QUANTIFYING SPATIAL INDICATORS OF ECOLOGICAL QUALITY IN A COCOA LANDSCAPE IN GOASO FOREST DISTRICT, GHANA

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FEBRUARY, 2016

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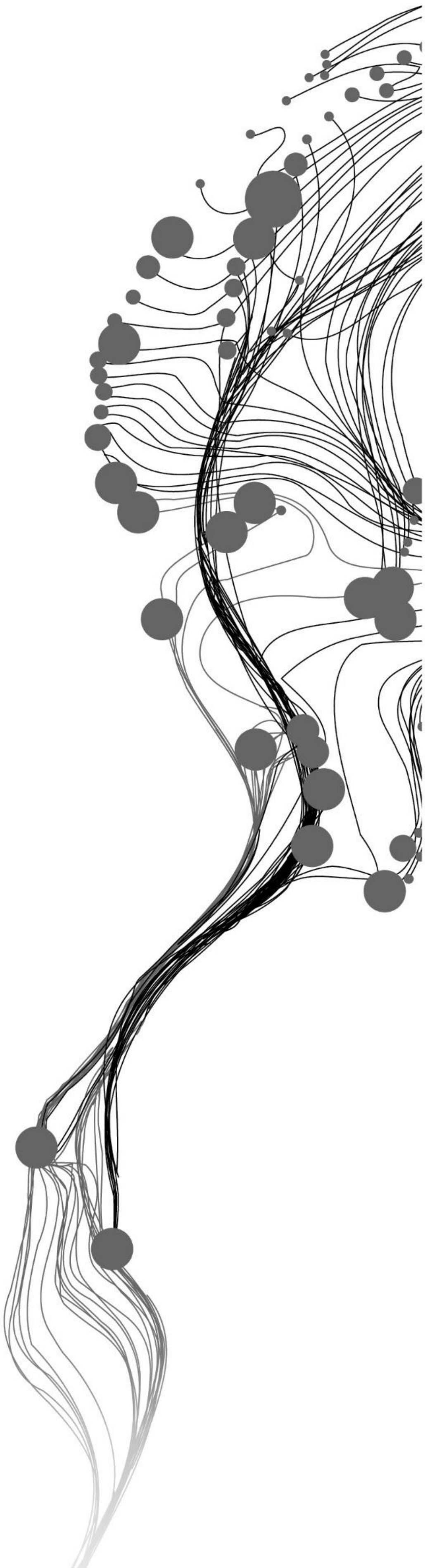

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ABSTRACT

Cocoa agriculture is considered to have played a significant role in the transformation of tropical landscapes in Africa, Latin America and Asia in the past and continues to do so. In recent decades, intensification mechanisms such as the use of hybrid varieties and application of agrochemicals have been promoted in Ghana as a means to improve cocoa sector performance. Such expansion and intensification of cocoa agroforestry systems have often led to replacing the original forest ecosystem and the removal of native trees. For effective conservation and management of natural habitats, a thorough knowledge and sustained monitoring of ecological quality of cocoa landscapes is essential. Such assessments and monitoring may be conducted in the broader context of cocoa certification audits. However, current methods used in certification audits rely mainly on field observations which are subject to auditors' discretion. This also leads to challenges in assessing requirements that are not easily quantifiable from physical observations. Additionally, farm-level assessments in voluntary schemes limit the assessment of indicators that are better expressed at the landscape scale, such as connectivity. This study is thus conducted to develop a method for assessing ecological quality of a cocoa landscape based on non-cocoa woody vegetation.

In this study, ecological quality, defined by the abundance, distribution, structure and configuration of non-cocoa woody vegetation within a cocoa landscape was assessed based on the context of selected Sustainable Agriculture Network certification standards. The assessment was conducted for two management objectives. A conservation objective which assesses ecological quality from the viewpoint of ecologists and environmentalists in maintaining or enhancing habitats and native vegetation; and a Productivity objective which is based on the perspective of cocoa farmers and production stakeholders whose interest is to improve yield and income. A combination of these two objectives was then used to assess potential suitability for meeting the selected certification requirements.

Four spatial indicators were identified for the assessment, namely tree density, crown cover, biomass and connectivity based on the SAN certification standards, Ghana Cocoa Manual and literature. Biomass is included based on its increasing relevance and use in providing information on the value of ecosystems. Norms for the indicators are specified based on the two assessment objectives. For the conservation objective, the SAN Guidelines recommendation for optimum shade is used as the norm for crown cover. Higher biomass value was considered higher quality based on existing knowledge that it represents larger, mature trees which provide several essential ecological services. Norms for connectivity were assigned based on the observed movement characteristics of an indicator species, Flying Squirrel.

For the productivity objective, the norms for tree density and crown cover were set by the optimal number of trees per hectare and shade tree cover for cocoa production as recommended by the Ghana Cocoa Manual.

The spatial indicators were quantified based on a satellite image of the study area and data acquired from field observation. Object-based image analysis was used to identify and map non-cocoa trees as well as other land covers on a Worldview-2 image of the study area. From the derived tree segments, tree density was quantified by calculating the number of individual tree segments within an overlayed 100m X 100m grid. Crown density was quantified similarly by calculating the percentage area of non-cocoa tree segments within a 100m X 100m grid. Biomass was quantified by use of an allometric equation which is based on DBH and was derived in Ghana. To apply the biomass model, a regression model was used to predict DBH of non-cocoa tree segments from their crown projection area (DBH). Connectivity was assessed by aggregating polygons within a threshold distance of 25m based on the movement characteristics of the indicator species. Spatial Multiple Criteria Evaluation (SMCE) was used to assess ecological quality for each objective by combining the standardized pixel values of the corresponding indicator maps into an ecological value for

each pixel. The resulting maps for the two objectives were then further combined to derive a map of potential suitability for certification based on the selected spatial indicators.

Keywords: ecological quality, cocoa, spatial indicators, monitoring, sustainable agriculture

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LIST OF ABBREVIATIONS

CPA	Crown Projection Area
CSSVD	Cocoa Swollen Shoot Virus Disease
DBH	Diameter at Breast Height
DD	Data Deficient
ESP	Estimation of Scale Parameter
FAO	Food and Agriculture Organization of the United Nations
GIS	Geographic Information System
GPS	Global Positioning System
ILWIS	Integrated Land and Water Information System
IPCC	Intergovernmental Panel on Climate Change
IUCN	International Union for Conservation of Nature
LC	Least Concern
LiDAR	Light Detection and Ranging
MRV	Monitoring Reporting and Verification
OBIA	Object-Based Image Analysis
REDD+	Reduced Emissions from Deforestation and Forest Degradation
RMSE	Root-Mean-Square Error
SAN	Sustainable Agriculture Network
SMCE	Spatial Multiple Criteria Evaluation
USDA	United States Department of Agriculture

1. INTRODUCTION

Forest degradation and deforestation are estimated to account for about 20% of global greenhouse gases (Gullison et al., 2007). This has been attributed to the fact that tropical forest trees hold high carbon stocks, large extents of which are lost through continuous deforestation (Achard et al., 2010). Several benefits are provided by tropical trees, ranging from monetary returns to less quantifiable environmental and socio-cultural services. However, continued benefit from the various tropical forests is threatened by deforestation and degradation (Damnyag et al., 2013).

Cocoa agriculture is considered to have played a significant role in the transformation of tropical landscapes in Africa, Latin America and Asia in the past and continues to do so. Cocoa (*Theobroma cacao*) is currently grown in about 50 tropical countries around the world. Smallholder farmers grow most of the world's 3 million tons of the cash crop annually. However, cocoa production has been a driver of deforestation. In the past two decades, intensification mechanisms including the use of hybrid varieties and application of agrochemicals have been promoted as a means to improve cocoa sector performance (Wiredu et al., 2011). More recent plantations are using even newer hybrids that tolerate more direct sunlight, allowing farmers to remove larger shade trees and plant more cocoa for higher yields (Filou & Kenny, 2009). Such expansion and intensification of cocoa agroforestry systems usually lead to replacing the original forest ecosystem (Schroth & Harvey, 2007). As an intervention, planting and maintenance of shade tree species within cocoa landscapes are encouraged. Sustainable cocoa production initiatives also require that farmers implement measures to maintain the quality of forest and other high conservation value ecosystems.

On the other hand, when compared to other land use replacements for original forests, cocoa agroforests with complex and diverse shade structure are considered more likely to conserve significant portions of the original forest biodiversity (Asare et al., 2014).

The ecological role played by non-cocoa trees within cocoa landscapes is vital for ensuring the dynamics of the ecosystem. They serve as nesting places for wildlife, including squirrels and bird species. Many animals also feed on tree fruits or invertebrates in dead wood. Insects such as bees and wasps, which are important for pollination, site their nests in tree hollows. Small mammals such as the deer and antelope require the shelter of tree patches for safe movement within the landscape (Rose, 2005). Non-cocoa trees also provide other ecosystem services including as shade, carbon sequestration, erosion and pest control, income and medicinal uses (Greco et al., 2012; Sinare & Gordon, 2015). Indeed, faunal diversity is typically highest in those cocoa agroforests that have high plant diversity, structurally complex canopies, and abundant surrounding forest cover (Schroth & Harvey, 2007).

Non-cocoa trees have played an important role in Ghana's cocoa farming systems for decades and have provided useful benefits to the crop, the environment and humans. The cocoa crops benefit from the shade they provide. The environment benefits from the forest-like habitats created be trees which harbour tropical biodiversity in a fast degrading landscape. The maintenance of indigenous timber species such as *T. Superba* (Ofram), *Terminalia ivorensis* (Emere) and *Ceiba pentandra* for such purposes also helps to sustain the timber production as a buffer to dwindling forests. In effect, the trees also serve as an economic incentive for smallholder cocoa farmers as well as the state (Asare & Prah, 2011).

In Ghana, most people depend on the forest resources for basic livelihood needs such as fuelwood and other non-timber forest products (Aduse-Poku et al., 2003). In spite of this, Ghana has lost 80% of its total original forest cover in the past century (Repetto, 1990). This negative phenomenon has been attributed to factors such as encroachment from cocoa expansion, persistent bush fires, illegal logging and surface mining activities. There is usually no simple solutions to these environment problems. However, an important first step is the commitment of stakeholders to the conservation of resources and to appreciating the impacts of management and stress (Dale & Beyeler, 2001).

National interventions to address the problems of deforestation and land degradation are usually based on promoting sustainable management and landscape restoration measures, including tree planting on degraded lands (Damnyag et al., 2011). A key national effort has been to highlight rehabilitation and restoration of degraded landscapes through plantation development in the review of the Ghana forest and wildlife policy (Ministry of Lands and Natural Resources, 2012). At the cocoa landscape level, restoration efforts are made to ensure connectivity of fragmented forest patches. These include maintenance of shade trees, live boundaries and hedges as well as the planting of trees alongside crops in an agroforestry system. These activities are carried out through national level programs such as Reduced Emissions from Deforestation and Forest Degradation (REDD+), of which agroforestry is identified as an integral and strategic option (Minang et al., 2014). At the farm level, conservation of native vegetation and habitats is also encouraged through voluntary certification schemes.

Certification, a market-driven tool is used to encourage responsible and sustainable production as well as control the impact of production on the environment (Pinto et al., 2014). This is usually done through a standard made up of principles, criteria and indicators. Producers who are certified as complying with these standards benefit from international market access and price premiums.

The Sustainable Agriculture Network (SAN) standard is a typical example that is used in this study. It has been applied in over 40 countries (including Ghana) to certify over 3 million hectares of 87crops representing more than 1800 certificates (Sustainable Agriculture Network, 2015). More than 927,000 hectares of cocoa have been certified under this scheme, mostly in Ivory Coast, Ghana and Indonesia. The Standard has 10 principles, including a principle on Ecosystem Conservation (Principle 2). This principle emphasises the protection and restoration of ecosystems, for example by re-establishing riparian forests, while recognizing the potential of farms and forests as sources of timber and non-timber forest products. The standard is further interpreted in local guidelines for Ghana to conform to the national socio-political and legal context. The interpreted standard leads to additional value for cocoa farmers, including the setting up of tree nurseries by farmer groups based on recommendations for shade trees (Paschall & Seville, 2012). Criteria 2.8 and 2.9 of the SAN standard refer to requirements for the maintenance of shade trees, canopy cover and connectivity which are considered indicators for the assessment of the ecological quality of the landscape.

Ecological quality has been defined in the context of biological integrity and ecosystem health, expressed by the deviation from natural or undisturbed conditions. This concept is being utilized in legislative changes such as the Rio Declaration on Environment and Development towards improving and harmonizing environmental standards while encouraging societal involvement (Paetzold et al., 2010). There are several factors that define the ecological quality of a landscape including biodiversity, water, soil and other biophysical properties. Previous studies have shown that parameters that are typically evaluated to assess the quality of habitat patches include structural characteristics and landscape configuration such as connectivity and isolation (Spanhove et al., 2012). In this study, the ecological quality is defined by the distribution, structure and configuration of non-cocoa woody vegetation within the landscape. Based on this definition, indicators and norms were derived for the assessment of ecological quality.

Two main management objectives within a cocoa landscape are considered in this study. First, there is conservation of ecosystems, seeking to maintain, recover or enhance natural habitats. The SAN standard and local interpretation provide guidelines for this management objective. Habitat requirements of specific indicator species were also included to put such an assessment in a more functional context in terms of conservation. This is also consistent with the well-established tradition of using an indicator species for monitoring and assessing environmental conditions in ecology, agriculture and related disciplines (Noss, 1990). The other objective considered in this assessment is cocoa productivity, which seeks to improve cocoa yields and associated benefits. The Ghana Cocoa Manual (Cocoa Research Institute of Ghana, 2010) provides local guidelines for this management objective. These two objectives differ in the stakeholder needs they address and as such their guidelines (norms), though sometimes similar, are not always the same.

1.1. Research Problem

Various definitions of ecological quality have been made, either generally or with the view to developing specific management standards. It has been defined by various concepts such as biological integrity and ecosystem health which are expressed by the deviation from natural or undisturbed conditions (Paetzold et al., 2010). Similarly, the definition of ecological quality of a cocoa landscape will include several factors such as biodiversity, water quality, provision of ecosystem services, and so on. For the purpose of this study, the scope of ecological quality is limited to the characteristics of non-cocoa woody vegetation. Figure 1.1 further details the specific aspects of ecological quality that are focused on in this study.

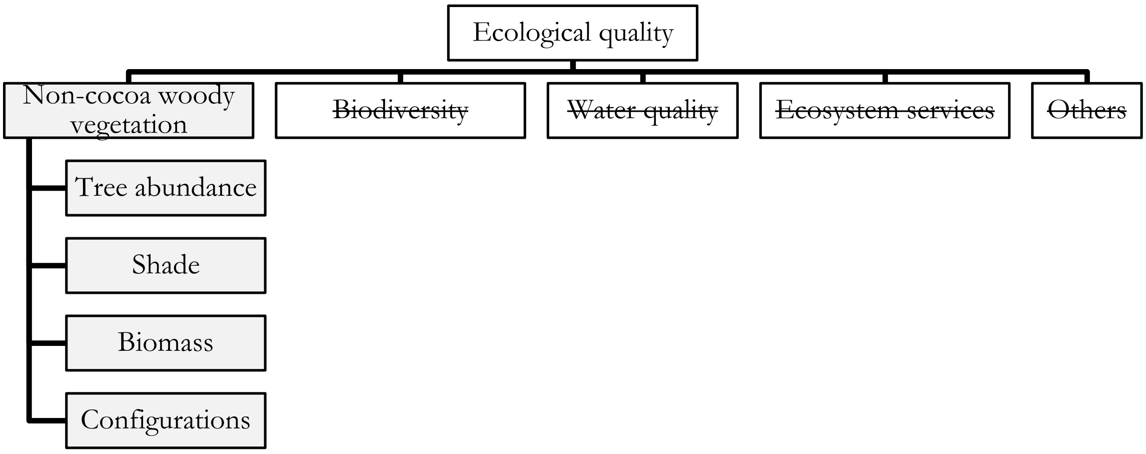


Figure 1.1 Scope of ecological quality for this study (in grey)

Spatial assessment of the ecological quality of a landscape, though very necessary for its management, can be very challenging and multifaceted. It requires the identification of specific, measurable indicators of ecological quality as well as corresponding local, national or regional norms suitable to the scale and context of the assessment. The management objective of the assessment must be explicitly defined for this purpose (Paetzold et al., 2010). The assessment of ecological quality must be based on indicators that are simple enough to allow regular monitoring but detailed enough to ensure that they capture the complexities of the landscape (ecosystem) being assessed (Dale & Beyeler, 2001). To ensure usability, the identification of these indicators must be based on specific stakeholder needs or goals. The norms for assessing these indicators should be as much as possible grounded in approved standard requirements or guidelines for achieving the identified stakeholder goals. Thus, it is imperative that opinions of the people who significantly influence decisions on land use and resource allocation be taken into account (Lee et al., 2014).

The application of remote sensing techniques in such assessment is a widely used approach that needs to be further explored (Boggs, 2010; West, 2009). Such approaches also come with their inherent technical bottlenecks. One such issue is the identification and discrimination of different vegetation types in a non-homogeneous landscape due to their similar reflectance characteristics on a remotely sensed image. Many studies have been conducted into the use of pixel-based classification as well as object-based image analysis for identifying tree canopies (Boggs, 2010; Hung et al., 2012). This research uses object-based image analysis on a Worldview-2 image to identify non-cocoa tree canopies for the assessment of ecological quality. This is expected to work well as high-resolution spatial data have been found useful in quantifying forests at individual tree level (Bai et al., 2005; Bunting & Lucas, 2006). The use of remotely sensed images allows for assessment and monitoring of ecological quality at the cocoa landscape level instead of individual farm levels

as is the case in current certification audits. It also ensures that sustained monitoring can be conducted over time without further disturbance to the ecology (Willis, 2015).
For effective conservation and management of natural habitats, a thorough knowledge and sustained monitoring of ecological quality is essential (Spanhove et al., 2012). Actors in sustainable cocoa production recommend continuous improvements of standard setting and assessment while shifting focus from farm level towards landscape-scale impacts (Mankad et al., 2014). Current methods of certification assessments rely mainly on field observations which are subject to auditors' discretion. While this may not be an issue in explicitly defined requirements such as the number of shade trees per hectare, there is a cause for concern with requirements such as connectivity and optimum shade that are not easily verifiable from observations alone. From discussions conducted, SAN certification auditors in Ghana confirmed that the easily quantifiable characteristics of non-cocoa (shade) trees such as tree density and crown cover are checked by physical observation during assessments of indicators 2.8 and 2.9 of SAN standards. They, however, identified challenges in assessing connectivity due to assessment units (farms) being too small and also difficulty in estimating connectivity from field observations alone. To ensure the integrity of assessment conclusions, it is essential that auditors have access to robust methods of assessment and monitoring to ascertain the state of ecological quality of cocoa landscapes and changes in time. It is also necessary to monitor continual improvement in the operations of a producer, an objective that is highlighted in several parts of the SAN and most certification standards. Similarly, REDD+ requires objective methods for assessing biomass and hence carbon stocks in its monitoring reporting and verification (MRV) systems (Paudel et al., 2015).. To ensure applicability of an assessment to management scenarios, effort must be made to link them to specific objectives.

1.2. Research Objectives

The main objective of this research is to develop an approach for assessing ecological quality of a cocoa landscape based on non-cocoa woody vegetation.
Therefore, the specific objectives of the research are

1. To identify spatial indicators and norms for assessing ecological quality of the cocoa landscape.
2. To map non-cocoa tree configurations within the cocoa landscape.
3. To quantify selected spatial indicators of ecological quality of a cocoa landscape.
4. To assess the quality of the cocoa landscape based on spatial indicators and norms.

1.3. Research Questions

The following research questions were answered to meet each specific objective of the research

1. For objective 1,
    a. What are suitable measurable spatial indicators for assessing landscape quality?
    b. What are the applicable norms for assessing the indicators in 1.a.?
2. For objective 2,
    a. What is an appropriate approach to mapping non-cocoa woody vegetation in a cocoa landscape?
3. For objective 3.
    a. How can tree configurations and connectivity be quantified within a cocoa landscape?
4. For objective 4,
    a. How can GIS data and field data be integrated to assess the ecological quality of the cocoa landscape in the study area?
    b. What is the ecological quality of the cocoa landscape in the study area from production and conservation perspective?
    c. Which areas would qualify for certification based on the assessed ecological quality indicators?

1.4. Research Approach

The objectives of *conservation*, as well as cocoa productivity, are considered in the assessment of ecological quality in this study. The conservation objective looks at the perspective of ecologists and environmentalists in maintaining or enhancing habitats and native vegetation. The Productivity objective looks at the perspective of farmers and cocoa consumers in ensuring improved yield and income from cocoa. Though different in their intended goals, both objectives have common ground in the fact that they seek a continuity (sustainability) of their respective benefit flows. The conservation objective, for instance, will want to maintain habitats and biodiversity. Similarly, the productivity objective wants to sustain yield and income. The productivity objective also takes on a somewhat conservation-oriented approach. This is evident in the recommendations for optimum non-cocoa shade, density and spacing. A balance between these two objectives through a combination of areas ecological quality in both cases could, therefore, identify its potential suitability for certification in based on the applicable criterion.

This research assessed ecological quality for the two management objectives using indicators based on non-cocoa tree parameters. These indicators are connectivity, biomass, crown cover and tree density.

The method developed by this study is intended to be adoptable, with modification as required, for real application cases including certification audits, environmental baseline assessments and performance monitoring (by comparing quality at different times).

2. LITERATURE REVIEW

2.1. Cocoa Production in Ghana

Cocoa production is mainly done in developing countries, with most prominently in West Africa (Basso et al., 2012). Ghana is a major producer of cocoa in the world; only second to Ivory Coast in terms of total annual production. A major exporter of raw cocoa beans to various countries, Ghana also processes cocoa beans domestically into various products such as chocolate, beverages and skin care products. These products are sold to both local and international consumers. The importance of cocoa cultivation as an economic activity and land use in Ghana cannot be overstated. Traditional cocoa production was mainly done on partly cleared forest land with the standing tree patches providing shade for the cocoa trees. More recently, cocoa management practices in Ghana have been attributed to increasing deforestation and maintenance of little or no shade trees. The resultant issues of conservation and agriculture in Ghana thus border on how to balance the economic requirements for higher productivity through agricultural expansion with the need to conserve biodiversity, and ensure continued flow of important ecosystem services (Asare et al., 2014).

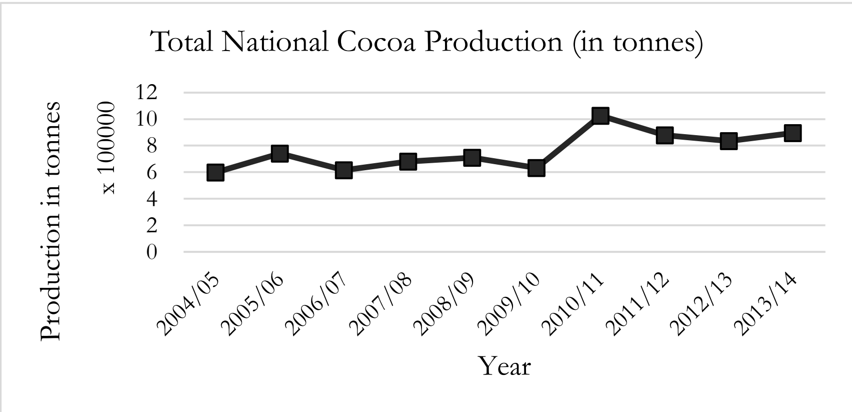


Figure 2.1 National Cocoa Production trend between 2004 and 2014 (source: Ghana Cocoa Board)

Cocoa production trends (Figure 2.1) in Ghana showed a steady increase until 2010/11 after which there was a decrease. Most recent production figures indicate a slight recovery in production. These fluctuations between annual production figures have been attributed to factors such as disease outbreak, insufficient fertiliser application, declining labour force and poor crop management. Some increments, for example in 2014, are thought to be due to smuggled cocoa beans from neighbouring Ivory Coast (Hardman Agribusiness, 2015). Total harvested area of cocoa in Ghana was estimated to rise from 1.45 million hectares

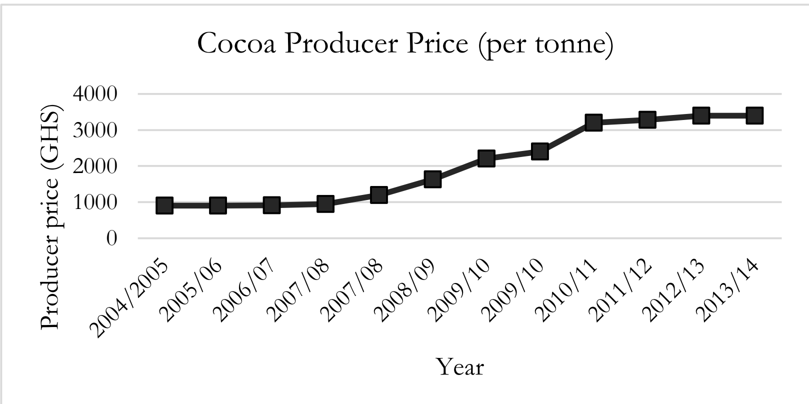


Figure 2.2 Cocoa production price development between 2004 and 2014 (source: Ghana Cocoa Board)

in 1970 to 1.5 million hectares in 2000 (FAO, 2004). More recent estimates suggest a further increase to 1.6 million hectares with farmers planting between 300 and 400 cocoa per hectare.

Cocoa producer price in Ghana per tonne has generally increased in the past ten years (2004 to 2014). The trend as depicted in Figure 2.2 shows a gradual producer price increase from 2004 until 2008 after which there was a sharp rise till 2011. After then the producer price increases barely over the two years till 2014.

2.1.1. Cocoa Intensification

Cocoa intensification refers to recent advancements in cocoa production where the overall objective has been to increase productivity. Cocoa intensification in Ghana is conducted through a multi-stakeholder approach to making changes to traditional farming and other management practices. (Asare & David, 2011). This is done through the introduction of hybrid varieties of cocoa that are more resistant to diseases and pests, early bearing and high yielding. There are also other important properties of such enhanced cocoa varieties. These includes an increased tolerance for sunlight and less requirement for shade. The traditional practice of establishing ecologically favourable complex shade in cocoa cultivation is threatened by recent initiatives towards cocoa intensification. (Vaast & Somarriba, 2014) This threatens the multifaceted roles of shade trees in sustainable cocoa production and ecological conservation.

2.2. Cocoa certification

There are several environmental assessments that can be conducted within a cocoa landscape. In Ghana, state extension services conduct assessments to identify and manage risks of diseases, with special emphasis on the Cocoa Swollen Shoot Virus Disease (CSSVD). Other environmental assessments are conducted as part of voluntary third-party certification schemes. Certification is considered as a market-driven tool used to promote sustainability in the cocoa production value chain as well as to improve the socio-economic well-being of cocoa farmers (Basso et al., 2012). This is done by assessing the farm management operations against a standard based on a set of principles. These principles are usually broken down into more specific sets of criteria, indicators and verifiers.

There is an increased demand for cocoa that is produced ethically and sustainably. Cocoa certification schemes exist to provide evidence of such responsible production. There are several available cocoa certification schemes. Examples of some common schemes are Rainforest Alliance, Fair Trade, UTZ and USDA Organic. An integral part of all these certification schemes is the requirement for some form of ecological conservation and/or protection. These requirements aim to ensure that the ecological quality of the landscape within which cocoa is produced will be improved or at least maintained. To ensure the integrity of certification schemes and affirm consumer confidence, it is inevitable to establish robust assessments and consistent practical methodologies.

In Ghana, group certification schemes are most common as most farmers are smallholders with less than 3ha of farmland (Basso et al., 2012).

2.3. Assessing Ecological Quality

The concept of ecological quality and its assessment thereof can be very broad and even sometimes ambiguous. This is because of the subject-specific nature of perceived qualities of an ecosystem. In simple terms, what is considered good quality or otherwise depends largely on the focus and purpose of the assessment. It is important to specify these as a context for the definition of ecological quality. For the purpose of this study, the definition of ecological quality of the cocoa landscape was limited to parameters of non-cocoa trees. This is because conservation requirements in the SAN Standard (Sustainable Agriculture Network, 2010) and guidelines for shade management in the Ghana Cocoa Manual (Cocoa Research Institute of Ghana, 2010) focus on abundance and structure of non-cocoa trees within the farm (Sustainable Agriculture Network, 2010).

2.4. Indicators and Norms of Ecological Quality

Ecological quality of a landscape and its assessment encompass several factors. These factors could include biodiversity, air quality, soil suitability, ecosystem services and many more. Due to this, several studies on ecological assessment use multivariate approaches to analyse multiple criteria and indicators in ecological assessments. (Mossman et al., 2015; Wang & Li, 2008; Wu et al., 2014). It is, therefore, essential in an assessment to define the scope and indicators of ecological quality to suit the intended purpose. The scope and indicators are in turn determined by the stakeholder needs and the use case scenario.

For instance, an assessment based on improving cocoa productivity in Ghana may consider a distance between trees of 10m by 10m as optimally connected since this is the recommended planting distance between shade trees (Cocoa Research Institute of Ghana, 2010). For the purposes of assessing a certification requirement (SAN), the local guidelines on spacing between shade trees (between 22m by 22m and 24m by 24m) will be used as the connectivity threshold in the assessment (Sustainable Agriculture Network, 2009). In another example where the purpose of assessment is for carbon sequestrated, for instance in a REDD+ scenario, more emphasis will be placed on the biomass of trees within the landscape, of which about 50% is considered to be the amount of carbon sequestered (West, 2009).

For the purposes of this research, ecological quality is defined by parameters of non-cocoa trees because the play a crucial role in maintaining biodiversity and conserving habitats (Asare et al., 2014). An approach to assessing ecological quality based on tree parameters is the identification and quantification of some essential metrics of the trees. These may include density, canopy cover and biomass. Another important indicator which is also used in this research to assess ecological quality at the landscape level is the connectivity between trees. This is essential as it affects movement or genetic flow of species, a key process for their survival within a heterogeneous and fragmented agroforestry landscape (Burel & Baudry, 2005).

2.4.1. Connectivity

Burel & Baudry, (2005) define connectivity as the degree to which the landscape facilitates or impedes movement among resource patches. Maintaining connectivity or otherwise, may be desirable based on the management objective. It is favourable for gene flows, dispersal and species movement. On the other hand, reducing connectivity will be better in the scenario of species invasion or spread of pests and diseases (Galpern et al., 2011). Based on the purpose and scale of assessment connectivity may be defined in terms of flows between protected forest reserves (Asare et al., 2014), or at a much higher resolution and lower scale between individual tree patches within a landscape. The latter definition is adopted for the purpose of this research within a cocoa landscape.

Though connectivity is seen to be an important characteristic of a landscape, a precise definition has been elusive while accurate quantification and implementation has been difficult. This has been attributed partly to the differences between structural (habitat) and functional connectivity of a landscape from the perspective of an indicator organism. Structural connectedness relates to the physical continuity of a habitat or patch type within a landscape. Functional connectedness, on the other hand, is defined by the process of interest or the indicator organism (McGarigal, 2015). Thus, patches that may be connected for birds may not be connected for lizards or fire spread or seed dispersal. Some researchers argue that the ultimate influencing factors of connectivity as perceived by an organism are the scale and pattern of their movement as related to the structure of the landscape (Kimberly A. With, 1995).

Functional connectivity , which is assessed in this research, may be based on: (1) strict adjacency (touching) or some threshold distance (a maximum dispersal distance); (2) some decreasing function of distance that reflects the probability of connection at a given distance; or (3) a resistance-weighted distance function (McGarigal, 2015). This research uses a threshold distance to denote connectedness based on observed movement (gliding) characteristics of the indicator species, *Anomalurus spp* (Flying squirrel).

The indicator species is used in this study not only as an example but also to incorporate functionality in the assessment. For such assessment of ecological quality or status, it is important that the selected suite of indicators represent key information about the structure, composition and function of the landscape (Dale & Beyeler, 2001). This attempts to reflect the already complex intricacies of an ecological system as depicted by J. F. Franklin (Wilson & Perez, 1988) and Noss, 1990. The Flying squirrels are considered as a suitable example for this study due to their preference for high forests with tall emergent trees (IUCN, 2015). They have IUCN status classification of LC (Least Concern) or DD (Data Deficient) (IUCN, 2015).

2.4.2. Indicator Species for Tree connectivity

Tree connectivity was assessed within the landscape to estimate the level of connectedness of non-cocoa trees. In the Conservation objective, connectivity of tree patches was assessed for the purposes of habitation by an indicator species Flying squirrel, *Anomalurus spp*. The species is selected only as an example for the case of this research. Other organism(s), genetic flow(s) or process(es) may be used based on specific stakeholder goal(s) and suitability for the intended objective(s) for assessing connectivity.

Image of *Anomalorus beecrofti*, (Wolf, 1851)

Flying squirrels are classified under the genus *Anomalurus*, known to be the largest genus of the rodent family Anomaluridae. It has four species and is the only genus in the subfamily Anomalurinae; *beecrofti, derbianus, pelii* and *pusillus*.

Apart from the *pusillus*, all other Anomalurus species are found in Ghana and several other West African countries from Senegal to Cameroon and southwards to the Central African Republic.

The species *pelli* is endemic to the Upper Guinea Rainforest Zone from The west of the River Volta in Ghana through to the eastern part of Liberia.

Though considered as pests by most farmers (Greco et al., 2012), squirrels are hunted for food have for many years served as a major source of protein for Ghanaians (Asibey, 1974; Davies & Brown, 2008).

Flying squirrels have IUCN status classification of LC (Least Concern) or DD (Data Deficient) (IUCN, 2015). The main threat to these terrestrial species is the deforestation, mainly as a result of land conversion for logging and agricultural use. This has led to the removal of much of the preferred habitat, which is low altitude tropical moist forests. IUCN recommends that more research is conducted on their population distribution, threats, life history and ecology (IUCN, 2015).

Research has found that the flying squirrels have a glide distance between 5m and 25m (Vernes, 2001). Therefore, a threshold distance of 25m between non-cocoa trees was used for the analysis of connectivity in the Conservation objective.

2.4.3. Biomass

Biomass estimation is becoming an increasingly relevant topic of scientific studies and national development planning as a means of assessing tree contributions to the global carbon cycle (Basuki et al., 2009). Information on the biomass of an area is primary for the assessment of carbon sequestered. Generally, larger trees are considered to represent larger and important proportions of biomass within a landscape (Henry et al., 2010). In an assessment of ecological quality, larger trees, represented by higher biomass could be said to also have a higher ecological value from a perspective of ecosystem conservation (Hartley, 2002). High biomass is indicative of old trees which serve as seed banks for natural regeneration and are harder to replace when lost. These large trees also provide food and nesting resources for a wide range of species, warranting the assigned high ecological quality (Parkes et al., 2003). It can be directly inferred that they have more sequestered carbon, which forms about half of their biomass (Basuki et al., 2009). Their larger trunks are preferred nesting places for some animal species. Certain animals (example flying squirrel) require such emergent trees with higher canopies for their movement (gliding) (IUCN, 2015).

2.5. Object Based Image Analysis

For very high resolution image analysis, traditional classification approaches which are pixel-based are considered poorly suited (Drăguţ et al., 2010). This can be attributed to the fact that spectral heterogeneity within an object increases with increasing spatial resolution. This has led to the rise of object-based image analysis (OBIA). OBIA seeks to realize the real-world value of image objects which is considered to satisfy the human understanding more than pixel values alone (Goodchild et al., 2007).
Image objects are first crated through the aggregation of spectrally similar pixels through segmentation, a process of splitting the remotely acquired image into spectrally discrete objects or regions. These regions are considered homogeneous depending on spatial and/or spectral characteristics. This process is done to account for the spectral heterogeneity within objects of the same class in a very high resolution image (Drăguţ et al., 2010).

2.5.1. Segmentation Accuracy

The accuracy of segmentation in OBIA is a major issue as it affects the accuracy of classification and of all subsequent analysis conducted using the segments. The accuracy of the segmentation is determined by the accuracy parameters used in defining the ruleset. Therefore expert knowledge of the user plays a key role here. Different methods may be used to assess the accuracy of segmentation in OBIA. User perspectives were collected in a study to estimate the spatial and thematic accuracy of OBIA results (Lucian Drăguţ & Eisank, 2012). In another example of tree crowns, digitized polygons of sample trees were compared with segment results by overlaying. Intersecting areas beyond a given threshold were considered 1 to 1 matches. The ratio of total matching polygons to total digitized samples was then considered as the accuracy of the segmentation (Mutanga, 2012).

2.6. Allometric Equations

In tree ecology, allometry refers to the statistical relationships between different characteristics of trees. The assumption is that under similar conditions, individual trees within a population develop in a similar way. Based on this, the relationships between characteristics that are easier to quantify such as diameter at breast height (DBH) and height and other characteristics that are harder to quantify such as biomass and volume (Henry et al., 2013). Allometric equations have been used severally as a direct approach used for estimating above ground biomass (Basuki et al., 2009; Damnyag et al., 2011; IPCC, 2003). Since it is impractical for model input parameters to be measured for all trees, an allometric equation developed based on a representative sample is used instead. Statistical methods are then used to validate the model by comparing the derived predictions with observations that are independent of those used for fitting the model. Cross-validation is an example of such validation where the sample dataset is split into two subsets; one subset for fitting the model and the other subset for validating the model. Several criteria may be used to compare the predicted values from the model with the observed values, such as R^2 of the regression and root-mean-square error (RMSE) (Breu et al., 2012).

2.7. Spatial Multiple Criteria Evaluation

Spatial Multiple Criteria Evaluation (SMCE) refers to a process that accepts multiple input geographical data, combines the data into an output decision. The decision is derived based on the pre-specified preferences and configurations according to the user decision rules and requirements. It differs from conventional multi-criteria decision analysis due to the extent to which factors are interrelated as well as the large number of factors considered. In essence, SMCE aggregates multi-dimensional data into one-dimensional decision values (M. Sharifi & Retsios, 2003).

3. MATERIALS AND METHODS

This chapter details the flow of activities carried out in the study. It gives an account of how data collection was done, including the description of the study area and sampling strategy. It further describes the processes of analysing the empirical data from the field together with the satellite data outlined by the flowchart in Figure 3.2. It shows how the ecological quality of the study area was assessed through a method of integrating field and image data.

3.1. Data, Software and Equipment

Worldview-2 image (acquired on 24th January, 2013) of the study area was used for the study: Empirical data, acquired through field data collection within the study area was also used in the study.
Field equipment used for the study include a GPS, iPAQ (with ArcPAD software) for navigation, a diameter tape for measuring tree DBH, a Haga clinometer for measuring tree height, a surveyor's tape and chalk for sample plot demarcation. eCognition Developer 9.0 (Trimble) was used for object image analysis. ArcMap 10.3 was used for GIS operations in quantifying the indicators as well as for map visualization. Microsoft Excel 2013 was used for statistical analysis of field and image data, including biomass estimation. ILWIS 3.3 (52North) was used for SMCE to assess ecological quality.

3.2. Study Area

The study area (Figure 3.1) is located in Goaso Forest District of the Brong Ahafo region in Ghana, West Africa. It is located south west of the Goaso town, between latitudes 6° 36' 13" N and 6° 41' 6" N and longitudes 2° 37' 10" W and 2° 34' 17" W.

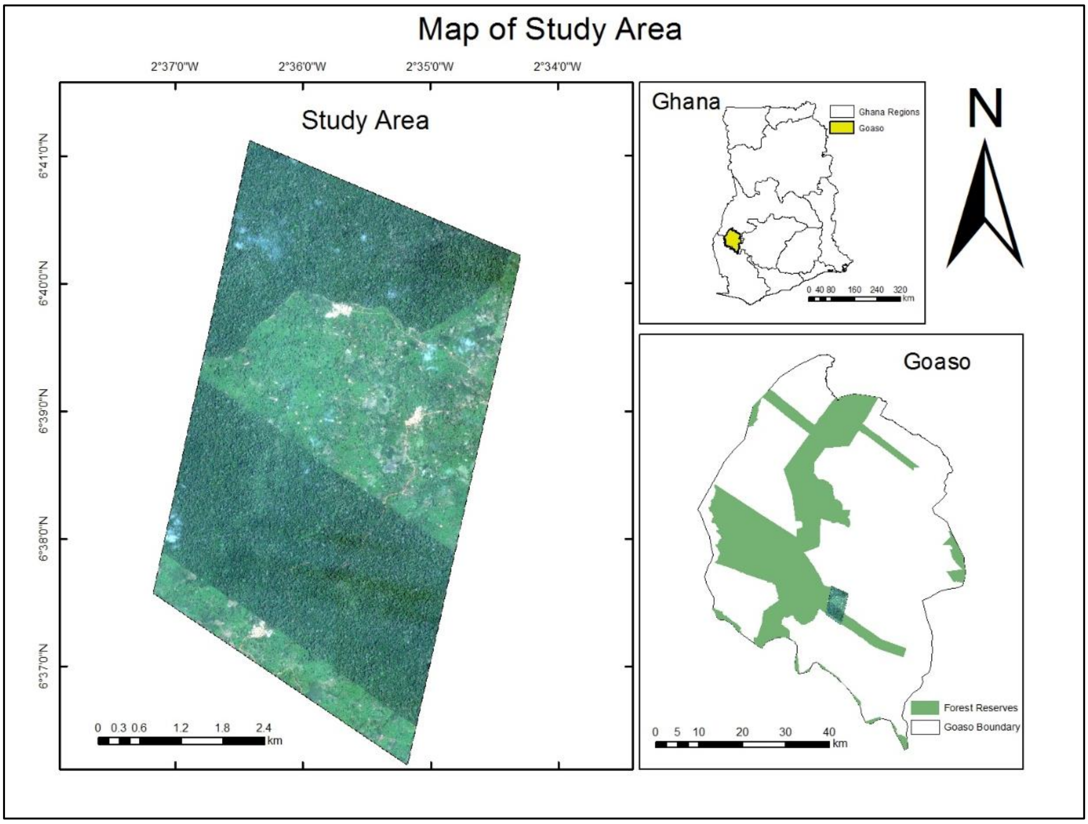


Figure 3.1 Map showing location of the Study Area

Goaso Forest District has forest that are categorized as "moist semi-deciduous – northwest subtype" and is located within Ghana's high forest zone (Gelens et al., 2010). The study was conducted on the cocoa landscape adjacent to but excluding the Aboniyere Shelterbelts and Bonsam Bepo Forest Reserves. The main economic activity of the population is farming, with a predominant land use of rain-fed agriculture.

3.2.1. Climate

The local climate is humid and tropical with annual rainfall between 1250mm and 1750mm. There are two main seasons; the wet season starts from May-June to October/November and the dry season starts from December-January to May-June. There are also two peak rainfall seasons, one in April-July and another in September-October. The area has relatively uniform temperatures and monthly averages range between 26°C and 29°C (Gelens et al., 2010).

3.2.2. Vegetation

The forest type in Goaso is classified as moist semi-deciduous. Forests outside the protected reserves have been converted for other land uses, mostly agriculture. Agriculture is the main land use as well as the economic mainstay in Goaso. Cocoa is the most prominent cash crop grown in the area. Other crops such as cassava, plantain, cocoyam, fruits and maize are mostly grown for subsistence (Aduse-Poku et al., 2003).

3.3. Flowchart

The research activities are schematically depicted in Figure 3.2 below. First indicators and norms of ecological quality were identified and based on them, field data collection was conducted. A satellite image of the study area was then segmented and classified. The identified indicators were then quantified and used for the assessment of ecological quality. Appendix 1 shows specific detailed flowcharts of selected processes.

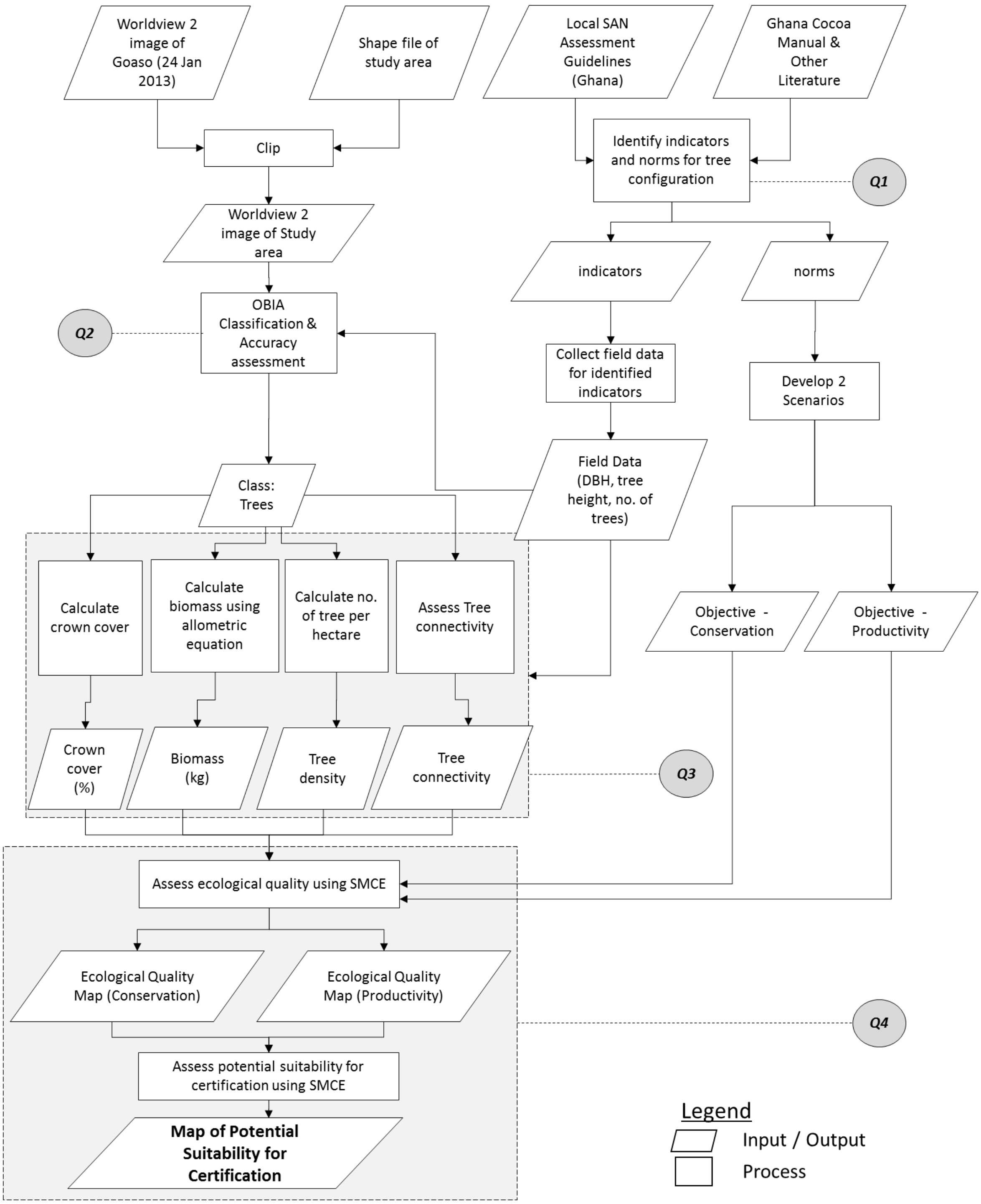


Figure 3.2 Flowchart of research activities

3.4. Identification of Indicators and Norms

Standards, guidelines and literature were used to identify indicators of ecological quality of the cocoa landscape for two alternative assessment objectives (Productivity and Conservation). The Sustainable Agriculture Network Standards (Sustainable Agriculture Network, 2010) was the main document used for this purpose since the research seeks to develop a more robust method for assessing ecological quality, in the context of certification. Focus was on requirements of Criteria 2.8 and 2.9 of the SAN standard as they emphasize the requirements of maintaining ecological quality through shade trees and ensuring connectivity. The Ghana Cocoa Manual (Cocoa Research Institute of Ghana, 2010) was used to identify norms for tree connectivity and tree density for the Productivity objective. Although, the guidelines in this document are ultimately aimed at achieving higher yields, they endeavour to ensure sustainable production by maintaining landscape quality and reducing impact. The following specific indicators were selected to assess ecological quality in the area.

For Conservation objective:

- Connectivity of non-cocoa trees: the nearness of non-cocoa trees from one another within a threshold distance. An indicator species was used to define the threshold distance
- Crown cover of non-cocoa trees: the percentage of crown cover area per hectare. This is defined by the percentage ratio of non-cocoa trees within an area of 1 hectare.
- Biomass of non-cocoa trees: the calculated above ground biomass of non-cocoa trees.

For Productivity objective:

- Crown cover of non-cocoa trees: the percentage of crown cover area per hectare. This is defined by the percentage ratio of non-cocoa trees within an area of 1 hectare.
- Tree density: number of non-cocoa trees per hectare.

Similar indicators to the above are have been used in a study which focuses on the ‘habitat hectares’ approach to assess the quality of native vegetation, based on explicit comparisons between vegetation features and benchmarks (Parkes et al., 2003).

In the Conservation objective, patch connectivity of non-cocoa trees was assessed for the functional purpose of an indicator species, Flying squirrels (*Anomalurus spp*). The species was selected as an example for this assessment due to its gliding movement between high tropical trees (Vernes, 2001). An indicator species with ground movement only would not be suitable for the assessment since the canopy of cocoa trees alone could provide enough cover for movement.

Biomass was used as an indicator in the Conservation objective. It is widely recognised that non-cocoa tree biomass is a key driver of carbon storage in cocoa landscapes (Acheampong & Dawoe, 2014). The assumption here was that higher biomass represented a higher ecological value. This assumption is derived from the notion that larger trees generally have higher biomass and that the removal of bigger trees leads to significant decrease in biomass and carbon (Acheampong & Dawoe, 2014). This then translate into higher sequestered carbon which is estimated to be about 50% of biomass (Basuki et al., 2009).

Norms for the indicators are specified based on the two assessment objectives of different stakeholder groups. The *Conservation* objective assesses ecological quality at a pro-environmental perspective. Here conservation goals of stakeholders, such as ecologists and environmentalists are considered. The *Productivity* objective assesses indicators for the purpose of cocoa productivity. Stakeholders such as farmers and Ghana Cocoa Board are considered in this case as the main goal of their activities is to maximise yield (and income). Certification schemes seek to achieve balance between conservation and productivity goals. Consequently, specific local audit guidelines (SAN Local Interpretation for Ghana) have been used in both alternative objectives.

More specifically, the norm for assessing crown cover and tree density were derived from the SAN guideline on non-cocoa shade tree cover. For the assessment of connectivity of non-cocoa tree patches in the Conservation objective, the example indicator species Flying Squirrel (*Anmalurus spp*) was selected to arrive at parameters that relate to a functional use of the indicator. The norm for biomass was set based on the recommended shade tree density (number of trees per hectare) in the SAN standards. Table 3.1 summarizes the indicators and their respective norms.

Table 3.1 Indicators and norms of ecological quality used in the study

Objective	Indicator	Norm	Justification / Source
1. Ecologically sound optimization of productivity	Crown cover of non-cocoa trees (per hectare)	≥40% cover	Ghana Cocoa Manual & SAN Guidelines
	Non-cocoa Tree Density (per hectare)	15 to 18 trees per hectare	Ghana Cocoa Manual & SAN Guidelines
2. Conservation	Connectivity of non-cocoa tree patches	up to 25m	SAN Standard (indicator) & Gliding distance of Flying Squirrel (norm)
	Crown cover of non-cocoa trees (per hectare)	≥40% cover	Minimum shade (SAN Guidelines)
	Biomass of non-cocoa trees	The higher the better	Literature (Parkes et al., 2003)

3.5. Field Data Collection

Stratified random sampling was conducted to select representative plots within the study area for the collection of field data. The study area was stratified based on visual image assessment of tree cover. The area was divided based on tree cover into two categories; “dense” (more trees) or “open” (less trees). Within each stratum, random sampling was done to ensure that selected plots are representative of the landscape within the study area to draw conclusions to the whole. The field sampling prioritised cocoa farms, while avoiding inaccessible areas such as dense forest patches and swampy areas. Figure 3.3 shows the output of the field stratification and sampling.

3.5.1. Non-cocoa tree characteristics

Fieldwork was conducted to collect data for the assessment in the study area in September and October 2015. Data was collected in a total of 49 sample plots. For each sample, a circular plot of radius 18m (area≈1000m2) was laid within which tree parameters were collected based on a predesigned data sheet in (Appendix 2). The parameters measured were plot crown cover, number of trees, average height and diameter at breast height (DBH) of each tree within each plot. The species of each tree was also identified and recorded. After tree identification, the DBH of each tree was measured using the diameter tape at a height of 1.3m from the base of the tree. The average height of the trees within the plot was measures using the Haga clinometer. A densitometer was intended to be used for measuring crown cover in the field. However, in most cases, it was found ineffective as the crown of cocoa trees interfered with observations. Therefore, visual estimations of percentage crown cover of non-cocoa trees was done. Due to subjectivity of such visual estimations, crown sizes from the segmented trees were used instead to calculate crown cover

percentages over the study area. Additionally, for biomass modelling, data on sample non-cocoa trees were collected in the field. The data collected for this purpose were coordinates, DBH, height and species.
Discussions were conducted with stakeholders of cocoa production in Ghana to provide further background on the cocoa sector, with emphasis on environmental assessments. The questionnaire (Appendix 3) was used more as a guideline. The discussions were open and did not strictly follow the questionnaire. Further institutional data such as Annual Producer Price and National Production Trends were acquired. The stakeholders interviewed are listed in Appendix 3.

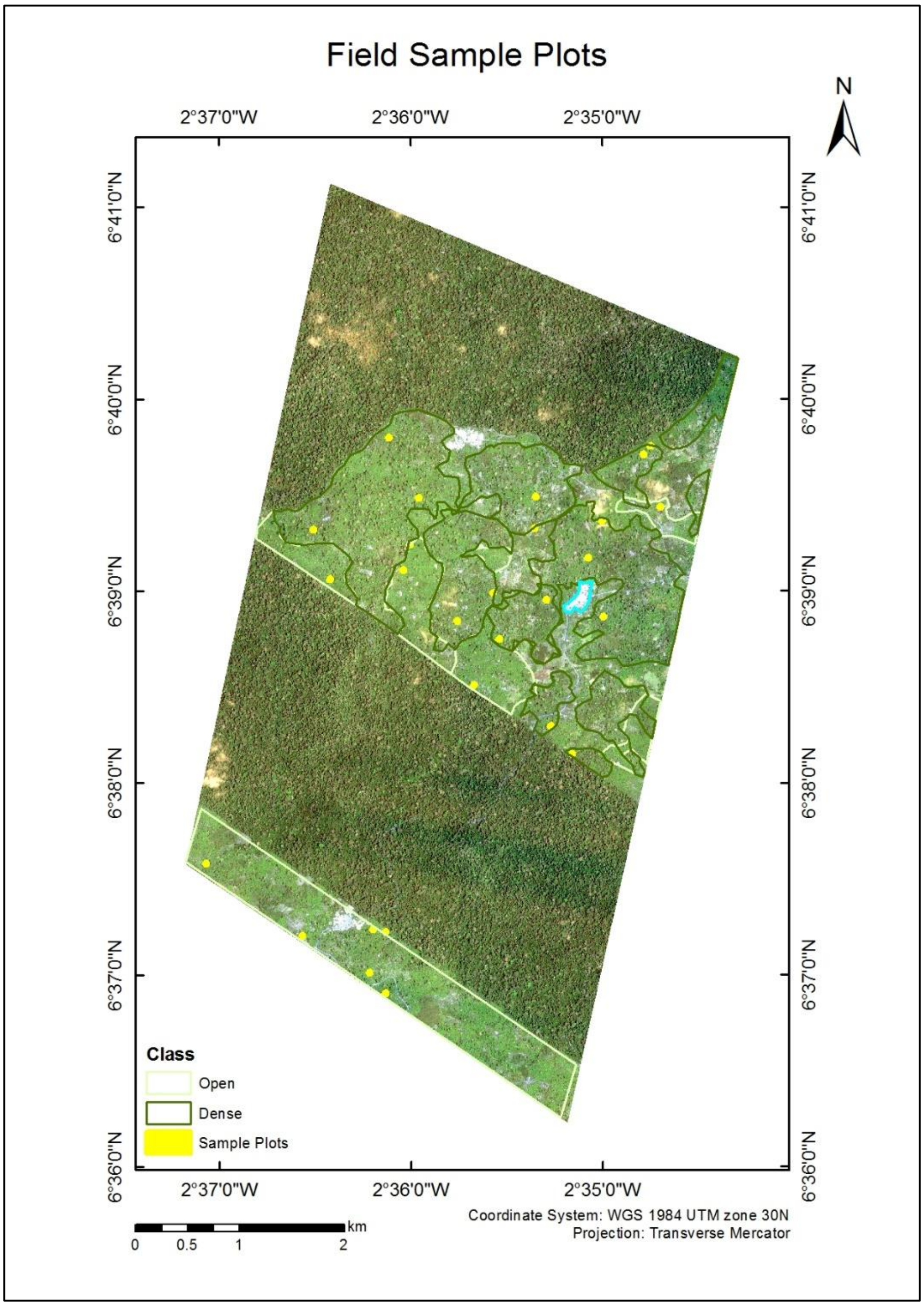


Figure 3.3 Field sample plots and stratification

3.6. Object Based Image Analysis

A very high resolution image covering the study area was acquired from Worldview 2, an optical satellite sensor. The date of image acquisition was 24th January, 2014. Worldview-2 provides panchromatic images at 0.46m and multispectral data at 2m. Four spectral bands were used in this research as described in Table 3.2.

Table 3.2 Spectral bands Worlview-2 image of the study area

Band	**Wavelength (μm)**
2 – Blue	0.45 – 0.51
3 – Green	0.51 – 0.58
5 – Red	0.63 – 0.69
8 – Near infrared	0.86 – 1.04

Object-based image analysis was conducted on the Worldview-2 image to identify and separate tree crowns and patches from other land cover types.

Spatially neighbouring pixels with similar spectral characteristics were grouped by multi-resolution segmentation based on an algorithm described below. Starting from a single seed pixel, neighbouring pixels are evaluated to see whether they fall within a range that is defined based on an algorithm. The pixels are then assigned to the object of the seed pixel in a process called region-growing (Trimble, 2015b). Thus, from the centre pixel, the algorithm is used to find boundaries, such as pixels distinct from the seed pixel and its neighbours.

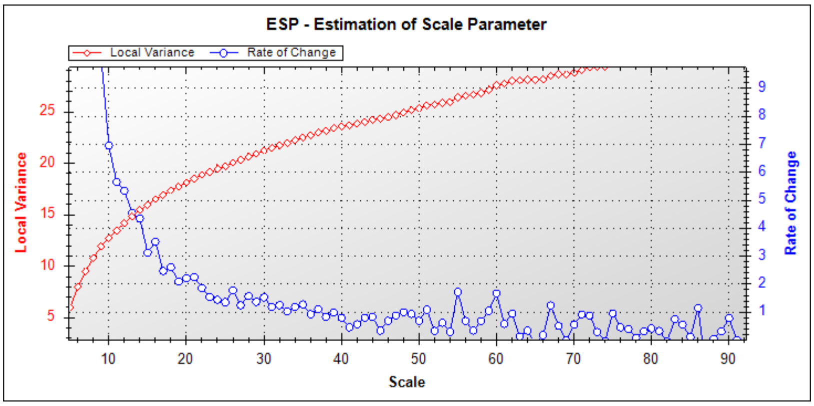
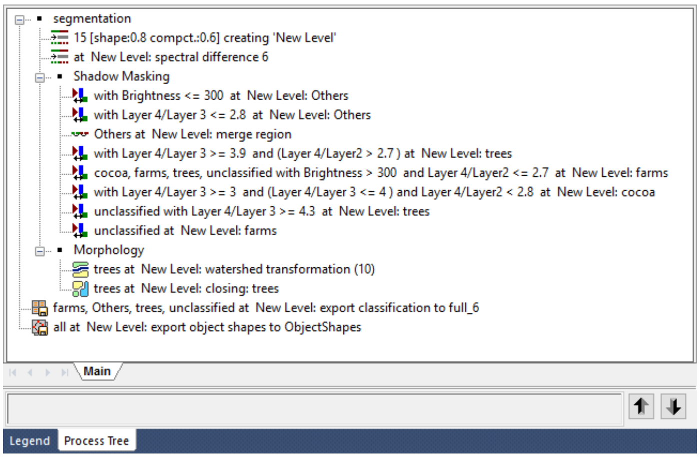


Figure 3.4 Output of Estimation of Scale Parameter showing Local variance and Rate of Change

The entire image is divided into segments. For segmentation, a scale factor of 15 was used based on the output of the Estimation of Scale Parameter(ESP) tool, as shown in Figure 3.4 (L Drăguţ et al., 2014).

Also, shape and compactness were assigned 0.8 and 0.6 respectively. After segmentation, the classification was conducted at the segment level, instead of the pixel level as is done in traditional image classification. Shadows and other non-vegetative land cover were classified separately (Others) by selecting layers with brightness values <300.



Two simple ratios between layer 4 and layer 3 and layer 4 and layer 2 were used to further separate non-cocoa trees from other vegetation types. Segments with values more than or equal to 3.9 in Layer 4/ Layer 3 and greater than 2.7 in Layer 4/ Layer 2 were classified under the non-cocoa tree class "Trees". The values

Figure 3.5 Ruleset used for image segmentation and classification in eCognitiom

were arrived at through trial and error and appeared to give the best result. The resulting classification was further refined using Morphology algorithm. Watershed transformation was used to separate tree clusters. This process is based on a similar concept to watershed in hydrology by "flooding intensity valleys" of neighbouring objects until borders are formed. Figure 3.5 shows the ruleset used for OBIA in eCognition Developer 9 (Trimble, 2015a).

The image was finally classified into four land cover types;

- Trees (non-cocoa): non-cocoa trees,
- Cocoa: cocoa trees,
- Other crops: all other crops including maize, cassava, plantain and cocoyam.
- Other land cover: all other land cover types, such as bare soil and built-up areas.

Field sample points and visual interpretation were used as guides for linking spectral characteristics to land cover classes. These classes were selected based on the need to quantify tree parameters which are identified as the indicators of ecological quality in this study.

3.6.1. Assessment of Segmentation Accuracy

After the segmentation and classification, accuracy assessment was conducted on tree crown segments. This was done by comparing the segmented crowns with manually digitized crowns of tree samples collected in the field as depicted in Figure 3.6.

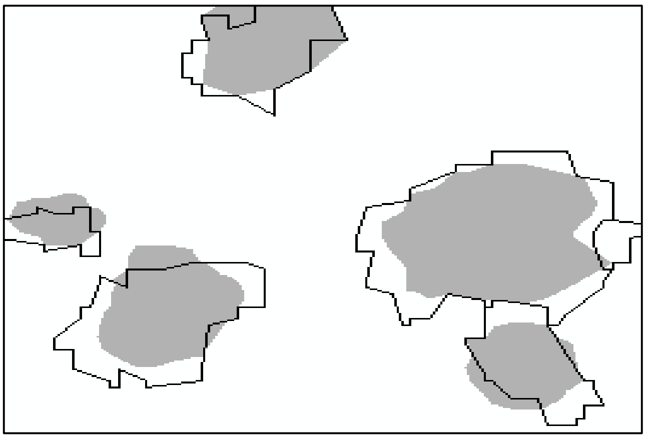


Figure 3.6 Validation of tree segments (black outline) with digitized crowns (grey)

The approach of assessing the segmentation goodness (D) was used. This process was used by Clinton et al. (2010) in their review of several segmentation accuracy measures. They came up with a modification of Relative Area measures, originally developed by Möller et al. (2007). The modified approach uses over-segmentation and under-segmentation as given in below in Equations 3.1 and 3.2.

Equation 3.1

$$Over\ segmetation = 1 - \frac{Area\ (x_i \cap y_j)}{Area\ (x_i)}$$

Equation 3.2

$$Under\ segmetation = 1 - \frac{Area\ (x_i \cap y_j)}{Area\ (y_j)}$$

Where x_i is the reference object (digitized), and y_j is the corresponding segmented object.

The values of over segmentation and under segmentation range within 0 to 1 (Clinton et al., 2010). A perfect segmentation is achieved when values for both over-segmentation and under-segmentation are equal to 0, then it is considered as perfect segmentation. It will mean that the segments and digitized reference polygons fit perfectly.

The D value (segmentation goodness) is further calculated from the over-segmentation and under-segmentation values. Equation 3.3 below shows the formula for calculating the D value.

Equation 3.3

$$D = \sqrt{\frac{Oversegmentation^2 + Under\ segmentation^2}{2}}$$

Similarly, D value also ranges within 0 and 1 with a D value of 0 meaning perfect segmentation. The closer to 0 the D value is, the higher the segmentation accuracy. Appendix 1 shows the flowchart for assessing accuracy segmentation.

3.7. Connectivity

Connectivity between non-cocoa tree patches was assessed based on nearness to each other. Based on the selected indicator species (Flying squirrels), a threshold distance of 25m (see Section 3.4) was used. This in effect means that trees within a distance of 25m from each other represent a connected patch and the area is thus considered connected for the functional use of the indicator species. The Aggregate tool in ArcMap (Environmental Systems Research Institute, 2015), which combines polygons within a specified distance of each other into new output polygons, was used to aggregate tree segments derived from the object based image analysis. The resulting polygons represented areas where trees are connected according to the set criteria. A flowchart showing how connectivity was assessed is shown in Appendix 1.

3.8. Crown Cover

Crown cover was calculated from the segmented crowns of non-cocoa trees as derived from the object-based image analysis. This was done to replace the visual estimations of percentage crown cover. Unlike the visual estimation, the element of bias or subjectivity was avoided in the automated process. However, it must be emphasized that the accuracy of the crown cover calculations is dependent on the accuracy of the segmentation.

A 100m by 100m grid was used in this process since crown cover is estimated and assessed at the farm level and minimum farm size in Ghana, as found in previous studies is 1 hectare (Acheampong & Dawoe, 2014). Area per hectares for each segment in the class "Trees" was calculated using Calculate Geometry tool in ArcMap. The percentage of this area relative to grid area (1ha) was in effect a measure of crown cover. Crown cover was then calculated as the percentage ratio of total area of tree crowns within a polygon of a stratum (dense or open) as defined in the sampling. See Appendix 1 for detailed flowchart.

3.9. Tree Density

A 100m by 100m grid was used to estimate non-cocoa tree density. This was done through a similar process to the crown cover quantification. The tree segments were intersected with a grid (Fishnet) of the study area. The resulting output gave polygons of trees in each grid. From this output, the count of tree segments per grid was used to represent the tree density, under the assumption that each segment represented an individual tree. A flowchart of operations conducted to calculate tree density is shown in Appendix 1.

3.10. Biomass

Above-ground biomass in kilograms was calculated for all non-cocoa tree segments derived from the OBIA. A tree allometric equation which is based on diameter at breast height (DBH), was used for the biomass modelling. Previous studies have also been conducted to successfully predict the DBH of a tree using its crown projection area (CPA) from a remotely sensed image (Verma et al., 2014). Hence CPA was used to predict the DBH of the non-cocoa tree segments. CPA as used here refers to the proportion of ground covered by the vertical projection of non-cocoa tree crowns (IPCC, 2003).

To build a DBH-CPA model, DBH and exact coordinates for 54 sample trees were acquired through field measurements and also from previous study in the same study area, conducted by ITC and Centre for Remote Sensing and Geographic Information Service, Ghana under a collaboration project which ended in 2014. The crowns of these sample trees were located on the image by their respective coordinates and digitized manually on the Worldview-2 satellite image. From each digitized crowns, CPA was calculated, using the Calculate Geometry tool in ArcGIS (Environmental Systems Research Institute, 2015).

The observed DBH of 30 of the sample trees was then regressed against their corresponding CPA to derive a DBH-CPA model. Equation 4.1 is derived from the resulting DBH-CPA model. The R^2 of the relationship was used as a measure of the robustness of the regression model.
After applying the DBH-CPA model, the remaining 24 trees were used to independently validate the model by comparing the predicted DBH with their corresponding observed DBH in a process known as cross-validation (Breu et al., 2012). In addition to R^2, root-mean-square error (RMSE) between predictions and observations was calculated as a measure of their differences(Henry et al., 2010).
Using the predicted DBH, the biomass for all non-cocoa tree segments was calculated with an allometric equation (Equation 3.4) which was derived in the Western Region, Ghana using the DBH (Henry et al., 2010). The equation resulted from study carried out in Boi Tano Forest Reserve, classified as wet-evergreen in the tropical rainforest ecological zone. It also has similar climatic conditions to that of the study area in this research.

Equation 3.4

$$\mathbf{Biomass} = \mathbf{0.29543} * (\mathbf{DBH})\verb|^|(\mathbf{2.3085})$$

The Field Calculator tool in ArcGIS was used to apply both the DBH-CPA model and the biomass model to the tree segments. A flowchart of steps taken for biomass estimation is shown in Appendix 1.

3.11. Assessment of Ecological Quality using Spatial Multiple Criteria Evaluation

The ecological quality of the cocoa landscape within the study area was assessed based on the identified indicators and norms. Spatial multiple criteria evaluation (SMCE) was used to assign values of ecological quality to each cell within the study area. A spatial analyses software Integrated Land and Water Information System (ILWIS), was used to conduct the multi-criteria analysis. Input maps for the SMCE were derived from the output of the assessment of the 3 indicators of ecological quality; patch connectivity, crown cover and biomass. For each objective, the indicators were assigned weights based on their relative importance for the specific purpose of this study. Table 3.3 below shows the input parameters for each objective in the SMCE.

Table 3.3 Inputs for Spatial Multiple criteria Evaluation

Objective	Input (Indicator)	Threshold	Standardization
Conservation	Connectivity of non-cocoa tree patches	up to 25m	1
		Otherwise	0
	Crown cover of non-cocoa trees(per hectare)	≥40%	The more the better
		<40%	0
	Biomass of non-cocoa trees		The more the better
Productivity	Non-cocoa Tree Density (per hectare)	15 to 18 per ha	1
		Otherwise	0
	Crown cover of non-cocoa trees (per hectare)	Up to 40%	The more the better
		>40%	0

In both objectives, all indicators were assigned equal weights of influence in the Criterion Tree. This is because the assigned weights depict a comparative importance of each indicator (M. Sharifi & Retsios, 2003) and sufficient information on stakeholder priorities was not acquired for this study as would be required for making such judgement. The values of all indicators were standardized between 0 and 1.

4. RESULTS

This chapter presents the results attained from the various activities conducted within the research methodology. Using tables, charts and maps, it shows the summary of results of field data collection based on the selected indicators and norms. It also outlines the outputs of the analysis of the individual indicators within the study area. Finally, it shows the final output of the ecological quality assessment in a map with description. The chapter is structured according to the specific research questions (RQ).

4.1. Field Data Collection

New empirical data on the parameters of non-cocoa trees within the study area was acquired from the field data collection. Table 4.1 below shows a summary of the data collected per land cover class. A total of 49 plots were sampled with most of them falling within the predominantly cocoa land cover.

Table 4.1 Summary of field data

	Land Cover			
	Cocoa	Forest	Other Farms	*Total*
Number of Plots Sampled	**37**	6	6	*49*
Average No. of Trees per ha	**27.30**	93.33	43.33	*33.88*
Average DBH per plot (cm)	**40.92**	38.12	17.20	*36.71*
*Average crown density (%)	**26.86**	76.67	23.00	*30.96*

*Average crown density was visually estimated in the field and as such was likely to be subject to bias.

The distribution of the tree parameters per land cover is shown by the graphs in Figures 4.1, 4.2 and 4.3.

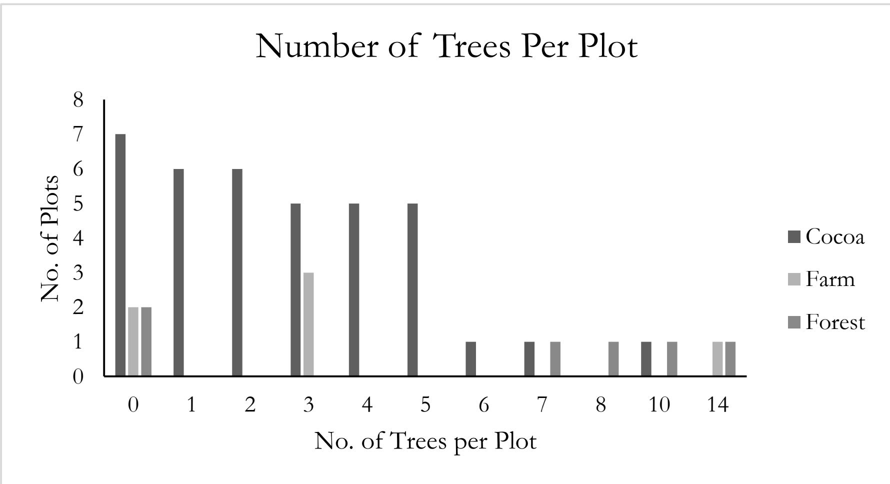


Figure 4.1 Distribution of number of trees per plot for each land cover

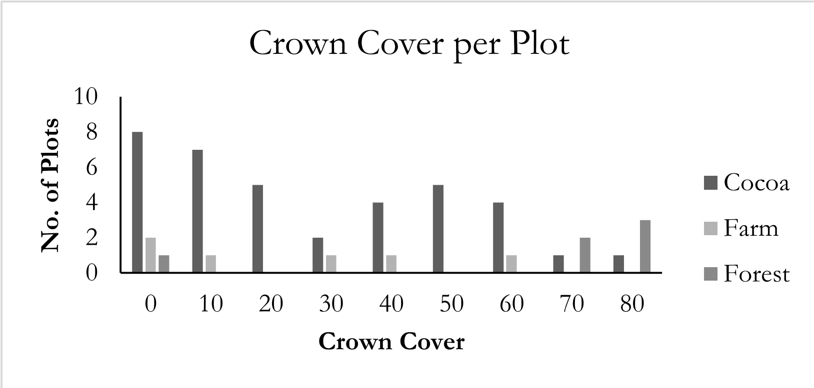


Figure 4.2 Distribution of crown cover per plot for each land cover

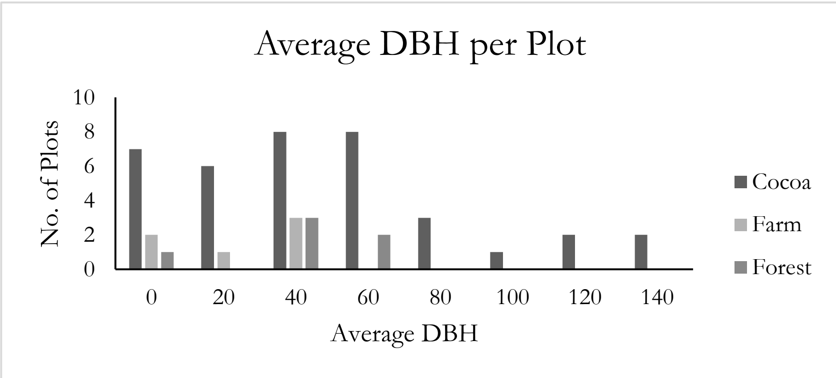


Figure 4.3 Distribution of average DBH per plot for each land cover

4.2. Segmentation Accuracy and land cover classification *(RQ 2a)*

Using object-based image analysis, the satellite image of the study area was segmented and classified into four land cover types based on differences in their spectral characteristics. The accuracy of segmentation in the OBIA was assessed for only the class "Trees" by comparing the amount of over-segmentation and under-segmentation of non-cocoa between the manually digitized and segmented tree crowns. The amount of over-segmentation was found to be 0.36 while under-segmentation was 0.51. Thus, a goodness of segmentation (D) value of 0.52 was attained for the class "Trees". This represents a very low accuracy and though insufficient to draw representative conclusions of the study area, is used in the study for the purpose of applying the approach.

The classes attained after classification were "Trees", "Cocoa", "Other Crops" and "Others". The study area was found to be predominantly covered by crops, with cocoa representing almost half of the total land cover. Non-cocoa trees were also found to cover about 30% of the total study area. The table 4.2 below shows the area distribution of the four land cover classes after OBIA and their corresponding percentage of the total.

Table 4.2 Distribution of area (in hectares) of four land cover classes within the study area

Land Cover	Area (hectares)	Percentage
Trees	353.55	30.38%
Cocoa	559.30	48.06%
Other Crops	123.74	10.63%
Others	127.05	10.92%
Total	1163.64	100.00%

The map in Figure 4.4 shows the output of the segmentation and classification using OBIA.

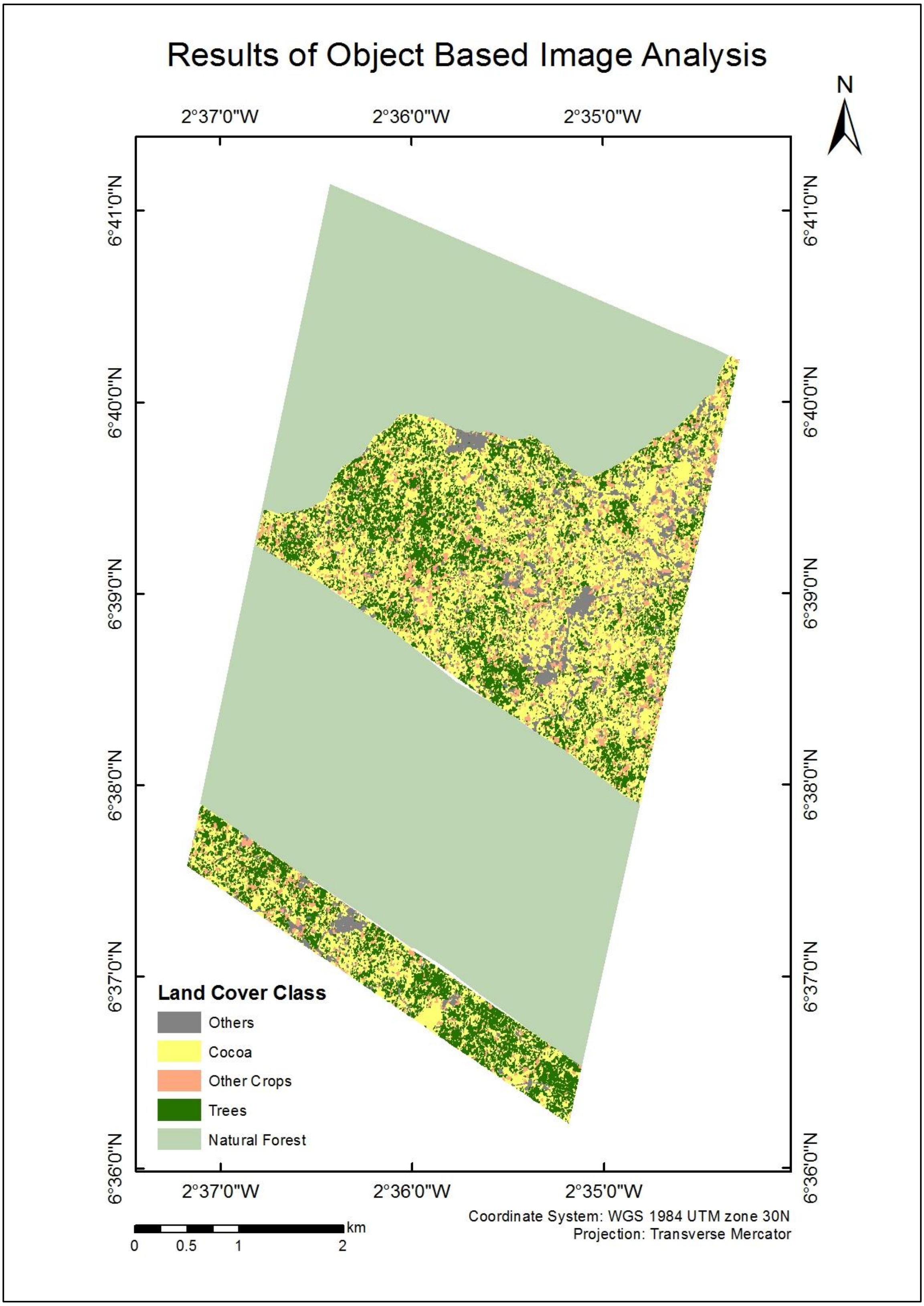


Figure 4.4 Map of study area showing land cover classes after OBIA

4.3. Quantification of Indicators and Norms *(RQ 3a)*

The following sub-section shows the outputs of the quantification of each the four identified indicators, namely tree density, crown cover, biomass and connectivity. The results for each indicator are categorized based on the respective norms and visually presented in an indicator map.

4.3.1. Tree Density

The tree density map (Figure 4.5) shows the number of non-cocoa trees per hectare at different parts of the study area after data analysis. It was found that tree density ranged from 1 to 43 per hectare. These have been categorized into three main groups; 1 to 14 trees per hectare, 15 to 18 trees per hectare and 19 to 43

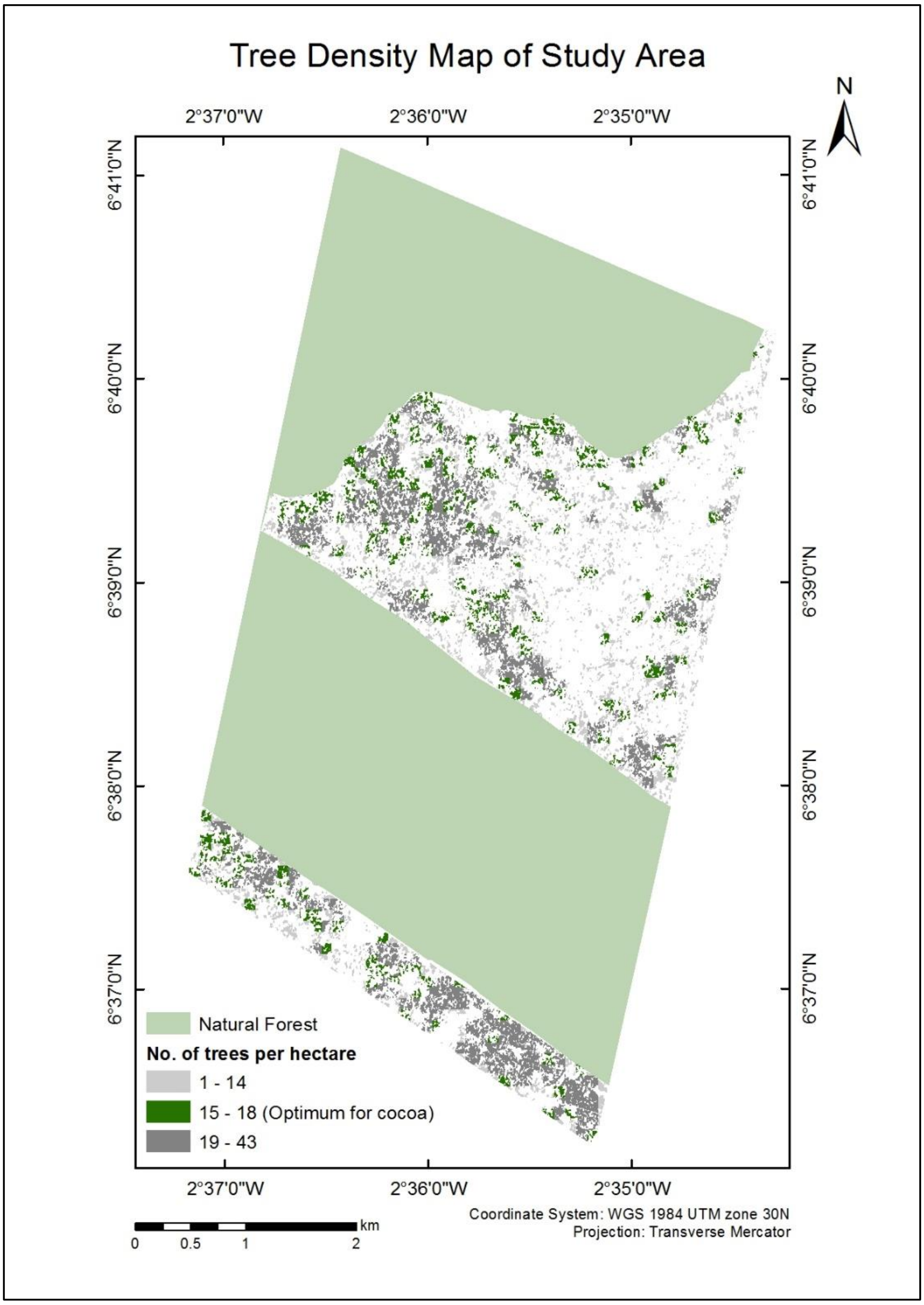


Figure 4.5 Map showing non-cocoa tree density in the study area

trees per hectare. Based on the guidelines in the Ghana Cocoa Manual, areas with 15 to 18 trees are considered suitable for cocoa productivity as there provide the recommended shade. More than 18 trees per hectare are therefore considered to be too much shade, and thus for cocoa production in these areas, excess trees must be removed to attain optimal shade.

Table 4.3 below shows the total number of non-cocoa trees in each category. A total number of 16,347 non-cocoa trees were found to be in the study area representing an overall density of 14 non-cocoa trees per hectare.

Table 4.3 Non-cocoa tree density distribution per land cover class in the study area

Tree Density (/ha)	Cocoa		Other Crop		Others		Total	
	Trees	%	Trees	%	Trees	%	Trees	%
1 to 14	4725	80.59%	556	9.48%	582	9.93%	5863	100%
15 to 18	2728	86.19%	277	8.75%	160	5.06%	3165	100%
19 to 43	6585	89.97%	479	6.54%	255	3.48%	7319	100%
Total	14038	85.88%	1312	8.03%	997	6.10%	16347	100%

4.3.2. Crown Cover

The map shown in Figure 4.6 is the output of the analysis of crown cover of non-cocoa trees. Crown cover, assessed per 1-hectare grid was found to range from 0.16% to 100% over the study area. These were categorized into two groups (0% to 40%) and (40% to 100%). From the assessment a total area of 778.05 hectares, representing 68.31% of the study area was found to have up to 40% crown cover. On the other hand, an area of 360.88 hectares, representing 31.69% of the study area had more than 40% crown cover. A more detailed summary of crown cover per land cover class from the results is shown in Table 4.4.

Table 4.4 Non-cocoa crown cover per land cover class in the study area

Crown Cover	Cocoa		Other Crop		Others		Total	
	Area (ha)	%	Area (ha)	%	Area (ha)	%	Area (ha)	%
Up to 40%	640.10	82.27%	69.09	8.88%	68.86	8.85%	778.05	100%
More than 40%	325.55	90.21%	25.23	6.99%	10.10	2.80%	360.88	100%
Total	989.50	86.88%	88.61	7.78%	60.70	5.33%	1138.93	100%

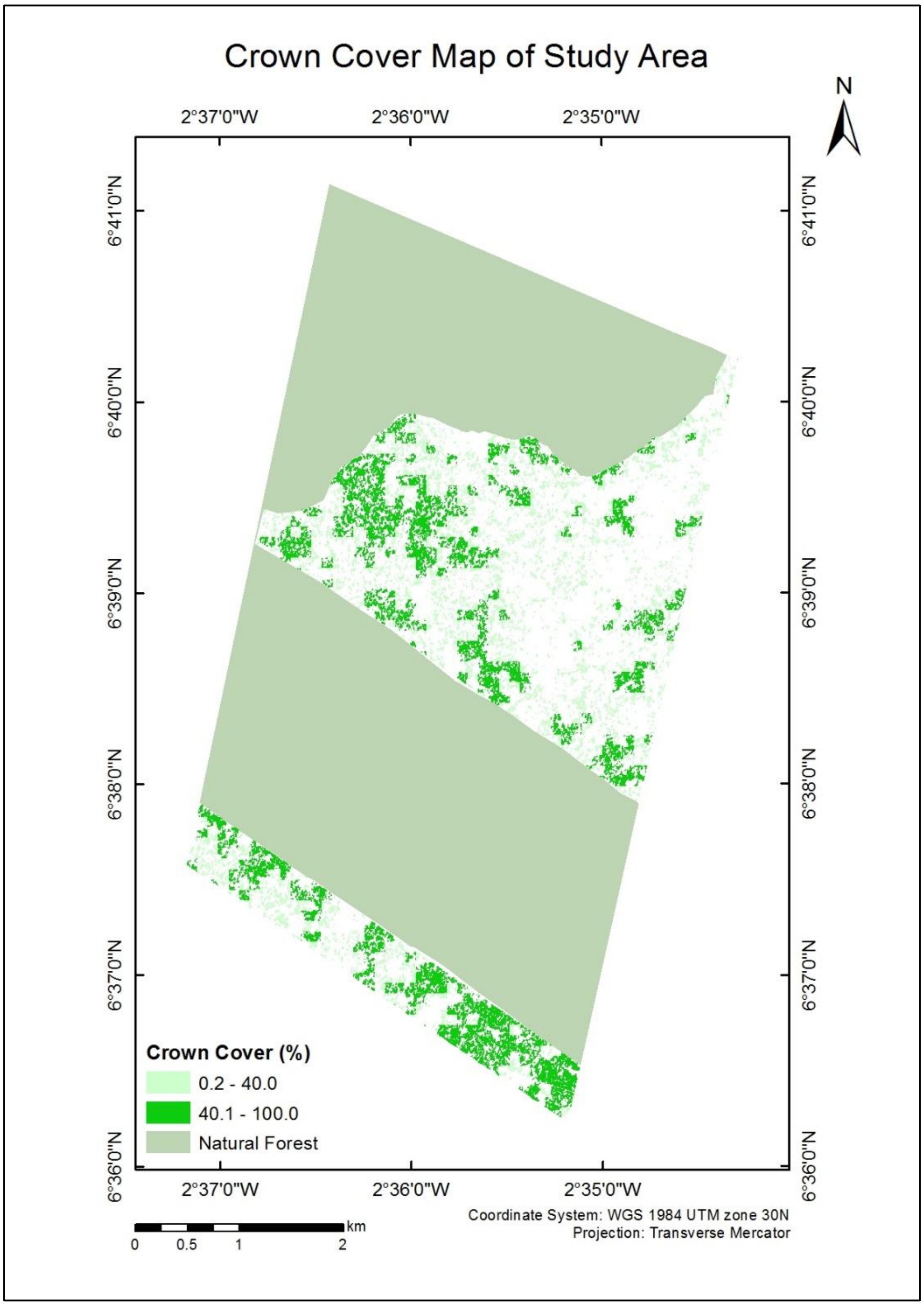


Figure 4.6 Map showing percentage crown cover per hectare on non-cocoa trees

4.3.3. Biomass

Figure 4.9 shows the map of non-cocoa tree biomass within the study area. The above-ground biomass of non-cocoa trees was estimated by applying an allometric equation (Equation 3.4) to their crown segments as described in Section 3.8. This equation uses DBH for the estimation of biomass. DBH was thus derived for each tree based on their CPA using Equation 4.1. Figure 4.7 shows the relationship between DBH and CPA for 30 sample non-cocoa trees. R^2 value of 0.71 means that the as a measure of the model robustness, the CPA values explain about 71% of the DBH values.

Equation 4.1

$$DBH = 0.1795 * CPA + 35.861$$

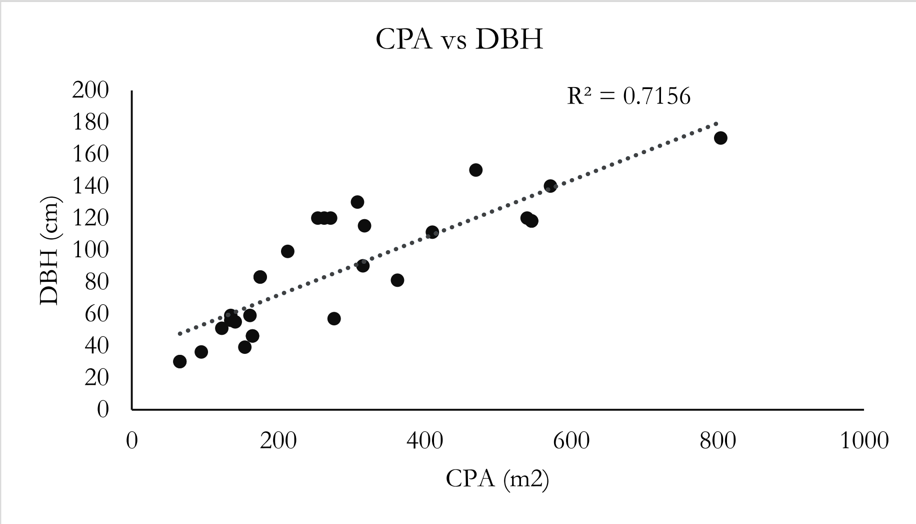


Figure 4.7 Relationship between DBH and CPA of 30 sample non-cocoa trees

The remaining 24 sample trees were used to validate the DBH model. The validation results are presented in the graph in Figure 4.8. It shows the relationship between the observed and predicted DBH of the 24 sample non-cocoa trees using equation 4.1. An R^2 of 0.66 is recorded for the validation. A root-mean-square error (RMSE) of 22.86 was recorded, representing the difference between predictions and observations.

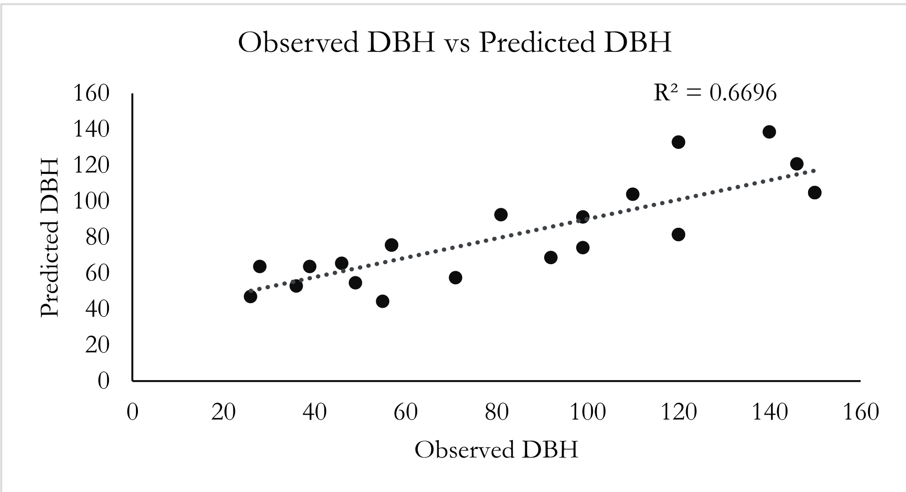


Figure 4.8 Relationship between observed and predicted DBH for 24 sample non-cocoa trees

Total non-cocoa tree biomass within the study area was found to be 140,512 tonnes. The biomass for non-cocoa tree segments was found to range between a minimum of 1,146 kg and a maximum of 964,967 kg. Biomass per hectare in the landscape was 1163.64 kg. Table 4.5 shows the total biomass per land cover class.

Table 4.5 Biomass (tonnes) per land cover class

Land Cover	Biomass (tonnes)	%
Cocoa	122,076.11	87%
Other Crop	10,974.34	8%
Others	7,462.38	5%
Total	140,512.84	100%

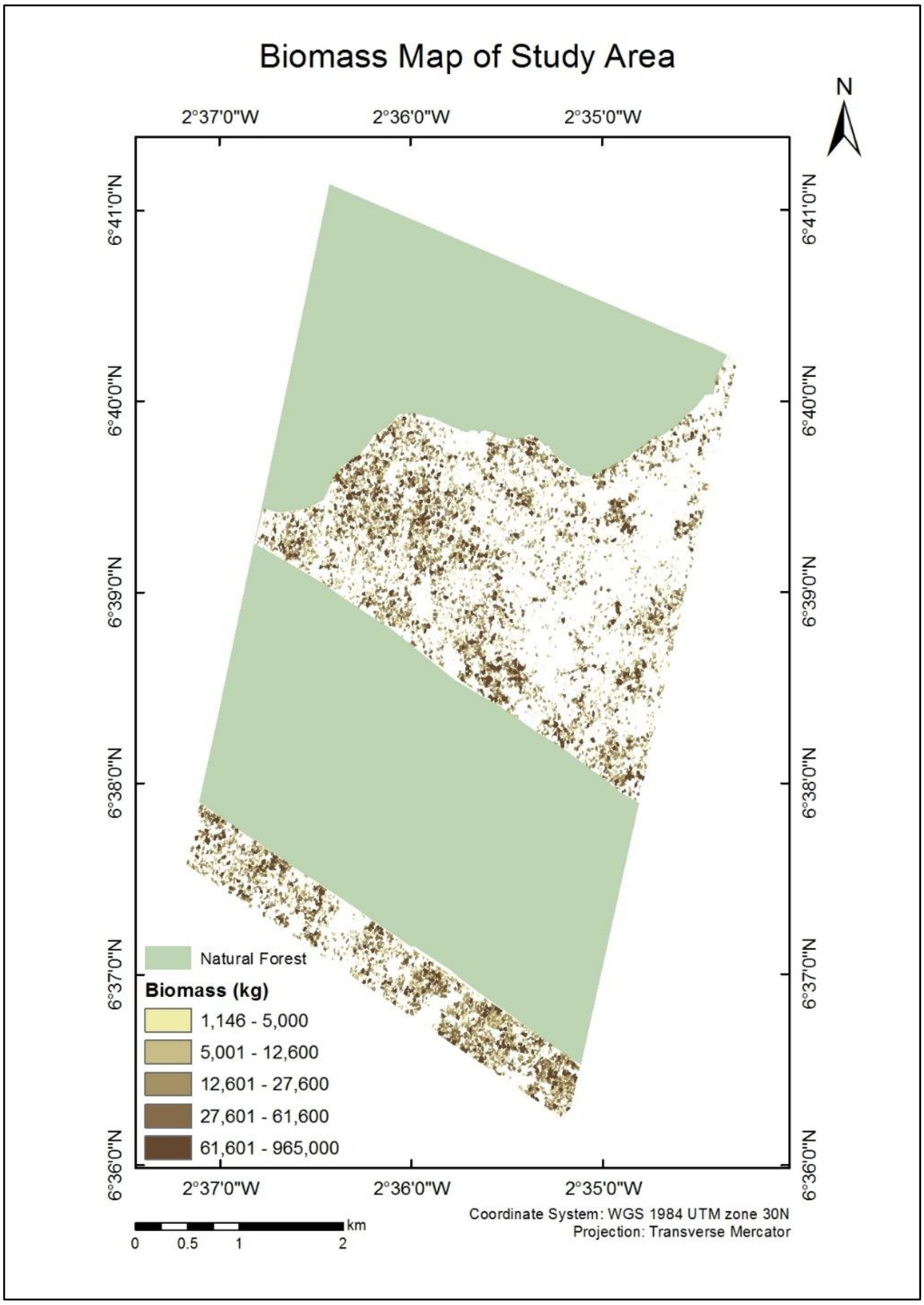


Figure 4.9 Map showing biomass (in kilograms) per tree for non-cocoa trees within the study area

4.3.4. Connectivity

The output of the assessment of connectivity is shown visually by the map in Figure 4.10. Areas where trees are connected, thus within a distance of 25m of each other are shown as aggregated polygons. A total of 324 patches covering an area of 573.16 hectares was found to meet this connectivity criterion. The mean patch size of connected trees was 1.77 hectares while the largest connected patch was 284 .41 hectares.

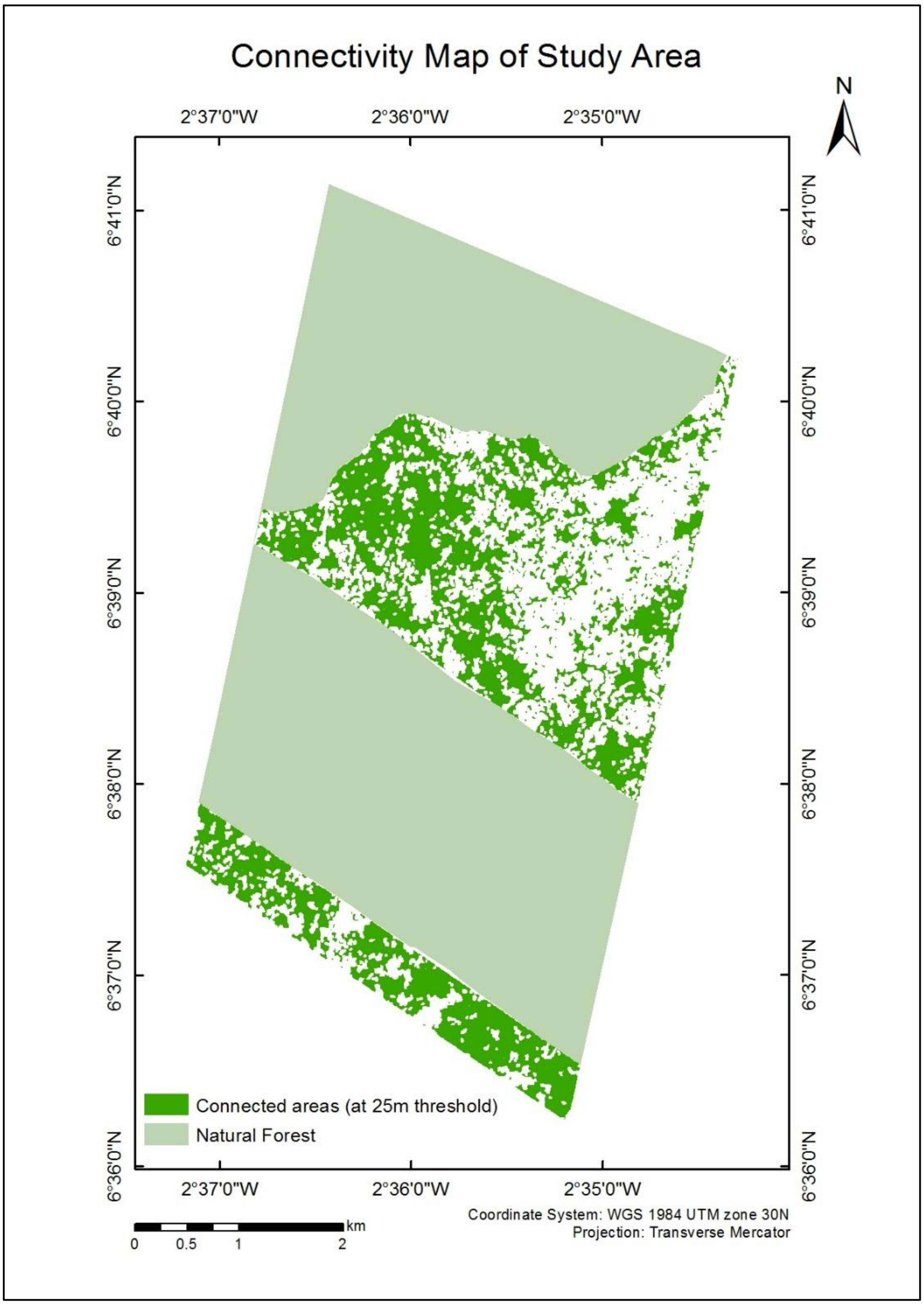


Figure 4.10 Connectivity map of the study area

4.4. Outputs of Ecological Quality Assessment *(RQ 4b, c)*

The outputs of the indicator quantifications were combined in a spatial multi-criteria analysis based on the two Objectives. The following subsections show the resulting maps for each assessment objective. Finally, the resulting maps for both objectives were combined to show the score of areas for both conservation and cocoa productivity.

4.4.1. Conservation Objective *(RQ 4b)*

The following map in Figure 4.11 shows the results of the assessment of ecological quality based on The Conservation objective. It shows the output of a spatial multi-criteria analysis that combined the standardized indicator maps of connectivity, crown cover and biomass within the study area.

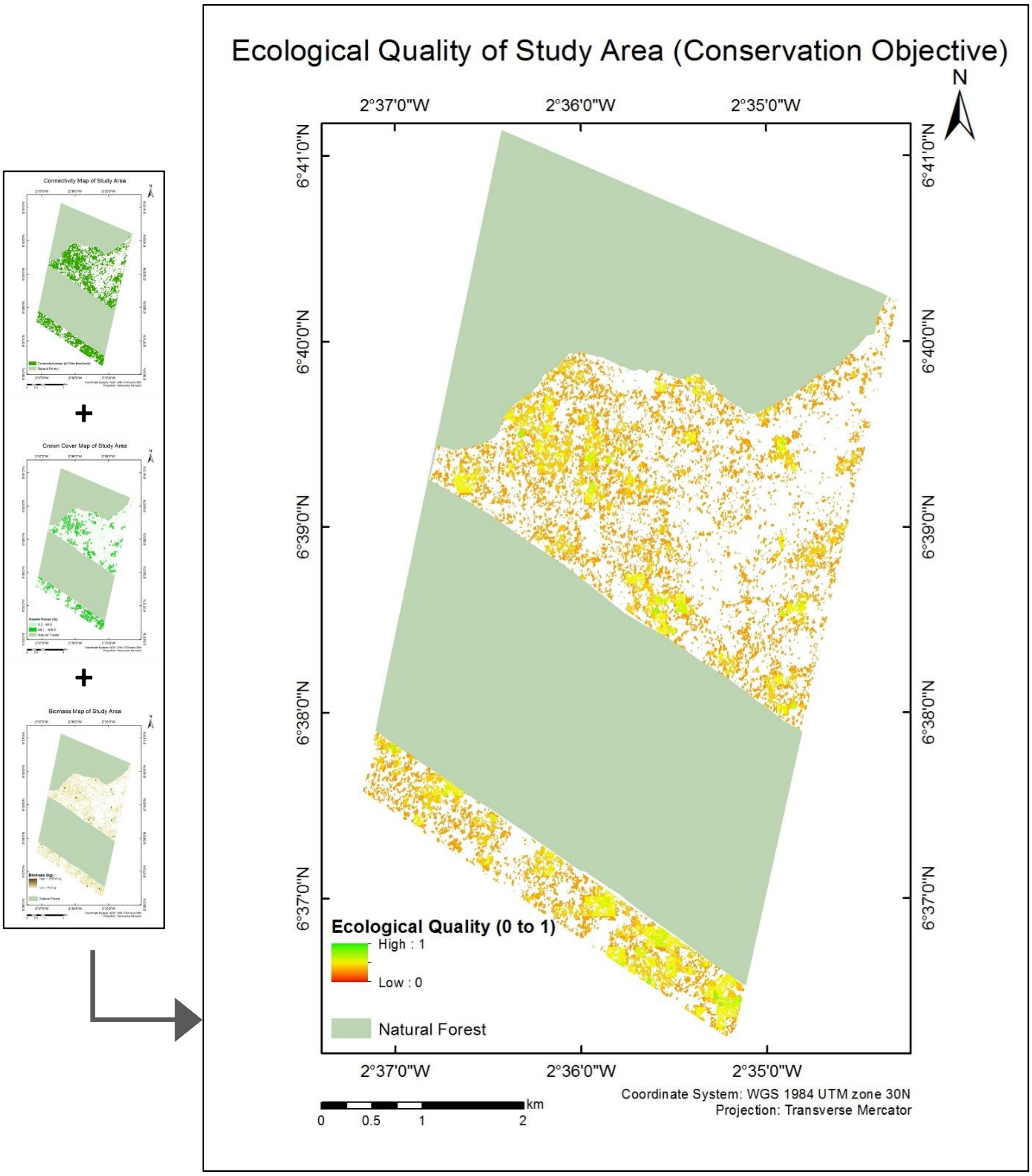


Figure 4.11 Map showing Ecological Quality within the study area based on Conservation Objective

The ecological quality of each area is scored between a range of 0 (lowest quality) and 1 (highest quality). The minimum score in the area was found to be 0.33, represented by a total area of 23.05 hectares. The maximum score attained was 0.86, found for an area less than 1 hectare. The most prominent score was 0.34, which covered the largest area of 98 hectares.

4.4.2. Cocoa Productivity Objective *(RQ 4b)*

The output map for Cocoa productivity Objective is shown in Figure 4.12. The map results from the combination of indicator maps of tree density and crown cover standardized based on their respective norms.

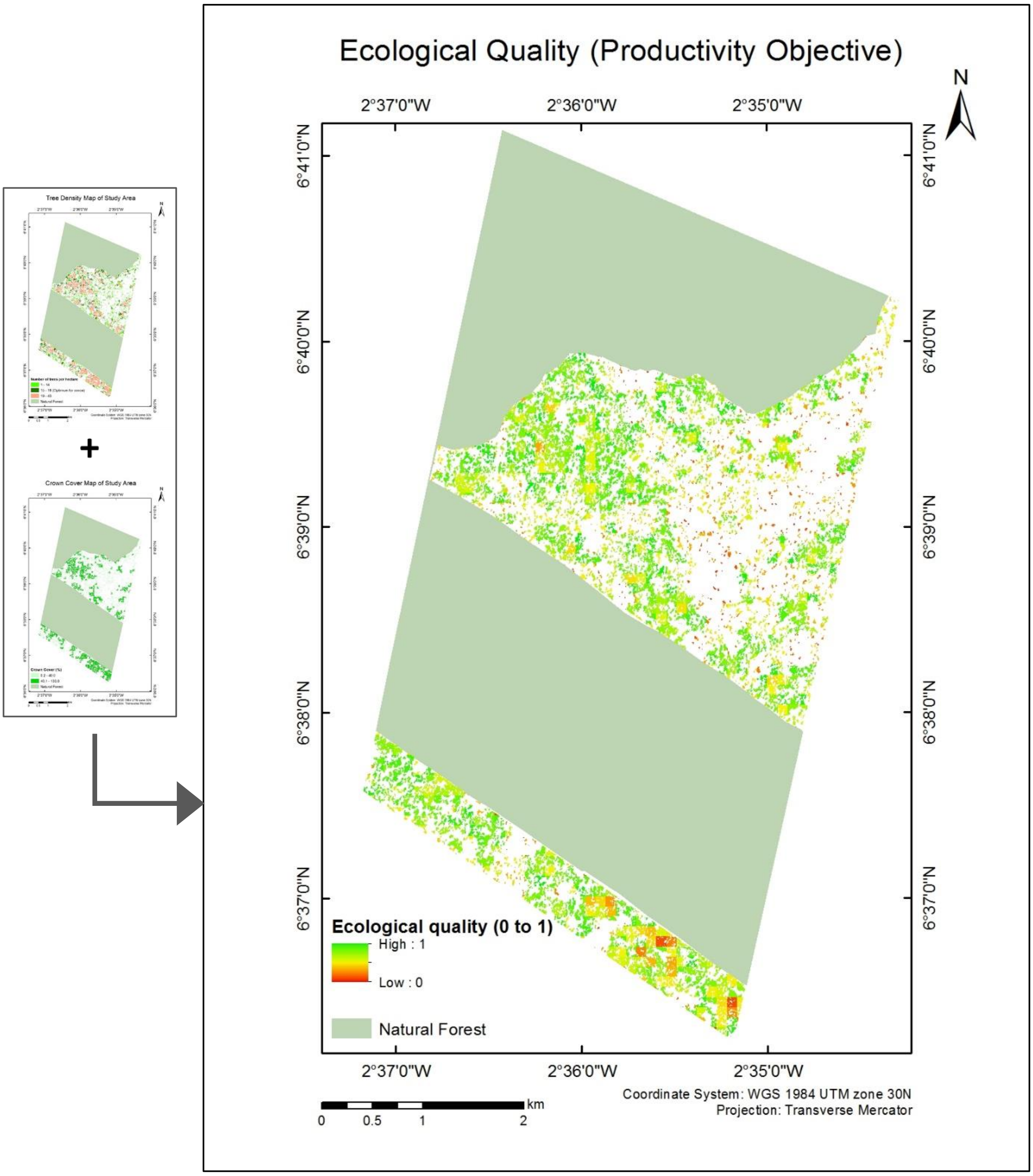


Figure 4.12 Map showing Ecological Quality within the study area based on Productivity Objective

The resultant map shows the suitability of each area, standardized between a range of 0 (unsuitable) and 1 (highly suitable). The highest suitability score of 1 was found to cover 3.1 hectares of the study area. On the other hand, the lowest score of 0 was found to cover an area of 0.02 hectares. The score of 0.84 was found to cover the largest area of 11.58 hectares.

4.4.3. Potential Suitability for Certification based on four Indicators *(RQ 4c)*

The map in Figure 4.13 shows the output after combining the outputs of the Conservation and Productivity objectives. The map gives a final score for each location in the study area, standardized between 0 and 1. A low score represents areas that have low ecological quality from a conservation perspective as well as low suitability for cocoa productivity based on the assessed indicators in the context of SAN certification. The lowest score recorded was 0.19, recorded over an area of $96m^2$. The highest score of 0.87 was also recorded over an area of 0.1 hectares. A score of 0.66 was found to be most prominent covering a total area of 25.06 hectares. The map was reclassified into based on their potential suitability for certification based on the quantified indicators only. Areas with a score less than 0.5, considered unsuitable totalled 62.45 hectares while areas with a score greater than 0.5, considered suitable totalled 291.7 hectares. Based on the thresholds, 24% of cocoa land cover fall under potentially suitable areas while 76% fall into unsuitable areas.

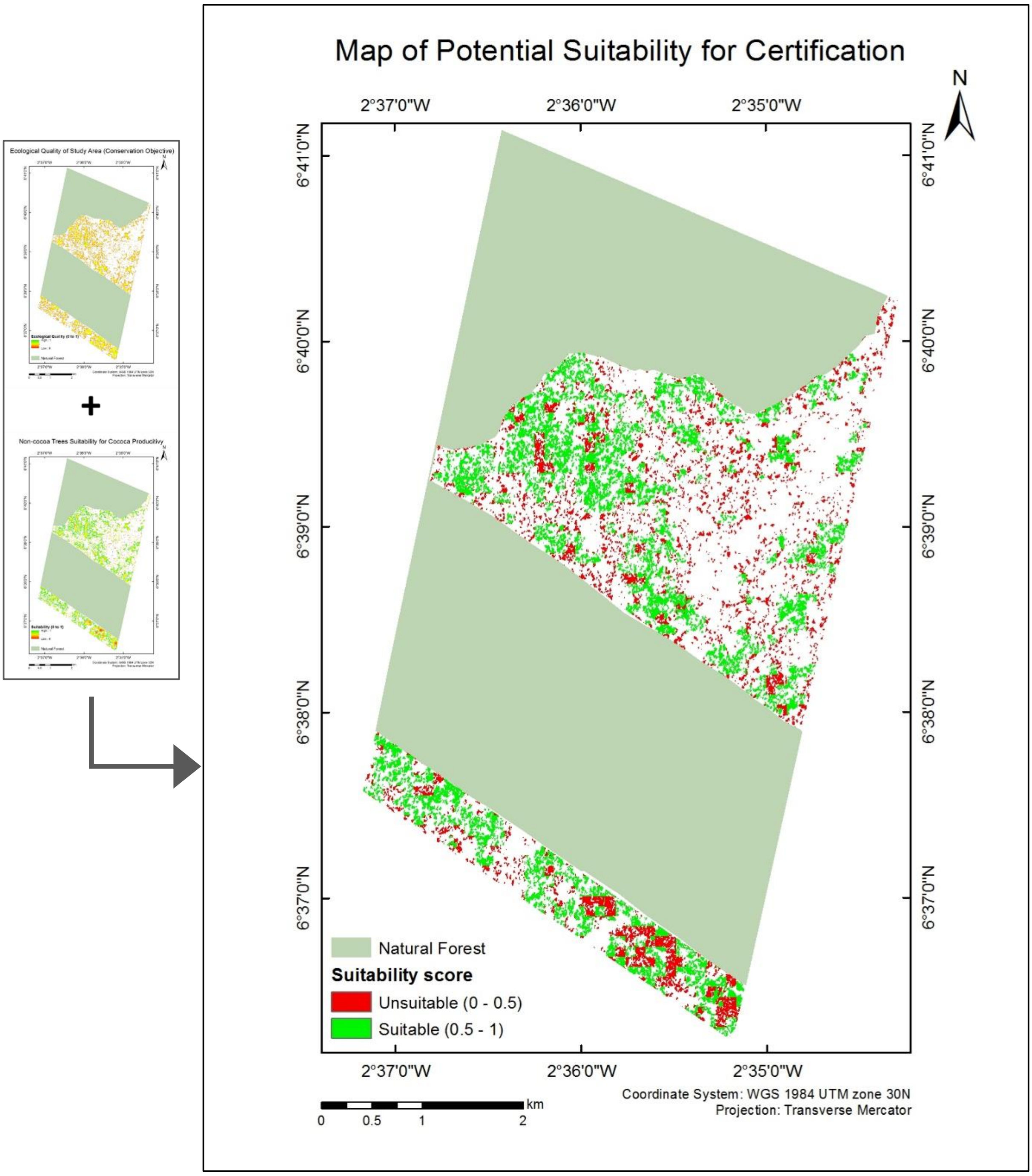


Figure 4.13 Map showing combined score for both Conservation and Productivity objectives

5. DISCUSSION

This chapter presents an analysis of the method developed in this study, sources of errors and implications of low accuracy and the general applicability of the assessment methodology.

5.1. Indicators and Norms of Ecological Quality

It cannot be overstated that the assessment of ecological quality and similar landscape status must be done based on a specific purpose or management objective. This purpose must be based on stakeholder need, identified through processes such as effective consultation and review of standards and guidelines. The need to take into account stakeholder priorities is highlighted by several studies (Deat, 2004; Hickey & Innes, 2008; Théau et al., 2015). Similarly, in the process of identifying indicators, effort must be made to ensure they are specific, relevant and measurable to be able to draw applicable conclusions. This is seen in the study of Hickey & Innes, 2008 where they mention that their hierarchy of indicators of sustainable forest management ensure they are broad enough to apply at landscape level but specific enough for local management units as well. This can be achieved by reviewing applicable standards, legislation and guidelines. Measurability of indicators is another key issue. While may be easily achieved with discrete and continuous indicators (e.g. density, abundance, financial cost), it is more cumbersome with categorical indicators (e.g. goodness, quality, social cost). A number of indicators are used in this assessment instead of a single indicator in an attempt to represent the intricate and complex status of the landscape (Noss, 1990). This use of multiple indicators is common in most assessments of the status of an ecosystem (Aguma, 2002; Andam et al., 2008; Parkes et al., 2003; Wang & Li, 2008).

Similarly, norms for identified indicators must also be well-grounded on acceptable requirements. From the stakeholder discussions conducted in this study, certification auditors highlighted the indicators of tree density and shade (non-cocoa tree cover) as the main indicators that are observed in the field for assessing criteria 2.8 and 2.9 of the SAN standard. Cocoa extension officers also mentioned the same indicators as the non-cocoa tree characteristics they monitor as too little or too much shade affects cocoa yield negatively. In this study, the selected indicators are based on the SAN certification standard and local interpretation for Ghana (connectivity, crown cover), Ghana Cocoa Manual (tree density, crown cover) and literature (biomass) (Parkes et al., 2003). These sources are chosen because they represent the stakeholder perspectives that are used in the formulation of the two assessment objectives (Conservation and Productivity). The norms are identified from the same sources. However, for connectivity, since specific guidelines are not given in the SAN local interpretation, the observed movement characteristics of an indicator species, the Flying Squirrel was used. This introduces the element of functionality for an organism into the assessment for the conservation objective. The use of an indicator species can also be said to be a traditional practice, well established and applied in ecology, forestry and related fields (Noss, 1990). The choice of the four indicators is comparable to previous studies such as Parkes et al., 2003 where similar indicators are included in the so-called "habitat hectares approach to assessing the quality of native vegetation. Other studies have used some connectivity indices as part of indicators for assessing the functionality of ecological networks (Théau et al., 2015). Vegetation mapping and monitoring studies also usually take into account their structural attributes such as density and cover (Skidmore, 2002). Biomass, and in effect carbon storage, is being increasingly used in assessments and monitoring of sustainable production (Stupak et al., 2011). High biomass is indicative of large and old trees. Such trees represent a high value within a landscape because of their role in maintaining biodiversity by serving as seed banks or desirable "mother trees" for natural regeneration. They also provide habitat and food for a wide range of animals, including the Flying squirrel.

5.2. Landscape Overview

From the output of the OBIA, it can be seen that the non-cocoa trees are scattered over the study area, without a clearly distinguishable pattern. Visually inspecting the resulting land cover map, the non-cocoa trees are also seen to occur mostly within cocoa and other farms, and less so around the settlements and built-up areas. Instead, closer to the settlements (class "Others"), the cocoa and other farms are more predominant. This confirms the preference for farming near the home as found by other studies (Nyaga et al., 2015). Non-cocoa trees are also seen in bigger clusters farther away from the settlements. Larger tree clusters may be attributed to areas where traditional cocoa farming is still being practiced or areas that may be inaccessible or unsuitable for cocoa farming due to their terrain or marshy nature.

Many areas classified as cocoa and other farms have no non-trees occurring there at all. This is also in agreement with the findings of data collection where many plots had tree density value of zero. From the same results, some plots had very high average DBH (>100cm). This is because such plots usually had one or very few very large trees with big DBH. Similarly, other studies in Ghana also found few forest trees per cocoa farm (Asare et al., 2014; Ruf, 2011).

5.3. Interpreting outputs

The results of analysis of the selected indicators are presented as quantities that need to be translated into meaningful interpretations about the landscape in terms of the intended objective and in the perspective of the stakeholder. For instance, the SAN local guidelines used in this study are meant for implementing good agricultural practices and also provide guidance in audits (Sustainable Agriculture Network, 2009). In effect, the attributes associated with maps must be translated into "conformance" or "non-conformance" to the relevant requirement. To do this, the applicable norms, identified for the indicators must be applied.

For connectivity, areas within the defined threshold of 25 meters are considered connected (for the indicator species) and all other areas are not connected. For biomass, more is better in terms of conservation as higher biomass is expected in bigger trees whose loss would significantly affect the carbon stock (Acheampong & Dawoe, 2014). For the crown cover, 40% shade is recommended in both objectives. However, while more than 40% shade is considered positive for the conservation of habitats, it is undesirable for cocoa productivity and even suggests that the excess shade must be removed for optimal cocoa growth (Cocoa Research Institute of Ghana, 2010). This divergence of opinion on the interpretation of tree density and shade was further confirmed in the stakeholder discussions. The importance of stakeholder perspective is thus re-echoed in the interpretation of outputs. Thus, areas that will be conforming to a requirement depend on the norms which are in turn dependent on the assessment objective. It is, therefore, imperative in an assessment of ecological quality that norms for the selected indicators be representative of stakeholder opinions and priorities.

5.3.1. Connectivity

The approach of measuring connectivity in this study by use a threshold distance based on an indicator species is similar to that of Burel & Baudry, 2005 in their assessment of habitat quality and connectivity on agricultural landscapes. Several other studies using similar and diverse approach such as least cost path geometry, structural geometry, weighted and unweighted linking and graph assembly metrics are discussed in the study by (Galpern et al., 2011). The output of connectivity assessment shows that, although about half of the total study area meets the connectivity criteria, these are made up of scattered "patches" of connected areas. The largest of these connected areas covers almost a quarter of the study area, with the remaining made up of much smaller dispersed patches. This is visible in the patterns shown on the output connectivity map.

Visual comparison of the connectivity map with the land cover map shows that along the natural forest boundaries, there is evidence of connected non-cocoa tree patches, intermittently disrupted by settlements (class "Others") on the boundaries. From the functional perspective of the flying squirrel, these patches are potential "pathways" for moving between the protected natural forest and the cocoa landscape. Larger patches of connected areas are seen to occur farther away from the bigger settlements. From a management perspective, these areas are important for conserving native habitat and vegetation. On the other hand, cocoa and other farms with no little to no connected patches are areas for potential agroforest establishment asserted by Asare et al., 2014 and Ruf, 2011.

5.3.2. Biomass

A simple linear regression model was used to predict DBH because there is only one independent variable (CPA), an assumption of linear models (Breu et al., 2012). For biomass, more is considered better as posited by several other studies, with the arguments including their representation of mature bigger trees, which serve as seed banks, nesting places among other ecosystem services (Basuki et al., 2009; Hartley, 2002; Henry et al., 2010).

From the output biomass map of the study area, some non-cocoa tree segments are seen to have very high biomass values. Although very large trees occur, extreme values are potentially due to multiple adjacent crowns which were not separated by the segmentation and classified as one. Furthermore, apart from a few exceptions, that similar biomass values are observed across the landscape, with slight variations. This is consistent with the description of trees outside forest reserves in Ghana as "highly scattered" (Gelens et al., 2010). The contribution of these isolated trees to the overall landscape biomass also goes to confirm their importance in the broader context of landscape restoration (Rietbergen-McCracken et al., 2012). Consistent with the connectivity, lower biomass values and fewer scattered trees are seen closer to the settlements, compared to the higher biomass values in larger clusters closer to the protected forest. Large areas of cocoa farms are also seen to have little or no non-cocoa tree biomass. This could be potentially attributed to "full sun" cocoa farming as described by (Ruf, 2011).

5.3.3. Tree Density and Crown Cover

For the quantification of tree density and crown cover, it is shown that the method applied allows for a general landscape overview. Using grids of appropriate dimension, the tree density and crown cover per unit area can be derived. Several other studies also used tree count per unit area to represent tree density (Vaast & Somarriba, 2014; Verma et al., 2014; Vernes, 2001). The results show that only about 20% of the area has optimum tree density for cocoa production. Also, 68% of the study area had up to 40%. The remaining 32% with more than 40% shade are areas considered high ecological quality for conservation but also unfavourable for cocoa productivity. The field data summaries also show that most samples plots had very few or no trees as well as crown cover, especially in the cocoa land cover class. This could be attributed to the cultivation of newer hybrids which require less shade.

From visual inspection of the tree density and crown cover maps, it is seen that most areas with the high tree density also have high crown cover. The few exceptions can be attributed to a few individual trees with very big crowns or conversely many trees with smaller individual crowns. Closer to settlements (class "Others"), both crown cover and tree density are low. Along the natural forest, higher crown cover and tree density are observed, although this pattern is not continuous.

From a management perspective, low tree density and crown cover are areas for potential non-cocoa tree establishment, either for conservation or for optimum cocoa productivity. The dilemma arises however in areas with more than 40% shade and/or more than 18 trees per hectare. While this is favourable in conservation, cocoa productivity guidelines recommend the removal of excess trees/shade (Cocoa Research Institute of Ghana, 2010). The SAN certification standard (Criterion 2.1) attempt to address this with requirements that prohibit the removal of existing natural ecosystems for farming purposes (Sustainable Agriculture Network, 2010).

5.4. Sources of Error

Some identified primary and secondary sources of errors and uncertainty are discussed below.

5.4.1. Field data collection

A primary source of errors and uncertainty in the assessment of ecological quality is the collection of field data (Rae et al., 2007). Field observations were used to acquire empirical data for accuracy assessment of segmentation, for biomass modelling and to validate automated quantifications such as.

Crown cover of non-cocoa trees was estimated visually in the field when it was impractical to use the densitometer due to the underlying cocoa canopy. This visual estimation inevitably introduces subjectivity and uncertainty in the data collected which will then be propagated throughout the analysis. This was addressed by automatically calculating crown cover based on the digitally segmented non-cocoa trees. Although this addresses the issue of subjectivity, it must be noted that the inherent low accuracy of segmentation means that the resulting crown cover calculations are also not reliable. Other studies used crown diameter measurements (mean of major and minor axes) measured on the ground (Kalita et al., 2015). Digital photographic tools such as fish-eye cameras have been found as a useful and inexpensive alternative for quantifying tree canopy properties, although they have a major drawback in their output sensitivity to exposure and image processing (Chianucci & Cutini, 2013).

It is worth noting that, as confirmed by discussions with field auditors and cocoa extension officers in Ghana, visual estimations are mainly used by auditors in current farm assessments for requirements such as percentage cover of non-cocoa shade trees.

5.4.2. Segmentation

Secondary sources of error occur during data analysis and processing (Rae et al., 2007). Image segmentation of relevant land cover classes is the foundation of the assessment of ecological quality in this study. It is the process used to identify and map the main areas of interest, non-cocoa trees, cocoa, other crops and other land covers. The quantifications of all indicators are conducted on the output of the object based image analysis, specifically on non-cocoa trees. Therefore, it is crucial that the segmentation and classification of objects be as accurate as possible. The issue of error propagation is also important here as the errors in segmentation are carried on in subsequent analyses and estimation.

The accuracy of segmentation of the class "Trees" in this study, represented by a goodness of fit (D) value of 0.52 is very low as compared to other studies using a similar classification approach in similar conditions (Mutanga, 2012; Tesema, 2015). This also implies that the accuracy of segmentation must be improved for application in real management cases. However, with the broader objective of developing a method of assessing ecological quality only, the subsequent steps were carried out using the acquired output. The low segmentation accuracy is attributable to a number of factors. First, the four bands of the available Worldview-2 image was not sufficient to accurately differentiate the reflectance characteristics of the different vegetation types (non-cocoa trees from cocoa). The brightness values alone were adequate to separate shadows. A simple ratio of Band 4/Band 3 was also enough to identify vegetation from non-vegetation cover. However, due to overlapping reflectance characteristics of cocoa and non-cocoa trees in the available bands and band combinations, separating them in classification was a challenge. It is expected however that the addition of height data in the OBIA will improve accuracy and help differentiate the two vegetation types. This approach is seen in Tesema, 2015 where Light Detection and ranging (LiDAR) data was used together with Worldview-2 image. Boggs, 2010 also attains accuracies from 85% to 95% after OBIA, using QuickBird imagery with similar spectral bands as used in this study and spatial resolution of 0.6m for mapping tree cover in savannas. This and further refining of the algorithm for OBIA are expected to improve results.

5.4.3. Biomass estimation

Tree height data, which was acquired using the Haga clinometer was considered inaccurate for the estimation of biomass. To address this, an allometric equation which uses only DBH was used for biomass modelling. Again, more accurate height data, for instance, acquired from laser based height measurement would be more suitable for inclusion in the modelling and improve accuracy. DBH for all trees segments was estimated was based on a regression between DBH of tree samples taken in the field and the CPA of their respective manually digitized crowns on the satellite image. Limitations in the biomass modelling such as being based on only a small number of samples and not being species specific could account for errors in the predictions(Breu et al., 2012). Verma et al., 2014 in their study used 172 individual trees and 52 tree clusters of *Eucalyptus* to build an allometric equation for estimating their DBH based on crown projected area. A manual for building allometric equations also recommends the taken into account of natural variability for building allometric equations (Breu et al., 2012).

The result of the DBH model depends on the sample taken and is likely to change significantly when different samples are chosen. Other studies use bootstrapping to address issues of small samples (Taskinen & Warton, 2013).

Additionally, from the graph of the validation of DBH (Figure 4.8), it is visible that the trend line does not go through the origin. This means that at 0 observed DBH, the model still predicts a positive DBH value. These factors underlie the need for a more robust DBH model.

5.5. General Applicability of the Method

The method applied in this study is intended for adaptation in management decision making for specifically identified objectives such as in certification audits, environmental baseline assessments. This goes to further the argument in favour of the potential role of GIS and remote sensing application to support certification and monitoring of natural resources (M. A. Sharifi & Hussin, 2004). The use of GIS and remote sensing also facilitates assessments of indicators that are otherwise cumbersome to be carried out on the ground, such as connectivity. This approach provides the opportunity for a landscape-level instead of farm-level assessments, as currently used in voluntary certification and monitoring.

Different levels of information can, however, be derived from this approach. At the landscape level, patterns of ecological quality and their indicators can be observed and compared over time. This information will be useful for landscape level management in land use and policy decision making as well as impact monitoring over time.

Farm boundaries can also be overlayed on the outputs of landscape assessments for more detailed interpretation. This could be particularly useful for voluntary certification assessments which are limited to the boundaries of participating farms. Ecological quality can also be compared between certified and uncertified farms as a means of assessing the impact of certification based on the selected indicators.

Pixel level information may also be derived for specific points of interest to inform further management decision. These could be points of disease outbreak (example CSSVD), currently monitored by the Monitoring and Extension Department of Ghana Cocoa Board.

The possibility of using Google Earth imagery for the assessment was explored as this would be a cheaper and more operational alternative to the Worldview-2 image. However, it was found that Google Earth Imagery was available for free download in Red, Green and Blue (RGB) bands (.jpg format). This was considered not independently suitable for separation of vegetation cover classes such as tree crowns and farms. Also, since several separate tiles of images were required to cover the extent of the study area at a high enough resolution, georeferencing errors would lead to shifts at the joints of tiles that would further introduce errors in segmentation and subsequent analyses.

6. CONCLUSION AND RECOMMENDATION

Although the results obtained in this study are based on low accuracy inputs such as segmentation and estimation of biomass, the method applied for the assessment of ecological quality is proposed as useful and practical, not only in telling the status of a landscape but also for monitoring the performance over time of the landscape based on identified indicators.

The use of a remote sensing and GIS-based approach provides various levels of information on ecological quality depending on the level of detail required in a specific use case. At the landscape level, the outputs give an overview of the ecological quality from which patterns can be determined. This is particularly important as a guide to support landscape-level management decision. It will also be useful for monitoring the impacts of implementation of such decisions by comparing changes in quality over time. Farm level ecological quality can also be derived by overlaying the boundary of farms. This will be exceptionally useful for purposes related to certification and sustainable management. Ecological quality can be compared between uncertified farms and farms implementing some sustainability measures (such as certification), as a measure of the impact of such measures. Within individual farms, areas of low ecological quality can be identified and corrective actions taken in preparation for certification audits. Finally pixel-level ecological quality can be derived when required for specific points of interests.

For application of this approach in real case situations, it is recommended that the method be subject to further research and refinement as well as constructive stakeholder feedback. To ensure applicability and to meet the full potential of this promising approach, it is recommended that the research be scaled up beyond the initial goal of meeting an academic requirement into the scope of a full-scale project. The following improvements must be incorporated in such follow-up:

- Segmentation of non-cocoa trees should be improved by refining OBIA algorithm and including spatial height data (LiDAR). This will provide a more accurate input for the assessment of the indicators, leading to subsequently more accurate outputs.
- More rigorous field data collection, leading to more representative field samples for biomass estimation and for validating segmentation. The assessed indicators must also be compared with their corresponding field observations as a means of verification. This is expected to minimize errors and hence increase the accuracy of the derived outputs.
- Stakeholder consultation should be conducted to identify indicators and norms. It is also important to ascertain weights of indicators for different objectives at the local level based on stakeholder priorities and needs. This will then be used to improve the building of Criterion Tree in the spatial multiple criteria evaluation (SMCE).

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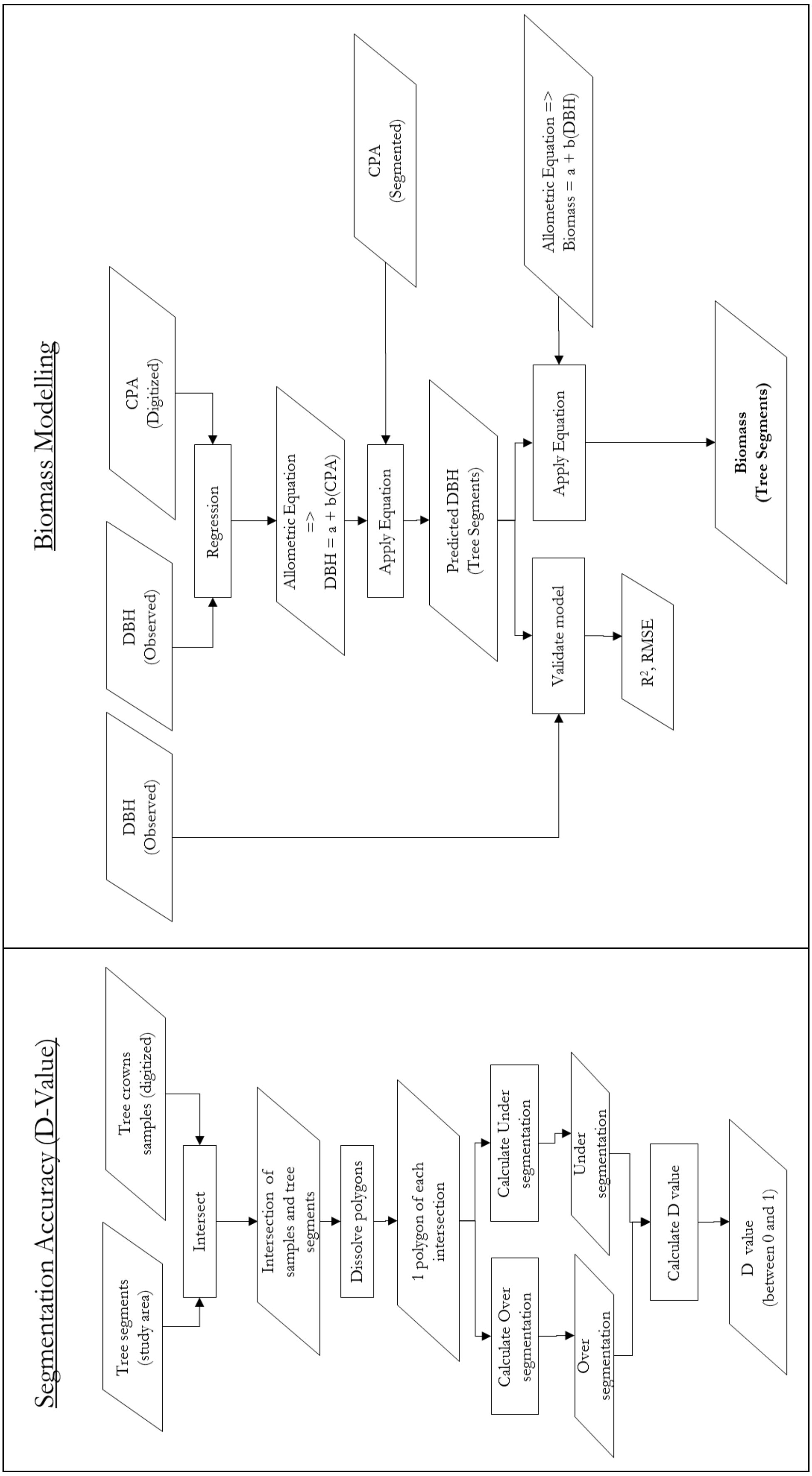
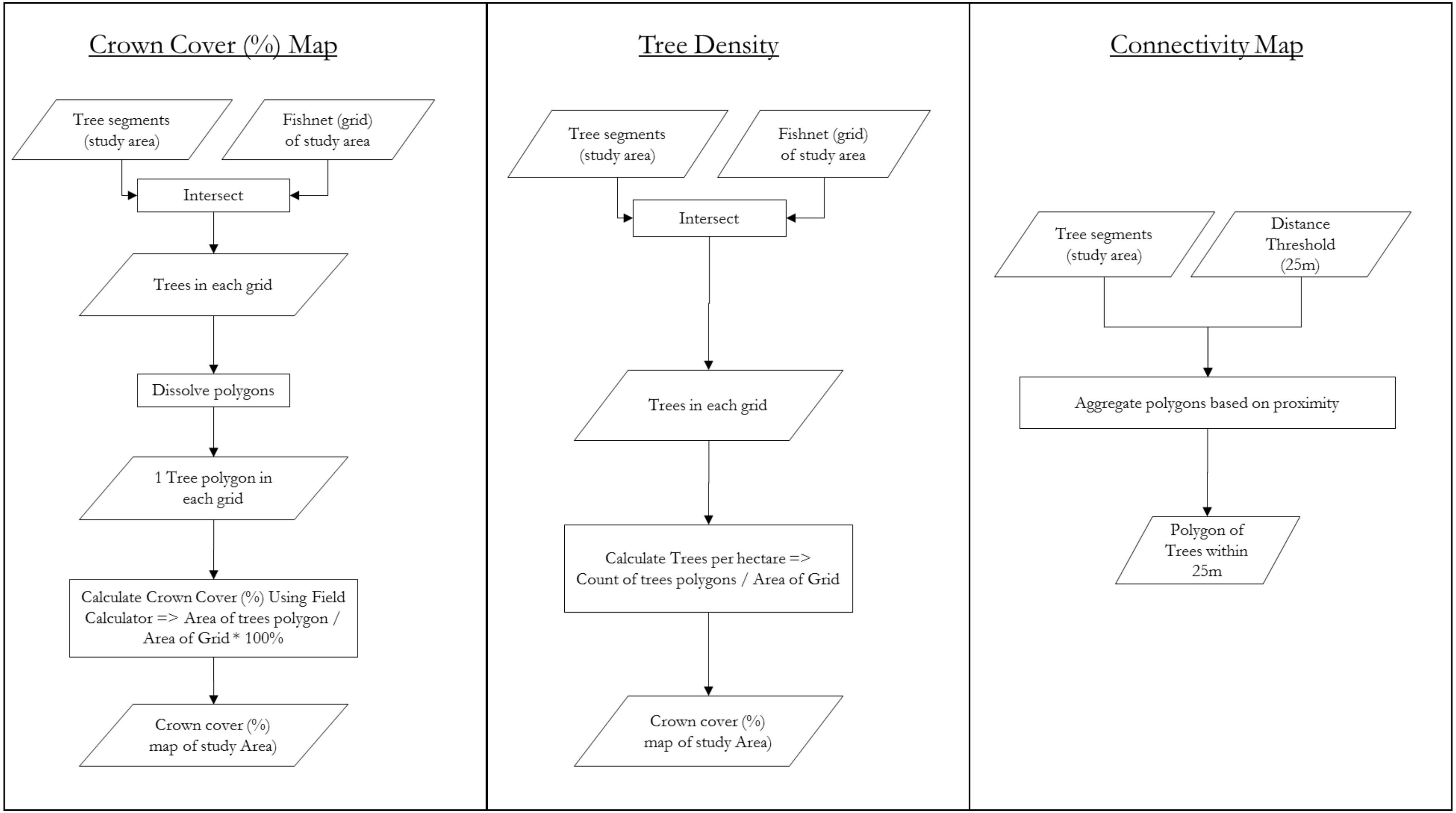
APPENDIX 1: FLOWCHART FOR SPECIFIC OPERATIONS




Crown Cover (%) Map
Tree segments (study area)
Fishnet (grid) of study area
Intersect
Trees in each grid
Dissolve polygons
1 Tree polygon in each grid
Calculate Crown Cover (%) Using Field Calculator => Area of trees polygon / Area of Grid * 100%
Crown cover (%) map of study Area)
Tree Density
Tree segments (study area)
Fishnet (grid) of study area
Intersect
Trees in each grid
Calculate Trees per hectare => Count of trees polygons / Area of Grid
Crown cover (%) map of study Area)
Connectivity Map
Tree segments (study area)
Distance Threshold (25m)
Aggregate polygons based on proximity
Polygon of Trees within 25m

APPENDIX 2: FIELD DATA COLLECTION SHEET

Field Data Collection Sheet

Plotno:	
X	
Y	
Plot size:	
Date:	
Observer's name:	

#	Tree Species	DBH	Tree Height	Crown Density	Remarks

APPENDIX 3: STAKEHOLDER DISCUSSION QUESTIONNAIRES

MSc RESEARCH QUESTIONAIRE

Organization: RAINFOREST ALLIANCE
Name of Respondent:
Position/Role in Organization:

1. What indicators and norms are used for assessing ecological quality with reference to SAN criterion 2.9 in Ghana? Please provide relevant reference documents.

2. What methods are currently used by auditors for field assessment of indicator 2.9?

3. Are farmers willing to be involved/engaged in assessments? If so, how are they involved?

4. What are the challenges with existing methods and their implications on audit findings?

5. Currently, how is Remote Sensing and GIS applied in assessment and monitoring?

6. What has been the impact of SAN certification on cocoa production in Goaso (and/or Ghana in general) in terms of yield, income, etc.? Please provide supporting data or data sources?

MSc RESEARCH QUESTIONAIRE

Organization: CONSERVATION ALLIANCE
Name of Respondent:
Position/Role in Organization:

1. What indicators and norms are appropriate for assessing ecological quality of a cocoa landscape? Please provide relevant reference documents.

2. What methods does CA use to assess ecological quality of a cocoa landscape in Ghana?

3. What are the challenges with existing assessment methods?

4. How does CA engage, support and interact with farmers in the field (e.g. extension)?

5. How is Remote Sensing and GIS currently applied in assessment and monitoring activities?

6. What are farmers' perceptions of impacts of environmental assessments (e.g. certification) on their productivity (yield, income, etc.)? Please provide supporting data or data sources?

MSc RESEARCH QUESTIONAIRE

Organization: COCOBOD
Name of Respondent:
Position/Role in Organization:

1. What efforts are Cocobod undertake to maintain the ecological quality of a cocoa landscape in Ghana? Please provide relevant reference documents.

2. How was the introduction of hybrid cocoa species conducted?

3. What is the impact of the hybrid cocoa, in terms of the environment, production & income?

4. How is Remote Sensing and GIS currently applied in the monitoring of cocoa plantations?

5. Are there plans for a national environmental assessment (certification) scheme?

6. How does Cocobod interact with voluntary certification schemes (e.g. SAN Cert)?

7. What have been cocoa production trends in Ghana over the years? Please provide supporting data or data sources?

8. APPENDIX 4: LIST OF STAKEHOLDERS CONSULTED

Name	Role	Organization	Stakeholder Group
Christian Mensah	Auditor	Rainforest Alliance	Certification Body
Patricia Offei	Certification Services	Rainforest Alliance	Certification Body
Walter Hevi	Auditor	Rainforest Alliance	Certification Body
Benjamn Asare	Auditor	AfriCert	Certification Body
Kwabena Agyeman	District Officer	Amajaro	Produce Buying Company
Faustina Badu	Monitoring and Evaluation	Ghana Cocoa Board	National Agency
William Minta Wiafe	Monitoring and Evaluation	Ghana Cocoa Board	National Agency
Kwadwo Kissiedu Kwapong	Research	Ghana Cocoa Board	National Agency
Emelia Crentsil	Research	Ghana Cocoa Board	National Agency
E. N. A. Aryeetey	Cartography	Ghana Cocoa Board	National Agency
Randy Boaitey	Extension Officer	Ghana Cocoa Board	National Agency