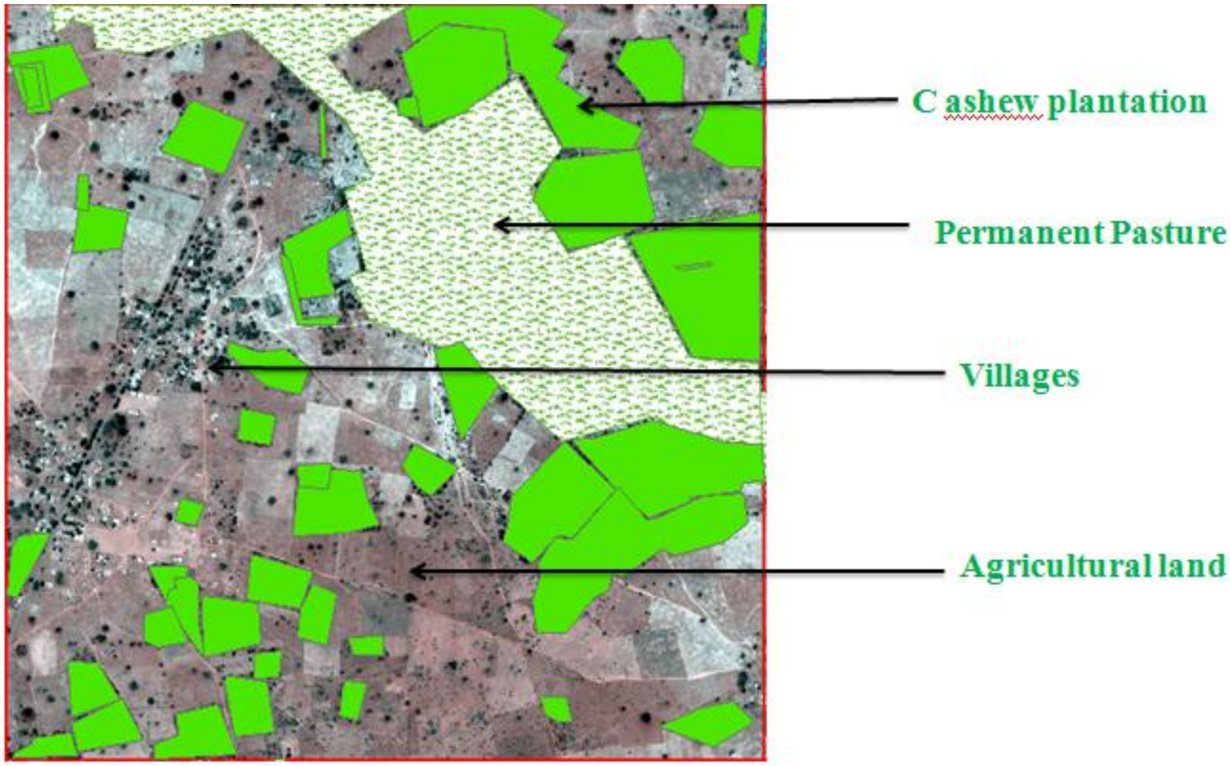
$$CPA = \pi * 1/2 \text{ of the maximum diameter} * 1/2 \text{ of the diameter at } 90^{o}$$

Two points regarding this approach are warranted. First, remote sensing data could be used to define the actual circle of the crown, rather than the cross diameters. Just as I use "heads up" manual digitizing of tree crowns using polygon construction tool in ArcGIS 2010, it is also possible to outline the best polygon. This is a subject for a future study. Second, we attempted to use automating the digitizing of crown polygons in the GOES Lab but there has been some limited success (Appendix). This too could be the next step in this work, and would lead to an ability to process massive amounts of data and cover very large areas at very low costs.

2.2.4. Stratification of the study area

It is important to have precise and accurate plot dimensions and locations as they determine which tree is in or out of the sampled plot and can be cross-mapped from field to imagery using detailed GPS coordinates. The strata map (Figure 2.4) is produced to indicate the spatial variation of tree density. The field sample protocol I used requires the determination of the number of plots, their size and shape, their location, and the type of parameters to be measured within each plot. It also requires a stratification scheme so plots can be used as samples and scaled up to a larger area. Stratification also narrows the variation in the regression model.

Figure 2.4 Block SOK 7 and the different strata



The stratification uses of satellite imagery to establish the sample frame. The field data collection sites are selected within the former Senegalese/German Cashew Development project area (Figure 1.4). The work was done in two specific sites in the villages around the cities of Sokone and Karang within an area measuring 6 km x 6 km (36 km^2) which corresponds to two Worldview 2 satellite images (Figure 2.2). For each 36 km^2 area, ERDAS Imagine software is used to generate a sample grid of 9 blocks (2 km x 2 km).

The different strata are determined and the area of each stratum digitized for both Sokone and Karang zone (Tables 2.3. and 2.4.)

Table 2.3 Stratification for Sokone zone

SOKONE								
	SOK 1		SOK 4		SOK 7		Total	
Strata	**Area (ha)**	**%**	**Area (ha)**	**%**	**Area (ha)**	**%**	**Area (ha)**	**%**
Cashew	96	24	116	29	44	11	256	21
Agricultural land	208	52	245	61	350	88	803	67
Villages	29	7	8	2	6	1	43	4
Permanent pastures	67	17	31	8	0	0	98	8
TOTAL	**400**	**100**	**400**	**100**	**400**	**100**	**1200**	**100**

Three blocks (SOK 1, SOK 4, and SOK 7) are selected for Sokone zone and the different strata identified are: cashew plantation, the agricultural lands, the dwellings (villages) and the permanent pastures.

The same number of blocks is selected in Karang (KAR 1, KAR 8 and KAR 9) as showed in the following Table 2.4:

Table 2.4 Stratification for Karang zone

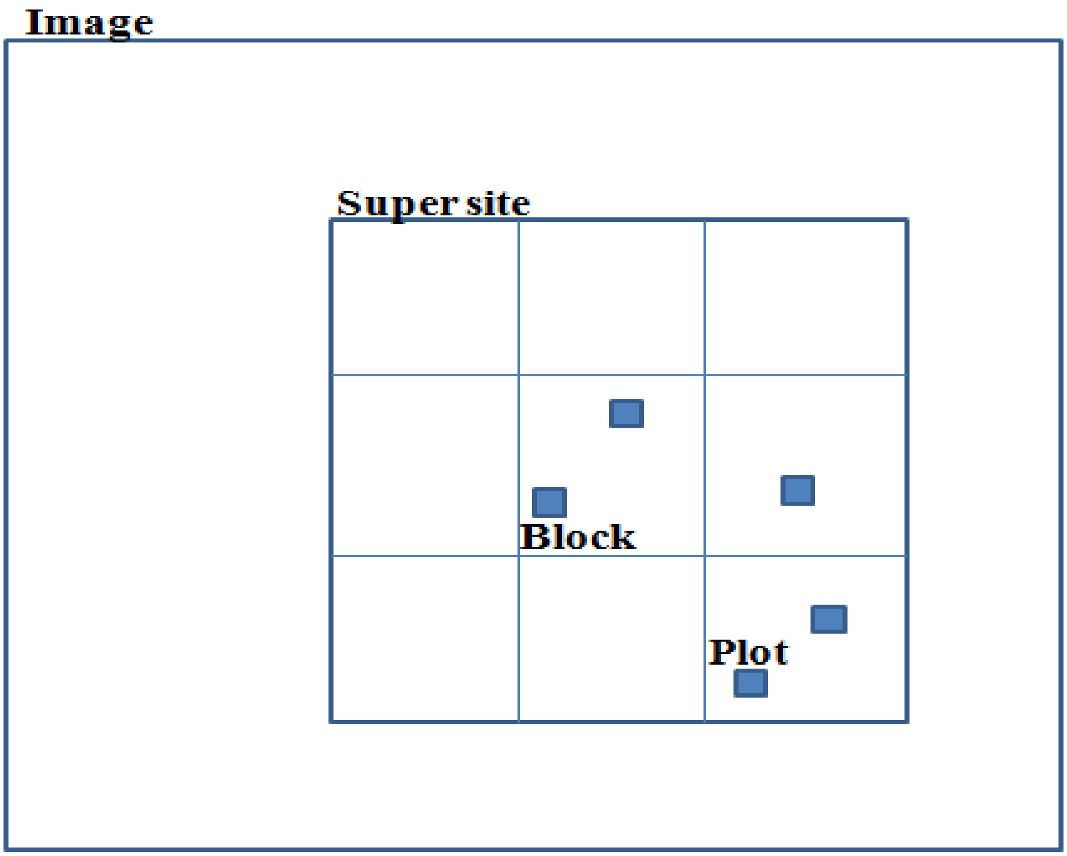
KARANG								
	KAR 1		KAR 8		KAR 9		Total	
Area (ha) and % of strata	**Area (ha)**	**%**	**Area (ha)**	**%**	**Area (ha)**	**%**	**Area (ha)**	**%**
Cashew	30	8	67	17	23	6	120	10
Agricultural land	171	43	221	55	333	83	725	60
Permanent pastures	199	50	112	28	44	11	355	30
TOTAL	**400**	**100**	**400**	**100**	**400**	**100**	**1200**	**100**

2.2.5. Selection of sampled plots

The boundary of each stratum is digitized and the area determined using the calculate geometry tool in Arc GIS. The number of plots to be sampled is determined based on the land cover type and proportionately to the area covered. Three options were possible for the sampling design: a) locate plots randomly, b) locate plots systematically, or c) proceed by stratified sampling of the landscape.

As mentioned by Ravindranath and Ostwald (2008), determination of the appropriate number of sample plots is a critical step but "the complexity of sampling methods and procedures may force researchers to adopt a standard number of plots based on the visible heterogeneity of vegetation, soil and other conditions" (Ravindranath and Ostwald, 2008). I also acknowledge that there is a trade-off between the level of precision in carbon stock assessment and the cost of getting that level of precision. For the purposes of this study, I was only able to collect a limited number of sample plots. I evaluated the number of sample plots to reach 10% accuracy using the Winrock sample tool (Winrock, 2008) and in some cases the number of plots exceeded 500. My sample is thus under-represented. Having noted this, it should be pointed out that the Winrock sample guide is meant to provide guidance for field sampling in a measurement framework that uses the samples to extrapolate to the entire landscape. On the other hand, my methods is focused precisely on developing an alternative to sample-based estimation and moves directly to whole landscape estimation by direct measurement from remote sensing. Thus, the critical issue for my model was not the number of plots, but the relationship between allometric measurement variables. In this instance more samples or heavily stratified samples could provide low variance in regression model.

Figure 2.5 Ground sample frame



Also it should be noted that sample plots that I have established were not aimed at providing samples for extrapolation but a geographically distributed means to collect a lot of individual tree data. At the same time, these samples could be used for validation.

In the Sokone site, because of the high density of cashew plantations, a minimum of ten (10) plots of 1024 m^2 (32*32) were randomly selected for this stratum for each of the three selected blocks except for block SOK 7 where only 7 plots were sampled because of the low density in cashew plantation. For the other scattered TOF in agricultural land, a minimum of six (6) plots for each selected block was randomly sampled. A total of 50 plots were finally sampled in the Sokone site (Table 2.5.).

Table 2.5 Number of sampled plots for each stratum in the Sokone site

	SOKONE		
	Number of plots in cashew plantation	**Number of plots in agricultural lands**	**Total**
SOK 1	10	6	**16**
SOK 4	11	6	**17**
SOK 7	7	10	**17**
Total	**28**	**22**	**50**

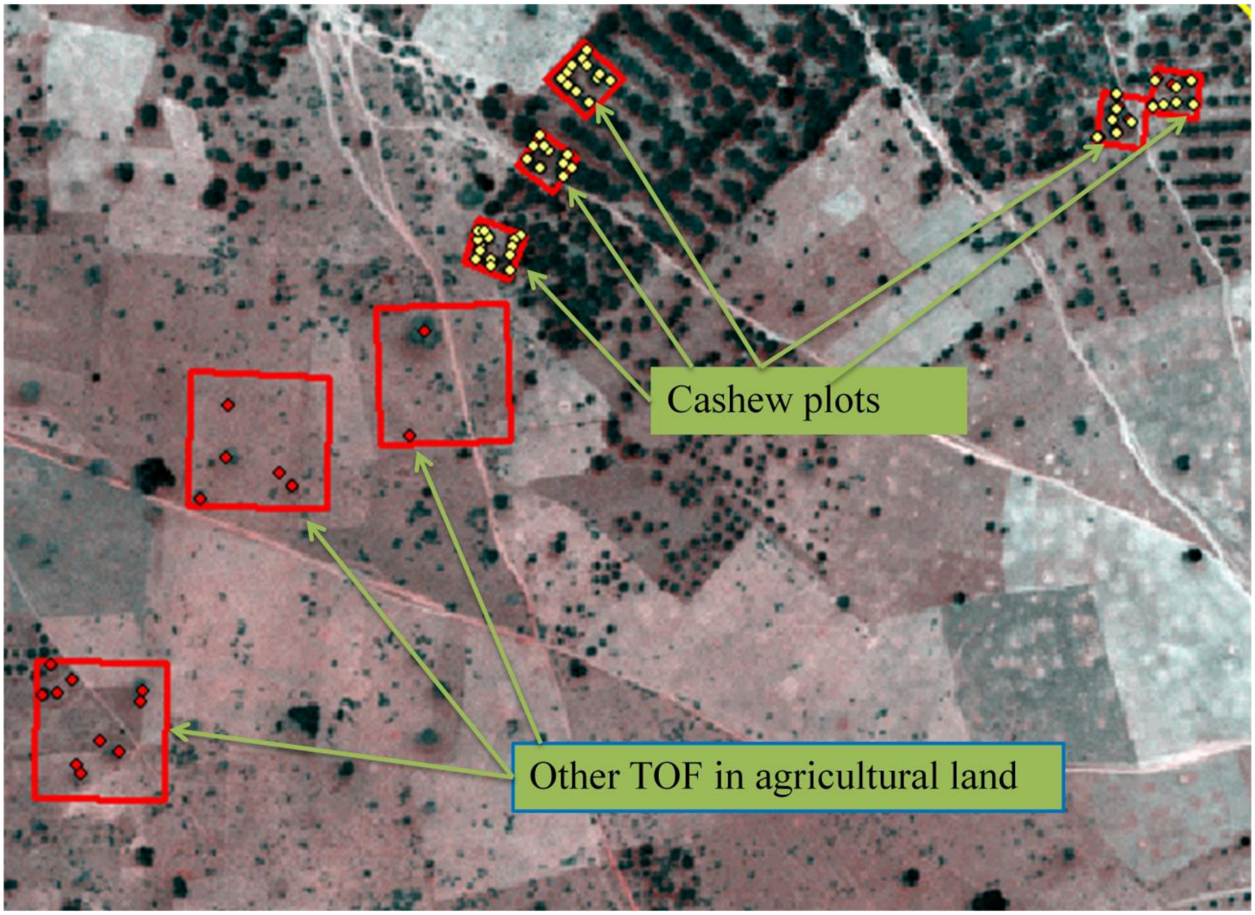
For the Karang site, the agricultural lands are dominant and because of the low area covered by cashew plantation, a minimum of five (5) plots were sampled for this stratum except for block KAR 9 because it has only 6 % of its area covered by cashew. Overall, a total of 54 plots were sampled in the Karang site (Table 2.6.).

Table 2.6 Number of plots for each stratum in the Karang site

	KARANG		
	Number of plots in cashew plantation	**Number of plots in agricultural lands**	**Total**
KAR 1	5	14	**19**
KAR 8	9	14	**23**
KAR 9	3	9	**12**
Total	**17**	**37**	**54**

The geographic locations of all measured trees were recorded with a global positioning system device (GPS), as this allows for data entry into a geographic information system analysis (GIS) and possible return to the site.

Figure 2.6 Example of the layout of sampled plots and measured trees in the Sokone site



Because of the dominance of cashew agroforestry in the study area, I sampled more plots on these plantations and each sample plot having sides of 32 x 32 m for a plot area of 1024 m^2 (0.1 ha). Most protocols recommend a plot size large enough to include at least eight to ten trees within the plot boundaries (Winrock, 2005). With the 1024 m^2 plot area, and the most common 10 x 20 m cashew tree spacing used in the 2 sites of the study area, 60% of the plots have at least 8 trees per plot (Table 2.7.).

Table 2.7 Number of plots and their density for cashew plantations

# of trees/ plot	# of Plots	%
3 to 5	8	17.78
6 to 7	10	22.22
8 to 10	12	26.67
11 to 12	6	13.33
13 to 14	3	6.67
15 to 17	3	6.67
18 to 23	3	6.67
Total	**45**	**100**

Although rectangular-shaped plots can be more representative than square or circular plots of the same area (Hairiah *et al.,* 2010), a method used in India (Singh and Chand, 2012) was chosen. It is a square-shaped plot which also helps comply with the linear tree planting systems used by farmers. The plot sizes are determined depending on the type of strata. A 32 x 32 m (1024 m^2) plot is dedicated to block cashew plantation, and a 100 x 100 m (1 ha) for scattered trees within the agricultural lands. I first measured the length or the breadth and use the diagonal to ensure a true right angle at each of the four corners (Ravindranath Ostwald, 2008).

2.2.6. Data analysis

Data collected during the field work included the diameter at breast height (DBH), and two crown diameters, the largest and the one perpendicular to it that are used to calculate the tree crown area. These data were processed using EXCEL and SPSS. Data collected from all trees were used for this analysis as they have been all identified in the satellite image and digitized using ArcMap. The digitized crown area was to be later used to correlate with the field measured tree DBH and then compared with the tree crown projection area measured from the field to validate the regression model.

2.2.6.1. Manual delineation of trees

To build the regression model, the crowns of all measured trees were manually digitized. A pan-sharpened image is used to improve the view of the tree crowns and display the image in RGB using combination bands 132 and 432 in ArcGIS 10. At a 1:1000 scale, we were able to clearly identify trees and delineate crown diameters. In some cases where the edge of the tree crown is not easy to determine, we compared the different band combinations 132 and 432 before performing the manual digitizing of crown diameters using the Editor Construction Tool in ArcGIS 10.

The following rules were set before starting the manual digitizing:

- Use the same scale (1:1000) for the delineation
- Use the tree points shapefile overlaid in the image as a reference for delineation.
- Digitize all the sampled trees whose field measurements are available

2.2.6.2. Correlation Analysis

I used the Pearson product-moment correlation coefficient (r) to determine the direction of the correlation while the coefficient of determination R^2 helps measure the strength of the correlation between the field-based crown projection area and tree DBH. The correlation is used to measure the strength, direction and the linear relationship between tree DBH and tree CPA. The coefficient of determination (R^2) is used to interpret the percentage of the variation in the DBH that is associated with the CPA.

2.2.6.3. Regression Analysis and validation of the models

The regression analysis is used to predict one variable, given the other by determining the relationship between these two variables. It is used to describe how, given the value of one variable or attribute (x) often called the independent variable, one may find the corresponding value for the other variable or attribute (y), called the dependent variable. In the case of this study, the tree DBH is the dependent variable and the crown projection area (CPA) the independent variable. The purpose of the regression analysis is to estimate the change in the DBH from a given change in the CPA by finding a formula that represents the relationship between these two variables. The eventual aim is to be able to predict DBH from remote sensing measured CPA by finding an approximate value of the tree DBH from the value of the remote sensing CPA.

To develop regression models for the relationship of CPA with DBH, biomass, and carbon a simple linear ($y= a+b.x$) function was used. Throughout this process, the *method of ordinary least squares* (OLS) is used to determine the values of the constants a and b and determine the best fit of the straight line which is the position that makes the sum of the squared deviations of the observed Y values from the regression line a minimum (Husch *et al*., 2003). For this case, the method is used to determine the regression coefficient that describes the strength and the sign of the relationship between the remote sensing crown projection area as the explanatory variable and the field measured DBH as the dependent variable.

2.3. RESULTS

The results of the correlation analysis are interpreted using a classification of the size of a correlation coefficient made by Hinkle *et al*., (2003) and presented in the following table.

Table 2.8 Rule of Thumb for interpreting the size of a correlation coefficient

Size of Correlation	Interpretation
.90 to 1.00 (-.90 to -1.00)	Very high positive (negative) correlation
.70 to .90 (-.70 to -.90)	High positive (negative) correlation
.50 to .70 (-.50 to -.70)	Moderate positive (negative) correlation
.30 to .50 (-.30 to -.50)	Low positive (negative) correlation
.00 to .30 (.00 to -.30)	Little if any correlation

2.3.1. Relationship between field measured DBH and field measured CPA

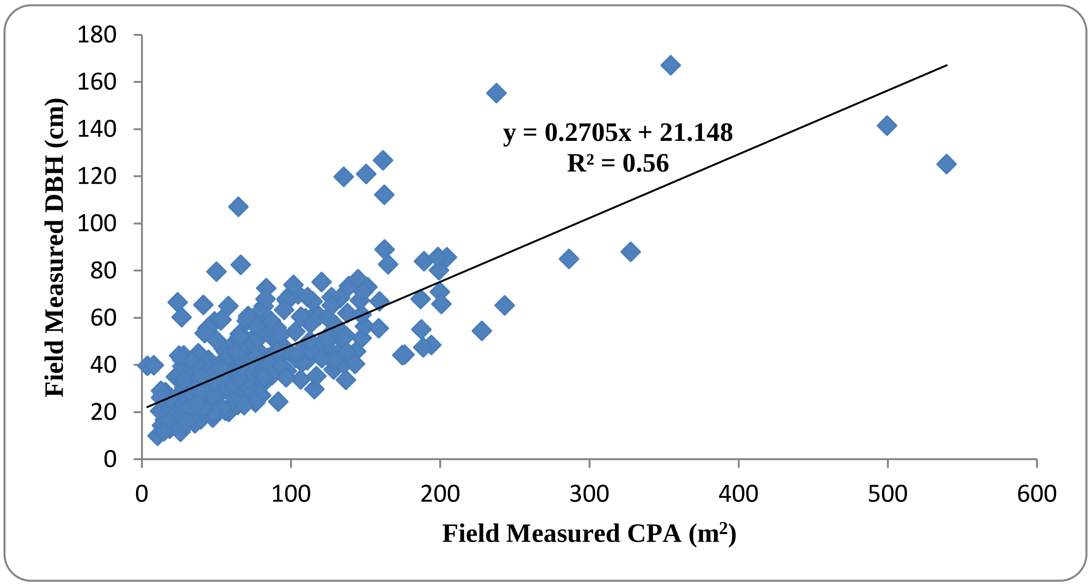
2.3.1.1. Model development

The relationship between field measured tree DBH and crown projection area (CPA) calculated from field data is established to estimate an initial model. To describe this relationship, data from the Sokone site (377 sampled trees) are used for model development and data (317 trees) from the Karang site for validation.

The relationship between field DBH and CPA is established to observe the prediction of tree DBH from observations of crown projection area (CPA).

In Figure 2.7 the graph shows the relationship between the field measured Crown Projection Area (CPA) and the field measured DBH for sampled trees of all types in Sokone site. This includes all cashew and all other TOF trees combined. There is a linear trend within the range of the 377 plotted trees that have been used. The pattern of the scatter plot shows a moderate correlation between the two variables with a coefficient of determination R^2 = 0.56 for the fit of these data. That means that 56% of the variation in the tree DBH can be explained by variations in the value of the CPA based on the model.

Figure 2.7 Correlation between field measured DBH and field measured CPA for sampled trees of all types (N= 377) in the Sokone site



After classifying trees based on the number of stems, the model was applied for single stemmed as well as for multi-stemmed trees. Results of this relationship between DBH and CPA from field data presented a better coefficient of determination, which is 0.594 for the 314 single stemmed trees and 0.664 for the 63 multiple multi-stemmed trees. This is consistent with findings from Samek *et al.* (2011) working on a GOES project in multi-stem-lychee plantations in Southeast Asia, where a crown-based allometric model worked better for multi-stem trees. Also, my results present a better correlation compared to those from plantation data collected in the Rukinga Ranch in Eastern Kenya by the Wildlife Works Kasigau Corridor REDD project. The correlation between DBH and crown diameter in Rukinga shows a lower R^2 (0.514) for multi-stemmed trees (CBP, 2012) However, it is important to mention that the sample for the Rukinga data is dominated by small trees as 98.5 % (843 out of 855 trees) have less than 50 cm DBH.

When applied to 297 sampled trees of only cashew (*Anacardium occidentale*) in the Sokone site the relationship between the field measured crown projection area (CPA) as the independent variable and field measured tree DBH shows a moderate correlation between the two variables with a coefficient of determination R^2 = 0.57. That means that 57% of the variation in the tree DBH can be explained by variations in the value of the CPA based on the model.

The same procedure was applied to the non-cashew sampled trees. A total of 80 trees were used in the Sokone site, and a moderate positive correlation between the two variables was found with a coefficient of determination R^2 = 0.62. That means that 62% of the variation in the tree DBH can be explained by variations in the value of the CPA based on the model.

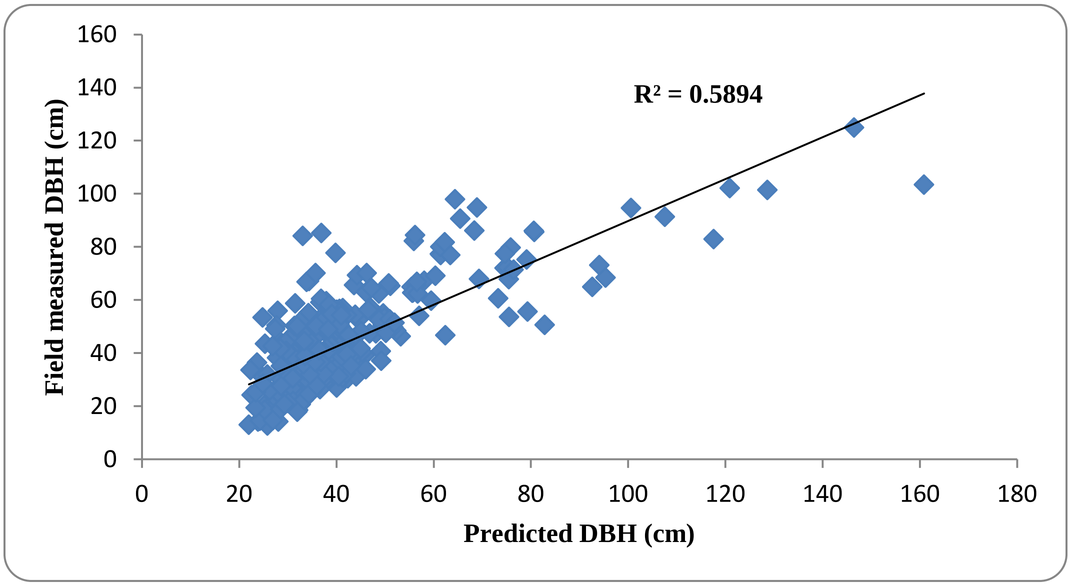
2.3.1.2. Model validation

To validate the model, the following Equation 1 is used:

*Field measured DBH = 0.2705 * Field measured CPA + 21.148* *Equation 1*

The equation is applied to the 315 trees in the Karang site to calculate the predicted values of their DBH from the model sample in the Sokone site. This validation is done by comparing the DBH predicted by the model and the field measured DBH of the same trees. The predicted DBH were plotted against the field measured DBH (Figure 2.8) which gives a R^2 of 0.58, meaning that 58% of the field measured DBH was explained by the predicted DBH from the linear regression model.

Figure 2.8 Scatter plot of model validation measured vs. predicted DBH

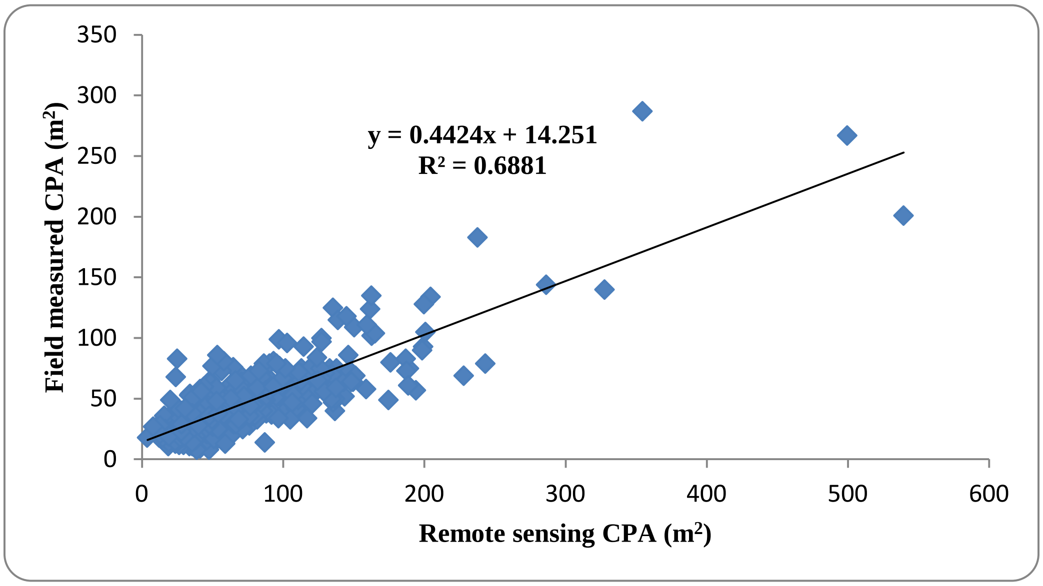


2.3.2. Relationship between field measured CPA and remote sensing measured CPA

To measure the closeness of both data sets, the relationship between field measured and remote sensing CPA is established by comparing these two CPA data sets. A simple linear regression is applied and the regression was done for all trees in Sokone (Figure 2.9) and Karang (Figure 2.10) and a combination of both sites (Figure 2.11).

For the Sokone site, a total of 377 sampled trees were used to explain the relationship between the remote sensing and the field measured crown projection area (CPA) in the scatter plot shown in Figure 2.9. The pattern of the scatter plot shows a moderate correlation between the two variables with a coefficient of determination $R^2 = 0.688$. That means that we have 68% correlation between field measured and remote sensing

Figure 2.9 Relationship between Remote sensing and field measured CPA of all sampled trees (N=377) in the Sokone site

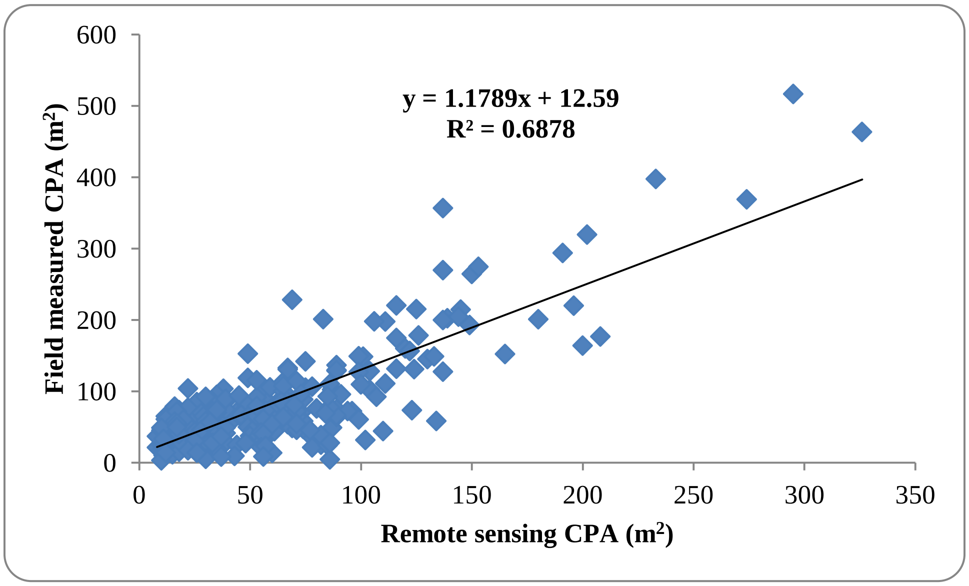


For the 297 *Anacardium* trees in the Sokone site, the relationship between the remote sensing and the field measured crown projection area (CPA) shows a moderate correlation between the two variables with a coefficient of determination R^2 = 0.629. That means 62% accuracy between field measured and remote sensing CPA based on the model.

The other 80 trees have more promising results with a strong correlation. The coefficient of determination is 0.766 suggesting 76% accuracy between field measured and remote sensing CPA and showing a better fit of the model for natural trees.

For the Karang site, a total of 315 sampled trees were used to explain the relationship between the remote sensing and the field measured crown projection area (CPA) in the scatter plot shown in Figure 2.10. The pattern of the scatter plot shows a moderate correlation between the two variables with a coefficient of determination R^2 = 0.687. That implies a 68% accuracy between field measured CPA and remote sensing CPA based on the model.

Figure 2.10 Relationship between Remote sensing and field measured CPA for all sampled trees (N=315) in Karang

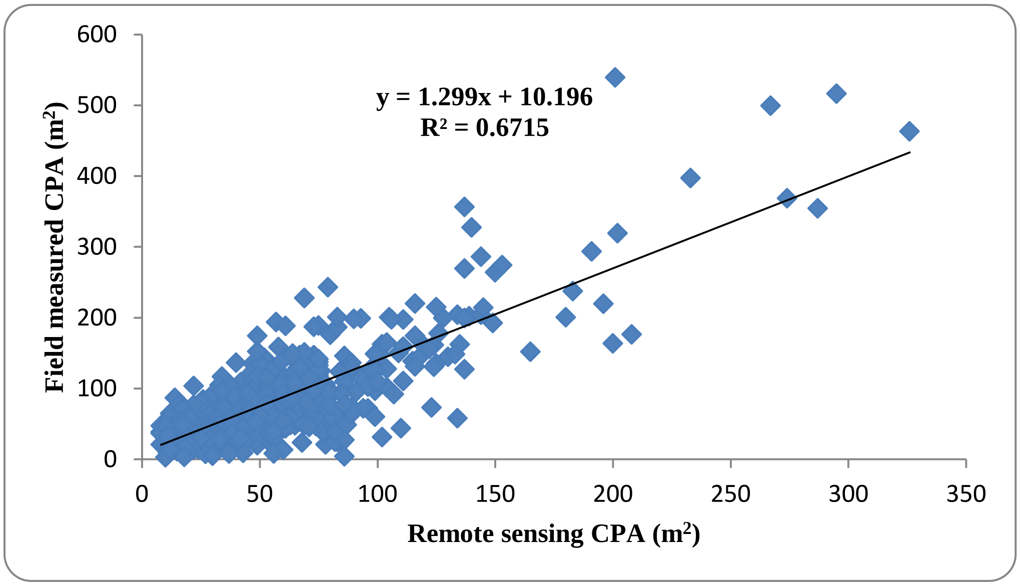


When applied to only *Anacardium*, a total of 182 trees were used and the relationship between the remote sensing and the field measured crown projection area (CPA) revealed a low positive correlation between the two variables. A coefficient of determination R^2 = 0.368 suggested only 36% accuracy.

When the *Anacardium* were excluded and the model was applied to the other 133 non cashew tree species alone, the relationship between the remote sensing and the field measured crown projection area (CPA) represents a 0.736 coefficient of determination suggesting that 73% accuracy between field measured CPA and the remote sensing CPA based on the model.

When data from both sites are combined, the relationship between the remote sensing and the field measured crown projection area (CPA) was also tested for all 692 trees. The scatter plot presented in Figure 2.11 shows a moderate correlation between the two variables with a coefficient of determination $R^2 = 0.671$, and therefore 67% accuracy between field measured CPA and remote sensing CPA based on the model.

Figure 2.11 Relationship between Remote sensing and field measured CPA in both sites (N=692)



The application of the model based on tree species also shows significant results in both cashew (*Anacardium occidentale*) and non-cashew trees. Using the simple linear regression, an R-squared of 0.597 was obtained for cashew trees and 0.729 for the non-cashew natural trees.

2.3.3. A Model to predict DBH from remote sensing CPA

2.3.3.1. Model development

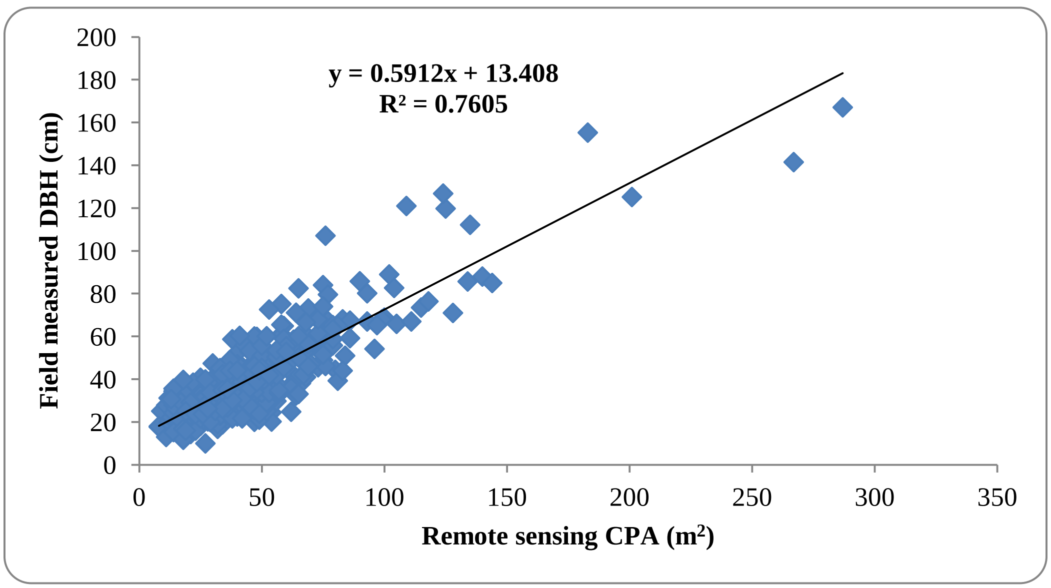
This model is built on the correlation between the remotely sensed crown projection area and the field-measured tree DBH. After describing the relationship between field based DBH and field based crown projection area, the field measured CPA is replaced by the remote sensing-based measurements to predict DBH to build the model which is applied for all trees in both the Sokone and Karang sites.

The simple linear function is used to estimate a model between remote sensing CPA and DBH, using the field data for DBH. The resulting linear model is:

DBH = 0.5912 (RS CPA) + 13.408 *Equation 2*

The model data shows a linear relationship of the two variables for the 377 sampled trees in the Sokone site. As shown in Figure 2.12, the pattern of the scatter plot shows a strong correlation between the two variables with a coefficient of determination $R^2 = 0.760$, which means that 76% of the variation in the tree field measured DBH can be explained by variations in the value of the remote sensing CPA based on the model.

Figure 2.12 Model-based DBH using Remote sensing CPA in Sokone (Linear model)

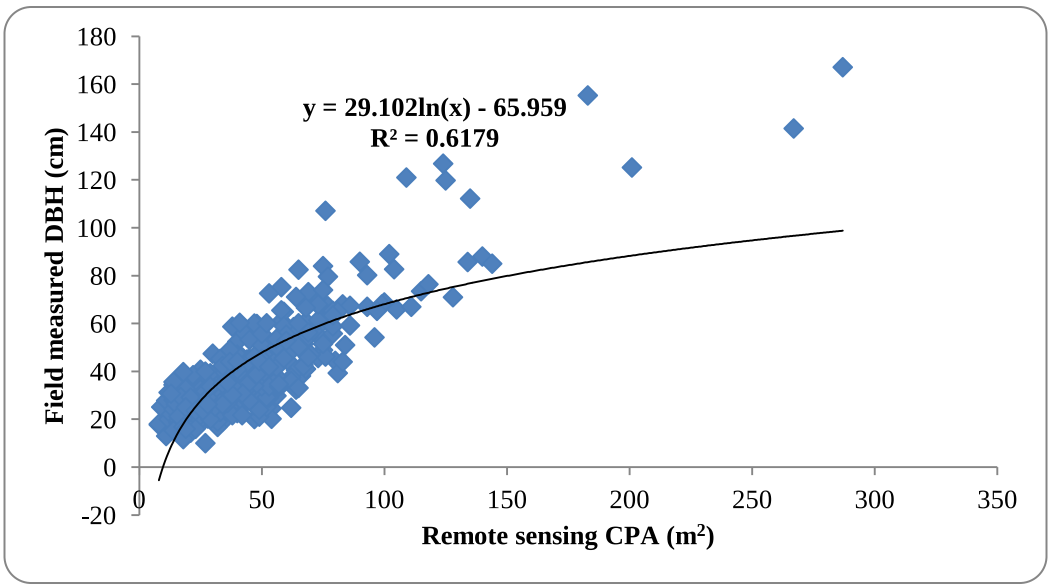


When applied to the 297 sampled *Anacardium* trees in the Sokone site, a linear model from remote sensing CPA shows a positive linear relationship. The coefficient of determination R^2 is 0.711, which means that 71% of the variation in the tree field measured DBH can be explained by variations in the value of the remote sensing CPA based on the model.

Better results were found when only applying the model to the other 80 TOF tree species, with a coefficient of determination $R^2 = 0.84$ suggesting that 84% of the variation in the tree field measured DBH can be explained by variations in the value of the remote sensing CPA based on the model.

A non linear model shows a lower coefficient of determination R- squared of 0.61 (Figure 2.13) compared to the linear model which suggests that the linear function is the best fit of the model. However more work could be done to refine the specific non-linear model and alter its coefficients.

Figure 2.13 Model-based DBH from Remote sensing CPA for all sampled trees in the Sokone site (Non- linear model)



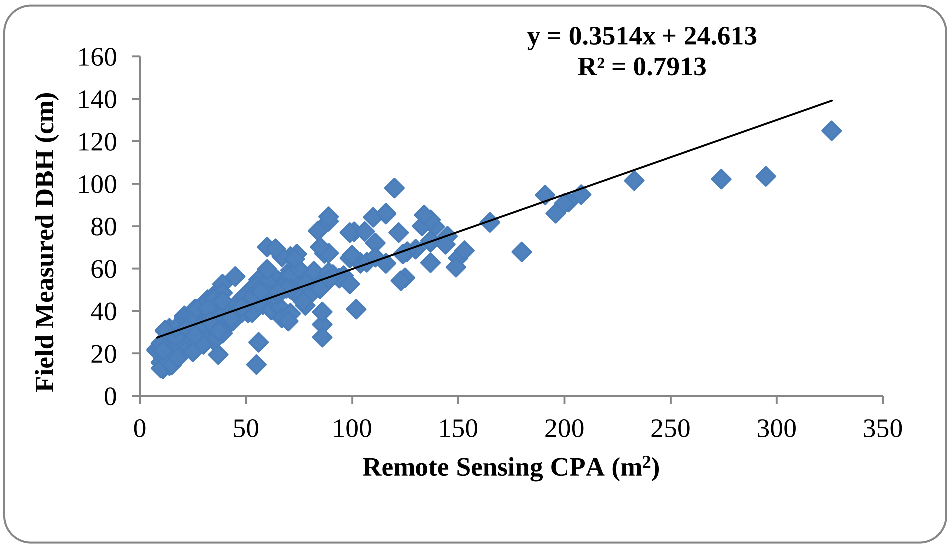
In the Karang site, the results for all 315 trees show a positive linear model based on the remote sensing CPA. As shown in Figure 2.14, the model shows a strong prediction with a coefficient of determination $R^2 = 0.791$, which means that 79% of the variation in the tree field measured DBH can be explained by variations in the value of the remote sensing CPA based on the model. The resulting linear model is:

DBH = 0.3514 (RS CPA) + 24.613 *Equation 3*

The model coefficient of determination is 0.71 when applied to only the *Anacardium* trees, suggesting that 71% of the variation in the 182 field measured DBH can be predicted by variations in the value of the remote sensing CPA based on the model.

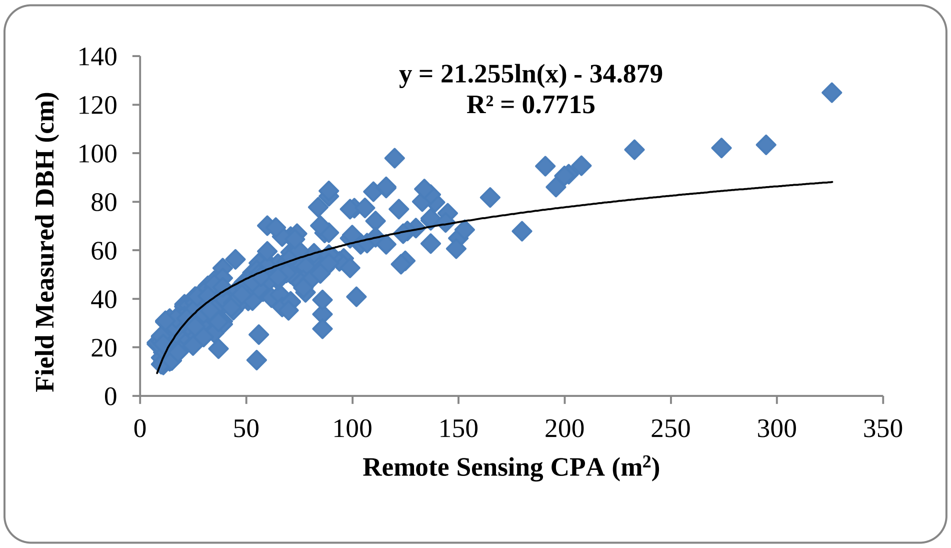
When applied to the other 133 non-cashew trees, the coefficient of determination is 0.664.

Figure 2.14 Model-based DBH from Remote sensing CPA for all sampled trees in the Karang site (linear model)



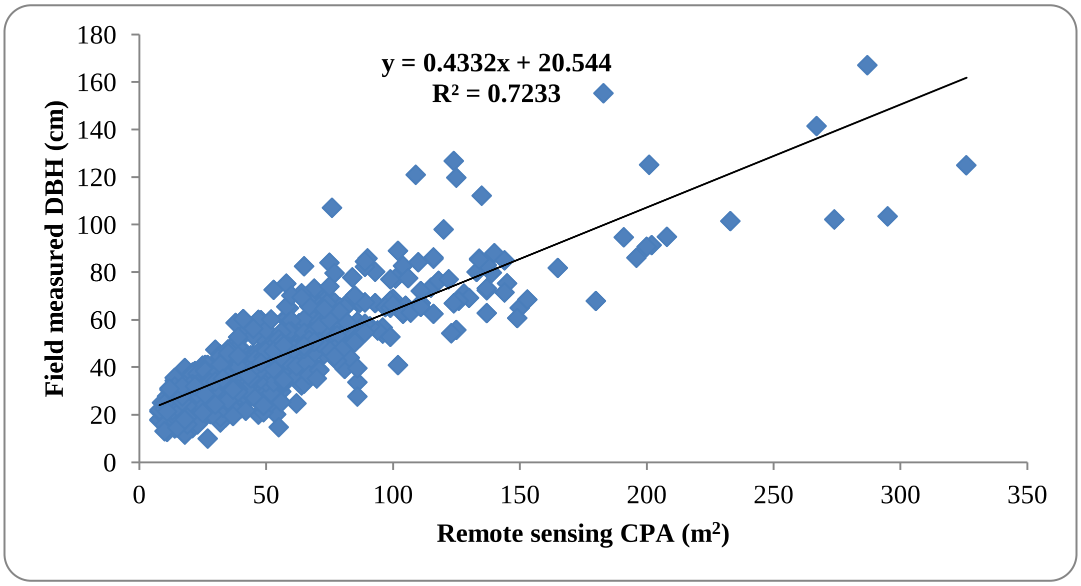
This linear model shows a better result (R-squared = 0.79) compared to the non linear model for which the coefficient of determination is 0.77 (Figure 2.15)

Figure 2.15 Model-based DBH from Remote sensing CPA for all sampled trees in the Karang site (Non-linear model)



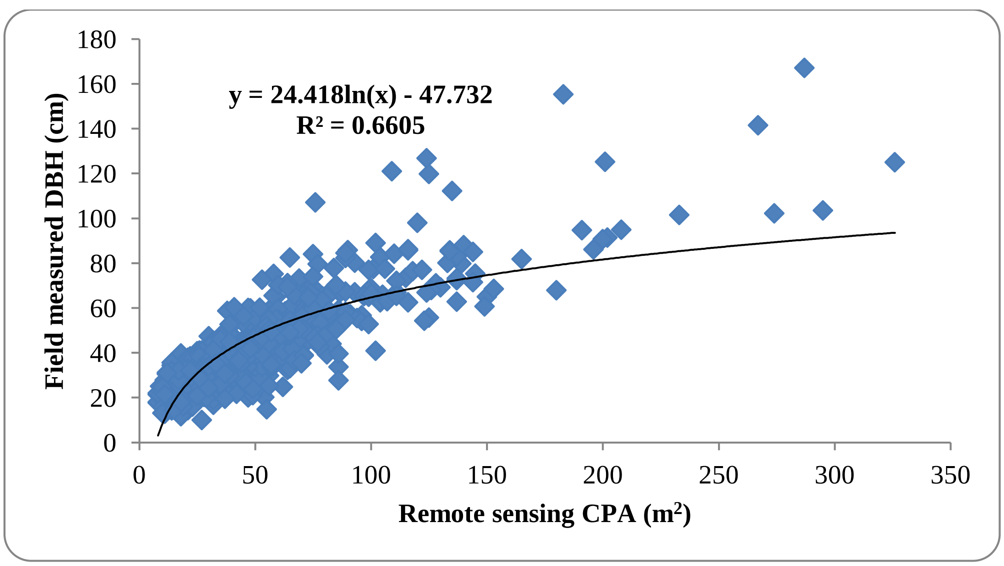
The model was also estimated from all the species in both Sokone and Karang sites combined. The results for all 692 trees show a positive linear model between the remote sensing CPA and DBH (Figure 2.16). However, the coefficient of determination R^2 = 0.723 is slightly lower than those obtained when the correlation is established by site. This suggests a probable impact of site condition and characterization.

Figure 2.16 Relationship between field based DBH and Remote sensing based CPA of all sampled trees in both Sokone and Karang sites (linear model)



Compared to the linear, the non linear function presents also a lower coefficient of determination (R-squared= 0.66); suggesting a better results for the linear (Figure 2.17).

Figure 2.17 Relationship between field based DBH and Remote sensing based CPA of all sampled trees in both Sokone and Karang sites (Non-linear model)



2.3.3.2. Results comparison with CBP study in Western Kenya

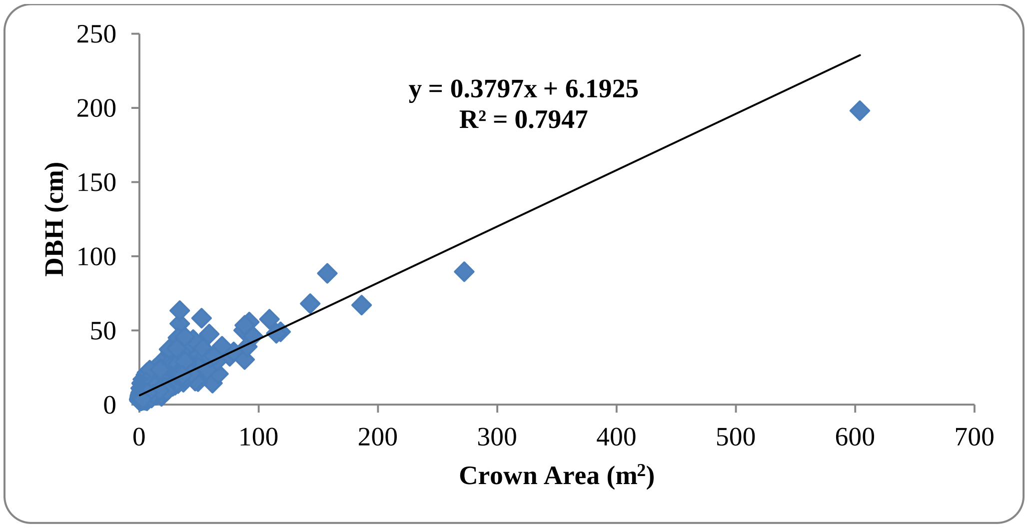
Through the Carbon Benefit Project (CBP), MSU and ICRAF researchers collected data in western Kenya along the Yala River Basin in three established blocks: lower Yala, middle Yala and upper Yala. The objective of that study was to develop a generic allometric equation to establish a valid basis for scaling up above and below ground biomass carbon at landscape scale.

Unlike our data where the DBH ranged between 10 and 167.1 cm, the CBP data are for trees whose diameter at breast height (DBH) > 2.5cm. 834 out of the 855 trees, representing 97.5 % of all sampled trees are less than 40 cm DBH.

An examination of these Kenya results regarding the relationship between DBH and crown has shown a good linear relationship with a R-squared of 0.80 (Figure 2.18).

It is interesting to note that the Senegal model and the Kenya model are similar. The slope of the prediction is closely the same, but varies in the Y-offset. Given the logic that no tree with zero crown would have any DBH (except perhaps a dead tree) we could do a little more work to refine the y-intercept of these models so that they were closely similar and then we would have a general model for dry systems.

Figure 2.18 Relationship between DBH and Crown area in Western Kenya for 855 trees (ICRAF, 2010)



2.3.4. Regression model for Remote sensing CPA and field measured DBH

The results obtained by correlating field measured DBH and field measured CPA confirmed the difficulties of measuring tree crown size with very high accuracy in the field as compared to remote sensing. Consequently, results of correlation between remote sensing CPA and field DBH are more significant with an R-squared of 0.760 and 0.791 for Sokone and Karang sites respectively than those between field measured CPA and field measured DBH (R-squared of 0.564 and 0.589 respectively). For this reason, the remote sensing CPA can be used for correlation with the field measured DBH to measure the closeness of the linear relationship between these two variables. A simple linear regression analysis was developed and applied for each of the two sites of Sokone and Karang.

For the Sokone site, the results of the regression analysis appear as follows:

Table 2.9 Regression model and validation statistics for the relationship between Remote sensing CPA and field measured DBH for all sampled trees in Sokone site

Regression model	Constants		Multiple R	R Square	Adjusted R Square
	a	b			
DBH = a+b*RS CPA	13.408	0.5912	0.8720	0.7605	0.7598

The regression equation is given in the form of y= 13.408 + 0.5912 (x). The adjusted R squared is = 0.7605, which means that 76% of the DBH is determined by the CPA. Also we notice that R square and adjusted R square have almost the same values, 0.7605 and 0.7598 respectively, showing a minimal shrinkage based on this indicator and indicating that the equation can be generalized.

For all sampled trees in the Sokone site only, the regression equation is given in the form of:

DBH = 0.5912 (RS CPA) + 13.408 *Equation 2*

For the Karang site, the results of the regression analysis for all sampled trees appear as follows:

Table 2.10 Regression model and validation statistics for the relationship of Remote sensing CPA and field measured DBH for all sampled trees in Karang site

Regression model	Constants		Multiple R	R Square	Adjusted R Square
	a	b			
DBH = a+b*CPA	24.613	0.351	0.8895	0.7912	0.7906

The regression equation is given in the form of y= 24.613 + 0.351 (x). The adjusted R squared is = 0.7906, which means that 79% of the DBH is determined by the CPA. Also, both R squared and adjusted R squared have the same values (0.79), showing no shrinkage based on this indicator and suggesting that the equation can be generalized.

For all sampled trees in the Karang site only, the regression equation is given in the form of:

DBH = 0.351 (RS CPA) + 24.613 *(Equation 3*

Results of the DBH estimation model accuracy show a good correlation between the measured and the predicted DBH. For all cases, the coefficient of determination (R^2) is more than 0.7.

Using a general linear model that includes tree height, effective crown area, soil type, and age factors, Prieditis *et al*. (2012) found a strong relationship between predicted and measured DBH with an R-squared of 0.87. The highest coefficient compared to our results can be explained by the various parameters integrated in the model. These authors suggested that "models that use field or remotely-sensed measurements of a tree height as a predictor variable can be expected to produce a reasonably accurate estimate of DBH (R^2= 0.792)" which is close to the R^2 of 0.757 and 0.791 that we found for Sokone and Karang respectively, although their model is applied in forest area. However, when the model uses crown dimension measurements and information about age and soil type, the accuracy of DBH increases with an R^2 = 0.872 (Prieditis *et al*., 2012).

2.4. DISCUSSIONS AND CONCLUSION

In this chapter a model was developed that combined remote sensing and ground data that can be used to estimate biomass in trees outside of forests (TOF). The role of CPA (crown projection area) from high resolution satellite images to predict tree DBH was explored, and the relationship between tree crown projection area (CPA) obtained from Remote sensing techniques and the field measured tree DBH investigated.

The crown projection area was measured through remote sensing and used as the independent variable to predict the tree DBH. Also, tree crowns measured by remote sensing were compared with the crowns of trees measured on the ground.

For the relationship between Remote sensing CPA and field measured CPA, the results have shown a good relationship between remote sensing tree crowns and the field measured CPA in the Sokone site. The R^2 values are ranging from 0.62 (only cashew trees) to 0.76 (natural trees) and 0.68 when the model is applied for all trees combined (377).

For the Karang site, the R^2 values are 0.68 for all trees combined (315), 0.36 for only cashew (182) and 0.73 for natural trees (133). These results suggest that the model works better for natural trees.

However, there were some limitations to the methods used that might affect these results. The first important weakness is the period between the image acquisition and the field campaign. The satellite images were acquired in 2010 while the field data used was collected in 2013. This might explain for most trees why the values of the field measured CPA were bigger than those of the remote sensing.

For example, by correlating field measured CPA as the dependant variable with the remote sensing CPA as the independent variable the following equation is produced for all trees in Sokone: y = 0.4424 x + 14.251 meaning that

RS CPA = 0.4424 FM CPA + 14.251* *Equation 4*

For the Karang site the results are similar and the equation obtained for all sampled trees is: y = 1.1789 x + 12.59 meaning that

*RS CPA = 1.1789*FM CPA + 12.59* *Equation 5*

It is also important to mention cases where the remote sensing values are bigger due especially to disturbances including pruning and fire. The following pictures (Figure 2.19) are an illustration of the effects of these two forms of disturbances on trees.

Figure 2.19 The effects of tree disturbances on tree crown shape

a) Pruning reduces CPA

b) Fire reduces CPA

To determine the relationship between the remote sensing CPA and the field measured DBH, both simple linear and non linear regression analysis are used and applied for the three different cases (in the Sokone site, in the Karang site and for both sites combined). For the linear function, the coefficients of determination are very high for all cases with an $R^2 > 0.70$. The non linear function has R-squared values ranged between 0.61 for the Sokone site to 0.77 for the Karang site. Applied to the combined data of both site, the R^2 is 0.72. Compared to the non linear, results suggest that the linear model is the best.

Among the limitations of the methods, I acknowledge that the spatial pattern of the *Anacardium* plantations and their visibility in the satellite image are not as obvious as those of individual and scattered trees. As a result, the identification and delineation of tree crowns using remote sensing is less accurate than for the individual trees. This is confirmed by the coefficient of determination of field measured CPA vs. remote sensing CPA for *Anacardium*, which is low specially for the Karang site where it falls to 0.36 compared to the other species where it reaches 0.76.

Secondly, some individual scattered trees have experienced disturbances that affect the shape and the size of their crown. As mentioned earlier, pruning and fire are the major causes of these disturbances: trees lost some branches and/or even part of their bark, which in turn reduces the size of the crown.

Also, the *Anacardium* pattern and the distance between them usually create a situation of intermingling, i.e. the growth of some trees may be affected by the proximity of another tree, which in turn reduces the crown size and modifies the shape of the tree. Consequently, the relationship between DBH and crown area can be affected because of its sensitivity to crown competition factor (Anderson *et al*., 2000).

There is also a significant correlation between field measured DBH and remote sensing crown projection area with coefficients of determination of 0.76 and 0.79 for the Sokone and Karang sites respectively (Figures 2.12 & 2.14). These values can be compared and are close to those found by Kuyah *et al.* (2012) in Western Kenya. Using destructive sampling, they found that the relationship between crown area and DBH has shown a coefficient of determination R^2= 0.85 for harvested trees.

The model is also applied to *anacardium* species alone in both Sokone and Karang sites and the results show a high R-squared of 0.71 in regards to the correlation between remote sensing CPA and field measured DBH, and 0.63 and 0.36 respectively for Sokone and Karang site in regards to the relationship between the remote sensing CPA and the field measured CPA.

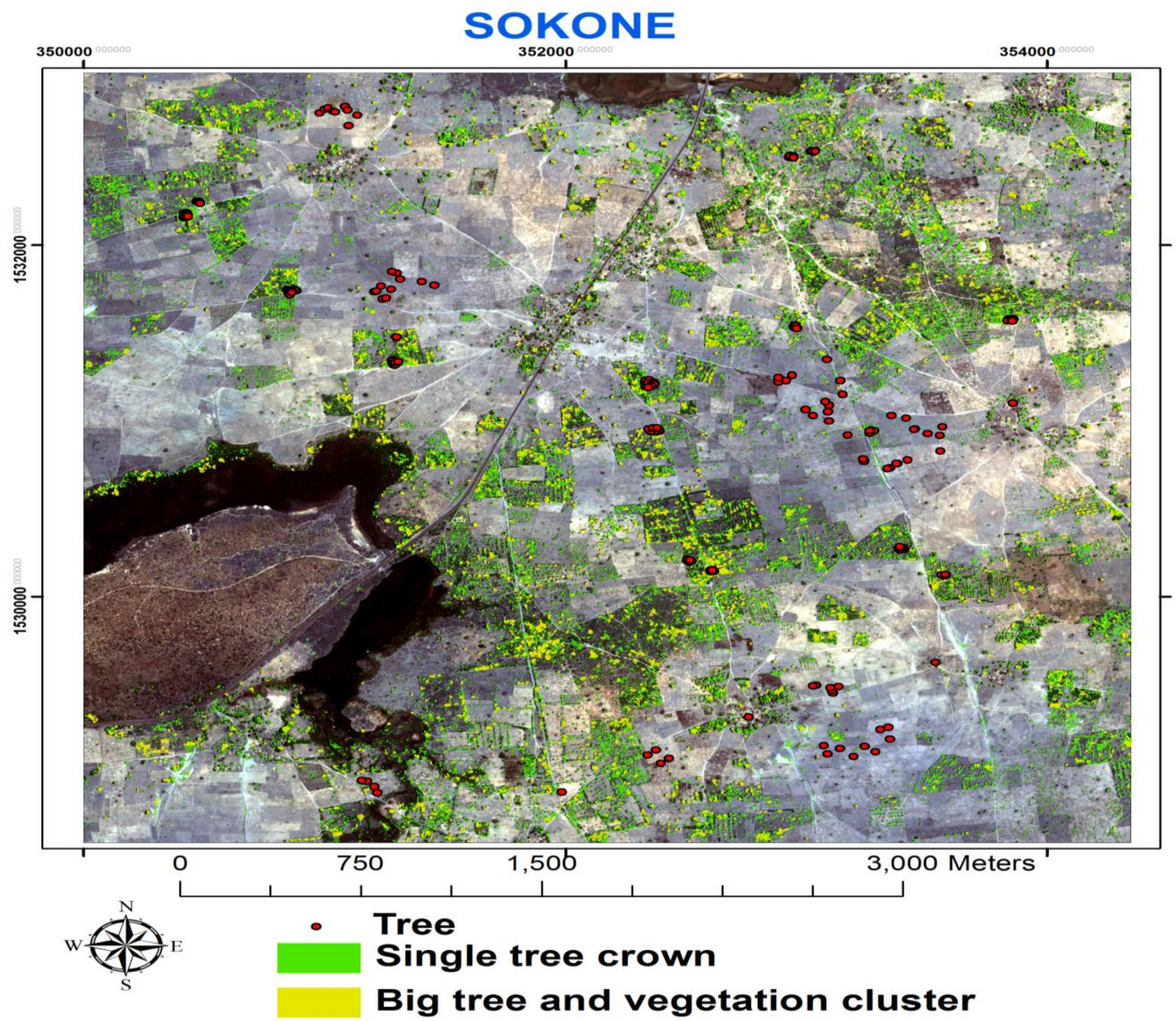
When applied to natural trees, the coefficient of determination is higher (0.84) in Sokone than in Karang (0.66) for the correlation between remote sensing CPA and field measured DBH, and 0.76 and 0.73 regarding the relationship between the remote sensing CPA and the field measured CPA.

In all cases, the strength of the relationship of field measured DBH with remote sensing CPA is high with R-squared > 0.70. Also the y-intercepts in all cases have positive values suggesting that the equations are suitable for predicting DBH of trees with a delineated CPA outside the range of sampled trees (Anderson *et al*., 2000). Overall, results of this study show that this developed model can be used to predict tree DBH using high resolution satellite image—especially individual trees outside forests where the detection is easier than for clustered trees, and natural trees better than managed trees.

APPENDIX

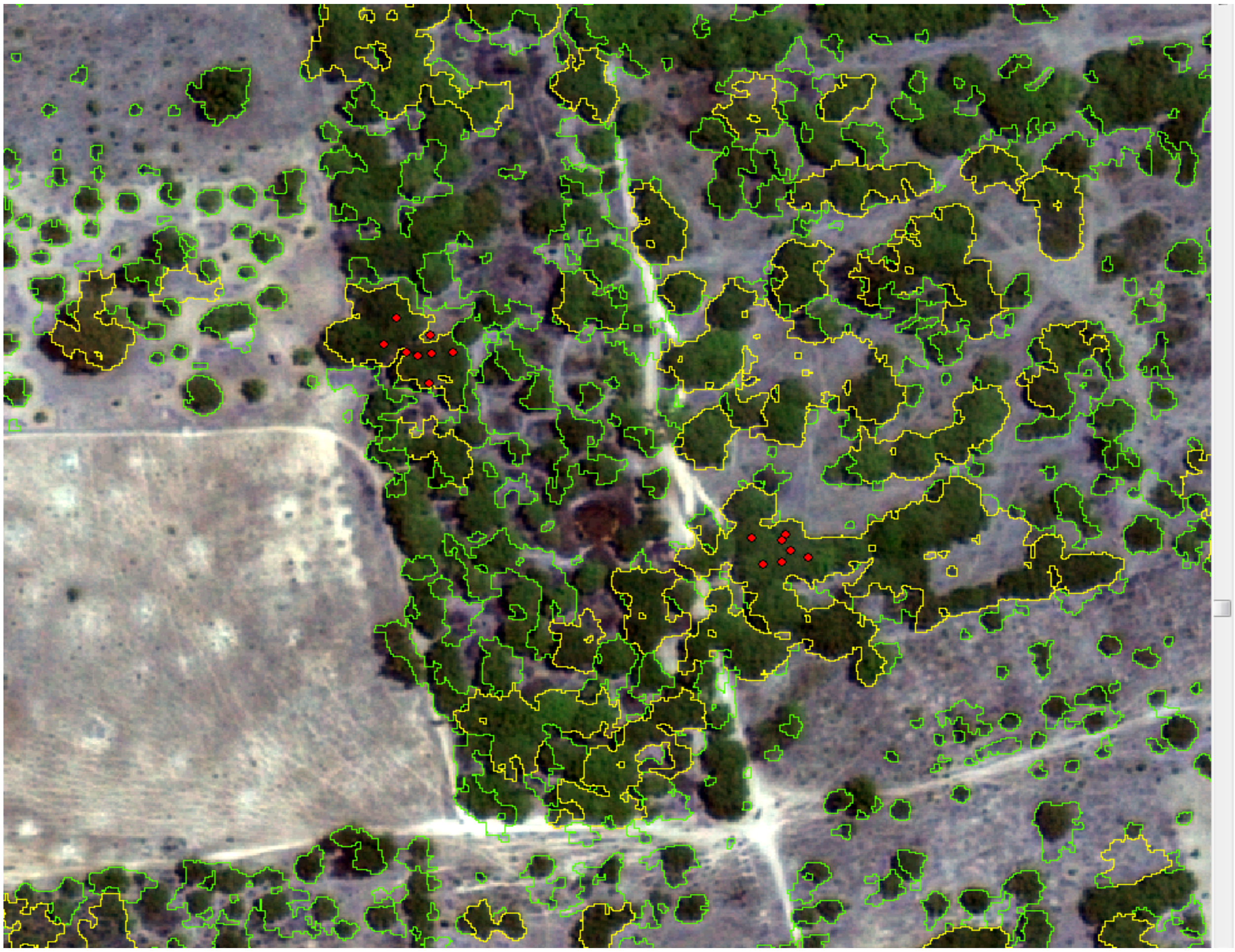
Appendix A: PRELIMINARY RESULTS WITH AUTOMATED DETECTION OF TREE CROWM PROJECTION AREA (CPA)

Figure A.1. Automated detection in the Sokone landscape



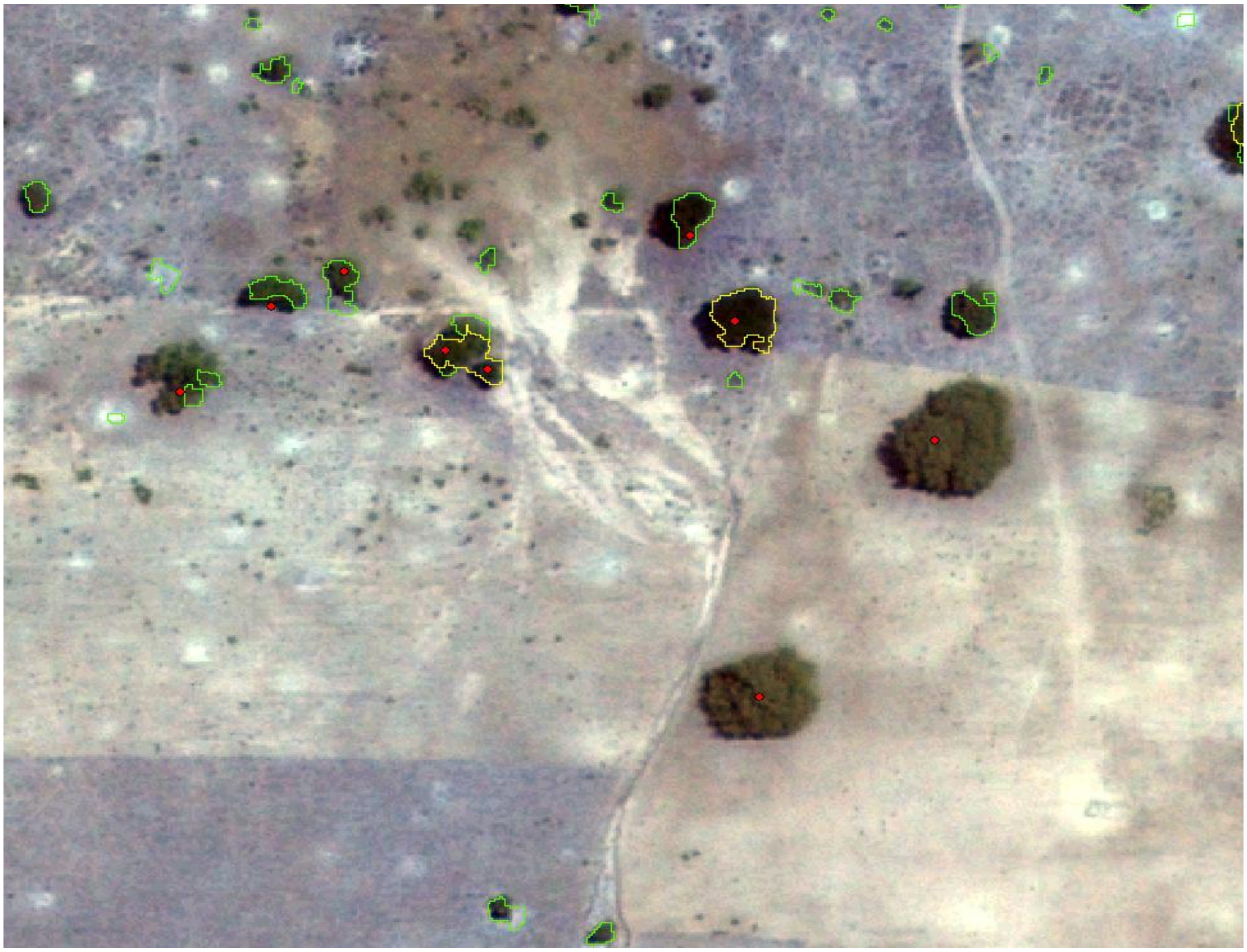
Some testing with automated individual tree detection and automated CPA delineation has promise, but some error of omission remain.

Figure A.2. View of automated detection in cluster vegetation



In some region, the detection result of cluster vegetation area is not good

Figure A.3. View of automated detection in individual big trees



... some big trees have lower NDVI, and that cause some loss of detection

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CHAPTER 3 . THE ROLE OF REMOTE SENSING IN MEASURING BIOMASS AND CARBON AT THE LANDSCAPE LEVEL IN SAVANNA SYSTEMS

3.1. INTRODUCTION

In many tropical countries, especially in rural areas, there is a reduction of forest areas due to many factors including forest clearing for agricultural and ranching purposes, shifting cultivation, removal of dry savanna vegetation and firewood, and agricultural waste burning (Crutzen and Andreae, 1990). Some studies have suggested that disturbance in open forest systems is quantitatively as important as in closed forests (Erickson *et al.* 2002; Murphy and Lugo 1995; Serca *et al.* 1998), especially because disturbances in these systems may have longer term degradation effects with lower probabilities of recovery than in closed forest systems. Observations of reforestation and biomass accumulation in trees on agricultural land is important because these data are needed to understand the global magnitude and capacity for carbon sequestration, and to inform decision and policy makers on options for carbon management practices that can remove carbon from the global atmosphere. There is considerable uncertainty on the current land area in woody perennials on farms in developing countries and the global potential for managing carbon sequestration in tree-based agriculture. Some estimates from international organizations suggest a large amount of carbon sequestration is already occurring in these managed landscapes (Verchot and Singh 2009).

Although frequently treated as a secondary priority to monitoring of the much higher biomass forests of the humid tropics, the dry and open forests of the world are more abundant than closed forests and usually are more prone to occupation and disturbance by humans. While these low density forests contain as little as 25% of the total carbon stock of humid tropical closed forests, the global area of low density forests is more than 30%

greater. Rates of disturbance are suspected to be equal to or greater than the closed forests, and less likely to recover lost carbon. Thus it is vitally important to begin to assess the global magnitude of open forest disturbances.

Additionally, what is often unrecognized is that while forested area is declining in developing countries, tree cover on farms is increasing, as farmers substitute annual cropland for the tree products which have formerly been available in local forests. Also farmers are increasingly seizing specific market opportunities to sell higher-value tree products (e.g. natural rubber, bio-fuels, bio-chemicals, timber). For example, remote sensing in 64 rural locations in Uganda revealed that between 1960 and 1995, forested area declined 50%, agricultural area increased 23%, and the proportion of agricultural land under tree cover increased 22% (Place 2001). Agricultural land now accounts for over double the area of forested land in Africa (FAO 2006), giving justification to the slogan that, “the future of trees is on farms.”

To pursue efforts on climate mitigation, global attention is shifting not only to tropical forests but also to trees outside of forests—especially trees on farms. Increasing woody biomass on farms in developing countries is seen as a possible global climate and carbon mitigation option that deserves serious attention. Montagnini and Nair (2004) have estimated that a vigorous program to introduce agro-forestry on farms in tropical Africa and Asia has the potential to sequester 3.5 Mg C ha-1 yr-1. However, for this to be a successful strategy it will be necessary to have sound detection and monitoring systems in place.

In the Africa context, and unlike in the developed countries, the farm sizes are small and are declining overtime (Jayne *et al.*, 2003). Although land use based smallholder carbon systems can provide multiple benefits, they are facing important constraints associated with small-scale measurement. Consequently, small-scale carbon sink projects occupy a limited place in global programs, and investors also have shown little interest in financing such projects (Boyd *et al.* 2007). It is necessary to explore the possibility of shifting the premise for measurement and monitoring carbon from individual farm plots to a whole landscape and from individual farmers to communities. However, for the time being, accurate measurement of woody biomass in landscapes is facing a significant challenge for efficient, timely and cost-effective automated monitoring of A/R/AF. Detecting and measuring individual tree objects that are sparsely planted or growing on farms, along roadways, or in backyards cannot be done accurately with low or moderate resolution satellite imagery where a single tree may represent only a small proportion of a single pixel. Although pixel unmixing techniques (Keshava 2003) can provide an estimate of the proportion of different land cover types represented by a single pixel, in general, these techniques are not amenable for accurate estimation of tree size, number or other measurements required for accurate assessment of forest cover change in sparsely planted landscapes. However, recent technological advancements in satellite image acquisition provide access to hyper-resolution imagery of the Earth and its land uses. The Worldview 2 satellite acquires 4 bands of multispectral data at 2 m resolution and a panchromatic band at 50 centimeters. Very high-resolution imagery enables the detection of objects in the landscape using remote sensing. Subsequent processing can be used to associate attributes, such as size or texture, with detected objects. Therefore, my work is beginning to demonstrate that it is possible to count trees, estimate size and evaluate change remotely.

For example, if one can detect individual trees and tree crowns, there may be a possibility to develop a crown-based allometry for individual trees (see previous chapters).

This requires the development of methods for ground measurements. Most reforestation projects use small sample plots in a sampling frame for forest inventory. This ground measurement protocol must be re-defined for systems of individually planted trees, and then also extended to the woodland or savanna landscape. The landscape approach allows one to inventory both land in forests (in this case savanna) and land on trees outside of forests (in this case agroforestry).

In recent years there has been substantial progress by the research community developing ways to detect land cover change in tropical forests with remote sensing. Remote sensing initially was focusing on measuring the conversion of tropical forests to non-forest land (Skole and Tucker 1993), but recent advances have made it possible to increase the variety of disturbances that can be detected for closed tropical forests to include deforestation, degradation, logging, fragmentation, reforestation, and fire (Matricardi *et al.* 2013, Matricardi *et al.* 2010; Matricardi *et al.* 2007; Wang and Cochrane 2005). Thus, there are now methods available to remotely detect a full range of disturbance intensities, from outright clearing to low levels of degradation, over large areas but these approaches have been successful only in very dense closed tropical forests, and in particular in key regions of the Amazon Basin, Central Africa, and South East Asia. There has been very little advancement of detection methods for two important other forms of land cover change: 1) deforestation and degradation of open woodlands such as the *cerrado* and the *chaco* ecosystems in South America, woodlands of East Africa, Savannas of West Africa, and other open forest ecosystems in the tropics and sub tropics, 2) regeneration systems on managed landscapes where biomass recovery occurs as plantations, orchards, agroforestry, and widely-spaced tree complexes associated with agriculture. This chapter is focusing on exploring the opportunities of using high resolution satellite images to:

- detect individual trees in landscapes in which tree cover is sparse or widely spaced and use remote sensing based crown projection area to predict DBH;
- select and apply an allometric model that estimates biomass or carbon stocks in Above ground live biomass (AGLB) based on accepted standards (ie. IPCC default allometric equations using DBH as inputs);
- estimate the model developed in chapter 2 which uses remote-sensing derived allometric parameters to estimate carbon stocks per tree;
- apply the model to inventory carbon stocks across an entire savanna landscape dominated by TOF.

3.2. MATERIALS AND METHODS

3.2.1. Study Area

The study area is located in two different sites: Sokone and Karang within an area measuring 6 km x 6 km (36 km^2) of two Worldview 2 satellite images. For each 36 km^2 area, a sample grid of 9 blocks (2 km x 2 km) is generated using the ERDAS Imagine software package. Three blocks of 2 km x 2 km representing an area of 400 hectares have been selected for sampling and data collection in each of the two sites of Sokone and Karang. Therefore, all of the previous calculations to develop the model of predicting DBH from remote sensing crown projected area have been done using data on this area. Also, for the carbon calculation, data for the six blocks (three in each site) are used at the sample level to apply the model to remote sensing and expand it at the landscape level. It covers an area of 2400 hectares, representing 1200 hectares for each of the two sites. For a large area application, we extend the area to eighteen blocks (nine in each site), covering an area of 7200 hectares (3600 hectares for each site) (Figure 2.2.).

3.2.2. Data used

Remote sensing data are from high resolution satellite image from Worldview 2 sensor which provides data in eight multispectral bands including;

- the coastal blue (400-450 nm) which supports vegetation identification and analysis;

- the blue (450- 510 nm)

- the green (510- 580 nm)

- the yellow (585- 625 nm) which assists in the development of "true color" hue correction for human vision representation;

- the red (630- 690 nm)

- the red-edge (705- 745 nm) which aids in the analysis of vegetation condition, directly related to plant health revealed through chlorophyll production;

- the NIR (770- 895 nm)

- the NIR 2 (860- 1040 nm) which supports vegetation analysis and biomass studies (Digital Globe, 2009). Four (red, blue, green, near infra red) of these bands are standard colors while the other four (red edge, coastal, yellow, near infra red 2) are new colors. This sensor has a resolution of 0.5 meter panchromatic (B&W) and 2 meters multispectral.

The data were acquired for the month of April 16, 2010 and were geo-registered in the Universal Transverse Mercator (UTM) coordinate system (WGS 84, zone 28). April is a period during which deciduous trees, which constitute the large part of trees outside forest in the study area, bear adequate foliage suitable to provide good remote sensing information as it makes the identification and the distinction of vegetation from other land cover features easier.

I digitized the crowns of all trees within the eighteen blocks and calculated their area and used it to predict their DBH for carbon estimation. I used the Arc Map Editor tool and created circular polygons around the area of the tree crowns.

3.2.3. Data Analysis

This sub-section addresses the question of how to measure carbon for trees outside of forests (TOF). Most techniques that use allometric equations to estimate total above ground biomass are using some combination of DBH, total height, and wood density as independent variables. For this study, crown projection area measured through remote sensing is used as the independent variable. Data from the remote sensing analysis of individual trees are calibrated with ground data. The regression equations developed in chapter 2 established a predictive relationship between crown and tree DBH. Those equations were used to predict DBH and estimate AGB using standard allometric equations that use DBH as the independent variable. To accomplish this task, remote sensing, correlation and regression analyses are combined.

3.2.3.1. Remote Sensing Analysis and manual delineation of trees

The complexity of smallholder agricultural systems in tropical areas compared to industrial agricultural systems requires fine resolution satellite data to allow tree measurements in agricultural landscape. This is possible with the availability of high resolution multispectral satellite imagery where single pixels (0.5 m) can be smaller than individual tree crowns, and even for trees as small as 10 cm in diameter at 1.3 m who often can have crown projection areas > 10 m^2 (Milne *et al*., 2013). High resolution images from

Worldview 2 were acquired for the study area. The selected images were taken during the dry season (April 16, 2010) to reduce the effect of cloud cover. The image projection is UTM Zone 28 N, WGS 84 datum.

To increase both the spatial, temporal and spectral resolution of the image, the Worldview Panchromatic image (0.5 m) was pan-sharpened with Worldview Multispectral bands MSS (2m). Individual tree crowns were manually digitized and the area of each tree crown is measured in the satellite imagery. The digitizing is performed using the polygon construction tool in ArcGIS 2010 and the area of each crown calculated and used to determine the relationship with the tree diameter at breast height (DBH) measured in the field. ERDAS and ArcMap software packages are used to perform these tasks.

ERDAS Imagine 9.2 software was used for pre-processing the satellite data while ArcGIS 10 helped create and merge the spatial database. The pan-sharpened images were displayed in ArcGIS 10 to perform the manual digitizing and tree crown delineation.

3.2.3.2. Regression Analysis

A regression analysis is used to estimate the change in the DBH from a given change in the CPA by finding a formula that represents the relationship between these two variables. This information is used to predict DBH from the given CPA by finding an approximate value of the tree DBH from the value of the CPA using a simple linear function. The regression established between these two parameters is used to estimate tree biomass and carbon on a tree-by-tree basis. With this relationship between CPA and DBH developed from ground measurements, the remote sensing delineated CPA is substituted with the ground measurements to cover the larger landscape.

3.3. RESULTS

In chapter 2, allometric models between tree crown projection area using a manual digitizing of Worldview 2 data and tree DBH measured during field surveys are developed. The model validation through a comparison between predicted and field measured DBH has shown satisfactory results with coefficients of determination of 0.760 and 0.791 respectively for Sokone and Karang sites. Equations 1 and 2 are used to predict DBH knowing the crown projection area from satellite data and estimated biomass and carbon. To measure the carbon on a tree basis, the IPCC general allometric equation (IPCC, 2006) is used. The carbon density and carbon stock in sampled plots is calculated for both Sokone and Karang sites.

3.3.1. Tree density at landscape level

To determine the stand densities for each block, remote sensing techniques have also been used, especially for the digitizing of the area of each stratum. After determining the area of strata for each site, the stand densities for each block were calculated from the number of standing trees per ha. Each block has an area of 400 ha but I excluded the area of pasture in some blocks which explains the difference. In the Sokone site:, block SOK 1 with an area of 333 ha, counts 4814 trees, which gives a stand density of 14.4 trees/ha. It is the second block with the highest stand density after block SOK 4 which has a stand density of 17.5 trees/ ha with an area of 369 ha and counting 6470 trees. The third block with the highest stand density is SOK 5 with 10.9 trees/ ha. All other six blocks in the Sokone site have less than 10 trees/ha (Table 3.1)

For the Karang site, the two blocks with the highest stand density are KAR 8 and KAR 5 with respectively 13.1 and 11.3 trees/ha. Al other blocks have less than 10 trees/ha (Table 3.1.).

Globally, the Sokone site has the highest stand density compared to the Karang site (Table 3.1.).

Table 3.1 Tree density by block in the study area

BLOCKS	Block Area (ha)	Number of trees	Stand density (trees/ha)
SOKONE			
SOK 1	333	4814	14.4
SOK 2	391	3868	9.8
SOK 3	356	2947	8.2
SOK 4	369	6470	17.5
SOK 5	294	3211	10.9
SOK 6	341	3211	9.4
SOK 7	400	2440	6.1
SOK 8	400	1847	4.6
SOK 9	400	1283	3.2
KARANG			
KAR 1	201	1839	9.1
KAR 2	203	446	2.1
KAR 3	292	1218	4.1
KAR 4	400	1813	4.5
KAR 5	179	2031	11.3
KAR 6	387	1714	4.4
KAR 7	387	2193	5.6
KAR 8	288	3798	13.1
KAR 9	356	1394	3.9

3.3.2. Carbon stock and carbon density at landscape level

The following equations developed in chapter 2 are used to predict tree DBH knowing the crown area based on remote sensing;

Equation 3 is used for the Sokone site and Equation 2 for the Karang site.

$$DBH = 0.5912\,(RS\ CPA) + 13.408 \qquad \textit{Equation 2}$$

$$DBH = 0.3514\,(RS\ CPA) + 24.613 \qquad \textit{Equation 3}$$

To calculate aboveground biomass, the following *Equation 6* is used:

$$ABG = \exp(-1.996+2.32*\ln(DBH)) \qquad \textit{Equation 6}$$

Where:

ABG = aboveground biomass in kg

DBH = diameter at breast height in cm

The below ground biomass is calculated by multiplying the above ground biomass by 0.24 which is the root-shoot (R/S) ratio. All values of above and below ground biomass are summed up to count for the total biomass converted into carbon by multiplying the biomass by 0.47.

Carbon stock and carbon densities in both Sokone and Karang are reported in the following Table 3.2. For the Sokone site, the carbon densities vary between 3.9 (block SOK 9) to 17 tC/ha for block SOK which has the highest density. It is followed by block 5 (SOK 5), block 6 (SOK 6), block 2 (SOK 2), block 4 (SOK 4) and block 3 (SOK 3) with respectively 16.4, 12.7, 12.5, 12.4 and 11.3 tC/ha. In addition to the presence of pasture which reduces the area, these high densities are explained by the high density of cashew plantation in these blocks.

Table 3.2 Carbon stock and Carbon density by block in the study area

BLOCKS	Area of Block(ha)	Carbon stock (t C)	Carbon density (t C/ha)
SOKONE			
SOK 1	333	5672.4	17.0
SOK 2	391	4889.8	12.5
SOK 3	356	4019.9	11.3
SOK 4	369	4588.4	12.4
SOK 5	294	4822.7	16.4
SOK 6	341	4315.1	12.7
SOK 7	400	1885.6	4.7
SOK 8	400	2374.0	5.9
SOK 9	400	1568.6	3.9
KARANG			
KAR 1	201	1543.2	7.7
KAR 2	203	415.9	2.0
KAR 3	292	773.4	2.6

Table 3.2 (cont'd)

KAR 4	400	2535.9	6.3
KAR 5	179	1446.0	8.1
KAR 6	387	1732.6	4.5
KAR 7	387	1318.8	3.4
KAR 8	288	1997.1	6.9
KAR 9	356	1446.8	4.1

3.3.3. Relative contribution of trees by DBH size to the total carbon

The classification of trees based of DBH size is helpful in determining the contribution of tree size to the total biomass and carbon. For the Sokone site, Table 3.3. and Figure 3.2. show the contribution of each DBH class to the total carbon for all nine blocks.

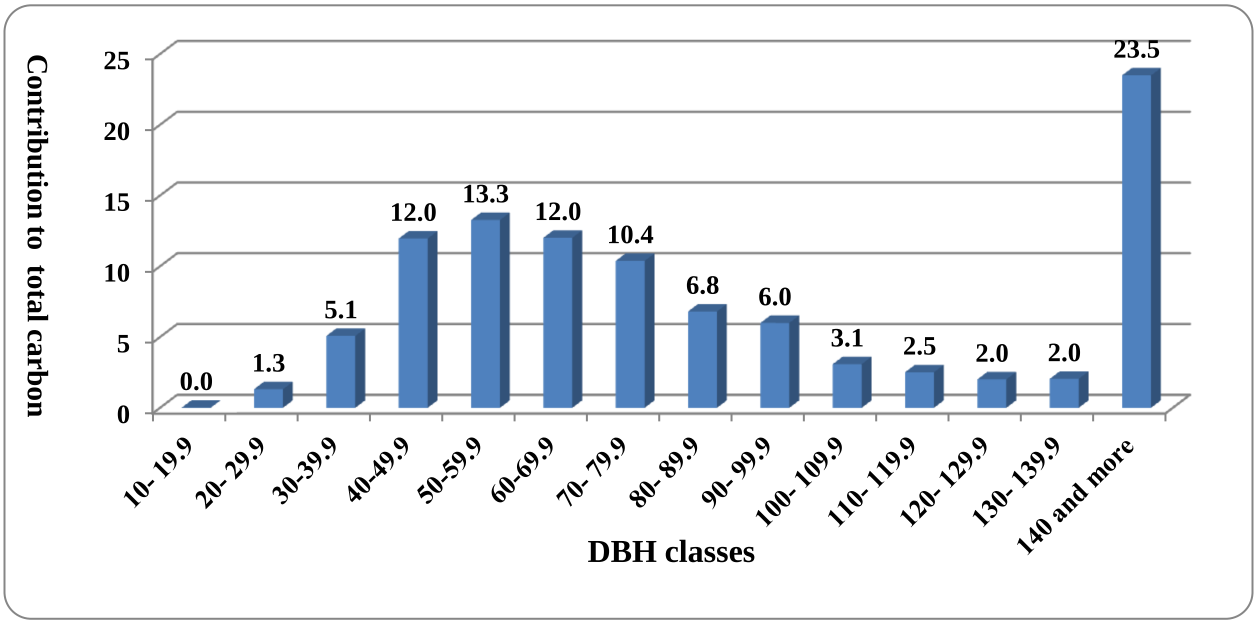
Table 3.3 Relative contribution of trees (tons of C) by DBH size to the total carbon in the Sokone site.

DBH Classes (cm)	BLOCKS									
	SOK 1	**SOK 2**	**SOK 3**	**SOK 4**	**SOK 5**	**SOK 6**	**SOK 7**	**SOK 8**	**SOK 9**	**TOTAL**
10- 19.9	0.5	0.1	0.0	2.8	0.1	0.0	0.4	0.0	0.6	4.4
20- 29.9	102.3	15.8	7.5	199.5	17.2	18.6	55.0	4.8	28.4	449.0
30-39.9	351.3	178.8	83.6	453.7	123.4	194.1	174.3	71.7	103.8	1734.7
40-49.9	581.4	602.3	423.6	843.2	439.6	458.6	313.1	297.5	123.9	4083.2
50-59.9	497.1	648.0	522.9	786.6	639.2	606.3	387.2	325.8	116.9	4530.0
60-69.9	651.5	661.1	558.8	551.1	511.0	552.9	164.7	284.5	166.9	4102.3
70- 79.9	400.6	567.8	527.9	508.2	507.3	344.3	252.4	309.5	126.6	3544.4
80- 89.9	266.9	346.5	413.3	328.4	351.5	155.9	107.4	219.0	135.5	2324.4
90- 99.9	673.5	211.4	227.6	254.5	197.6	148.6	88.3	115.2	130.5	2047.3
100- 109.9	318.7	109.9	119.2	77.0	127.5	115.1	43.5	82.4	60.8	1054.1
110- 119.9	83.7	132.5	147.5	115.8	148.6	57.6	55.7	51.3	65.5	858.2
120- 129.9	281.6	43.6	96.8	107.9	29.6	34.7	36.1	36.9	18.6	685.9
130- 139.9	196.4	39.7	59.9	87.6	108.7	68.6	35.0	40.8	62.4	699.1
140 and <	1266.8	1332.4	831.2	272.0	1621.5	1559.9	172.66	534.56	428.27	8019.5
TOTAL	**5672.4**	**4889.8**	**4019.9**	**4588.4**	**4822.7**	**4315.1**	**1885.6**	**2374.0**	**1568.6**	**34136.7**
Percentage	***16.6***	***14.3***	***11.8***	***13.4***	***14.1***	***12.6***	***5.5***	***7.0***	***4.6***	

Except for block 7, 8 and 9 (SOK 7, SOK 8, and SOK 9) which have the lowest amount of carbon, all other blocks hold at least 10 %. with the highest percentage for SOK 1 (16.6 %) followed by SOK 2, SOK 5, SOK 4, SOK 6 and SOK 3 with respectively 14.3, 14.1, 13.4, 12.6 and 11.8 %.

Figure 3.1 shows more details about the percentage of each DBH class to the total carbon for the whole nine blocks. 54 % of carbon is hold by trees with 80 cm DBH or less and 66.8 % of the carbon is hold by trees with less than 100 cm DBH. Although they represent only 1.14 % of the total tree density, big trees (140 cm DBH or more) hold almost a quarter (23.5 %) of all carbon. This is explaining by the very large DBH of some trees. In the Sokone site, many trees have more than 200 cm DBH.

Figure 3.1 Percentage contribution to total carbon by DBH classes in the Sokone site



Results from the Karang site also confirm this tendency of trees with less than 80 cm DBH to contain most of the biomass (Table 3.4. and Figure 3.2). The quantity of biomass contained in this range of trees is 70.6 % for the whole nine blocks in the Karang site. 87.4 % of the carbon is hold by trees with less than 100 cm DBH.

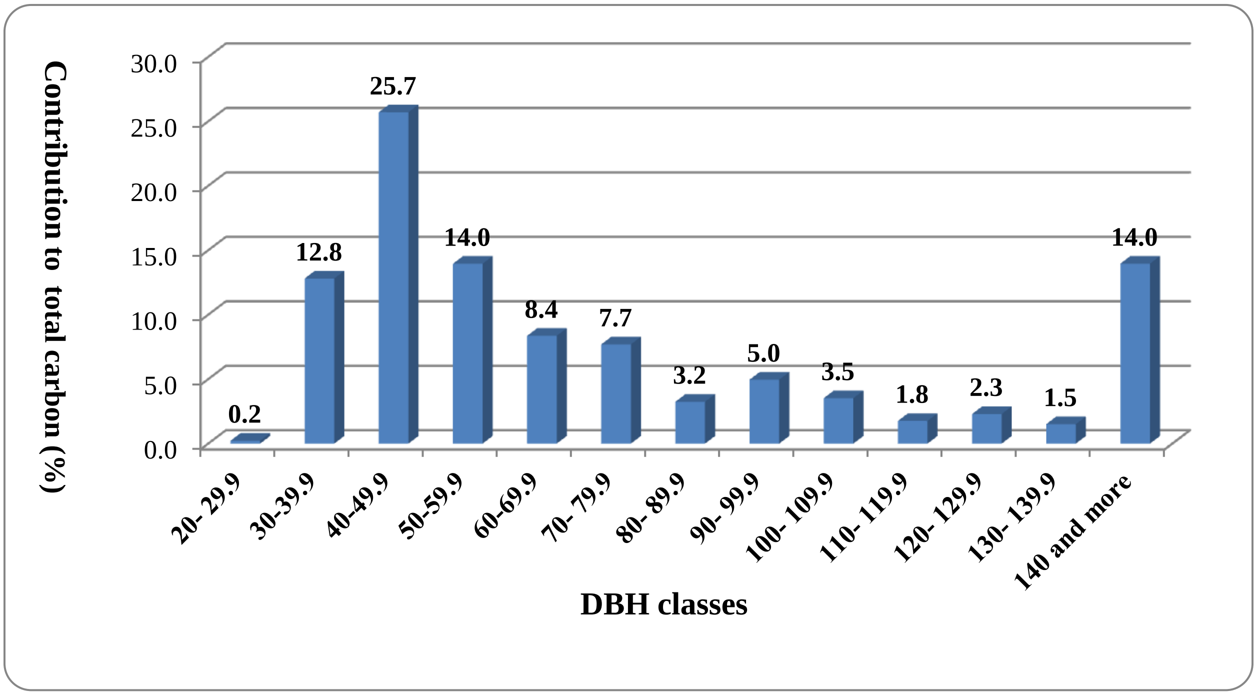
Table 3.4 Relative contribution of trees (tons of C) by DBH size to the total carbon in the Karang site.

DBH Classes (cm)	BLOCKS									
	KAR 1	KAR 2	KAR 3	KAR 4	KAR 5	KAR 6	KAR 7	KAR 8	KAR 9	TOTAL
20- 29.9	0.8	0.0	1.0	0.4	2.6	1.0	8.3	12.9	1.9	28.9
30-39.9	131.7	31.4	135.0	69.2	185.9	85.2	289.1	619.2	145.1	1692.0
40-49.9	493.5	116.7	291.3	332.9	477.7	360.8	403.0	712.5	207.5	3395.9
50-59.9	239.6	53.8	110.2	346.9	255.4	336.7	208.3	138.2	154.0	1843.2
60-69.9	115.4	30.3	66.0	292.8	128.2	212.8	127.9	58.0	72.7	1104.1
70- 79.9	66.5	25.2	40.3	255.6	101.8	171.0	72.1	65.5	218.8	1016.9
80- 89.9	34.3	14.1	26.9	136.3	34.5	75.7	11.8	16.7	78.7	429.0
90- 99.9	71.9	17.6	28.7	156.2	60.9	78.4	44.3	23.4	174.0	655.3
100- 109.9	40.3	11.9	7.6	130.9	55.5	84.6	36.4	11.9	86.1	465.2
110- 119.9	8.9	4.5	4.5	32.2	14.3	56.6	4.9	11.9	94.7	232.5
120- 129.9	39.1	22.2	11.0	97.0	22.4	34.3	21.8	5.4	49.8	303.0
130- 139.9	22.0	22.0	0.0	78.4	0.0	43.8	13.1	0.0	19.9	199.2
140 and <	279.0	66.2	50.9	607.1	106.8	191.7	77.7	321.5	143.6	1844.3
TOTAL	**1543.2**	**415.9**	**773.4**	**2535.9**	**1446.0**	**1732.6**	**1318.8**	**1997.1**	**1446.8**	**13209.6**
Percentage	***16.9***	***13.6***	***12.2***	***16.5***	***12.3***	***10.5***	***6.6***	***7.0***	***4.4***	

Like in the Sokone site, only three blocks (KAR 7, KAR 8, and KAR 9) have less than 10% of the total carbon for the whole site. KAR 1, KAR 4, KAR 2, KAR 5 and KAR 3 hold the highest percentage of carbon with respectively 16.9, 16.5, 13.6, 12.3 and 12.2 % of the total carbon.

More details about the percentage of each DBH class to the total carbon for the whole nine blocks are shown is Figure 3.2. Big trees with more than 140 cm DBH contribute to 14% to the total carbon. Like in the Sokone site, this is due to the very large DBH of some trees.

Figure 3.2 Percentage contribution to total carbon by DBH classes in the Karang site



In both Sokone and Karang, there is a variability of trees based on their DBH within the 9 blocks which reveals that the most densely populated of the blocks are those dominated by the cashew (*Anacardium occidentale*) species.

3.3.4. Comparison of remote sensing-based biomass and carbon estimation with field data

In this section, data from sampled plots within the 6 blocks (3 for each site) is used to do a comparison with the remote sensing model-based data for the same blocks. Biomass and carbon for each tree are calculated using the field measured DBH for both Sokone and Karang sites. To determine the carbon stock and carbon density for each of the six selected blocks (3 for each site) of the two sites, these different steps are followed:

A- Determine the total area of all sampled plots for each stratum

B- Determine the percentage of each stratum for each block

C- Calculate the quantity of carbon per tree in each plot

D- Calculate the total carbon per plot by summing up all carbon/tree within the plot

E- Calculate the carbon stock in all sampled plots for each stratum by summing up the amount of carbon per plot for all plots of the same stratum

F- Calculate the carbon density by stratum of each block by multiplying (E) by the area of that stratum within the block

G- Calculate the carbon stock within each block by summing up all carbon stock in all strata within each block

H- Calculate the carbon density for each stratum by dividing (F) by the area of each stratum

I- Calculate the carbon density of each block by dividing its carbon stock by the corresponding area

The calculation of the carbon stock and density estimates for a larger area is done by first extrapolating to the full hectare. An expansion factor determined by calculating the proportion of a hectare that is occupied by a given plot in the study area (Pearson *et al.*, 2007) is used. In both sites, the area of pastures is excluded for the biomass and carbon estimation as this land cover type is not part of this study. The area of dwellings (villages) is included with area of TOF in agricultural lands because individual trees within the villages are easily detectable and digitized to allow an application of the model.

Comparison between field based and remote sensing based carbon estimates shows that values of the field based carbon are higher than the model-based carbon for all blocks (Table 3.5.). The difference in carbon density estimation varies between blocks. For KAR 1, KAR 8 and KAR 9 blocks in the Karang site, the difference represents respectively 27.3, 30.6 and 35.1 %.

This difference is reflected in the carbon density with lower values for the remote sensing based data.

Table 3.5 Comparison between remote sensing based and field based carbon stock and carbon densities

BLOCKS	Area of Block (ha)	Remote sensing based		Field-based	
		Carbon stock (tC)	Carbon density (tC/ha)	Carbon stock (tC)	Carbon density (tC/ha)
KARANG					
KAR 1	201	1543.2	7.7	2124.0	10.6
KAR 8	288	1997.1	6.9	2876.2	10.0
KAR 9	356	1446.8	4.1	2229.2	6.3

Analysis of field data allows a comparison of carbon density by land cover. After estimating carbon stock and carbon density at the plot level and knowing the area of each stratum within the block, the carbon density for each stratum is multiplied by the area to estimate the carbon stock for the whole block.

For the Sokone site, the values of carbon stocks are higher for block SOK 1 with 9286.1 tons of carbon and decrease towards the south for block SOK 4 (6207.7 tons of carbon) and block SOK 7 (2950.2 tons of carbon) (Table 3.6.). This decrease is more pronounced for the cashew plantation where the densities vary between 78.6 t C/ha in SOK 1 in the northern part to 34.6 tC/ha for SOK 7 in the southern. The highest carbon densities are within the area of cashew plantation and can reach 78.6 t C/ha for SOK 1. This can be explained by the long tradition of cashew plantation in this area with the Senegalo-German Cashew Project (PASA) back to the 1980s.

Table 3.6 Carbon stock and carbon densities in the six blocks of the Sokone and Karang sites where sampled plots were located

BLOCKS	Cashew plantation			TOF in agricultural land			TOTAL		
	Area (ha)	Carbon stock (t C)	Carbon density (t C/ha)	Area (ha)	Carbon stock (t C)	Carbon density (t C/ha)	Area (ha)	Carbon stock (t C)	Carbon density (t C/ha)
SOKONE									
SOK 1	96	7548	78.6	237	1738.1	7.3	333	9286.1	27.9
SOK 4	116	5031.2	43.4	253	1176.5	4.7	369	6207.7	16.8
SOK 7	44	1523.1	34.6	356	1427.1	4.0	400	2950.2	7.4
KARANG									
KAR 1	30	1158	38.6	171	966	5.6	201	2124	10.6
KAR 8	67	1559.6	23.3	221	1316.6	6.0	288	2876.2	10.0
KAR 9	23	707.7	30.8	333	1521.5	4.6	356	2229.2	6.3

For the Karang site, results of the carbon stock at the plot level scaled up at the block level are similar to those for the Sokone site regarding the predominance of cashew plantations which explains the higher values of carbon stock for that stratum. Block KAR 8 that has the largest area of cashew holds 1559.6 t of carbon which represents 54% more than Block KAR 9 with only 707.7 t C. In the meantime, with the larger area of other TOF in agricultural land (333 ha), Block KAR 9 holds the highest carbon stock for this stratum with 1521.5 t C while Block KAR 1 with an area of 210 ha holds only 966 t C (Table 3.6.).

3.4. DISCUSSIONS AND CONCLUSION:

Measuring carbon in trees outside of forests is very challenging especially in savannas systems due to the high spatial variability caused by natural but mostly human disturbances events (Lyster *et al.*, 2013). Using remote sensing predicted crown projection area (CPA), we estimate biomass and carbon per tree for the whole eighteen (18) blocks of the study area in both Sokone and Karang sites.

Direct measurements using field inventories have been used to estimate biomass and carbon but present some challenges: it is time consuming, expensive labor intensive and difficult to implement in remote areas (Kuya *et al.*, 2012). Our results have shown that these challenges can be overcome by using remote sensing techniques.

With these techniques, I was able for example, to determine the number of trees for each of the blocks and calculate the stand densities (trees/ha). Using a remote sensing-based model, tree DBH is predicted knowing the crown projection area and run an allometric equation to calculate the carbon on a tree basis.

In each of the blocks of the study area, we estimated the carbon stock and the carbon density. The carbon densities vary between 17 t C/ha which is the highest (SOK 1) to 2 t C/ha the lowest (KAR 2). The classification by DBH of all trees in each block is used to determine the contribution of trees by DBH class to the total carbon. Unlike a common assumption that big trees hold the most amount of carbon, the classification by DBH class shows that most of the carbon is on trees with small and medium size DBH: 66.8 % of the carbon for the Sokone site and 87.4 % for the Karang site is concentrated on trees with less than 100 cm DBH.

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CHAPTER 4 . LANDSCAPE BIOMASS ESTIMATION AND CARBON MAPPING

4.1. INTRODUCTION

In many developing countries, especially in rural areas, forest areas are decreasing while in the agricultural landscape trees are still present and in some part in large amounts. This is very common in some countries where forest are converted to other land uses with increasing density of human population (De Foresta *et al*., 2013)

There are numerous landscape-wide deforestation and carbon measurement protocols for forests, particularly closed forests (Matricardi *et al.* 2010). However, there are few methods available for sparsely wooded systems, such as savannas, and virtually none for systems of trees outside of forests that can be used across whole landscapes. The current methods for landscape level carbon measurement are particularly problematic and are unlikely to meet scientific and rigorous standards (for example the requirements of the CDM Executive Board) and potential carbon project investors. Therefore, there is a lack of confidence in existing measurement systems with implications that go beyond the measurement of carbon credits and create doubts about the project viability. New advances in remote sensing of canopies and individual tree crown detection offer great promise

Currently, there is a growing interest in investing in agroforestry systems for this dual benefits of climate mitigation and livelihoods enhancements (ICRAF, 2008), and also as a set of innovative practices that strengthen the farming system's ability to cope with, or adapt to, adverse impacts of changing climate conditions (Verchot, 2007). In this context it is possible to view agroforestry as both a mitigation and adaptation option for small holders. Agroforestry practices can be applied across a variety of forms and range of intensities depending on local conditions to provide a locally relevant approach to sustainable agriculture production and soil fertility management. Agroforestry might become a key component of the African farmers' household portfolio of farming practices, and provide an important role in meeting farmers' food and non-food subsistence needs through its ecosystem services provided (Jonsson *et al*., 1999). There is also some evidence to suggest that the high production levels and economic values of agroforestry value chains may actually facilitate the production of financial capital beyond subsistence levels alone, thereby aiding in capital accumulation and re-investment at the farm level.

In Africa one of the more critical characteristics of the rural landscape is the preponderance of many small holder farming systems that are operating on the environmental and economic margins, where any newly introduced practice will be adopted only if it improves food security (and incomes) on a sustainable basis. Under such conditions, climate mitigation interventions, such as a increased carbon stocking with trees on farms, will need to demonstrate support for improved food production (and income) as well (Smith, 2012). In this context, climate mitigation becomes a co-benefit of a primarily food-focused enterprise. Hence, practices that minimize the rate of soil degradation, improve soil fertility, increase crop yields and raise farm income by using the "right tree at the right farming place" are keys to sustaining agricultural productivity which in turn provide better conditions for climate adaptation in many of the poor rural communities that might be most adversely affected by climate change and variability (Neupane, 2001), and then also provide added benefits for climate mitigation through increased greenhouse gas removals from the atmosphere. Agroforestry – as a system of "trees outside of forests" – readily bundles both mitigation and adaptation strategies and provides several pathways to a range of environmental and social co-benefits and outcomes, including food security, increased farm income, restoration and maintenance of above-ground and below-ground biomass and biodiversity, reestablishment of biological corridors between protected forests, maintenance of watershed hydrology, improved soil conservation, availability of timber and fuel wood, and ultimately a reduction of pressure on natural forests outside the farming domain (Pandey, 2002)

Many accepted methods for carbon measurement in programs or projects that are based on sequestration (cf. as opposed to avoiding emissions from deforestation) have been defined at a project scale with specified boundaries of the project, often on land parcels with a single owner. When trying to develop methods for rural poor farmers, experience suggests that a landscape approach is needed, whereby many farmers can be bundled into a single project, even if the parcels are not contiguous.

The landscape approach offers new opportunities for the participation of many more of the rural poor in carbon markets, but the means for landscape-scale measurement needs to be developed. Remote sensing offers a means to do landscape scale measurement and monitoring, but most advances methods in recent years have focused on closed forests, rather than open woodlands and savannas or, to be sure, systems of trees outside of forests.

This chapter is dedicated to estimate biomass and carbon at a landscape level using remote sensing techniques and producing carbon maps of the study area. The model applied combines advanced remote sensing and basic allometry in systems of "trees outside of forests" to a whole landscape. As developed in chapter 2, a moderate to high correlation between remote sensing crown projection area (CPA) and tree DBH enables us to predict DBH knowing the CPA through remote sensing. The equation from that correlation is used to scale up the calculation across a larger area in the semi-arid savanna ecosystems in Senegal (West Africa).

4.2. MATERIALS AND METHODS

4.2.1. Study Area

The study area is presented in chapter 3: nine blocks are selected for each of Sokone and Karang sites. Those eighteen blocks are shown in Figure 2.2.

4.2.2. Data used

The different data used include:

- land use and land cover data. I classified and digitized the area based on the different strata and determine the area of cashew plantation, the area of pasture and the area occupied by agricultural lands which hold the other TOF. These data is used to calculate the carbon stock and the carbon density. These land use and land cover data are from Worldview 2 high resolution satellite image;

- the biomass and carbon data are obtained using allometric equation and predicted DBH from remote sensing Crown Projection Area (Chapter 3).

4.3. RESULTS

4.3.1. Landscape application of the model

The stratification of the study area reveals a large area of pasture in both sites; which reduces the total area where the model is applied. For the nine blocks of the Sokone site, 8.76 %, representing 315 ha are permanent pasture and 16.03 % are occupied by cashew plantations. The area occupied by agricultural lands and where TOF are implanted, represents 75.22 % of the study area with 2708 ha (Table 4.1.).

For the Karang site, the 833 ha of permanent pasture represent 23.14 % within the nine blocks. At the same time, the area of cashew represents only 5.71 %. The agricultural lands occupied a large area of 2561 ha, representing 71.13 % study area in this site.

Table 4.1 Remote sensing stratification of the eighteen blocks in Sokone and Karang sites

BLOCKS	Area Cashew plantation(ha)	Area Other TOF (ha)	Area of pasture	Total Area (ha)
		SOKONE		
SOK 1	***96***	***237***	***67***	***400***
SOK 2	92	299	9	400
SOK 3	58	298	44	400
SOK 4	***116***	***253***	***31***	***400***
SOK 5	56	238	106	400
SOK 6	43	298	59	400
SOK 7	***44***	***356***	***0***	***400***
SOK 8	59	341	0	400
SOK 9	26	374	0	400
TOTAL	**577**	**2708**	**315**	**3600**
		KARANG		
KAR 1	***30***	***171***	***199***	***400***
KAR 2	4	199	197	400
KAR 3	15	277	108	400
KAR 4	11	389	0	400
KAR 5	15	164	221	400
KAR 6	18	369	13	400
KAR 7	30	357	13	400
KAR 8	***67***	***221***	***112***	***400***
KAR 9	***23***	***333***	***44***	***400***
TOTAL	**206**	**2561**	**833**	**3600**

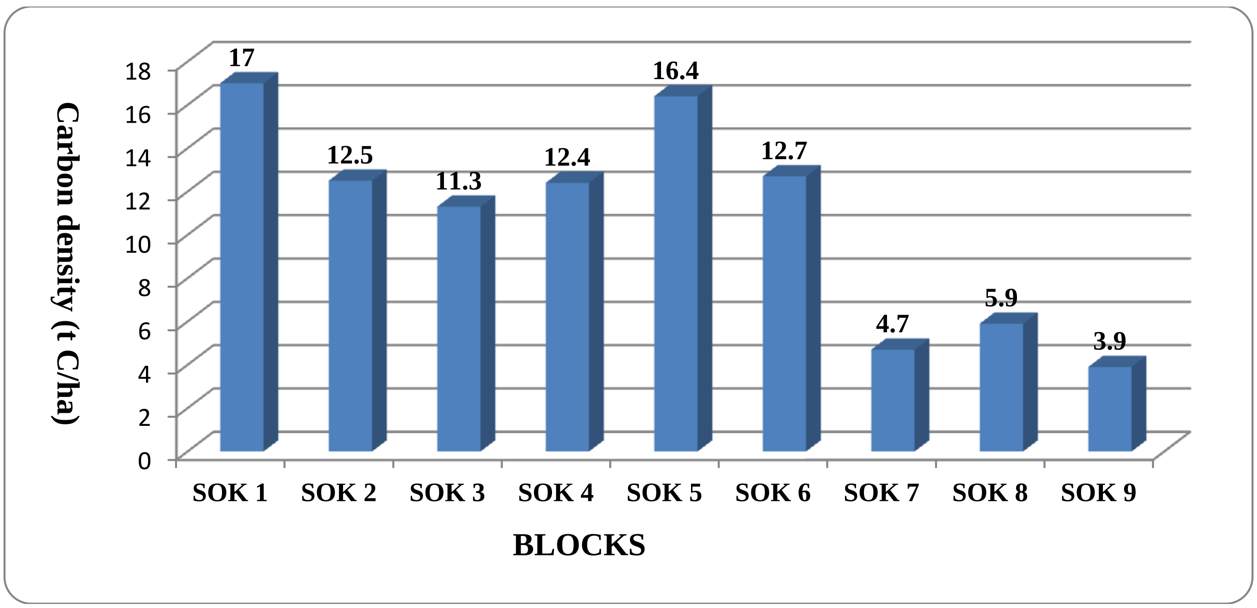
Although the study area is dominated by the scattered individual TOF in terms of area, the area occupied by cashew plantations is denser in terms of population and crown cover. This situation is confirmed by the results in the nine blocks (SOK 1, SOK 4 and SOK

7 for Sokone and KAR 1, KAR 8 and KAR 9 for Karang) where the sampling is done. These blocks are highlighted in Table 4.1.

4.3.2. Carbon density per block in the study area

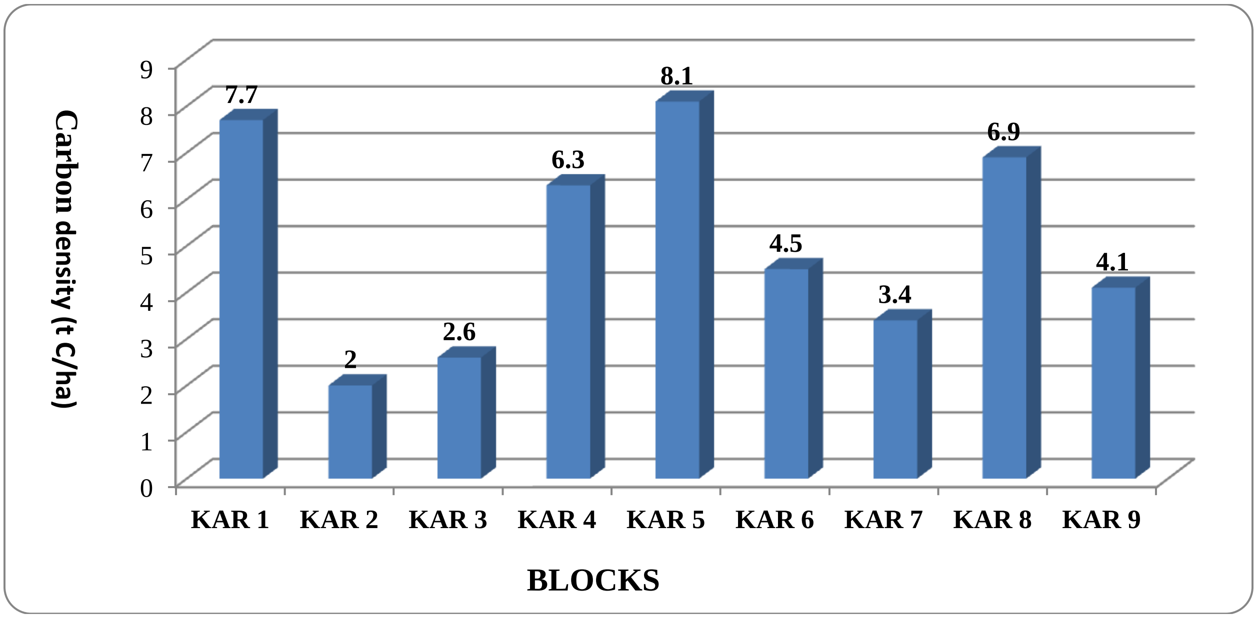
The carbon density for each of these blocks is calculated and results are presented in Figure 4.1. Block SOK 1 in the Sokone site has the highest carbon density with 17 t C/ha followed by blocks SOK 5 (16.4 t C/ha), SOK 6 (12.7 t C/ha), SOK 2 (12.5 t C/ha) and SOK 4 (12.4 t C/ha).

Figure 4.1 Carbon density (t C/ha) per block in the Sokone site



Except for blocks SOK 7 (4.7 t C/ha), SOK 8 (5.9 t C/ha) and SOK 9 (3.9), the lowest carbon densities are found in the Karang site with block KAR 5 having the highest carbon density (8.1 t C/ha) for this site.

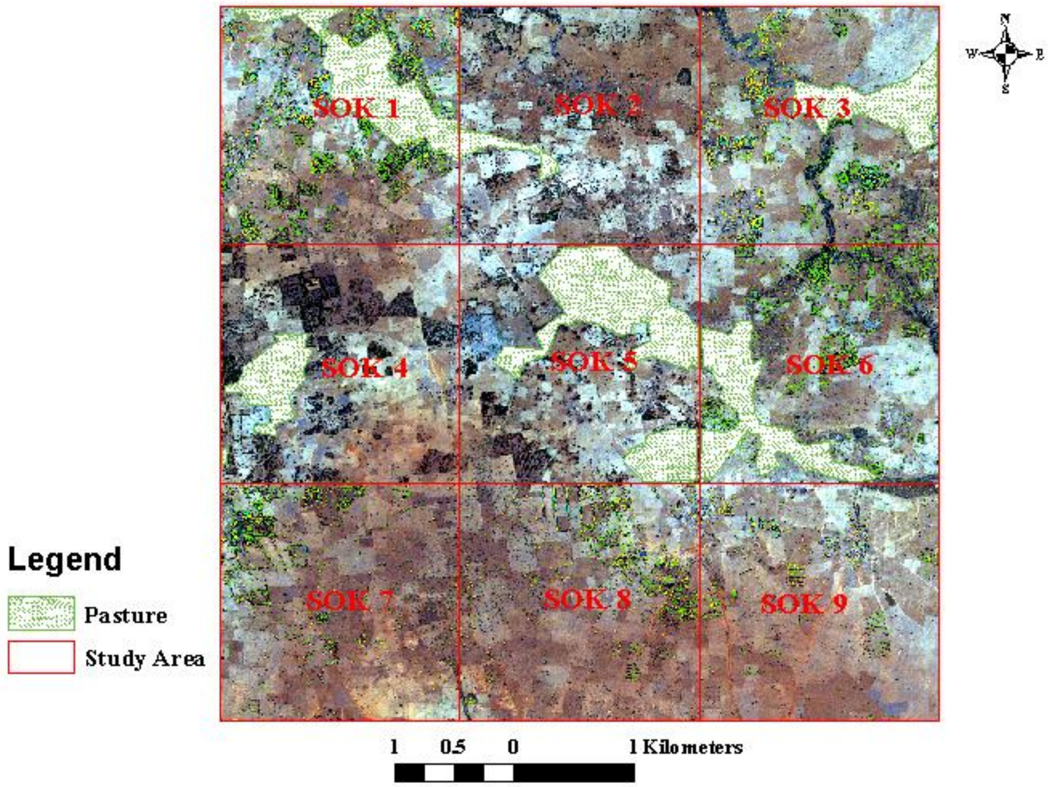
Figure 4.2 Carbon density (t C/ha) per block in the Karang site



4.3.3. Landscape carbon mapping of TOF

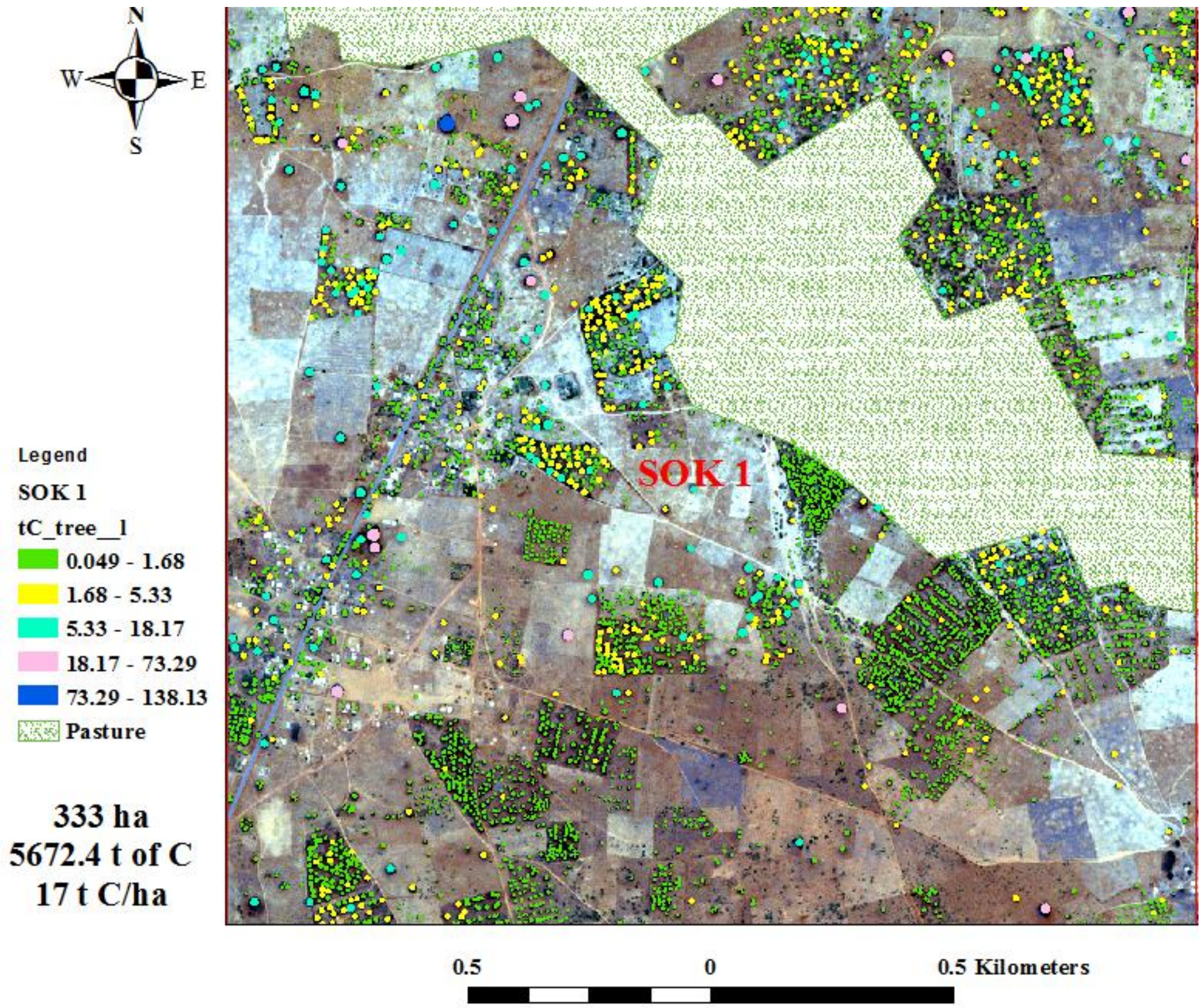
To develop a carbon map, the carbon stock is calculated on a tree basis. The DBH of each tree identified and digitized on the image is predicted using *Equation 1* for the Sokone site and *Equation 2* for the Karang site. After predicting the DBH based on the remote sensing based Crown Projection Area, the IPCC general allometric equation for tropical dry forest is used to calculate biomass and carbon for each tree. The frequency of the different types of trees and their size are determined all across the landscape. The following carbon maps were computed and show high and low biomass based on the type and size of trees.

Figure 4.3 Carbon in the Sokone site



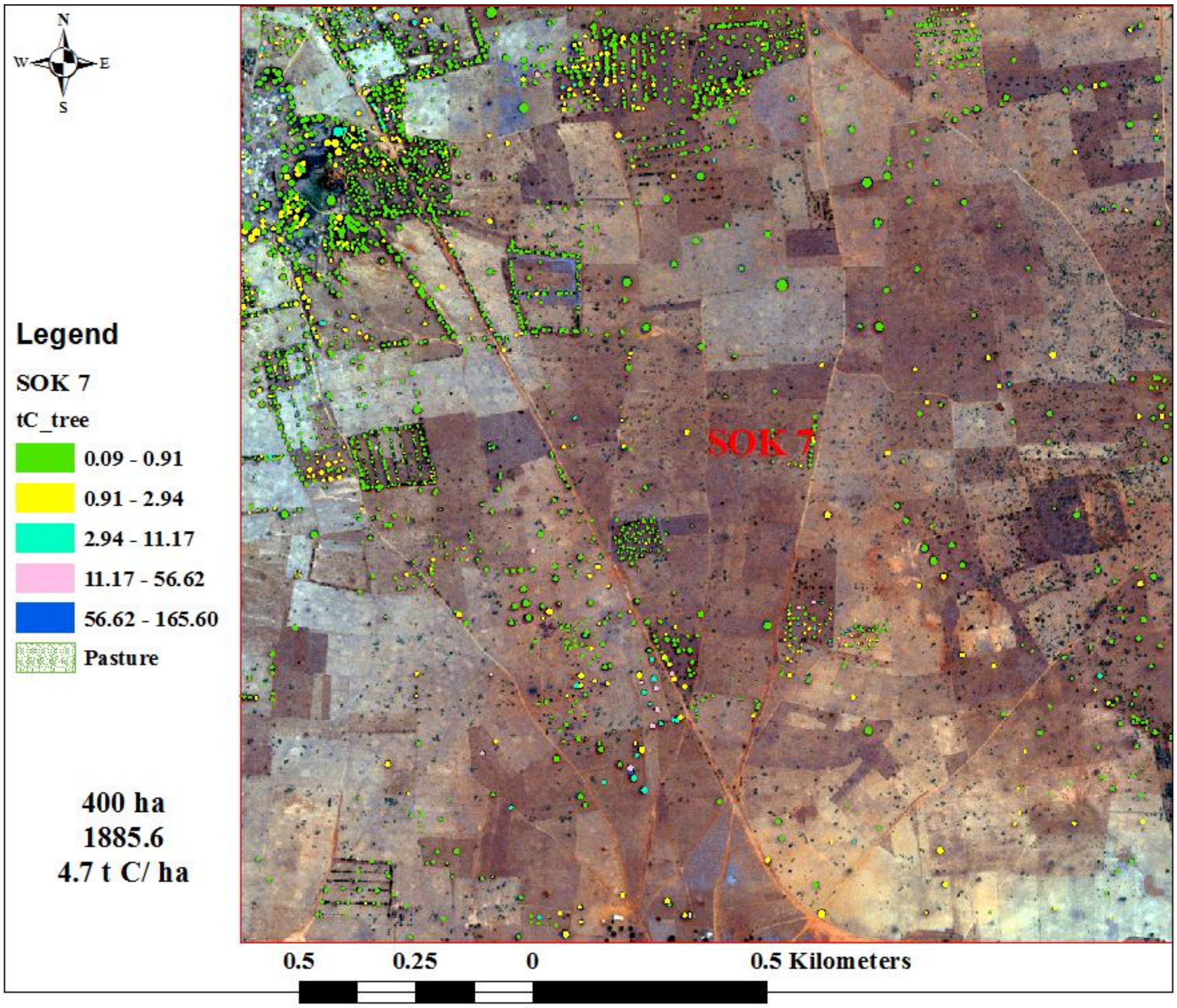
A carbon map of all nine blocks in the Sokone site are shown in Figure 4.3. Most of the carbon is concentrated in the cashew plantation. Block 7 (SOK 7) presented in Figure 4.4. is a good example.

Figure 4.4 Carbon map for block 1 (SOK 1) in the Sokone site



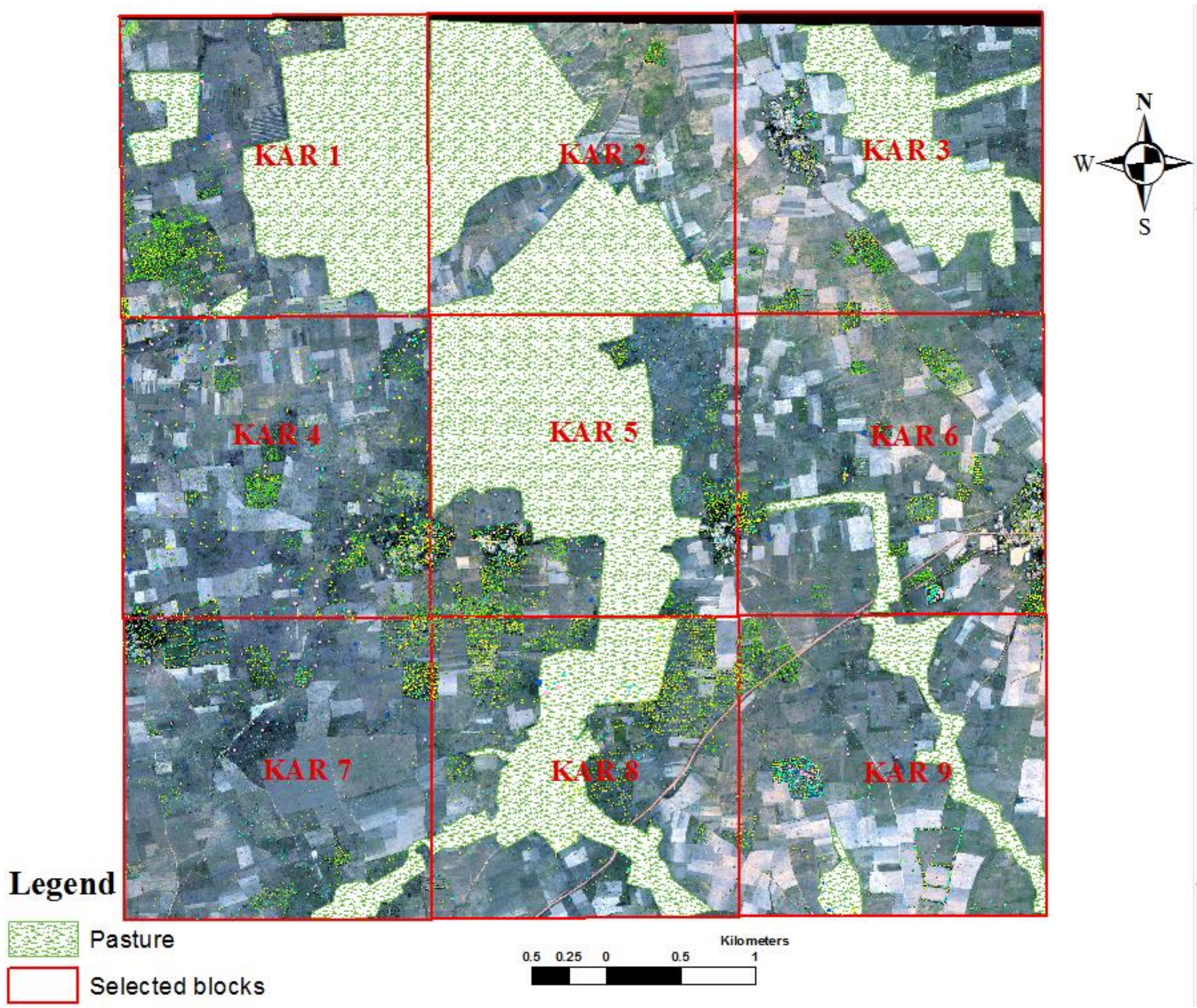
This block is 2x2 km which is an area of 400 ha but the model was applied for only 333 ha as there are 67 ha of pasture. These 333 ha have 5672.4 t of carbon stock which represent a carbon density of 17 t/ha. Most of this carbon is hold by cashew plantation which occupied 96 ha although this represents only 28.8 % of the area studied. Trees with low carbon content represented in green and yellow are dominant. They have between 0.049 and 5.33 t C/tree. These values are lower in block SOK 7 where there is few cashew plantations. Trees with the lowest carbon content have between 0.09 to 2.94 t C/tree (Figure 4.5). Only 11 % (44 ha) of this block area is occupied by cashew plantation.

Figure 4.5 Carbon map for Block 7 (SOK 7) in the Sokone site



Although there is no pasture in this block and the model is applied to the whole 400 ha, the carbon density is very low compared to block 1 (SOK 1). The carbon stock is reported to be 1885.6 t C representing a carbon density of 4.7 t C/ha. This is explained by the dominance of trees with low carbon content, especially small cashew plantation and other scattered TOF in agricultural land. They mostly have between 0.09 to 2.94 t C per tree (Figure 4.5.).

Figure 4.6 Carbon stock in the Karang site



The carbon densities are lower in the Karang site compared to the Sokone site As shown in Figure 4.6, the highest values are for cashew plantation. Like in the Sokone site, the whole landscape is dominated by trees with less than 3 t C/per tree (Figure 4.7). The rare trees that have more than 3 t C are located in the agricultural land. (Figure 4.8, Figure 4.9 and Figure 4.10).

Figure 4.7 A portion of a cashew plantation carbon map in the Karang site

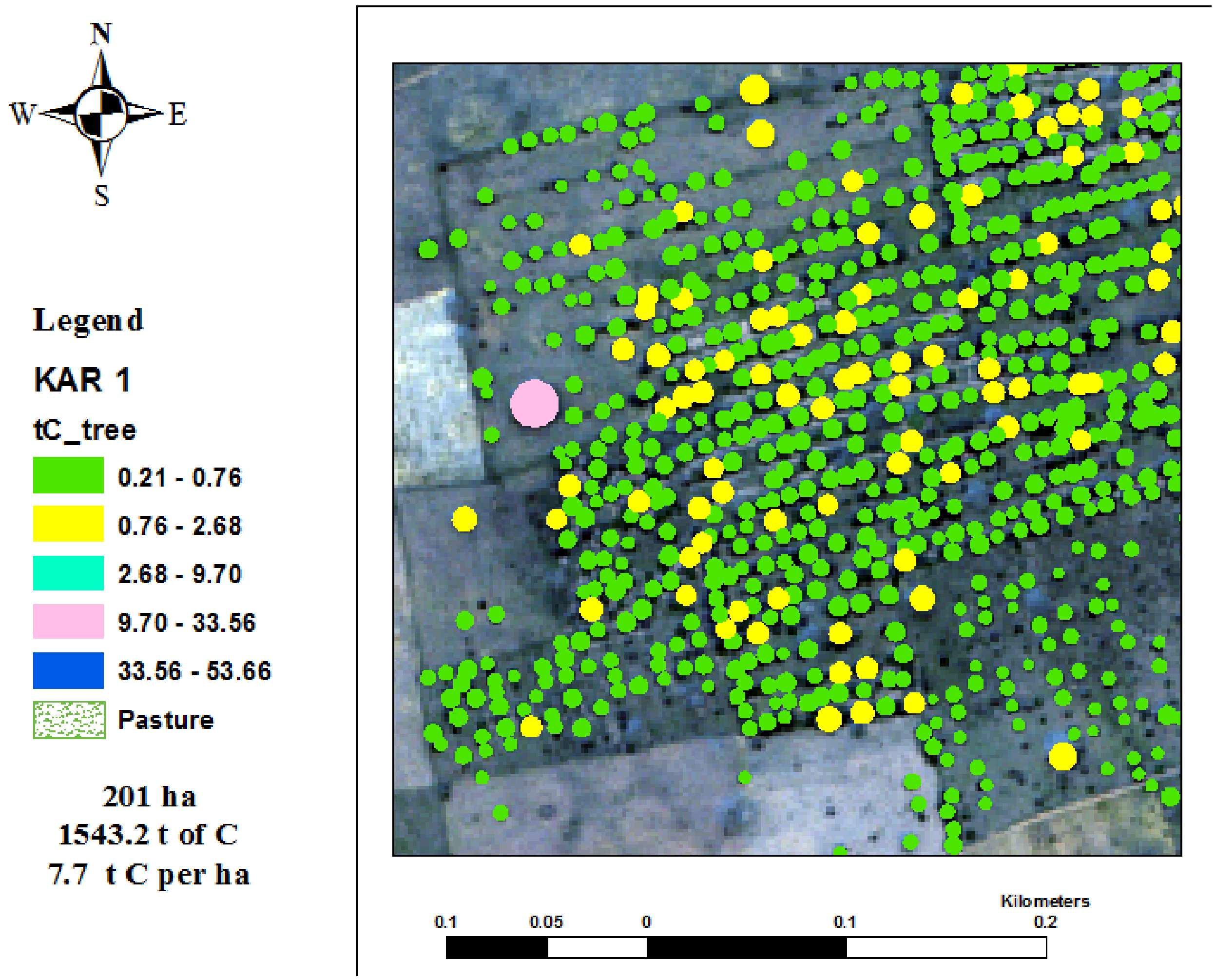


Figure 4.8 Carbon map of individual TOF in agricultural land in block 9 (KAR 9) in the Karang site

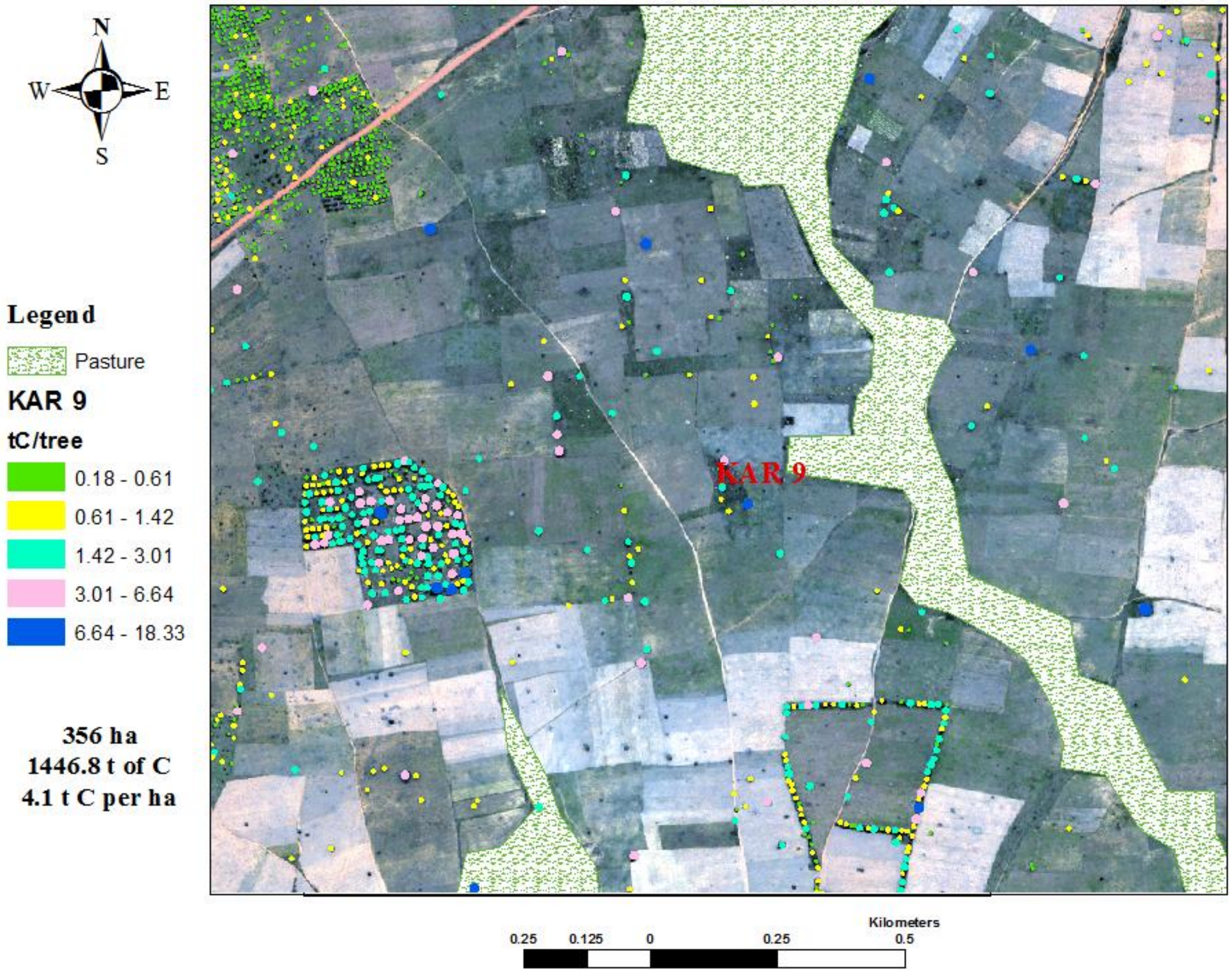


Figure 4.9 Carbon map in a low density block (KAR 2) in the Karang site

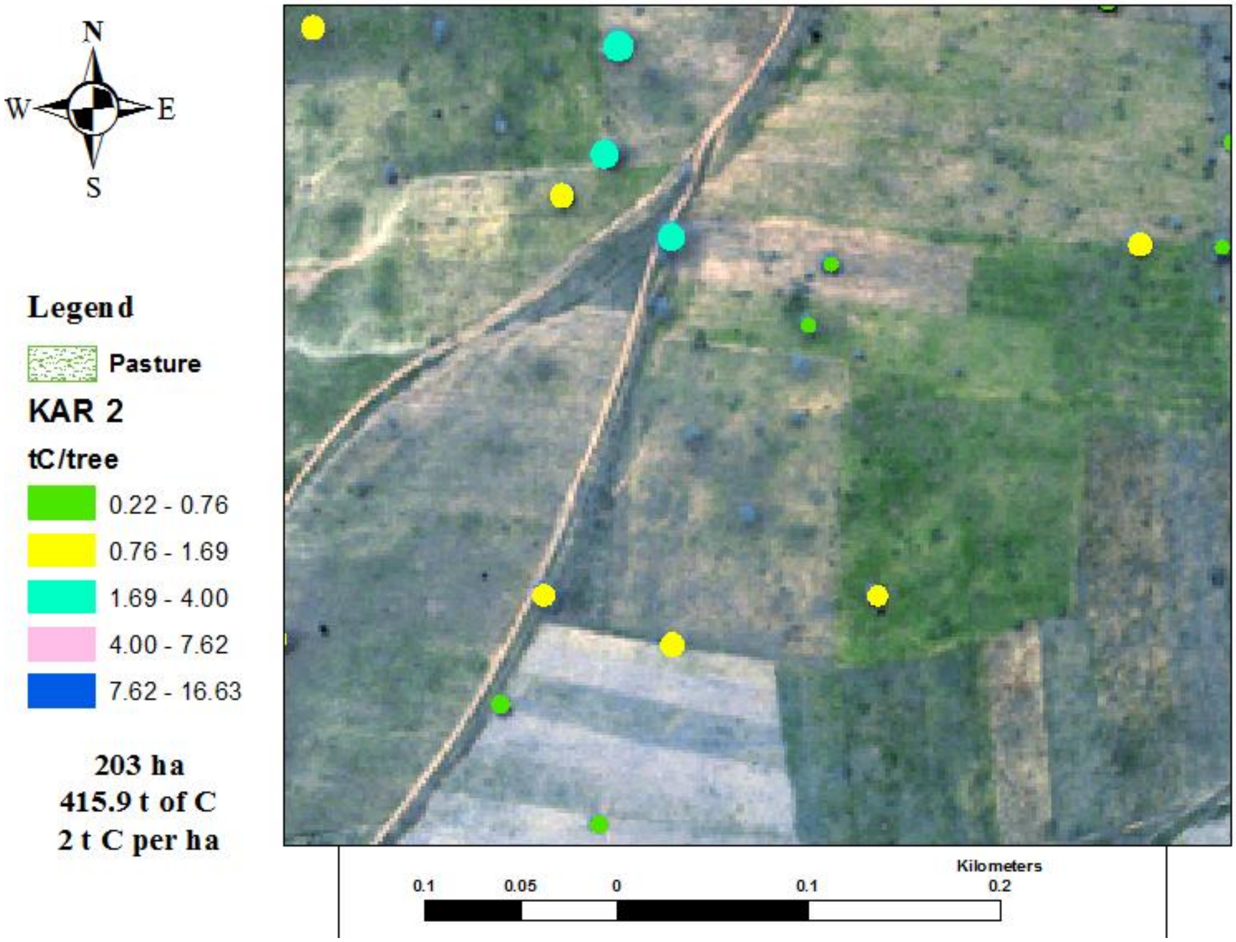
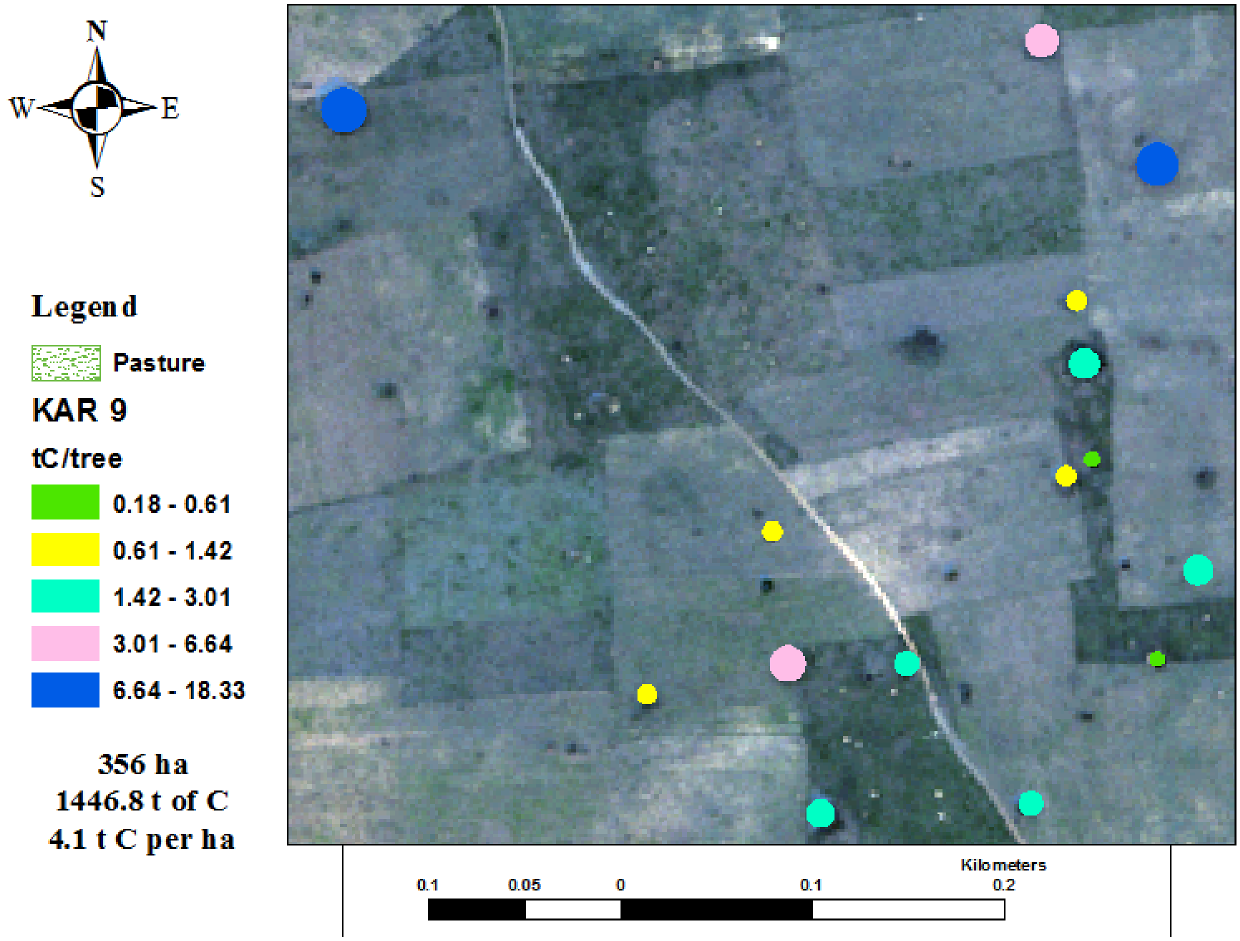


Figure 4.10 Carbon map in a low density block (KAR 9) in the Karang site



4.3.4. Comparison with other studies

Our results show that carbon densities vary depending on whether or not there are cashew plantations, their density and their age; which explains why values in the Sokone site are higher than those in the Karang site. Carbon densities ranged from 3.9 t C/ha in block 9 (SOK 9) to 17 t C/ha for block 1 (SOK 1) while the highest carbon density in the Karang site is 8.1 t C/ha for block 5 (KAR 5) and the lowest is block 2 (KAR 2) with only 2 t C/ha.

These estimates are compared with results from other studies:

- the first one is from Western Kenya where Kuyah *et al.* (2012) provided results with close agreement with our own. Using a destructive sampling method, they estimate the carbon density to be 20.8 t / ha. It is important to acknowledge at this point that field data are more accurate than model-based estimation, which can be a factor that explains the difference between the two results. Another factor is that the two studies are from different sites, although they are all carried out in the tropical zone with some similarities.

- the second study is by Baccini *et al.* (2012). Using the exact same area in Senegal, I compare their carbon density to my own results. The two maps of the comparison are presented in Figure 4.11 and Figure 4.12. Baccini *et al*. (2012) found that the values of aboveground live biomass are between 10 and 22 megagrams per ha. Converting the biomass into carbon (as 0.47 units C per unit biomass), I obtained values ranged between 4.7 and 10.3 t C/ ha which are very close to my results in some places of the study area. However, it should be noted that Baccini *et al.* used a "single average AGB value for each land cover class" which "introduces pseudo- replication, as multiple pixels containing the same land cover class will be given identical ABG values" (Mitchard *et al*., 2011) no matter the number of trees and the variation in size. Each of the different pixels represents the sum of the above-ground carbon for all trees in the pixel. That does not help to make a good comparison with our study because our data are individual tree based. Also, the pixel size (463.3 x 463.3) of the MODIS image used by Baccini *et al.* covered a large area with high heterogeneity. For example, block 1 (SOK 1) where we found the highest carbon density (17 t C/ha) is the block where Baccini *et al*. reported more pixels with lower values although it is an area of dense cashew plantation. Even in some places in my study area, they found no carbon while my results show a high potential of carbon.

Figure 4.11 Carbon map in the Sokone site based on Baccini *et al.* (2012)

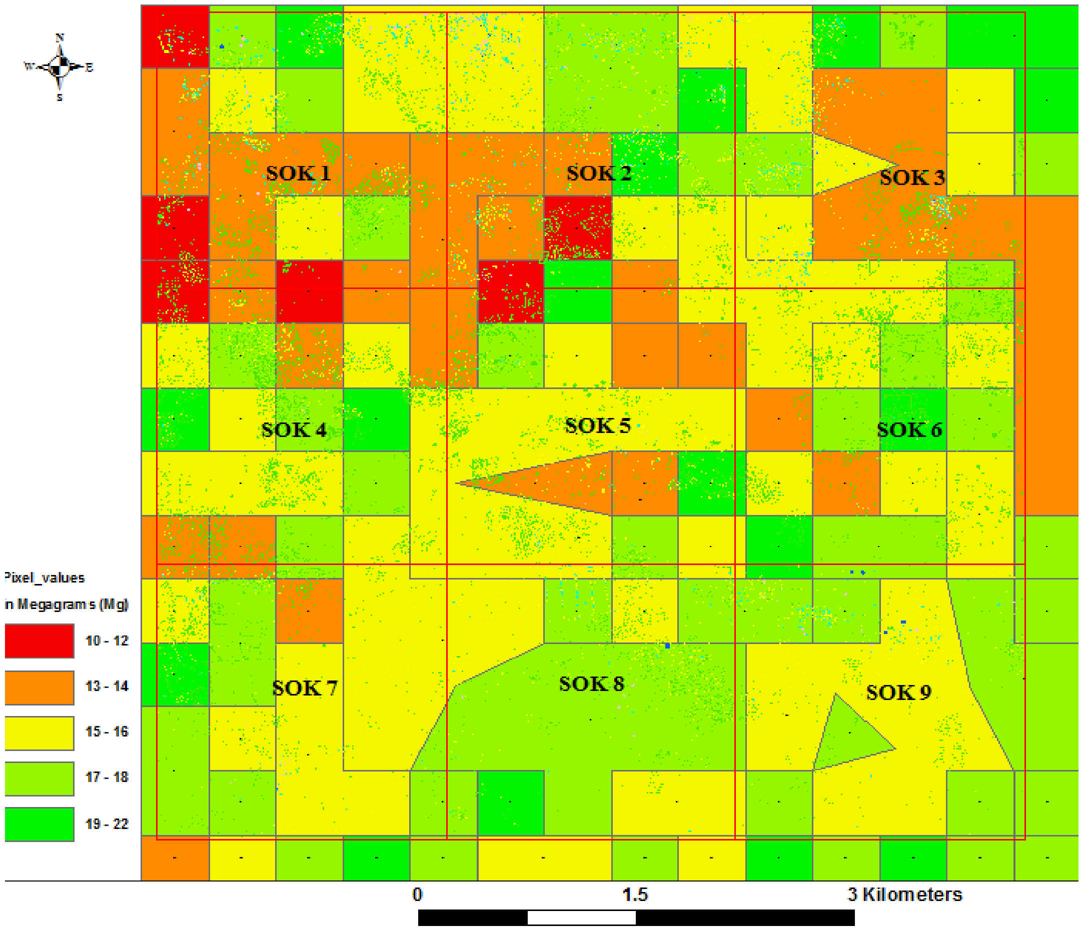
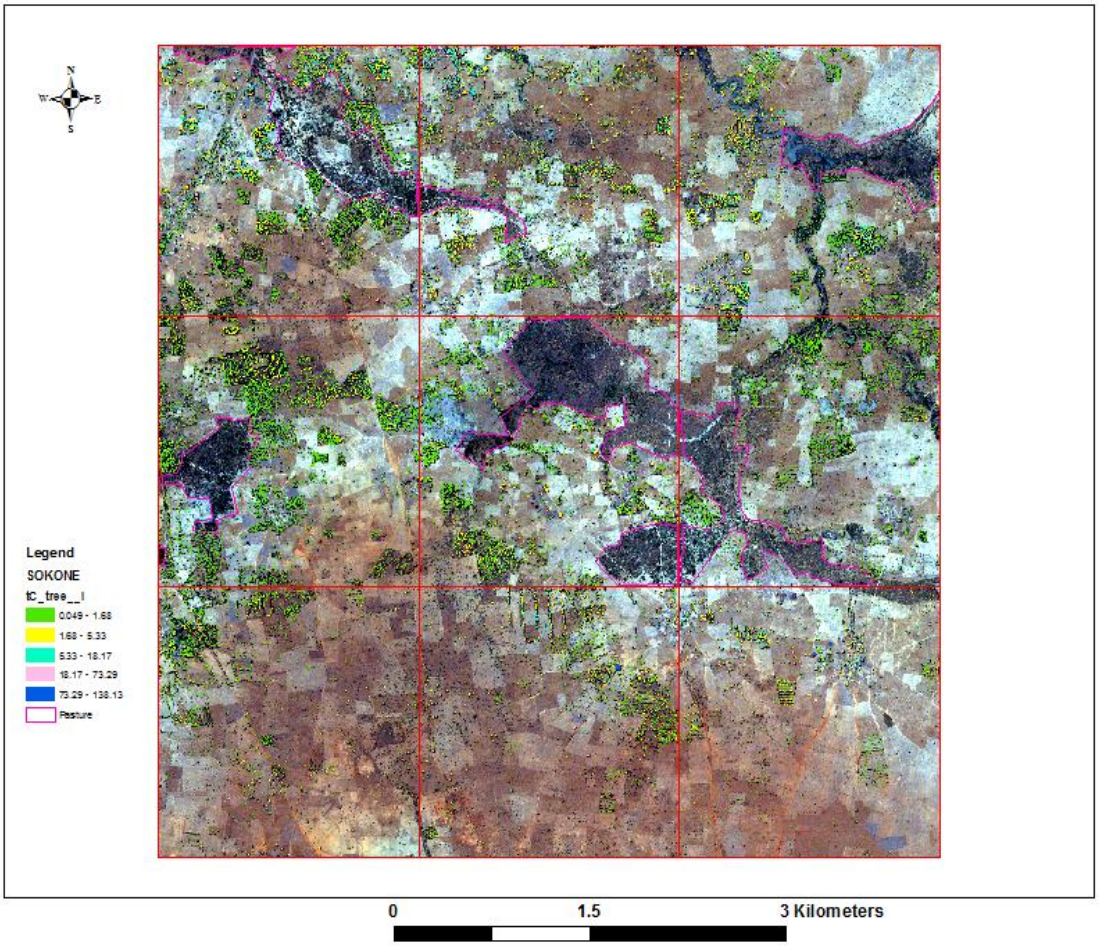


Figure 4.12 Carbon map in the Sokone site based on our model



4.4. DISCUSSIONS AND CONCLUSION

The model developed in chapter 2 is used to estimate biomass and carbon at landscape level. The carbon calculated using allometric equation on a tree basis is extrapolated on a plot and block level to cover large area. Combining remote sensing techniques and basic allometry in systems of "trees outside of forest" the carbon density in the study area is estimated and carbon maps produced.

Despite the limitations of the study, our results are close to those from other studies (Baccini *et al*. 2012; Kuyah *et al*.; 2012). As averages, it should be noted for our results that, the carbon densities are higher in some area such as in block 1 (SOK 1) in the Sokone site where the density is 17 t C/ha. These values are consistent with those of Kuyah *et al.* (2012) and Baccini *et al.* (2012) and this consistency provides more confidence about our remote sensing model but the values are still low and various factors can be used to explain this situation. Those factors include:

- Most of the study area is permanent pasture and this stratum was not surveyed as it was not included by the protocol. As this study is focusing on trees outside of forest, most of the pasture area meets the requirements of the country's forest definition and I classified them as forest;
- This study did not also take into account the other carbon pools including understory vegetation, shrubs and grasslands as well as trees with less than 10 cm DBH.
- Error of estimation: omission of trees during the digitizing process especially for cashew plantations trees are intermingled; which make difficult the delimitation of tree crown boundaries.

APPENDICES

Appendix B: TECHNICAL CONTRIBUTIONS THAT CAN BE MADE BY COMMUNITY PARTICIPATION: TOWARD COMMUNITY BASED CARBON MEASUREMENTS

B.1. INTRODUCTION

There is a rich body of literature on participatory or community-based monitoring of natural resources (e.g. Evans and Guariguata 2008). Although this literature, and the field that it embraces, are important, this chapter does not involve an analysis of participatory monitoring. The aim of this chapter is to assess communities' ability to accomplish carbon measurement of trees on their own farms. By asking the basic question as to whether local people can work closely with technical and professional experts to deliver accurate measurements, that in turn, support accepted rigorous international standards, is not participatory monitoring in its richest, or its fullest extent. As such, we recognize the limitations of this study to draw any broad conclusions about modalities or potentialities for long term sustained engagement of local communities, which is a full treatise beyond the rather narrow measurement scope of this study.

Having noted these limitations, this chapter is cognizant of the fact that there is a subject of current disagreement in the use of advanced technology by local communities, (Fry, 2011) points this out in his review of community forest monitoring potentials for REDD. Herold and Skutsch (2009), Skutsch *et al.* (2009), Abrell *et al*. (2009) and others have advocated the use of technologies by communities, such as GPS and GIS mapping while others (Danielson, 2005) remain less convinced. Similarly, there is some question as to whether local people can make measurements that are accurate and precise enough to be acceptable for scientific application (Evans and Guariguata 2008). Fry (2011) provides an organization structure to evaluate community measurement that includes accuracy as one of three elements, along with cost and sustainability and cultural relevance. There may be problems of accuracy and precision when non-professionals engage in scientific activities (Danielsen *et al.* 2005). Other studies have focused on the capacity of local communities to assess forest biodiversity and forest disturbance. For example Holck (2008) mentioned the increased focus of international forest policies in involving local communities in forest monitoring and management; this involvement being considered as a strategy to improve biodiversity conservation efforts and local livelihoods especially in developing countries. Also, the high level of commitment of village managers in monitoring resource extraction and disturbance has been studied by Topp- Jorgensen *et al.* (2005).

Case studies confirm that locally based, participatory monitoring must be simple to be successful: but how simple can the monitoring systems be and still maintain scientific validity? Danielsen *et al.* (2005) conclude that there is a major gap in understanding the comparability of data between scientifically and locally-collected data. Based on the few comparisons of scientific and local monitoring that have been conducted, the minimum amount of data to be collected by local monitoring programs to generate the same results as scientific methods appears to be high (Evans and Guariguata 2008). As an example, Larrazàbal *et al.* (2012) have demonstrated from the Kyoto Think Global Act Local (KTGAL) project's example that communities are capable of generating data that can meet the standards of the IPCC methodology. They found the data accurate and reliable as "there were no significant differences in the estimate of mean stock or in the confidence level between the experts' measurements and the communities" (Larrazàbal *et al*., 2012).

Also, for the time being, the importance of National Forest Inventory data to measure and monitor forest carbon is well documented. Getting local communities being familiar with tree data collection methods and techniques could help achieve the goals of National Forest Inventory in lowering cost and the data collected could reasonably be used for forest carbon assessment.

In the Global Observatory for Ecosystem Services laboratory at Michigan State University and through the Carbon2Markets model, the approach to measurement, reporting and verification systems used requires the participation of local communities in conducting the protocols and becoming collaborators in the team and the operation of the system. There has been on-going work with communities in Thailand, Vietnam, and Laos PDR which suggests that communities can be engaged as co-measurers using the full suite of rigorous international protocols and standards for measurement, particularly for the ground segments (Samek *et al.* 2014) but these have been experienced in closed forest, plantation systems, small-holder wood lots and agro-forestry in Asia but not yet in savanna environments of Africa. This project aims to gather more information and experience in a different measurement setting on how accurate and precise local communities can measure simple ground parameters and play a partnership role in data collection. This project recognizes that just because local land owners could (or not) make accurate contributory measurements does not mean they would or should, nor will it provide complete understanding of what conditions are necessary for full participatory engagement, as these issues are beyond the scope of this measurement study. Some of the limitations of the aforementioned work of the GOES Lab are that these projects all deal with forests or forest stands – small holder plantations, community forests, or REDD forests – and do not address the application of the Carbon2Markets MRV in systems of trees outside of forests nor agroforestry systems in predominantly agricultural landscapes. There is a need to explore the effectiveness, accuracy and precision of joint measurement campaigns in savanna landscapes and agroforestry systems outside forests. That is the aim of this chapter.

B.2. MATERIALS AND METHODS

B.2.1. The Study Sites

The study is carried out in thirteen Senegalese villages located within 190 km from the capital (Dakar) in the Fatick Region. The study area covered mainly the three rural communities of Toubacouta, Nioro Alassane Tall and Keur Samba Gueye. The thirteen villages are selected purposively using 3 criteria in order to capture a maximum of social, cultural, agricultural and ecological variation that exists in this area. The first criterion is related to the social and cultural side and includes ethnic groups (*Wolof, Serer, Bambara, Mandinka, Diola*). The second criterion based on the agricultural and ecological variation includes the soil and vegetation types and the presence of cashew plantation in the village. The third criterion is related to the village size and the distance from the nearest road. For accessibility purpose by the researchers, the village must be located at less than 5 km of the main road.

In the rural community of Toubacouta, the majority of the population is dominated by the Mandinka (50%), Serers (35%), Wolofs (5%) ethnic groups and other minority ethnic groups including Bambara and Poular (Table B.1.). In the rural community of Keur Samba Gueye, the population is dominated by Wolofs (60%), Mandinka (20%), and 20% represented by the Serers, Diolas and Poular ethnic groups.

Table B.1. Demographic characteristics of selected villages

No.	Villages	Rural Community	Dominant Ethnic Group	Total Population	Total Households
1	Boutilimith	Toubacouta	Mandinka	192	17
2	Dassilamé Socé	Toubacouta	Mandinka	1 061	100
3	Diaglé	Toubacouta	Serer	1 163	166
4	Ndoffane	Toubacouta	Mandinka	252	31
5	Senghor	Nioro A Tall	Bambara	391	42
6	Kouatine	Nioro A Tall	Serer	213	23
7	Niokholokho	Nioro A Tall	Serer	289	34
8	Ngouye Mary	Nioro A Tall	Wolof	253	27
9	Keur Bakary Camara	Keur S Gueye	Bambara	235	24
10	Keur Samba Guèye	Keur S Gueye	Wolof	1 378	186
11	Keur Samba Nosso	Keur S Gueye	Wolof	1 079	92
12	Keur Sett	Keur S Gueye	Poular	435	52
13	Sirmang	Keur S Gueye	Serer	1 091	98
	TOTAL			**2260**	**892**

The main types of soil are locally called Dior and Deck. The Dior soil, containing > 95% sand and few nutrients (< 2% organic carbon), are usually occupied by former dune slopes while the Deck soil are hydromorphic, occasionally flooded and contain 85 to 90 % sand and have 0.2% organic carbon (Badiane *et al.,* 2000).

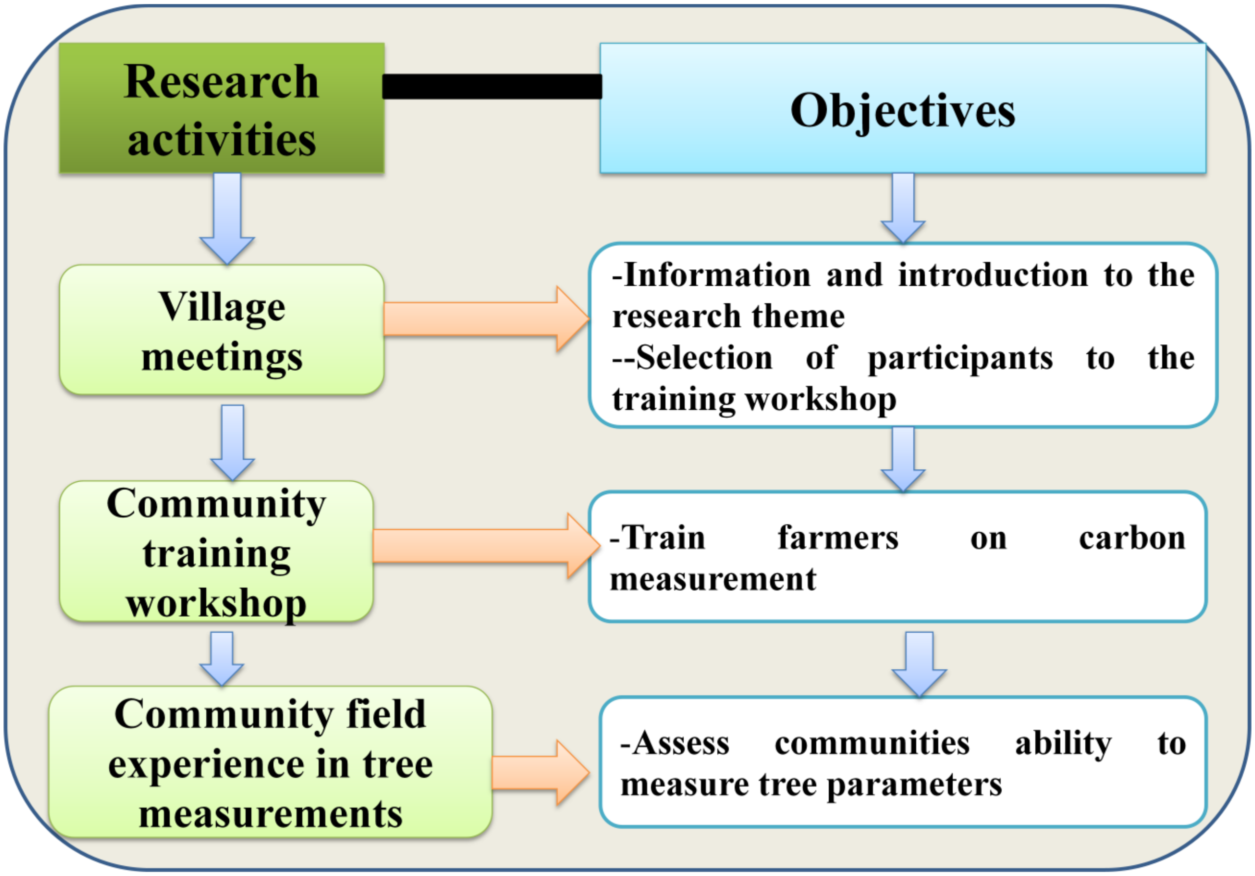
The climate is semi-arid and the annual rainfall ranges from 400 to 1000 mm with a rainy season usually lasting 3 months from July to September (Toubacouta) but can last 5 months (from June to October) in the Rural Community of Keur Samba Gueye where the annual rainfall can reach 1845 mm as it was the case in 2003 (LDP, 2009). This rainfall can vary significantly from year-to-year in quantity, spacing, and duration.

The main economic activity is the rainfed agriculture dominated by peanuts *(Arachis hypogaea)*, millet *(Pennisetum typhoides)* and cashew *(Anacardium occidentale)* production. The most common tree species that dominate the vegetation are *Cordyla pinata*, *Cola cordifolia*, *Mangifera indica*, and block plantations including *eucalyptus* and the large areas of *Anacardium occidentale*. In the south (Rural Community of Keur Samba Gueye), the vegetation is dominated by *Combretum glutinosum, Cordyla pinnata, Pterocarpus erinaceus, Adansonia digitata, Zizyphus mauritiana, Diospyros mespiliformis, Prosopis africana and Parkia biglobosa*.

B.2.2. Research activities

To assess the potential technical contribution of local communities to carbon measurements, different activities were held during the field campaign and are presented in the following Figure B.1:

Figure B.1. Research activities and their objectives



B.2.2.1.Village meetings

A village meeting was organized in each of the 13 villages of the study area to inform villagers about the objectives of the study through an introduction of the research theme. They were also given information about the necessity of selecting participants to the training workshop and the modalities of the workshop.

Figure B.2. Village meetings

Diaglé Village   Keur Samba Nosso village

At least two people were selected for each village for the training workshop. Efforts were made to ensure a minimum of two women were included in the focus group discussions and at least one woman for the training workshop.

The selection was based on the following criteria:

- Educational level: I suggested that trainees must have a minimum level of education to be selected as some of the tasks that they will perform required a minimum level of education which is to be able to read and write in French, in local language or in *Ajami*;

- Gender: I recommended that the gender dimension must be taken into account to encourage a high participation of women;

- Age range: I also suggested that the different group- aged people must be represented in the training.

B.2.2.2. Community training workshop

The training workshop was organized in Toubacouta, headquarters of the *Arrondissement* which includes all the rural communities of the study. We provided a budget to ensure their transportation. It was chaired by the *Sous Prefet* (Figure B.3) with the presence of one of the three presidents of the rural communities.

Figure B.3. Training workshop chaired by the State Representative *(Sous-Préfet)*

Before the start of the workshop, all the participants were interviewed using a questionnaire survey to understand whether or not they can measure trees and if so, what are the means and methods they use. This information was later compared with a post assessment after the workshop.

This workshop had four main components:

1. a presentation/ discussion on climate change, carbon and the role of trees on mitigating climate change;
2. laying out the different steps of a carbon monitoring process which include:
   - Landscape Mapping and Stratification (determine the boundary)
   - Establishing a system of biomass plots
   - Accurately locate permanent sample plots using GPS

- Doing tree biometric parameters used to calculate carbon stocks
- Recording all these data collected and time
- Upload data on an online geographic information system
- Calculation of carbon stock per plot

3. a presentation to introduce the GOES's MRV system to the participants;
4. an evaluation of the participants and what they had learned from the training was the fourth component of the workshop. After explaining during the training how to do all these tasks, each participant had been asked to give a ranking of how much they do think they can do each task. This step was followed by a field trip with all participants to put into practice what they learned during the theoretical training. After field work, each participant was re- evaluated based on how well he/she did the tasks and this evaluation is compared with the 'before' evaluation.

It is important to mention that selected participants from the villages of Keur Sett and Keur Bakary Camara did not participate the training workshop because of social ceremonies. Therefore, they did not participate in the field campaign as well.

B.2.2.3. Farmer's field experience in biomass data collection

Following the training workshop, a field campaign was planned for each group of participants in each village. All the participants were taken to the field to practice what they had learned from the training. This was followed by an evaluation of the performance of each participant. Each of the tasks was monitored to determine whether all the activities were carried out easily by participants or they were observed to be beyond their ability. This evaluation was based on how they manipulate the equipment (GPS), how much time they spend to accomplish each task and how accurate are their measurements compared to our own measurements for the same trees.

Figure B.4. Field crew in the field measuring trees and recording data

Participant manipulating GPS device to collect geographic coordinates

Participants measuring tree DBH

Participants measuring tree crown diameters

Participants recording data on the data collection sheet

B.2.3. Data Analysis

B.2.3.1. Training workshop

Prior to the training workshop, an a-priori assessment of communities' ability to measure trees had been issued. Descriptive statistics is used to analyze the data collected during this assessment. These data are compared with the post assessment data to determine the extent to which the workshop had contributed to increase their understanding of climate change, carbon, the role of trees in mitigating climate change, their interest in planting more trees in their farms, their understanding of the importance of measuring trees. The participants also provided information about whether or not they would participate in tree measurements. They also have been asked the conditions under which they will be willing to participate.

B.2.3.2. Communities' field experience in carbon measurement and reporting

Data on tree biometric parameters collected by local participants were analyzed statistically and compared with the data collected previously by the researcher for the same sampled trees. Also, an evaluation of how they perform each of the tasks is issued using descriptive statistics.

It is very common that what people say they know or can do is often contradicted by the reality in the field. In this phase of this study, participant observation were used to check against what the participants reported regarding their ability to measure trees during the assessment prior to the workshop.

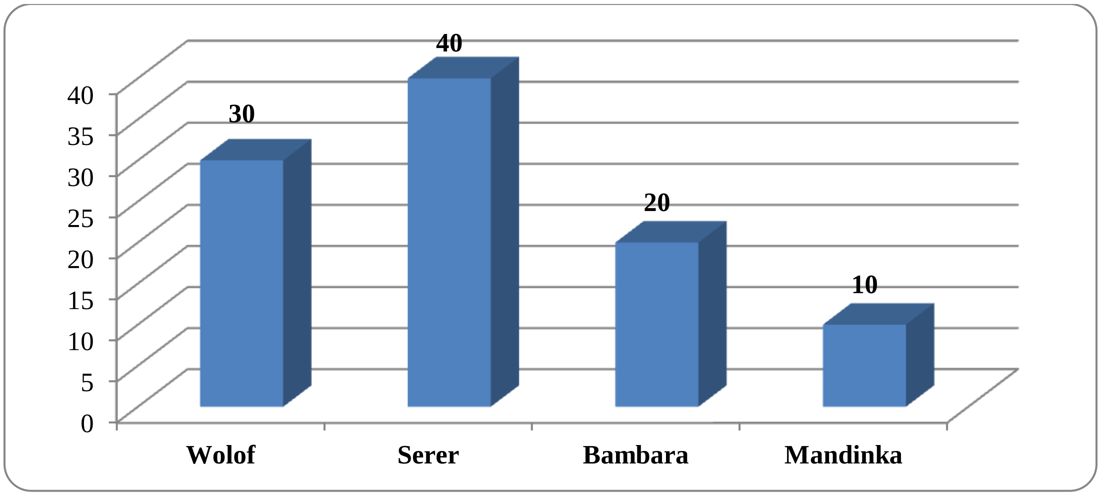
B.3. RESULTS

B.3.1. Evaluation of participants to the training work

B.3.1.1. Characteristics of the participants to the training workshop

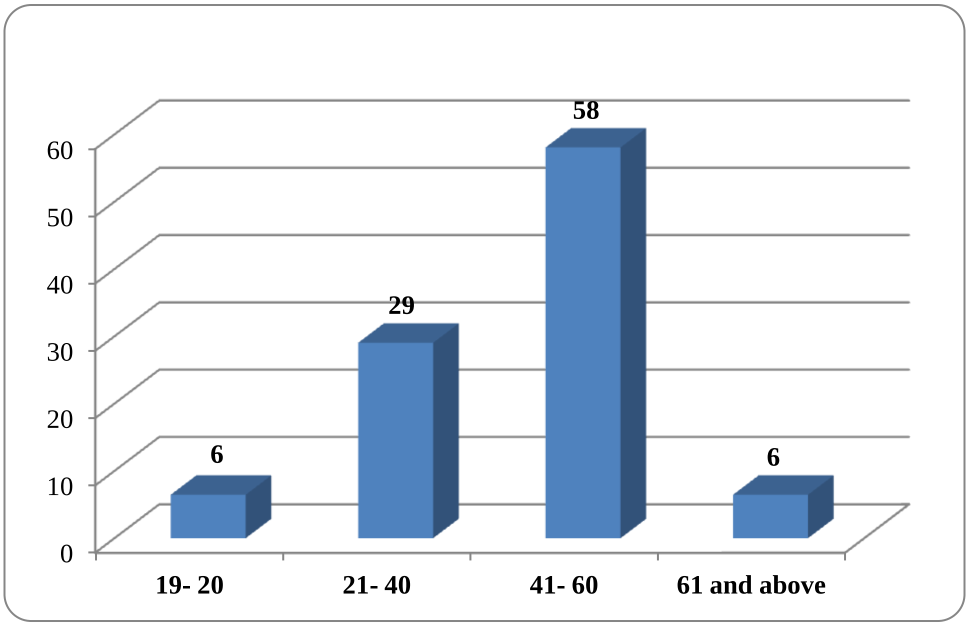
Of the 30 participants to the training workshop, 83.3 % were male and 16.6 % were female. The ethnic groups are composed of a majority (40%) of Serer, followed by the Wolof (30%), the Bambara (20%) and 10% of Mandinka (Figure B.5).

Figure B.5. Characteristics of the participants based on their ethnic groups



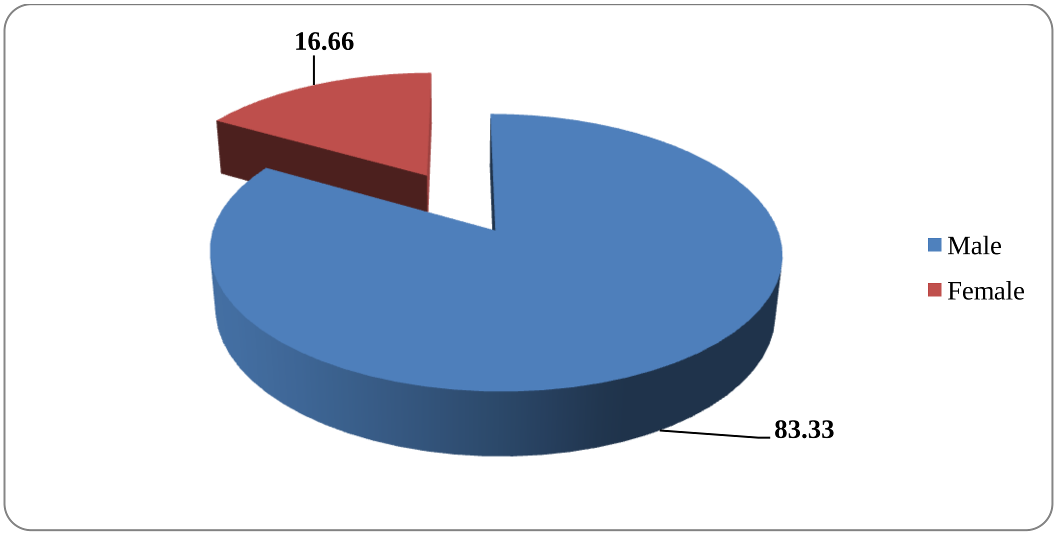
The majority (58%) are between 41 and 60 years old with 29% in the 21 to 40 year range and 6% for the ranges of 19-20 and 61 and above (Figure B.6). The average age of participants is 47 years, with the youngest reported as 19 years old and the oldest as 63 years old.

Figure B.6. Age strata of participants to the training workshop



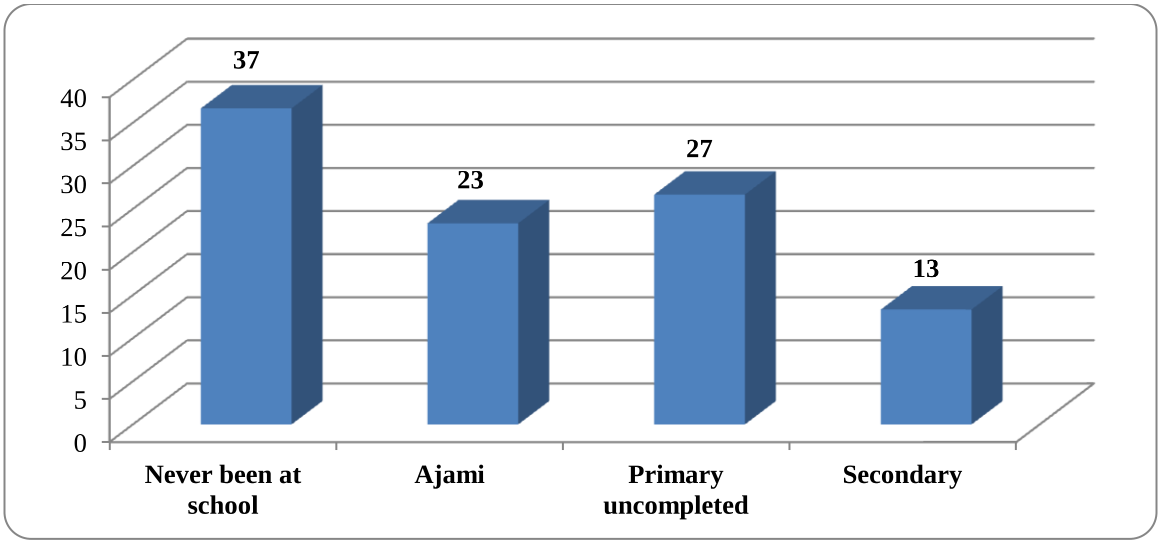
Despite a strong recommendation during the selection for a high representation of women, the percentage of females is very low (16.6 %) compared to the male which is 83.3 % (Figure B.7).

Figure B.7 Percentage of participants based on gender



About 2/3 of the participants (63%) can read and write either in French or in *Ajami* (a practice of writing other language (in this case Wolof) using a modified Arabic script): 27 % have a primary uncompleted level and 13 % a secondary level while 37 % who declared to never have been at school, can neither read nor write (Figure B.8).

Figure B.8. Level of Education

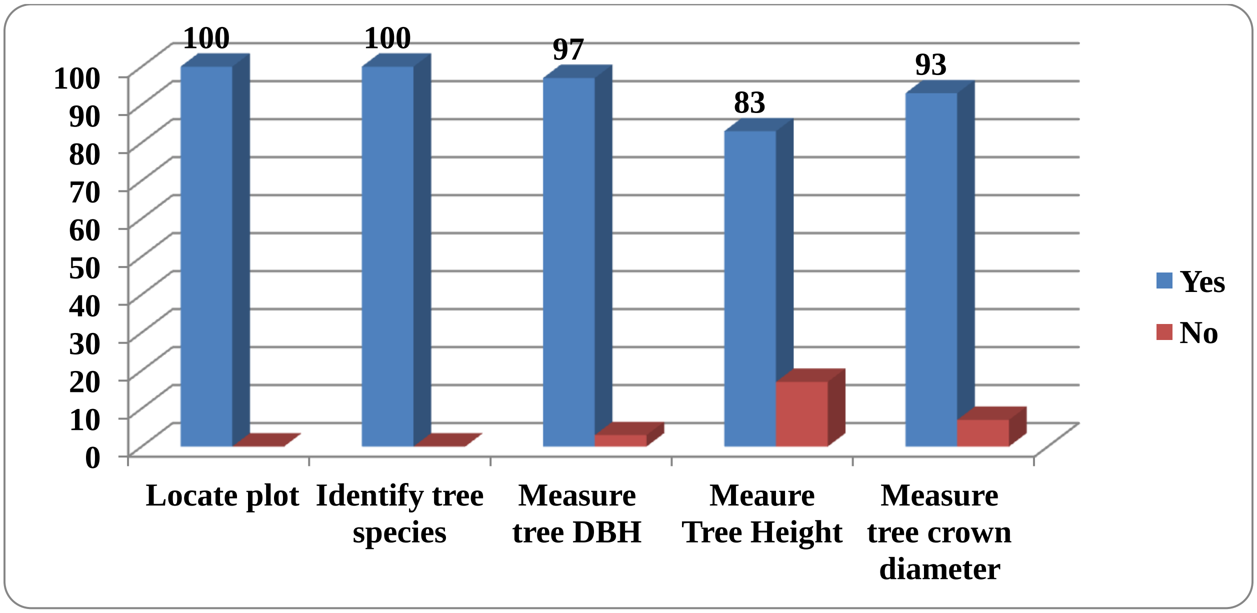


B.3.2. Results of a-priori assessment of communities' ability to perform tree measurements:

Through a priori survey before starting the training, we asked participants questions about whether or not they can measure tree diameter, tree height, tree crown diameter and if so how they do it. From this prior-assessment of farmers ability to measure tree parameters (DBH, height, crown), we knew many acknowledged knowing how to measure tree trunk diameter, tree height or tree crown diameter, although they have always used local techniques.

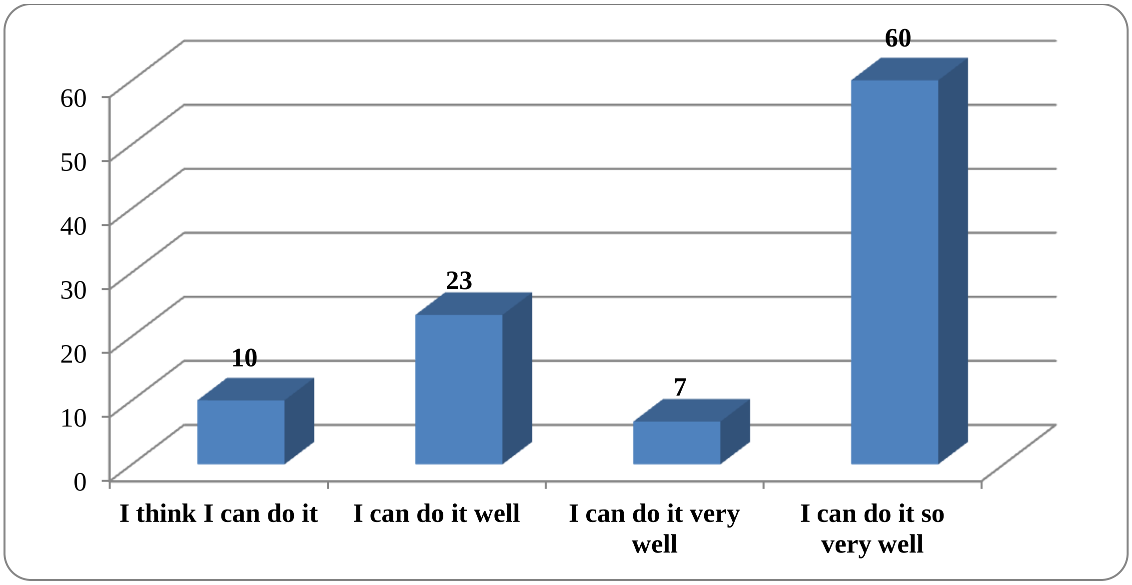
For questions regarding their ability to measure tree diameter, tree height or tree crown diameter, the majority of participants declared knowing how to perform these tasks: 97 %, 83 % and 93 % for trunk diameter, height, and tree crown diameter, respectively. Also, all the participants said that they could locate plots in the field and identify tree species on their farms and throughout the general landscape (Figure B.9).

Figure B.9. Self-reported knowledge of farmers on their ability to perform tree measurements



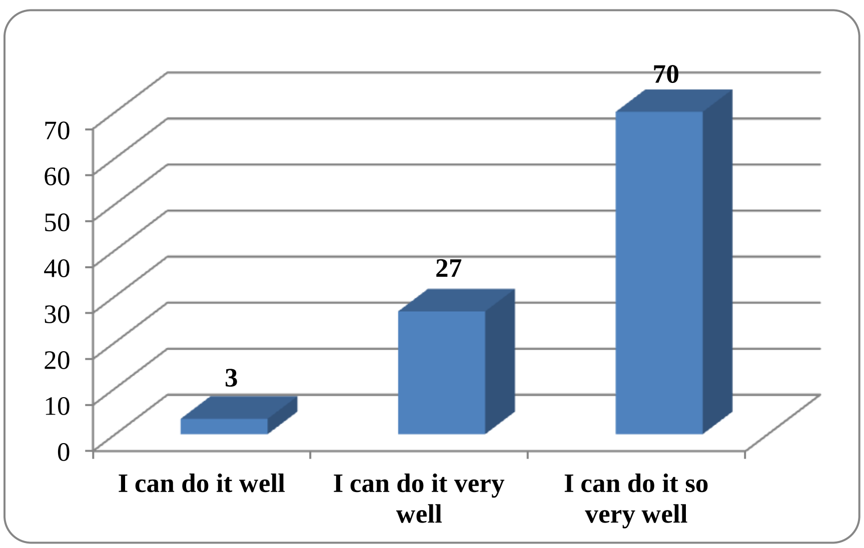
Although there was high number of participants who could perform these tasks, their performance was different. Regarding their capability of locating plots all participants declared knowing how to do it but their confidence level varied: 10% said they can do it, 23 % can do it well, 7 % can do it very well and the majority (60%) are more confident as they said they can do it so very well (Figure B.10)

Figure B.10. Participants rating on how much they do think they can locate a plot



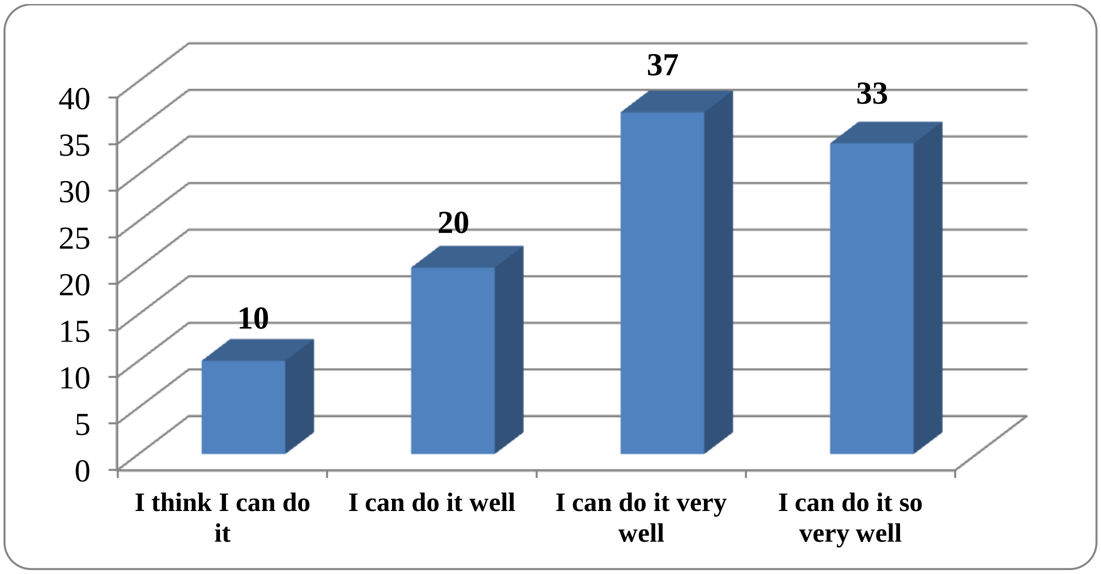
Participants are more confident in their ability to identify trees in their farms and even across the whole landscape. 70 % said they know so very well how to identify tree species, 27 % know it very well and 3 % said they can do it well (Figure B.11)

Figure B.11. Participants rating on how much they do think they can identify trees



Regarding their confidence in their ability to measure tree DBH, participants were classified into four groups: 10 % think they can just do it, 20 % said they can do it well, 37 % can do it very well and 33 % can do it so very well (Figure B.12)

Figure B.12. Participants rating on how much they do think they can measure tree DBH



Although their confidence about how much they think they can perform tasks is different, all the participants declared knowing how to locate a plot, identify tree species or measure tree DBH.

Some of the techniques that they used to do these measurements are modern especially when they used a tape while others use traditional techniques including bamboo rod to measure the top of the trees. Some participants are using the measuring rope to measure the diameter and the tops of the trees. The older, with their experience, use the shadow of the trees at certain times to determine both the height and the length of the crown diameter.

The results of this prior assessment is compared with the post assessment not only to assess what they really can do but also evaluate the impact of the training workshop and how it contributes to increase their knowledge on how to do tree measurement.

B.3.3. Communities' performance in carbon measurement and reporting

During the communities' field measurements, participants were rated and results of this rating in presented in Figure B.13.

Regarding how much they were able to accomplish tasks they were rated from 1 to 4 to determine their performance: we rated 1 when one participant was not at all able to accomplish the task, 2 when he or she did it with strong guidance, 3 when the task is accomplished with just little guidance and 4 when accomplished without any guidance.

Participants have a good familiarity with their environment and they did not have any difficulty locating plots. The assessment shows that all (100%) the participants were able to locate easily the plots without any guidance.

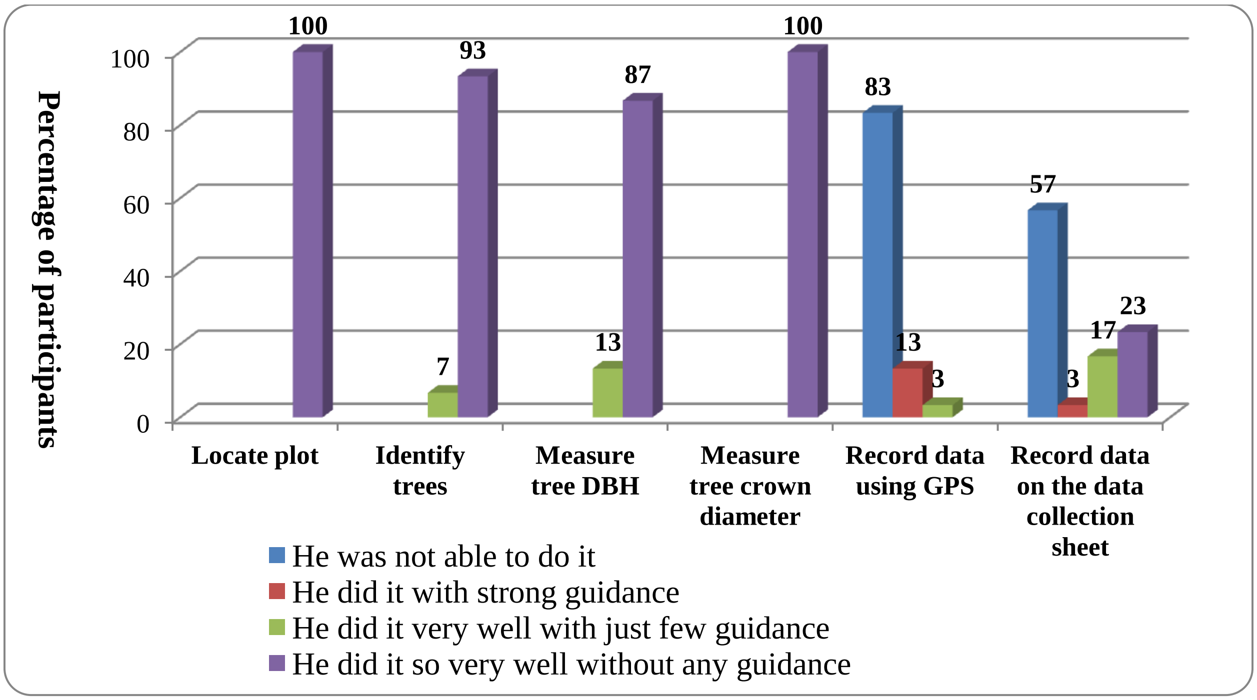
Tree identification is also a task that communities can accomplish: 93 % were able to identify all trees without any difficulty or guidance while 7 % were able to identify trees but they needed some guidance from other crews for some species.

Regarding their ability to measure tree DBH, of the 30 participants, 87% did the measurement correctly without any guidance, 13 % with few guidance.

Regarding the measurement of tree crown diameter, all participants were able to accomplish this task without any guidance contrasting with their ability to use GPS to record data where only one participant was able to accomplish this task with just few guidance, 83 % were not able to use the device.

Their ability to record data on the data collection sheet is also low as more than half (57%) were not able to accomplish this task. This can be explained by the low level of education of participants suggesting the need of recruiting educated people.

Figure B.13. Assessment of communities' experience in tree measurement

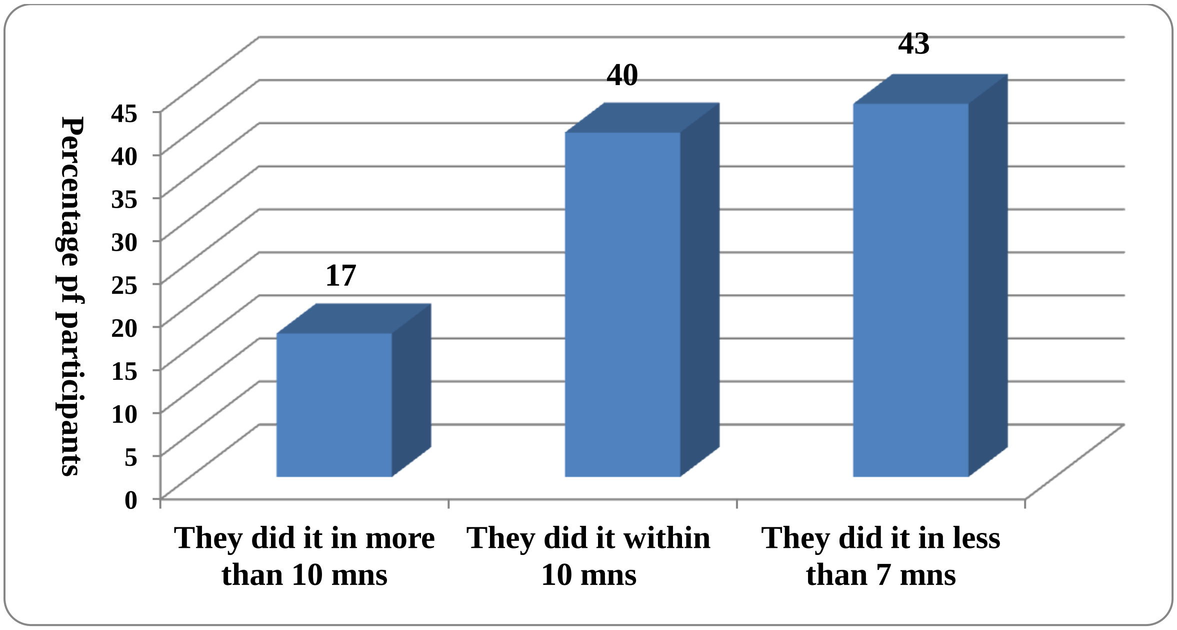


To measure tree attributes (DBH, crown diameters) and record all data including the GPS coordinates, our own experience shows a duration of 4 to 5 minutes for each tree. This time frame has been used to determine the ability of participants to finish tasks in a timely manner. However, we took into account the fact that they might need more time, and we doubled the amount of time and fixed it to 10 minutes for each tree.

I observed field crew teams measuring and recording during data collection and we rated each field crew team depending on how much they finished the tasks in a timely manner with three possible cases: when they finish within 7 or 10 minutes and if they needed more than 10 minutes. Results of the assessment show that of the 30 participants, 43

% accomplished all the tasks in 7 minutes or less while 40 % needed all 10 minutes to finish and 17 % went beyond the 10 minutes (Figure B.14).

Figure B.14. Percentage of participants finishing task in a timely manner



B.3.4. Reliability of communities' estimates

The reliability of the carbon estimates made by communities was tested by comparing them to our own measurements. DBH and crown diameters of the same trees were measured by both the researcher and the communities. Results of comparison between these two data show a slight difference. The biomass estimates of all trees that both we and the communities have measured are summed up. A comparison of the values shows that the difference in biomass estimation in all cases is less than 7 %. In some cases, including in Senghor (-2.82 %), Niokholokho (-0.60) and Diaglé (-1.09), the communities' measurements are lower than our own estimates. For the remaining cases, our estimates are lower.

Table B.2. Comparison between communities' biomass estimates and researcher's estimates

Biomass (sum of all Biomass/tree in Kg in each village)	Mean estimates by local communities	Mean estimates by researcher	% difference of mean
Keur Samba Gueye	10164.39	9987.59	1.74 %
Keur Samba Nosso	7499.53	7005.87	6.58 %
Sirmang	18319.30	17264.53	5.76 %
Senghor	4167.35	4285.06	-2.82 %
Niokholokho	9759.02	9817.80	-0.60 %
Ngouye-Kouatine	14497.08	14317.38	1.24 %
Diaglé- Ndoffan	26000.93	26285.04	-1.09 %
TOTAL	90407.6	88963.28	1.59 %

B.3.5. Conditions for communities to participate in carbon measurement

To identify the conditions for communities to participate in carbon measurements, we asked three major questions to the participants to the workshop and the field campaign. Based on the criteria on which they were selected, what they represent for their respective villages, and their potential ability of influencing the rest of the villagers, we assume that their responses to our questions are valid enough to represent the perceptions of a large community. The three questions that we asked are:

1- Will you be willing to participate in carbon measurement?

2- Under what conditions will you be willing to participate?

3- If you need compensation, what type of compensation would you looking for?

The responses to these questions are summarized in the following table B.3:

Table B.3.Willingness and conditions for communities to participate in carbon measurement

QUESTIONS	RESPONSES	Number	%
Will you be willing to participate in carbon measurement?	YES	30	100
	NO	0	0
Under what conditions will you be willing to participate?	Volunteer	2	6.6
	With compensation	28	93.3
If you need compensation, what type of compensation would you looking for?	Monetary compensation	29	96.6
	Community infrastructure	1	3.3

All participants are willing to participate in carbon measurement if they are solicited. However, their participation must be motivated by compensation. On the 30 participants only 2 accept to participate without monetary compensation. These two participants considered that the knowledge they gain from participating and the capacity they will have to accomplish the tasks by themselves are sufficient enough. The remaining 28 participants accept to participate in return for a payment of their participation. Additionally to the monetary compensation, most of the respondents would ask for field equipment including tape, GPS and camera. It is important to mention that a deeper investigation of the cost of community participation is needed because knowing the cost will determine the extent to which the participation of local communities on carbon measurement can constitute a strategy.

B.4. DISCUSSIONS AND CONCLUSION

The objectives in this chapter was to explore the effectiveness, accuracy and precision of joint measurement campaigns in savanna landscapes and agroforestry systems outside forests and test the ability of local communities to measure tree parameters for carbon estimation.

The findings show that local communities are able to perform some tasks in the process of measuring tree parameters to estimate carbon, although the majority of participants was illiterate in the sense that they did not attend formal education (defined as French school) and can neither read nor write. Our results show that even people with no formal education level can do some tasks including measuring tree crown dimension (holding the tape does not require a certain level of education). Some older people, with their higher level of experience, use the shadow of the plant at certain times to estimate the height of a tree. They also suggested that this technique can be used to determine the tree crown area but I did not test those techniques to assess their reliability and validity.

Regarding the data recording, people that have an arabic (*Ajami*) level can perform the task.

As shown in Table B.2, there is not a big statistical difference between our own measurements during the same period of the field work and for the same trees and the communities' measurements. This is a confirmation that, with a minimum training and although they might not receive a formal education, local communities can actively participate in forest inventories and tree measurement to estimate biomass and carbon.

Regarding the conditions under which local communities can participate to carbon measurements, most of the respondents considered monetary compensation as a condition of their participation.

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Appendix C:
EVALUATION OF FARMERS 'TRAINING WORKSHOP AND FIELD WORK EXPERIENCE

C.I- TRAINEE IDENTIFICATION

Name	Village	Gender	Age	Contact (phone/email)

C.II- A- PRIORI SURVEY

1.	Do you know how to locate plot?	|__| 1. Yes |__| 2. No	
2.	Do you know how to identify tree species?	|__| 1. Yes |__| 2. No	
3.	Do you know how to measure tree trunk diameter?	|__| 1. Yes |__| 2. No	
4.	If Yes, how do you do it?	....	
5.	Do you know how to measure tree height?	|__| 1. Yes |__| 2. No	
6.	If Yes, how do you do it?	....	
7.	Do you know how to measure tree crown diameter?	|__| 1. Yes |__| 2. No	
8.	If Yes, how do you do it?	....	

C.III- WORKSHOP EVALUATION

C.III.1. From 1 to 4, rate how much has the training workshop increased your understanding of Climate Change.

4 3 2 1

C.III.2.- From 1 to 4 rate how much has the training workshop increased your understanding of Carbon.

4 3 2 1

C.III.3.- From 1 to 4, rate how much has the training workshop increased your understanding of the role of trees in mitigating Climate Change.

4 3 2 1

C.III.4.- From 1 to 4, rate how much has the training workshop increased your interest in planting more trees in your farms.

4 3 2 1

C.III.5.- From 1 to 4, rate how much has the training workshop increased your understanding of the importance of measuring trees.

4 3 2 1

C.III.6.- From 1 to 4, rate how much do you think you can do each task.

Locate plot	1 2 3 4
Tree identification	1 2 3 4
Measuring tree DBH	1 2 3 4
Measuring tree height	1 2 3 4
Measuring tree crown diameter	1 2 3 4
Recording data using GPS	1 2 3 4
Recording data on the data collection sheet	1 2 3 4
Finish tasks in a timely manner	1 2 3 4

1: I can do it

2: I can do it well

3: I can do it very well

4: I can do it so very well

C.IV- EVALUATION OF FIELD EXERCISE

Locate plot	1 2 3 4
Tree identification	1 2 3 4
Measuring tree DBH	1 2 3 4
Measuring tree height	1 2 3 4
Measuring tree crown diameter	1 2 3 4
Recording data using GPS	1 2 3 4
Recording data on the data collection sheet	1 2 3 4
Finish tasks in a timely manner	1 2 3 4

1: The participant were not able to accomplish the task

2: The participant performs the task with strong guidance

3: The participant performs the task with few guidance

4: The participant performs the task without guidance

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CHAPTER 5 . GENERAL CONCLUSION

The objective of this research was to explore the possibilities of developing a protocol that allows landscape scale measurements of trees outside of forests combining high resolution satellite imagery and ground data; which protocol having the accuracy and the rigor scientifically acceptable and usable by the international community.

The findings and limits of the research along with the recommendations for further research are summarized as follows:

5.1. SUMMARIES AND RESEARCH QUESTION REVISED

The major research question of this study was:

- Can protocols be developed that allow for landscape scale measurements of trees outside of forests with the accuracy and rigor that is acceptable to the international community?

The developed model is applied to measure the carbon stocks in rural farming systems under agro-forestry systems including cashew as well as other individual trees in the agricultural landscape. Our results show that carbon in smallholder farms, especially for individual trees outside forest can be measured with accuracy comparable to what obtained from other studies.

A correlation between field measured DBH and remote sensing CPA has shown a strong correlation between the two variables for the linear model with coefficients of determination $R^2 > 0.70$ except when applied to the case of individual TOF (133 trees) in the Karang site where it is 0.66. By comparing the linear and the non-linear our results suggest that the linear model is the best one. These results suggest that this developed model can be used to predict tree DBH using high resolution satellite images—especially for individual trees outside forests where the detection is easier than for clustered trees. The model is slightly better for natural, unmanaged compared to managed trees.

The application of the model to estimate biomass and carbon at the landscape level has shown satisfactory results compared to other studies:

- the first one from Western Kenya where Kuyah *et al.* (2012) results are very close to our own carbon estimates. Using a destructive sampling method, they estimate the carbon density to be 20.8 t / ha where our results are between 3.9 to 17 t C/ha depending on the blocks.

- the second comparison is made with Baccini *et al.* (2012) using the exact same area. The two maps of the comparison presented in Figure 4.11 and Figure 4.12. show some closeness in some areas but in others, there are differences.

Based on these different results, the answer to the research question can be summarized as follows: it is difficult to directly validate the model against field measurement methods because allometry based on DBH has its own error and the sample size for this landscape needs to be several hundred plots. However, our results show that the model and field based methods closely concur. We concluded that a model that uses remote-sensing assisted landscape-scale carbon stock measurement has promise. The relationship between CPA detected from remote sensing and allometric scaling is something that can be refined but seems to be a workable approach. Refinements would include:

- Improved relationship model using non-linear relationships

- Developing a local allometric equation using destructive sampling, and specific parameters for the savanna or tree type/species

- Pursue and improve the automated detection to extract the crown features to replace the hand digitizing.

Regarding the potential of local communities to make accurate contributions to the carbon measurement process, our results have shown that they have skills and an ability to perform some tasks in the process of measuring tree parameters and estimate carbon. Despite the low percentage of literacy, most of the participants have shown a good performance in measuring tree crown dimensions, tree DBH, recording data and finishing tasks in a timely manner. Their measurements have also shown a high accuracy when compared to our own measurements made during the same period of the field work and for the same trees. Consequently, local communities have an important role to play on carbon measurement and our results confirmed that they can play that role.

5.2. LIMITS AND RECOMMENDATIONS FOR FURTHER RESEARCH

This research has some limitations presented as follow:

5.2.1. Regarding the tree object detection, we faced some difficulties related to the irregular pattern of the crown shape. It was not easy to manually digitize tree crown with minimal error. Also, when trees are intermingled as in the case of cashews, it was very difficult to determine the boundary between tree crowns.

5.2.2. Also the irregularity of the tree crown's outline does not facilitate the field measurements of CPA, which could affect the accuracy of the measurement.

5.2.3. The satellite image was acquired on April 2010 and the field data collected on May-June 2013. The time lag between image acquisition and field data collection may affect the size of tree crown which can be slightly bigger than in the World view image because of the growth season in between (Song *et al*., 2010). Also, it was not easy to identify pruned trees in the image. Building an algorithm to detect individual tree to replace the manual digitizing could produce more accurate results.

5.2.4. The carbon estimation derived from the use of a general allometric equation has also some shortcomings in terms of accuracy. Building a specific allometric equation, especially for *Anacardium occidentale* (cashew) would increase the accuracy of carbon estimates.

5.2.5. In this study, the formula for the area of an ellipse is used to calculate the field measured CPA of sampled trees. However, the definition of an ellipse in that way may include area not actually occupied by the crown (Anderson *et al.,* 2000), especially if the crown is not circular or has indentations. An overestimation or underestimation of the crown area might occur and influences the relationship between CPA and DBH.

5.3. IMPLICATIONS AND THE PLACE OF THIS STUDY IN THE GLOBAL CLIMATE CHANGE AND SUSTAINABLE DEVELOPMENT AGENDAS

Using a landscape based model to estimate carbon for trees outside of forest can be a useful tool to value the carbon stock in agroforestry and savanna systems. Such model has an important role to play in monitoring and managing carbon within these systems. Knowing the importance of carbon sequestration in mitigating climate change and the possibility of estimating carbon stored on TOF and valuing this carbon for the benefits of local communities may contribute to increase biomass carbon stock in trees outside of forest. Also, a landscape approach has an important role to play for development as it offers rural poor good opportunities to participate in carbon markets especially African countries.

This also provides significant carbon storage opportunities for the agricultural sector through land use and cultivation practices that promote more trees in farms. This perspective is even more beneficial that “for agricultural systems to achieve climate-smart objectives, including improved food security and rural livelihoods as well as climate change adaptation and mitigation, they often need to take a landscape approach" (Scherr *et al.*, 2012).

I addressed the ability of local communities to measure trees on their own farms. The results presented in Appendix A show that engaging local communities in measuring carbon in their farms requires a minimum training. When they can make the tree measurements to estimate the carbon on their own farms, they can be more motivated to participate in the carbon markets, reducing the barriers such as the measurement and monitoring costs that prevent developing countries from taking full advantage of the growing carbon markets. The model we developed will contribute to address the carbon measurement problem, especially in large areas for systems of trees outside of forests (cf. agro-forestry and related systems) in the savannas of Africa with 9 million km^2 of woodland of which 1.4 million for West Africa (Chidumayo *et al*., 2010) and 1,043,000 ha for Senegal (Mayaux *et al*., 2004). This carbon measurement problem is a serious obstacle in implementing initiatives such as REDD+ and other forestry activities that aim at combining tackling climate change and development.