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Monitoring Indigenous Tropical Montane Forests in the Taita Hills Using Airborne Digital Camera Imagery

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Tiivistelmä – Referat) Abstract

The loss and degradation of forest cover is currently a globally recognised problem. The fragmentation of forests is further affecting the biodiversity and well-being of the ecosystems also in Kenya. This study focuses on two indigenous tropical montane forests in the Taita Hills in southeastern Kenya. The study is a part of the TAITA-project within the Department of Geography in the University of Helsinki.

The study forests, Ngangao and Chawia, are studied by remote sensing and GIS methods. The main data includes black and white aerial photography from 1955 and true colour digital camera data from 2004. This data is used to produce aerial mosaics from the study areas. The land cover of these study areas is studied by visual interpretation, pixel-based supervised classification and object-oriented supervised classification. The change of the forest cover is studied with GIS methods using the visual interpretations from 1955 and 2004.

Furthermore, the present state of the study forests is assessed with leaf area index and canopy closure parameters retrieved from hemispherical photographs as well as with additional, previously collected forest health monitoring data. The canopy parameters are also compared with textural parameters from digital aerial mosaics.

This study concludes that the classification of forest areas by using true colour data is not an easy task although the digital aerial mosaics are proved to be very accurate. The best classifications are still achieved with visual interpretation methods as the accuracies of the pixel-based and object-oriented supervised classification methods are not satisfying.

According to the change detection of the land cover in the study areas, the area of indigenous woodland in both forests has decreased in 1955–2004. However in Ngangao, the overall woodland area has grown mainly because of plantations of exotic species. In general, the land cover of both study areas is more fragmented in 2004 than in 1955.

Although the forest area has decreased, forests seem to have a more optimistic future than before. This is due to the increasing appreciation of the forest areas.

Avainsanat – Nyckelord) Keywords
Kenya, Taita Hills, remote sensing, GIS, digital camera data, aerial photography, hemispherical photography, change detection

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Tiivistelmä – Referat) Abstract

Metsien väheneminen ja niiden laadun heikkeneminen on maailmanlaajuisesti tunnustettu ongelma. Metsien pirstoutuminen vaikuttaa biodiversiteettiin ja ekosysteemien hyvinvointiin myös Keniassa. Tämä tutkimus keskittyy kahden trooppisen alkuperäisvuoristometsän tutkimiseen Taita Hillsin alueella Kaakkois-Keniassa. Tutkimus on osa Helsingin yliopiston maantieteen laitoksen TAITA-projektia.

Tutkimusmetsiä, Ngangaoa ja Chawiaa tutkitaan kaukokartoitus- ja paikkatietomenetelmien avulla. Tutkimuksen pääaineiston muodostavat mustavalkoiset ilmakuvat vuodelta 1955 ja digitaaliset oikeaväri-ilmakuvat vuodelta 2004. Näistä ilmakuvista muodostetaan ilmakuvamosaiikit tutkimusalueilta. Alueiden maanpeite luokitellaan kolmella metodilla: visuaalisella tulkinnalla, pikselipohjaisella ohjatulla luokituksella sekä objekti-orientoidulla ohjatulla luokituksella. Metsäpinta-alan muutosta vuosina 1955–2004 tutkitaan visuaalisten luokitusten perusteella käyttämällä paikkatietomenetelmiä.

Tutkimusmetsien kuntoa arvioidaan lehtipinta-alaindeksin ja latvuksen sulkeituneisuuden avulla. Nämä parametrit saadaan käyttämällä hemisfäärisiä valokuvia. Lisäksi tutkimuksessa käytetään metsien kuntoa arvioivaa aiemmin kerättyä tutkimustietoa. Latvusparametreja verrataan digitaali-ilmakuvamosaiikeilta saatuihin tekstuurisiin parametreihin.

Yhteenvetona voidaan sanoa, että metsäalueiden luokitus oikeaväri-ilmakuvia käyttämällä ei ole helppoa, vaikka itse digitaali-ilmakuvista tehdyt mosaiikit olisivat erittäin tarkkoja. Parhaat luokitustulokset saavutetaan edelleen visuaalisella tulkinnalla, sillä pikselipohjainen ja objekti-orientoitu ohjattu luokitus eivät saavuta tarpeeksi hyvää luotettavuutta.

Tutkimusalueiden maanpeitteen muutostulkinnan mukaan alkuperäismetsän osuus on vähentynyt sekä Ngangaossa että Chawiassa 1955–2004. Ngangaossa metsän kokonaisala on kuitenkin lisääntynyt lähinnä eksoottisten puulajien istutusten vuoksi. Molempien tutkimusalueiden maanpeite on huomattavasti pirstoutuneempaa vuonna 2004 kuin vuonna 1955.

Vaikka metsäala on pienentynyt, tutkimusmetsien tulevaisuus näyttää paremmalta kuin aiemmin. Tämä johtuu lähinnä kasvavasta metsien arvostuksesta.

Avainsanat – Nyckelord) Keywords
Kenia, Taita Hills, kaukokartoitus, GIS, digitaalikamera-aineisto, ilmakuvaus, hemisfäärinen kuvaus, muutostulkinta

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ABBREVIATIONS

ASAL	Arid or Semi-Arid Lands
BBA	bundle block adjustment
BRDF	bidirectional reflectance distribution function
BRF	bidirectional reflectance factors
CCD	charge-coupled-device
CIR	colour infrared
CORE	Conservation of Resources through Enterprise
DBH	diameter at breast height
DEM	digital elevation model
DN	digital number
DVI	difference vegetation index
EAM	The Eastern Arc Mountains
EAWLS	The East African Wild Life Society
EVI	enhanced vegetation index
FAO	Food and Agriculture Organization
FD	Forest Department
FHM	Forest Health Monitoring
FRA	Global Forest Resources Assessment
GCP	ground control point
GIS	geographic information system
GLA	Gap Light Analyzer
GPS	global positioning system
II	infrared index
ITCZ	intertropical convergence zone
KIFCON	Indigenous Forest Conservation Project
KWS	Kenya Wildlife Service
LAI	leaf area index
LAI_e	effective LAI
LCCS	Land Cover Classification System
MAUP	modifiable areal unit problem
MMU	minimum mapping unit
MSAVI	modified soil adjusted vegetation index
MSI	moisture stress index
NDVI	normalised difference vegetation index
NIR	near-infrared
NN	nearest neighbour
PVI	perpendicular vegetation index
RMS	root means square
RS	remote sensing
SAVI	soil adjusted vegetation index
THBP	The Taita Hills Biodiversity Project
THEMS	Taita Hills Environmental Monitoring System

TMCF	tropical montane cloud forests
UNEP	United Nations Environment Programme
USAID	United Stated Agency for International Development
USDA	United States Department of Agriculture
VHR	very high spatial resolution

1 INTRODUCTION

This thesis can be categorised as a remote sensing study with a physical geography aspect. Although the two indigenous montane forests (Ngangao and Chawia) in the Taita Hills are the focus of this work, the situation of the Kenyan forests in general is also considered.

1.1 DEVELOPING COUNTRIES, FORESTS AND REMOTE SENSING

In recent times, changes in forest cover throughout the world have aroused increasing interest. The loss and degradation of forests are not new phenomena but currently they are problems, especially in the developing world. Fortunately, although the total forest area of the world continues to decrease, the rate of net loss is slowing (FAO 2006).

Thus, tropical forests are of special interest. The deforestation of these forests can have both local and global consequences. Forests provide foundations for life on earth through various means. Their ecological function cannot be underestimated, nor can their significance in biodiversity. Moreover, their importance for water balance and weather patterns and their role as regulators of the environment is increasingly valued in a world struggling with climate change. The role of forests for wood, food, medicines and furthermore for recreation and spiritual purposes should not be forgotten. However, at the same time, the pressure to have more agricultural land and increase timber harvest remains.

Remote sensing (RS) is a good and widely used method for mapping tropical forests. With the use of RS techniques, up-to-date information can be obtained for large areas at the same time. Availability of this kind of up-to-date data is a problem, especially in the developing world. RS offers, however, a possibility to monitor tropical forests.

1.2 OBJECTIVES OF THE STUDY

This study focuses on monitoring two indigenous tropical montane forests in the Taita Hills, South-East Kenya. In order to study these two forests, namely Ngangao and Chawia, different remote sensing (RS) techniques are used.

The objectives of the study are the following:

I. To study the present situation of Kenyan forests in general, emphasizing the indigenous tropical montane forests and the forests in the Taita Hills.

II. To produce high-resolution image mosaics from digital aerial photographs in the areas of Ngangao and Chawia in the Taita Hills.

III. To classify the produced image mosaics of the forests using three different methods (visual classification, object-oriented supervised classification and pixel-based supervised classification) and to compare these three classification methods.

IV. To study the changes in forest cover in Ngangao and Chawia between 1955 and 2004.

V. To study the condition and the structure of the forests using digital airborne data, hemispherical photographs and forest health monitoring (FHM) data (Hertel et al. 2000).

1.3 THE STRUCTURE OF THE THESIS

This thesis is divided into nine main chapters. This first chapter outlines the themes and objectives of the study as well as some definitions and previous studies in the area. The second chapter introduces the study area; both Kenya in general and the Taita Hills. The third chapter concentrates on the present situation of the forests in Kenya and the Taita Hills. The principles of remote sensing and digital airborne data are covered in chapter four. Chapter five introduces the data used in this study while the methods and analysis undertaken are covered in chapter six. Chapter seven details the results and the accuracy of the results. Chapter eight covers the discussion while the ninth chapter concludes the thesis.

1.4 THE TAITA PROJECT

This study is part of the TAITA project which is carried out by the Department of Geography at the University of Helsinki and funded by the Council of Development Studies of the Academy of Finland. The TAITA project, entitled *Development of land use change detection methodology applying geographic information systems in East African highlands*, started in January 2003 and ended in December 2006 (Pellikka et al. 2004a; Pellikka et al. 2004b; The Taita Project 2007).

The main objectives of the project are to develop a cost-effective and practical land use change detection methodology and to create a geographic database for the land use and its changes in the area. The general aim of the multidisciplinary project is divided into four main sub-objectives: studies in land use change, urban growth, spatio-temporal changes in land degradation, and development of the management systems of naturally protected forests (Pellikka et al. 2004b).

The work of the TAITA project is continued in a project called TAITATOO (2006–2009) (The Taita Project 2007). The three focus areas are the application of the compiled geographic database of land use and land cover for conservation and biodiversity studies, the possibilities of the participation of local communities for conservation and natural resource management and the creation of the Taita Hills Environmental Monitoring System (THEMS).

1.5 PREVIOUS AND ON-GOING RESEARCH PROJECTS IN THE TAITA HILLS FORESTS

The Taita Hills, as part of the Eastern Arc Mountains, are recognized as a global biodiversity hotspot (Mittermeier et. al 1998; Conservation International 2005). Therefore, it is small wonder that biodiversity has been and still is one of the main research subjects in the Taita Hills area.

The ecology of the forests of the Taita Hills was studied by Beentje (1988). The aim of the study was to assess the extent of the remaining indigenous forest patches, to assess their status and threats and to list species occurring in the forests.

Biodiversity has been studied within The Taita Hills Biodiversity Project (THBP), although the main objective of the project was to improve the human resources and infrastructure of the Department of Zoology of Kenyatta Univeristy and of the collaborating departments of National Museums of Kenya (Bytebier 2001). The project consisted of four research components: an ornithology research component, a mammalogy research component, an invertebrate zoology research component and a botany research component.

Biodiversity is the main focus also for a Belgian research group. They have studied especially the biodiversity of the birds living in the forest fragments of the Taita Hills (Brooks et al. 1996, 1998; Lens et al. 1998, 1999a, 1999b, 2000, 2002a, 2002b). Furthermore, the characteristics of remaining forest patches and connectivity between these patches have been studied in the projects.

In 1999, the USDA Forest Service began a project consisting of evaluation of forest health, land-use change and information sharing in the Eastern Arc Mountains (Hertel et al. s.a.; USDA Forest Service 2006). The primary objectives of the project were to: 1) research current trends in forest condition of the Eastern Arc Mountains through forest health monitoring technology, 2) increase local practitioners knowledge in the use of forest health and monitoring technology, 3) assist in developing and improving regional institutions and agencies' abilities to conduct forest health monitoring and 4) design and implement an information technology system to improve communications among Eastern Arc Mountains stakeholders. In order to determine and assess the long-term trends in forest health conditions, 44 permanent forest health monitoring plots were established in the Eastern Arc Mountain area. Within these plots, information on the status and trend of the ecosystem's health is determined by measuring several indicators such as growth, crown condition and damage indicators (Hertel et al. s.a.: 10; USDA Forest Service 2006).

The Taita Hills area was also the Kenyan component of the East Africa Cross Border Biodiversity Project, the aim of which was to reduce the rate of loss of forest biodiversity at specific cross-border sites of national and global significance in the region (Ondenge 2001; EAWLS 2005). The East African Wild Life Society (EAWLS) took on the project for the Taita Hills Mbololo and Kasigau forests from 2001 to 2004.

The CORE (Conservation of Resources through Enterprise) was a USAID natural resources management program during 1999–2004 in four regions in Kenya of which one was Taita/Taveta. This program's goal was to improve the conservation and management of natural resources through increased benefits to community and landowners in areas adjacent to government protected areas.

1.6 DEFINITIONS

In order to study forests and their change, it is necessary to define what is meant by "forest". Several definitions have been made, one being a definition given by the Global Forest Resources Assessment 2005 (FRA) (FAO 2004: 16). It defines forest as land with a minimum area of 0.5 ha where the tree crown cover (or equivalent stocking level) is more than 10% and the trees should have a minimum height of five metres at maturity. The earlier version of FRA, The Global Forest Resources Assessment 2000 (FAO 2001: 363) further divides forests into closed and open forests. Closed forests are "*formations where trees in the various storeys and the undergrowth cover a high proportion (> 40 percent) of the ground*" whereas open forests are "*formations with discontinuous tree layer but with a coverage of at least 10 percent and less than 40 percent*".

Furthermore, forests can be divided by their natural state. *Primary forest* is undisturbed indigenous forest while *modified natural forest* is somehow disturbed indigenous forest. *Plantations* can be divided into productive and protective plantations (FAO 2004: 17–18).

In this study, the following definition of forests applies: forests or woodlands are land with a minimum area of 0.5 ha where the tree crown cover is over 40%. However, in the forests of the Taita Hills, the crown cover is even higher. The forests of the Taita Hills can further be classified as modified natural forests with mainly protective but also productive plantations. Both the terms forest and woodland are used in literature with a rather similar meaning. In this study, the term forest is widely used. In classifications, the utilized term is woodland in order to differentiate whether the real forests or the classification result is meant.

When studying forest change, it is important to recognise different forms of change. Easily noticeable changes include deforestation, the conversion of forest to another land use purpose. The opposite of deforestation is afforestation, planting forest in areas that were previously used for other purposes (FAO 2001: 364). Moreover, forest area can grow through natural expansion. Another form of change is in the quality of forest. Altering the forest with negative effects to its structure is called degradation. Forest degradation can heavily affect the ecology of forests although the forest area is not changing. Degradation can happen though various forms of disturbance and it is hard to quantify.

In this study, several land cover classifications are made. Thus, it is important to distinguish between land cover and land use. *Land cover* can be defined as *"the observed (bio)physical cover on the earth's surface"* while *land use* is characterised by the *actions that humans undertake in a certain land cover type to produce, change or maintain it* (LCCS 2005: 3). Thus, land cover is more stable and also more appropriate term to use in this study.

1.7 THE SOFTWARE

As in all remote sensing (RS) and geographic information system (GIS) studies, the software utilised determines the workflow. The RS software used includes *EnsoMOSAIC* 5.0 and SUN, *Erdas Imagine* 8.5 and 8.7, *eCognition Professional* 4.0 and *Land Cover Classification System* (LCCS) 2.4.5. At the present, *eCognition Professional* is known as *Definiens*. However, in this study the name *eCognition* is used. The main GIS software package used in this study is *ArcGIS* 9. Hemispherical photographs are analysed with *Gap Light Analyzer* 2.0.

2 STUDY AREA

2.1 KENYA

Kenya, an independent country since 1963, is located in Eastern Africa between 4º21’ N and 4º28’ S and between 34º and 42º E. The country is bordered by Somalia in the east, Ethiopia and Sudan in the north, Uganda in the west and Tanzania in the south. In addition, the Indian Ocean delimits Kenya in the east (Figure 1). The total surface area of 582,600 km² includes 10,700 km² of lake area (Wass 1995: 7).

Figure 1. Kenya.

Kenya is divided into eight provinces, including the Nairobi area. The other seven are the Central, Coast, Eastern, North, Rift Valley, Western and North Eastern provinces. The provinces are further divided into administrative areas known as districts, which are subdivided into divisions (Taita Taveta district development plan 2002–2008… s.a.: 3–4; Government of Kenya 2006).

2.1.1 PHYSICAL FEATURES OF KENYA

During the Tertiary period (approximately 65–2 million years ago) significant earth movements changed the topography of East Africa (Mountjoy & Hilling 1988: 393). A sequence of uplift and downwarp created a chain of rift valleys that are known collectively as the East African Rift Valley System. One part of this system, the Gregory Rift Zone, which is approximately 60–70 km wide and 1,000 km, runs through Kenya in a north-south direction from Lake Turkana to the Lake Natron Basin in northern Tanzania. The Nyanza Rift Zone, although a lot smaller than the Gregory Rift Zone, is another important rift system in Kenya (Figure 2) (Nyamweru 1996: 20).

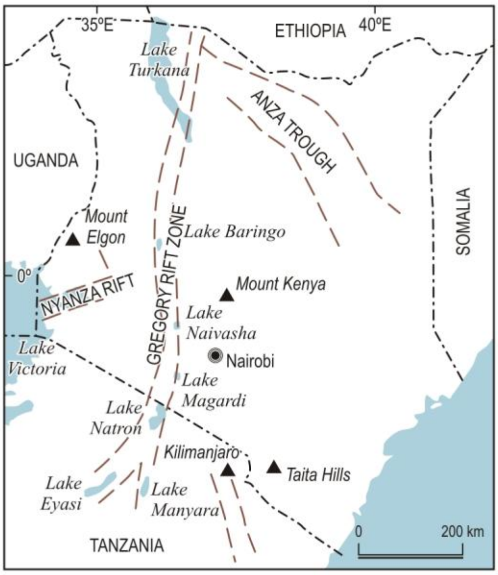

Figure 2. The rift systems of Kenya (modified after Nyamweru 1996: 20)

During the formation of rift systems in Kenya, extensive volcanic activity also occurred. Today there are several central volcanoes along the rift floor, including the calderas of Menengai, Longonot, Suswa, Silali and the Barrier. At least 50 km away from the edge of the present-day rift, a number of other volcanoes, e.g. Mount Elgon (4,321m) and Mount Kenya (5,199 m), as well as Kilimanjaro (5,895 m) across the border in Tanzania, are situated. Other prominent features are the shallow lakes in the sedimentary basins of the Gregory Rift. The salinity of these lakes ranges from hypersaline to freshwater, depending on the elevation (Nyamweru 1996: 21–22).

Tectonic activities with erosive powers have caused the land to rise from the coast to the eastern part of the country in a series of plateau steps (Wass 1995: 7). Four different physical regions can be distinguished: the Eastern Rift Valley, the East African Plateau, the Nyika and the Coastal Plain (Mountjoy & Hilling 1988: 395). Most of the Eastern Rift Valley region is comprised of Pre-Cambrian igneous and metamorphic rocks of the Basement Series. The highest areas are of volcanic origin (Mountjoy & Hilling 1988: 393). Alongside the Rift Valley is the East African Plateau which is composed mainly of Basement rocks. The Nyika is a planation surface that was formed in the late Tertiary period. The height of the Nyika averages 600 m a.s.l., although there are also some higher relict hill masses and inselbergs.

The Coastal Plain is low and only 15 to 60 km wide. It is composed of Quaternary sediments and coral reefs (Mountjoy & Hilling 1988: 395).

The variation in rock types, in relief and in climate has resulted in the formation of a wide range of soils (Muchena & Gachene 1988: 183). The nature of these soils depends mainly on the amount of quartz in the parent material. Most of the soils in Kenya are easily leached and lack humus. Deep fertile soils are rare and to a great extent confined to the highlands (Mountjoy & Hilling 1988: 399).

Kenya can be divided into five principal drainage areas: the Lake Victoria Basin, the Athi River Basin and Coast, the Tana River Basin, the Rift Valley Basin, and the Ewaso Ngiro and North (Wass 1995: 37). A number of rivers in Kenya are seasonal: during the dry season they are reduced to a series of muddy pools (Mountjoy & Hilling 1988: 395).

2.1.2 CLIMATE

The climate of Kenya varies widely: along the tropical coast the humidity and temperatures are high all year (27º C), while in the highlands the mean temperatures range between 10º C and 21º C. The equatorial location, together with the presence of highlands, forms the greatest influence on the climate of Kenya. One major factor in determining the climate is Kenya's location in the intertropical convergence zone (ITCZ), where the converging trade winds meet. During the period from November to April the ITCZ moves to the south, bringing northerly and north-easterly winds of cT type to Kenya. In the southern winter, the ITCZ moves back to the north with southerly airstreams. During this season, also the south-east trades of mT type blow from the Indian Ocean (Mountjoy & Hilling 1988: 396).

This twice-yearly passage of ITCZ causes a bimodal rainfall pattern across most of Kenya. More rain is received between February and May, while less rain falls from October to December (Mountjoy & Hilling 1988: 396). Both temperature and inland precipitation are related to altitude changes (Wass 1995: 7). The coastal zone and the highlands are the wettest areas in Kenya, while the lower and middle plateau areas receive less than 750 mm per year (Figure 3) (Mountjoy & Hilling 1988: 397; Third national report on the implementation… 2004: 62).

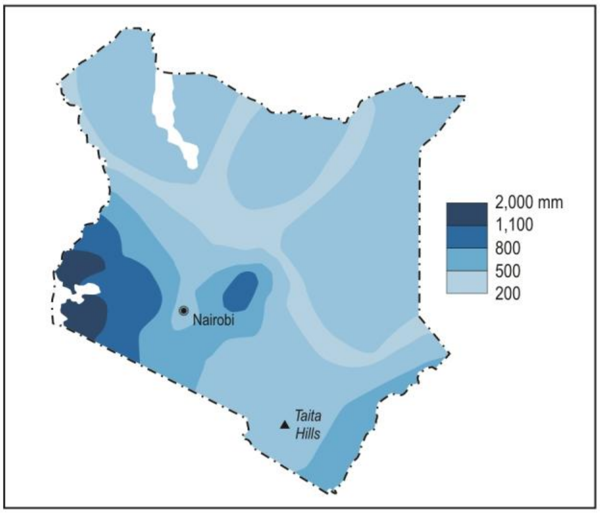

Figure 3. The average precipitation in Kenya (modified after Third national report on the implementation… 2004: 62).

2.1.3 LAND COVER

Kenya is dominated by land types that can be classified as Arid or Semi-Arid Lands (ASAL), as they comprise about 88% of the land area in the country. Moreover, a quarter of Kenya's population and half of its livestock live in these areas (Republic of Kenya 1992: 5). According to Wass (1995: 10), bushland, wooded grassland, grassland and desert occupy over three quarters of Kenya's land cover (Figure 4). In these areas, productivity varies significantly, subject to the area and time. Isolated hills and river floodplains are the most productive areas in the regions where dry land cover types dominate.

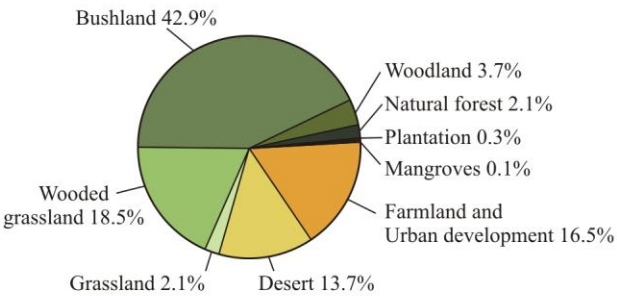

Figure 4. Land cover types in Kenya (Wass 1995: 8–10). Forest is defined as a continuous stand of trees at least 10 m tall with their crowns interlocking, woodland is an open stand of trees, at least 8 m tall, with a canopy cover of 40% or more, bushland is an open stand of bushes and climbers, usually between 3 and 7 m tall, with a canopy cover of 40% or more, wooded grassland is land covered with grasses and other herbs, with woody plants covering between 10% and 40% of the ground and the field is usually dominated by grasses.

2.1.4 HUMAN GEOGRAPHICAL FEATURES OF KENYA

The total population estimated for the year 2005 is 33,829,590, with an estimated population growth rate of 2.56%. Life expectancy for women is 47.09, while it is 48.87 years for men (CIA 2006). Population growth and population densities vary according to the degree of aridity in the area. The lowest densities, as well as the lowest growth rates, occur in the most arid areas. In the moister areas, population densities can be even higher than in many urban centres (Republic of Kenya 1992: 1; Wass 1995: 51).

Population growth in the medium- and high-potential areas has led more and more people to move to urban centres, as well as to the ASAL. This has caused the ASAL areas to suffer problems such as intensified cultivation, overgrazing, deforestation, acute water shortages, loss of biological diversity and soil erosion (Republic of Kenya 1992: 5; Mwagore 2002: 19). In the drier regions in Kenya, malnutrition affects over a quarter of the population. The droughts make matters even worse. Minor droughts are experienced every 2 to 3 years, while major droughts occur every 8 to 10 years (Mwagore 2002: 19–20).

The national economy is primarily agriculturally based: over 80% of the population is supported by agriculture, although much of the lower and middle plateau areas are not very suitable for agriculture. Agriculture is also responsible for 80% of the export earnings (Mountjoy & Hilling 1988: 397; Mwagore 2002: 5–6). Fishing is another important source of income, both for local consumption and export and for recreational sport (Mwagore 2002: 25).

2.2 THE TAITA HILLS IN THE TAITA-TAVETA DISTRICT

The Taita Hills are located in south-eastern Kenya at 03º20’ S, 38º15’ E, approximately 150 km inland from the coast and 25 km west of Voi in the Taita-Taveta district (Figure 5). The district covers an area of 16,959 km² and has six divisions: Voi, Mwatate, Wundanyi, Tausa, Taveta and Mwambirwa (Taita Taveta district development plan 2002–2008… s.a.: 4–7). The principal administrative town of the district is Wundanyi in the Taita Hills. Taita-Taveta is one of the Arid and Semi-Arid (ASAL) districts in Kenya with 89% of the district being classified as semi-arid or arid (Vogt & Wiesenhutter 2000: 1). Of the total area of the district, 62% is occupied by Tsavo East and West National Parks, 24% is range land (suitable for ranching and dry land farming) and only 12% is for rain-fed agriculture (Taita Taveta district development plan 2002–2008… s.a.: 6).

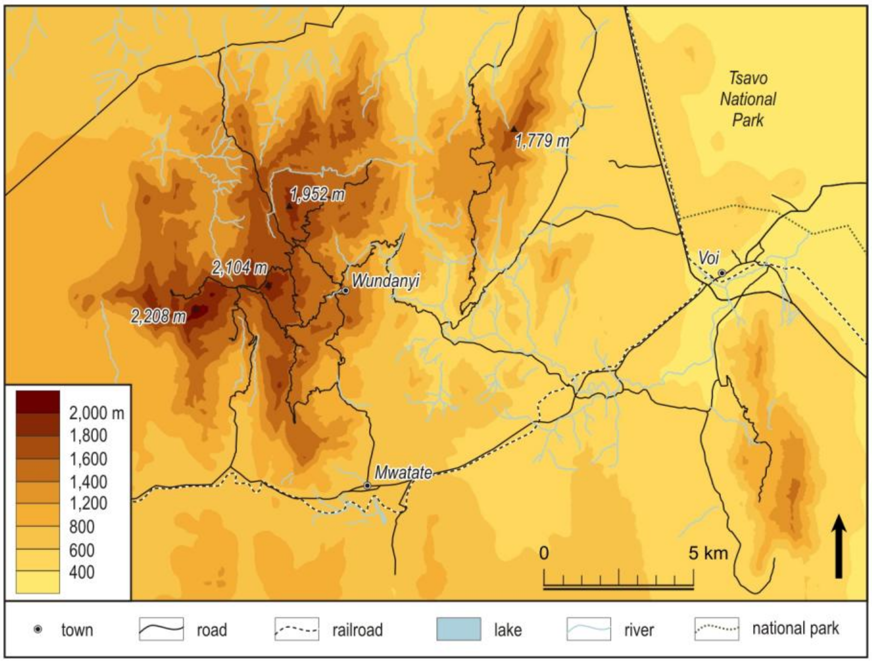

Figure 5. The Taita Hills.

2.2.1 PHYSICAL FEATURES OF THE TAITA HILLS

The Taita Hills, isolated from other highlands, rise abruptly from the surrounding plains, which have a general altitude of 600–700 m a.s.l. The Taita Hills are comprised of three distinct isolates: Sagalla (south of the town of Voi), Mbololo massif (also known as Mraru, north-east of the range) and the main massif Dabida. In this main massif are located the highest peak of Vuria (2,208 m a.s.l.) and the district capital Wundanyi. Kasigau (1,500 m a.s.l.) is situated 50 km southeast of the Taita Hills (Brooks et al. 1998: 120). The Taita Hills, together with the Sagalla and Kasigau inselbergs, form the upper zone of the Taita-Taveta district (other zones are lower zone and volcanic foothills) (Were & Soper 1986: 1; Taita Taveta district development plan 2002–2008… s.a.: 6).

The Taita Hills were formed about 180–290 million years ago by block-faulting of basement rocks in the Mozambique Belt (Vogt & Wiesenhutter 2000: 16). The rocks are mainly migmatic and granulitic gneisses with minerals, e.g. garnet, biotite, placioglace, quartzand amphibole (Hauzenberger et al. 2004: 256). The N-S trended folded lineaments of the Taita Hills relate the hills tectonically to the evolution of the East African Rift System (Vogt & Wiesenhutter 2000: 16). Erosional and sedimentary plains surrounding the Taita Hills, called nyika (meaning wilderness), are mainly covered by Recent and Pleistocene red-brown sandy soils and calcareous crustal deposits overlying undifferentiated basement rocks consisting of crystalline limestones and gneisses (Were & Soper 1986: 2). The dominant soils on the Taita

Hills are young soils, cambisols, which are of moderate fertility. In the upland areas cambisols are found together with highly weathered ferralsols with low natural fertility. Other soils developed on the Taita Hills are acrisols, rankers and rendzinas, which are common in the south-eastern part of the Taita Hills (Were & Soper 1986: 8).

Several rivers drain from the Taita Hills catchment areas. The Voi River drains from near Werugha to the east, while the Mwatate and Bura rivers drain to the south. Although these rivers are perennial at their headwaters, none of them carries any permanent flow far into the plains (Were & Soper 1986: 4; Vogt & Wiesenhutter 2000: 19).

2.2.2 CLIMATE

The climate of the Taita Hills is partly dependent on the intertropical convergence zone (ITCZ), which lies parallel to the equator but moves south and north with the seasonal passage of the thermal equator. The seasonal movements of the ITCZ cause a bimodal rainfall pattern in the Taita Hills: the long rains (March-May) and the short rains (October-December) (Tuhkanen 1991: 2; Vogt & Wiesenhutter 2000: 19). Mist and cloud precipitation, on the other hand, occur throughout the year in the Taita Hills. As the hills are the first barrier for moisture-laden air masses that blow in from the coast, orographic rains are also of great significance to the area (Beentje 1988: 23). The eastern and southeastern slopes receive more rain from these humid southeast trade winds than do the western and northern slopes that are in the rain shadow area (Vogt & Wiesenhutter 2000: 19). Altitude also has an influence on the rainfall pattern: higher areas get more rain than lower areas. The average annual rainfall ranges from 500 mm in the plains to 1,500 mm in the upper mountainous area (Figure 6) (Jaetzold & Schmidt 1983: 247).

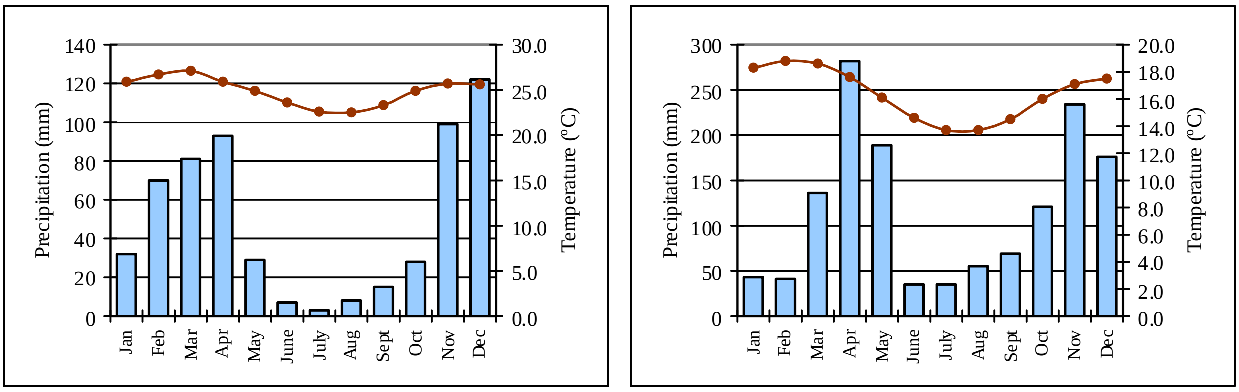

Figure 6. Mean annual precipitation and temperature at Voi, Meteorological Station (560 m a.s.l.) on the left (observation time is 71 years for precipitation and 32 years for temperature) and at Wesu hospital (1,675 m) on the right (observation time is 36 years for precipitation and 15 years for temperature) (Jaetzold & Schmidt 1983: 247–128).

The temperature in the Taita Hills is to a great degree determined by the altitude (Tuhkanen 1990: 3). In the plains, the annual mean temperature is 24.9ºC (Voi Meteorological Station, 560 m a.s.l.), while in the mountains, the annual mean temperature is 16.5ºC (Wesu Hospital, 1,675 m a.s.l.) (Jaetzold & Schmidt 1983: 248).

2.2.3 VEGETATION AND LAND USE

The Taita Hills were once covered with extensive montane cloud forests. However, today only small forest fragments remain on the highest peaks of the hills (see chapter 3.2). In the midlands of the Taita Hills (<1,200 m a.s.l.), woodland and dry forests occur with *Acacia-Euphorbia* species (Krhoda 1998: 32). The lowlands are mostly covered with bushland and thicket, with some sparsely scattered trees. In addition, woodlands, wooded grasslands, grasslands and riverine forests, as well as swamps, can be found in the plains (Were & Soper 1986: 10; Vogt & Wiesenhutter 2000: 36). Loss of natural vegetation in the Taita Hills area, among other reasons, has caused considerable gully erosion on the hillslopes and the foothills (see e.g. Hermunen et al. 2004; Sirviö et al. 2004).

The area of the Taita Hills can be divided into seven different agro-ecological zones (see Jaetzold & Schmidt 1983). These zones are based on altitude, rainfall, temperature, evapo-transpiration on relief and soils (Dijkstra & Magori 1994: 14–15; Krhoda 1998: 32). The zones found in the Taita Hills are presented in Table 1.

Table 1. Agro-Ecological zones and their characteristics in the area of Taita Hills (Jaetzold & Schmidt 1983: 248–257; Dijkstra & Magori 1994: 16).

Zone	Division(s) covered	Altitude (m)	Rainfall (mm / year)	Examples of cultivated plants
Wheat/maize-pyrethum (LH2)	Wundanyi	> 1,680	> 1,200	potato, cauliflower, carrot, spinach, lettuce, plums, passion fruit, wheat, maize
Marginal coffee (UM3)	Wundanyi	1,370 - 1,680	900 - 1,200	onion, cabbage, pineapple, maize, sorghum, macadamia
Sunflower-maize (UM4)	Wundanyi	1,220 - 1,520	700 - 900	cowpea, sorghum, maize, millet
Livestock - millet (LM5)	Wundanyi, Mwatate, Taveta, Voi	790 - 980	480 - 700	millet, sisal
Ranching (LM6)	National Park, Mwatate, Voi	< 790	< 500	not suitable for agriculture
Livestock - millet (L5)	Taveta, Voi, Mwatate	610 - 790	480 - 690	beans, millet, buffalo gourds, sorghum

2.2.4 THE POPULATION IN THE TAITA HILLS

It was at least 2,000 years ago when the first people arrived in the Taita Hills (Brooks et al. 1998: 121). Since then, agriculture in different forms has been the main source of livelihood. Especially since the 1960s, an increasing population has needed more land for living and cultivation. This increasing population, together with agriculture, has caused changes in the land use patterns (e.g. decreasing forests and woodlands, soil erosion, lowering water tables) (Pellikka et al. 2004b). Most of the farms are situated between 800 and 1,700 m a.s.l. in the most promising agricultural area in the Taita Hills (Bytebier 2001: 77). Large farms are rare in the area; most people have small fields, or *shambas*. Millet and sorghum cultivation are the major activities, along with livestock keeping (Krhoda 1998: 33).

The scarcity of arable land and other natural resources has forced people to move further up into the hills or to the nearby urban centres. Now, however, more and more people are moving to the lowlands in search of land (Soini 2005: 4). A restricting factor, when it comes to this need for land, is the location of the Tsavo National Parks. They almost surround the Taita Hills, thus restricting the spread of settlement to the lowlands.

The population growth in the Taita-Taveta district, as well as in the Taita Hills, has been significant in the last few decades. According to the latest censuses, the total district population has been as follows: 1962 – 90,150; 1969 – 110,742; 1979 – 147,597; 1989 – 207,273; 1999 – 246,671 (Were & Soper 1986: 17; Vogt & Wiesenhuetter 2000: 47; Republic of Kenya 1994: 42; Republic of Kenya 2001: 38). In 2002, the population size of the district reached 259,889 (Taita Taveta district development plan 2002–2008… s.a.: 8). However, the cumulative growth percentage has decreased lately: from 1979 to 1989 it was 3.45%, while from 1989 to 1999 the percentage was only 1.76.

The population distribution varies greatly in the district. In the cities and the most productive areas, such as in the Taita Hills and in Taveta, the population density is much higher than in the other parts of the district. The population density for the whole Taita-Taveta district is misleading, because the almost uninhabited Tsavo National Parks occupy over 60 per cent of the district's area (Table 2). Poverty is an everyday issue for many people in the Taita Hills: a recent study stated that about 64% of the population in Wundanyi division and 58% in Mwatate division live under the poverty line (CBS 2004, cit. Soini 2005).

Table 2. Population densities and distribution by divisions in 2002 (Taita Taveta district development plan 2002–2008… s.a.: 7).

Division	Area (km²)	Population	Density
Wundanyi	701.9	57,706	82.2
Mwatate	1,766.1	59,386	33.6
Voi	2,975.0	57,486	19.3
Tausa	318.9	21,361	66.9
Mwambirwa	43.3	5,191	119.8
Taveta	645.4	55,880	86.6
Tsavo National Parks	10,680.0	2,879	-
Total	16,959.0	259,889	40.3

2.2.5 THE INFRASTRUCTURE

The building of the infrastructure, especially roads, has been complicated due to the difficult terrain in the area. Despite this, there is a quite extensive road network in both the Taita Hills and the Taita-Taveta District. The most important road in the district is the Nairobi-Mombassa highway that traverses the district. Another important road runs from Voi to Mwatate and further to Taveta and Moshi in Tanzania. These roads, together with the road from Mwatate to Wundanyi, are the only tarmac roads in the area (Vogt & Wiesenhuetter 2000: 13). In total, there are 1,038 km of classified roads in the district. Many of the gravel and earth roads are in poor condition, especially during and after heavy rains.

The main railroad connection in the district is the Nairobi – Mombassa line that has a station in Voi. There is also another connection between Voi and Taveta and further to Moshi in Tanzania, but this line is not used as much as the more important Nairobi-Mombassa line.

The water availability varies greatly in the district, particularly between the lowlands and the highlands. In the highlands the water accessibility situation is good: most people are no more than one kilometre from the water, while in the lowlands the distance can be three kilometres (Vogt & Wiesenhuetter 2000: 57).

2.2.6 THE TAITA HILLS: PART OF THE EASTERN ARC MOUNTAINS

The Eastern Arc Mountains (EAM) are a chain of isolated mountain blocks in Kenya and Tanzania (Figure 7). They are influenced by the Indian Ocean; the northern part of the mountains has a bimodal rainfall pattern, while the southern part has a monomodal pattern. The EAM, from north to south, include the North and South Pare, West and East Usambara, Nguru, Nguu, Ukaguru, Rubeho, Uluguru, Malundwe, Udzungwa and Mahenge Mountains in Tanzania, and the Taita Hills in Kenya (Iddi 1998: 19).

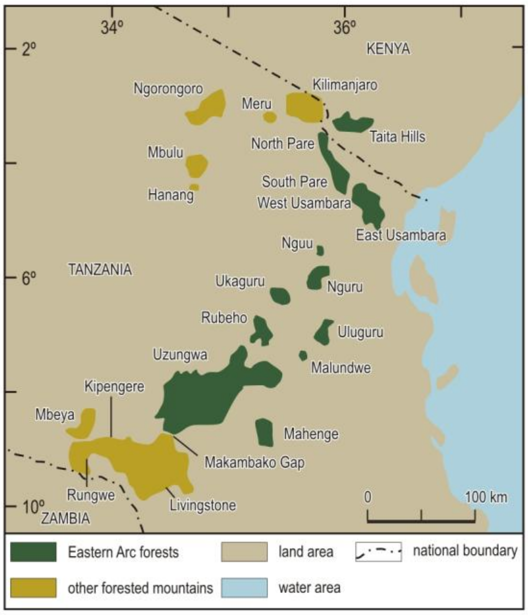

Figure 7. The EAM (modified after Eastern Arc Mountains Information Source (2002).

The ancient crystalline gneiss rocks of the EAM are part of the Precambrian Mozambique belt, which is composed of highly metamorphosed sediments and minor intrusive bodies (Griffits 1993 , cit. Lovett 1996: 632). These basement rocks have been periodically uplifted by faulting and weathering over millions of years (WildWorld 2005a). Northern and southern parts of the EAM are considered to have had a relatively similar long-term geological and climatic history (Lovett 1993a, 1993b), which has led to quite similar flora and fauna in the mountains.

Although the exact prehistoric impact coverage of forest in the EAM is unknown (yet, see e.g. Fjeldså & Lovett 1997), the existence of remnant patches of forest at varying elevations throughout the mountains suggests that nearly all of the EAM were forested before human occupation. Human disturbance and fire have caused extensive forest loss and fragmentation in the EAM (Newmark 1998: 29). In recent years, increasing human populations have placed an even greater demand on the resources of the EAM.

The maximum total area of the natural forest, both open and closed, in the Eastern Arc Mountains is 5,340 km² (Newmark 1998: 31). All of this remaining forest is highly fragmented: median natural forest patch size across all of the EAM is 10.2 km², while the mean is 58.0 km² (Newmark 1998: 31). The forests covering the mountains can be classified as montane, submontane or lowland / foothills (Hertel et al. 2000: 3).

The EAM are important at both the global and national levels (Iddi 1998). Globally, they are significant for their high biodiversity, which contributes to ecosystem stability, scientific value, a high potential for ecotourism and gene-pool value. At the national level, the EAM are vital, for instance, for water supply, wood fuel, timber, food and herbal medicines (Iddi 1998).

In the EAM, there are 1,500 endemic plants and 121 endemic vertebrates (Myers et al. 2000: 856). Because of this density of species, it is thought to be the hotspot most likely to suffer greatest plant and vertebrate extinction in the world (CEPF 2004). Thus, the EAM were previously classified separately as a biodiversity hotspot by Conservation International (Mittermeier et al. 1998; Myers et al. 2000), but now the region lies within the Eastern Afromontane hotspot (Conservation International 2005). Hotspots recognized by Conservation International consist mainly of heavily exploited, and often highly fragmented, ecosystems greatly reduced in extent (usually with less than 25% of original pristine vegetation remaining) (Mittermeier et al. 1998: 516). The EAM are also one of the Global 200 ecoregions (WildWorld 2005b).

3 FORESTS

3.1 FORESTS IN KENYA

It is widely accepted that forests in Kenya have been decreasing in size and in number in recent times, although Kenya has never been totally covered with forests in the recent geological past. This is due to the fact that only less than 20% of the land area in Kenya has a climate that could enable closed forests to grow (KIFCON 1994: 5). The main reasons for this forest decrease and degradation are similar in the whole country: the growing population has caused the need of land for housing and agricultural purposes. Also, uncontrolled commercial logging, charcoal making, unregulated grazing, extraction of wood for domestic and commercial purposes and overall industrial development have lessened the forest quality in Kenya (Table 3) (Foley & Barnard 1984: 43; KIFCON 1994: 1; MENR 1994: 39–40). In the 1980s, increasing uncontrolled exploitation led to a presidential decree which forbade logging of indigenous timber and grazing of livestock (KIFCON 1994: 7).

The forests of Kenya can be classified in several ways. In the classification introduced by Wass (1995: 11), these forests are divided into four regions (Figure 8): *coastal forest region*, *dry zone forest region*, *montane forest region* and *western rainforest region* (Table 4). In the dry zone forest region, most of the closed canopy forests occur in small isolated hills and mountains, such as the Taita Hills. Another classification has been compiled in the Kenya Forestry Master Plan using previous classifications done by Beentje (1990, cit. MENR 1994: 35) and Abell (MENR 1994: 35). In this classification, the forests of Kenya are classified as closed broadleaved forests, open broadleaved forests, coniferous forests, bamboo forests and mangrove forests. These forest types cover approximately 2% of Kenya (MENR 1994: 35).

Table 3. Direct uses of indigenous forests (MENR 1994: 44).

User group	Type of use	Goods and services obtained
Local households	Extractive and non-extractive subsistence and income-generating activities, both licensed and illegal	Fuel wood, charcoal, construction materials, timber, carving wood, hives, weapons, tools and domestic implements, grazing and fodder, medicines, honey, food, animal products, ropes, mats, bags, baskets and pots, minerals, water, habitation, cultivation, ritual and ceremony
Large-scale commercial enterprises	Licensed and illegal extractive activities	Timber and wood products
Leisure and educational visitors	Non-extractive activities	Leisure and holidays, research and study

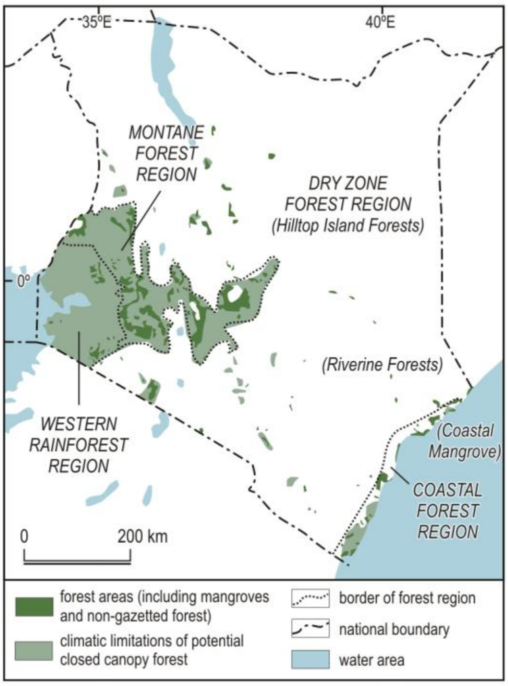

Figure 8. Forest regions in Kenya (modified after Wass 1995: 11).

Table 4. Forest Regions in Kenya (Wass 1995: 11).

	Area of closed canopy indigenous forest in the region (ha)	% of the total region	Additional plantations (ha)
Coastal forest region	82,500	9.9	3,200
Dry zone forest region	211,000	0.4	8,200
Montane forest region	748,000	18.0	102,800
Western rainforest region	49,000	1.9	18,600

Approximately 2,000 tree and shrub species can be found in the forests of Kenya (Wass 1995: 19). As Table 5 shows, these forests contain a large proportion of woody plants, birds and mammals. Due to the land cover change and degradation of forests, many of these species are threatened. The threatened trees and shrubs can be found at least in 60 inland and 65 coastal forests, although most of these rare species occur in coastal forests, in the Taita Hills and in the mountains east of the Rift Valley (Wass 1995: 25).

Table 5. Threatened species in Kenya (Wass 1995: 19).

	Total species		Threatened species		
	National	Forest	Forest	Savannah	Other
Woody plants	2,000	1,045	104	46	8 moorland
Birds	1,070	299	35	18	5 + 13 wetland
Mammals (over 500 g)	130	57	21	7	1 swampland

Forests are managed in many different systems in Kenya (Table 6). *Gazettement* means setting aside a certain area by the government through a Gazette notice (Matiru 2000: 29). Usually gazetted forests have been surveyed, demarcated on the ground and declared as a forest reserve. These gazetted forests are managed by the Forest Department (FD) on behalf of the state (MENR 1994: 38). Also de-gazettement of forests has to be done through Gazette and Legal notices (Matiru 2000: 29). Wass (1995: 81) and Matiru (2000: 29) have declared some of the other terms as follows. *Forest reserves* are state land or trust land, gazetted under the Forests Act. The FD manages the forest reserves on state land, and local authorities look after the ones that are on trust land. Forest reserves include indigenous forest, plantation and sometimes even grassland, prisons or colleges. *Nature reserves* are always parts of Forest Reserves where consumptive use is prohibited. They are gazetted especially for preservation of natural amenities, flora and fauna. Both *national parks* and *national reserves* are gazetted under the Wildlife (Conservation and Management) Act. National Parks are government lands managed by the Kenya Wildlife Service (KWS) while National Reserves are trust lands managed by the local authorities. *Trust land* is land held in trust for local people under the jurisdiction of the local County Council. However, Matiru (2000: 20) argues that these Councils seldom treat forestry as an important activity. In addition forests can be found on *sanctuaries*, *marine reserves*, *national monuments* or *private land*.

Table 6. Areas of indigenous forest held under different land tenures (Wass 1995: 82). All nature reserves occur within forest reserves and thus nature reserve includes 13,100 ha double gazetted as forest reserve and nature reserve. Furthermore, all of the marine reserves are assumed double gazetted as marine reserve and forest reserve.

Category of gazettement / holding	**Land Tenure**	**Area (ha)**
Forest reserve (terrestrial)	state land	1,200,000
Forest reserve (mangrove	state land	54
Nature reserve	state land	27
National park	state land	63
National reserve	trust land	14
Sanctuary	trust land	500
Marine reserve	state land	14
National monument	state, trust or private land	<100
Trust land	trust land	±100,000
Private ownership	private land	**

** data not available

Forests that are gazetted are still not totally safe from exploitation. In 1992 KIFCON estimated that gazetted forests are being lost in a rate of 5,000 hectares per year through the conversion of forest land to other uses (Hodgson 1992: 11). KIFCON has also estimated that there are 1.06 million hectares of indigenous forest in forest reserves and 0.18 million hectares of it outside the forest reserves, while the total amount of gazetted forest reserve area is 1.64 million hectares (Wass 1995: 14). About 40% of Kenya's forest estate occurs in large gazetted forests areas in the Montane Forest Zone. On the other hand, many of the other estates are extremely small and fragmented.

In 1992, Fries & Heermans (1992: 9) criticised the lack of forest management plans, and furthermore, of methods to apply those plans in Africa. However, in 1994 a new Kenya Forestry Master Plan was published. This plan, containing no operational guidelines, shows the direction that should be taken in general with forestry (MENR 1994). Although forest plans may have been missing, many different laws have considered the forest management in Kenya since 1891 (Hodgson 1992: 3).

The first forest policy was written in 1957 (White Paper No. 85) (Wass 1995: 75; Kigomo 1996: 102). A few modifications to the policy were done in 1968, and in 1994 the present forest policy received the Cabinet approval and thus replaced the outdated version (MENR 1994: 72; Matiru 2000: 9). The Constitution of Kenya itself makes no direct references to the environment or forests. The legislation, that concerns forests, is quite wide but it is spread over various Acts (see Matiru 2000: 6–8). Because most of these Acts have been sectoral, the Environmental Management and Co-ordination Act were enacted in 2000 in order to provide an appropriate legal and institutional framework for the environmental management (Matiru 2000: 15; KFWG 2005a). The Forests Act of 1962, revised in 1982 and 1992, was not appropriate for the current situation dealing with Kenyan forests. That is why a new Forest Bill 2005, approved by Parliament in 2006, was prepared (KFWG 2007). This Bill deals with all forests and woodlands on state, local authority and private land (Third national report on the… 2004). The Bill also puts a lot of emphasis on communities, as it discusses the community participation and multiple stakeholders in forestry (Mwan'gombe 1999; KFWG 2003b).

3.2 TROPICAL MONTANE CLOUD FORESTS IN THE TAITA HILLS

3.2.1 TROPICAL MONTANE CLOUD FORESTS

According to the definition given by Hamilton et al. (1995: 3) the tropical montane cloud forests (TMCF) are closed forests that are composed of forest ecosystems of distinctive floristic and structural form. These forests are usually found in relatively narrow altitudinal zone where persistent, frequent or seasonal cloud cover occurs. There is a significant variation in the altitude where TMCF can be found, depending whether it is situated on inland or coastal mountains: inland TMCF occurs typically between 2,000–3,500 m whereas coastal and insular TMCF may occur as low as 1,000 m. Terms considering this kind of forest vary a lot in different sources. The forests in the study area in the Taita Hills can be defined not only as TMCF, but also as upland moist or mist forest (Beentje 1988) as well as lower montane tropical forests (Niemelä 1988). Figure 9 presents the general vegetation zones in equatorial Africa as well as a cross-section of the Taita Hills.

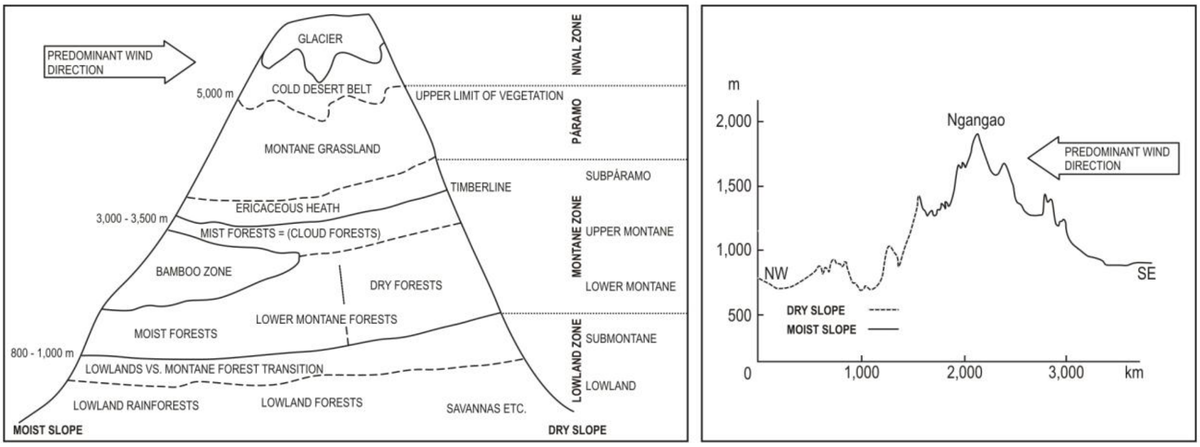

Figure 9. Vegetation zones in equatorial Africa on the left (modified after Niemelä 1988: 60) and north-west – south-east directed cross-section of the Taita Hills on the right. The cross-section goes through the forest of Ngangao.

3.2.2 CHARACTERISTICS OF THE TAITA HILLS FORESTS

The Taita Hills indigenous forests consist of small forest patches that are very fragmented, although the forest cover was once a lot more extensive. Since the 1960s, the forests have suffered substantial loss and degradation, and today less than 400 ha of natural forest remain as a scatter of 12 remnants, of which eight are smaller than 5 ha (Figure 10) (Beentje 1988; Brooks et al. 1998; Bytebier 2001: 30). The three largest forest fragments are Mbololo, Ngangao and Chawia. These forests are embedded in a mosaic of human settlements, smallholder cultivation plots and plantations of exotic trees (Brooks et al. 1998). The sizes of the forest patches vary a lot in different research reports (see Beentje 1988; Run 1995; Bytebier 2001). This is probably due to different methods: in some research aerial photographs have been used while in others only ground surveys have been made.

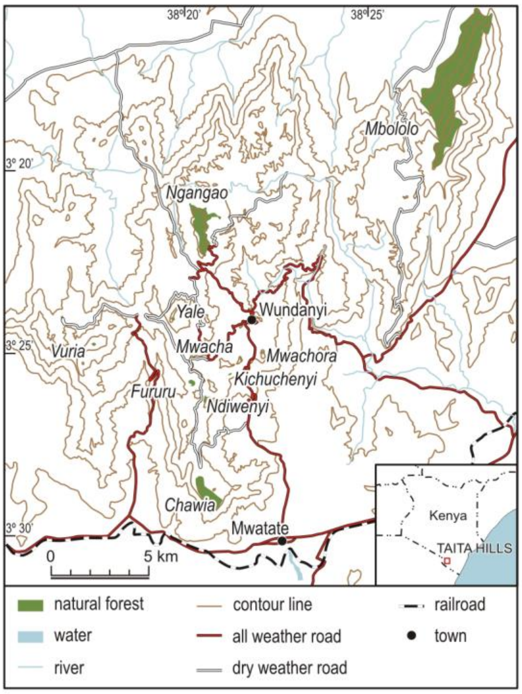

Figure 10. Natural forests of the Taita Hills.

The Taita Hills forests occur at elevation between 1,300 m a.s.l. and 2,200 m a.s.l. The moderately high rainfall (ca. 1,270 mm per year) that the area receives enables the existence of mist forests in the hills (Mbuthia s.a.). According to Beentje (1988: 25; Beentje 1990 , cit. Muthoka 1996 and KFWG 2003a), the forests in the Taita Hills can be classified as upland moist forest or upland mist forest. These forests are also called tropical montane cloud forests. The forests can further be classified into at least two forest types: 1) Ocotea forests that occur in the highest parts (above 1,600 m a.s.l.) and 2) Newtonia forests that occur at 1,250–1,800 m a.s.l. with annual rainfall of about 1,250–1,580 mm. Typical vegetation in Ocotea forests are *Ocotea usambarensis*, *Tabernaemontana stapfiana* and *Aningeria adolfi-friedrichii* and in Newtonia forests *Newtonia buchananii*, *Tabernaemontana stapfiana*, *Albizia gummifera*, *Strombosi scheffleri*, *Nuxia* spp., *Rapanea menlanphoels* and *Xymalos monospora*. These different vegetation types are intermingled in most of the forests.

In addition to indigenous forests in the Taita Hills, there are a few plantations of exotic trees. The oldest plantation forest is on Sagalla, consisting of *Pinus elliottii* (Beentje 1988) while Mwambirwa is the most extensive plantation also with *Pinus elliottii* located east of Wundanyi. Some of the plantations have been started on eroded hillsides (Beentje 1988: 25) but there are also plantations of exotic trees such as *Eucalyptus* sp., *Cupressus lusitanica* and *Acacia meansii* intermixed with the indigenous forests. Moreover, in some cases plantations were done to replace the forest that was destroyed because of forest fires (Beentje 1988 :25).

3.2.3 GAZETTEMENT

The gazettement situation of the Taita Hills forests is difficult to trace. What is known is that the Kenyan Forest Department started to get involved with the forests in the 1950s (Brooks et al. 1998: 122). In 1973 the County Council of Taita-Taveta began the process of transferring the forests from the Council to government ownership by approving 22 forest areas for gazettement. Several of these areas were plantation forests. A year later additional 10 forest areas were added. This addition, proposed to be gazetted, included the forest areas of Ngangao (139 ha), Mbololo (370 ha), Sagalla (1,280 ha) and Chawia (86 ha) (Beentje 1988: 24). According to Tetlow (1987, cit. Brooks et al. 1998: 122) a total of 43 forests had been approved for gazettement by 1984. However, it was not until 1991 when the first Taita Hills forests were gazetted under the legal notice 235/1991 (IUCN 1996, cit. Brooks et al 1988: 122; Matiru 2000: 49), although Collins & Clifton stated already in 1984 that Chawia had been gazetted as a national forest. The list of forests gazetted in the Taita Hills varies a lot in different sources: according to Wass (1995: appendix 2), none of the forests is gazetted while Hodgson (1992) and Matiru (2000) list a number of gazetted forests (Table 7).

Table 7. Gazetted forests in the Taita Hills and their areas (ha) according to Hodgson (1992) and Matiru (2000).

	Hodgson (1992)	**Matiru (2000)**
Chawia	86	-
Choke (Mnjonyi)	74	73.4
Figi	-	0.4
Fururu	14	14.12
Goye	8	8.23
Kilulunyi	0	0.36
Kinyeshamvua	50	19.5
Kulundu	-	0.08
Macha	15	14.57
Mbili	16	10.23
Mbololo Juu	69	-
Mwambirwa	18	-
Mchungunyi	8	8
Mdengu	-	0.36

	Hodgson (1992)	**Matiru (2000)**
Mgomenyi	-	0.2
Mtege	-	0.28
Mudugacha	-	3.4
Mwachora	6	6.4
Mwakamu 1	-	0.9
Mwakamu 2	2	0.6
Mwandongo	688	688
Ndiwenyi	6	5.6
Ngangao	123	-
Sagalla	70	-
Susu	2	1.7
Weni Mbogo	2	2
Weni Mwana	5	5.26
Yale	22	22.23

The Taita Hills are a special case when it comes to the management of the forests. The Forest Department manages the forests, also those not gazetted yet, on behalf of the Taita-Taveta County Council (Biodiversity Conservation at Taita Hills Forest 2001; Flora of Taita Taveta District 2002: 3; KFWG 2003b). In addition, the gazetted forests of the Taita Hills are managed under the Joint Management Memorandum of Understanding between the Forestry Department and the Kenyan Wildlife Service (Matiru 2000: 34). However, the gazettement process of the remaining forest areas still continues (Flora of Taita Taveta District 2002: 2; KFWG 2003b).

3.2.4 IMPORTANCE AND THREATS

Forests in the Taita Hills have recently reduced tremendously in size and in number. This decrease has been a consequence of human action in the area. Population pressure, logging, need for agricultural land and exotic plantations among other things have caused decreasing and degrading of the forests.

Nowadays not only scientists but also the local people recognize the value of the forests, although there are some serious conflicts between the efforts of local people trying to meet their requirements for income and food production and the efforts to sustain forest resources (Hertel et al. 2000: 4). The forests are very important in terms of local climate, water resources, soil erosion, commercial value and providing various forest products such as traditional medicine to the people living near the forests (Mbonye 1986: 15).

Because of the limited catchment area and continued forest clearance, none of the five rivers which drain from the hills (Lumi, Ruvu, Mwatate, Voi and Tsavo) no longer have a permanent flow in the plains (Taiti 1996: 40). Clearing the forests for agricultural use is particularly risky in mountainous areas, where steep hillsides require a variety of measures such as the construction of terracing and a careful choice of crops and ground cover plants to protect the soil (Foley & Barnard 1984: 7).

Population pressure is and has been the greatest risk for the forests in the Taita Hills (Flora of Taita Taveta District 2002: 2). The growing human population needs more farmland. In addition, the requirement for unsustainable forest activities such as logging and charcoal burning has increased (Conservation Profile of Taita-Taveta 2001: 5). The forests have been influenced by man since the first people occupied the Taita Hills centuries ago. The disturbance of natural forest vegetation has resulted among other things from firewood collecting, clearing for agricultural production and exotic plantations, fire, selective logging of high value timber species in the past, charcoal burning, and selective harvesting for high value medicinal plants (Beentje 1988: 25; Flora of Taita Taveta District 2002: 4). The challenge is to maintain the biological integrity of these forests while meeting the livelihood needs of the local people (Mbuthia s.a.). It is not only human related causes that act as threats to the forests; the indirect influences of damaging forest health agents such as tree pathogens, vines and invasive exotics need to be considered as well (Hertel et al. 2000: 4).

3.2.5 BIODIVERSITY IN THE TAITA HILLS

Changes in land use have caused the destruction and alteration of habitats in tropical forests. This in turn has led to decreased biodiversity also in the Taita Hills. Biodiversity is a widely used term. In this text it refers to both the genetic diversity of an individual species as well as the species composition or the number of endemic species in an area. It can also refer to interactions between organisms and their environment at any spatial scale where life occurs (Silver et al. 1996; Whittow 2000: 54). The rates in species extinction along with the loss of biodiversity depend on the number of species present in forest patches as well as the distribution of deforestation and the level of disturbance and degradation of the areas that remain forested (Whitmore and Sayer 1992: 8).

Despite the fact that the forests in the Taita Hills are quite small and very fragmented, they are still extremely rich in biodiversity, like other forests in the Eastern Arc Mountains. The Taita Hills forest flora consists of over 400 species. At least 13 taxa of plants are endemic to the Taita Hills forests, and in addition, 22 plant species are typical of the Eastern Arc Mountains (Beentje 1988: 25; The Taita Biodiversity Conservation Project 2001). Many of the tree species in the Taita Hills are shared not only with the Eastern Arc Mountains but also the Kenyan Highlands (Wilder et al. 1998: 182).

Most of the endemic plants occur in more than one of the forest patches, but dry parts of Ngangao and moist parts of Ngangao and Mbololo hold some endemics that do not occur elsewhere. *Zimmermannia ovata* and *Psychotria* sp. are restricted to the dry northern Ngangao, *Saintpaulia teitensis* and *Yprilopus* sp. nov., on the other hand, occur only in the moist undisturbed parts of Mbololo. Endemics occurring in the moist parts of Ngangao and Mbololo are *Diphasiopsis fadenii*, *Coffea fadenii*, *Impatiens engleri ssp. pubescens*, *Impatiens teitensis*, *Memecylon teitense* as well as *Psycothria* spp. and *Chassalia* spp. (Beentje 1988: 25–26).

The forests of the Taita Hills not only hold endemic plants but also endemic animals; they accommodate at least 9 taxa of animals found only in the Taita Hills (The Taita Biodiversity Conservation Project 2001). Furthermore, the forests are included in the Endemic Bird Area with the Eastern Arc Mountains of Tanzania (Stattersfield et al 1998 , cit. Brooks et al. 1999).

In the forests of Mbololo, Chawia and Ngangao lives an endemic race of the Sykes' monkey *Cercopithecus mitis kima*. The back-fanged snake *Amblyodipsas teitana* is endemic to Mbololo and the toad *Bufu taitensis* to the Taita Hills, while the frogs *Arthroleptis adolfifrederici* and *Callulina kreftii* are endemic to the Taita Hills and the Usambaras in Tanzania (Beentje 1988: 28–29; Flora of Taita Taveta District 2002: 2). In addition, there are three endemic butterfly species in the Taita forests: the Taita swallowtail *Papilio desmondi teita*, the Taita charaxes *Charaxes xiphares desmondi* and the Taita glider *Cymothoe teita* (Collins & Clifton 1984).

Three of the birds found in the Taita Hills are endemic: the Taita Thrush *Turdus (olivaceus) helleri*, the Taita Apalis *Apalis (thoracica) fuscogularis* and the Taita White-eye *Zosterops (poliogaster) silvana* (Beentje 1988: 29; Brooks et al. 1996, 1998). The Taita White-eye is the least demanding when it comes to its living environment as it is common even in very small forest patches. The Taita Apalis survives in the forest edge in most of the fragments whereas the Taita Thrush needs a closed forest (Brooks et al. 1996: 10). Ngangao is the only forest housing all the three endemic bird species (KFWG 2003a).

Environmental and genetic factors pose an increasing stress on natural populations. Lens et al. (1999a; 2002a) analyzed the influence of these factors on endemic birds in the Taita Hills. The more disturbed the forest was, the more the birds showed increased levels of fluctuating asymmetry and mortality (see also Lens & van Dongen 1999; Galbusera et al. 2000; Lens et al. 2000, 2002b). Furthermore, these studies reveal a highly male-biased sex ratio of the Taita Thrush in the most disturbed forest, while a less biased ratio has been found in the less disturbed forests (Lens et al. 1998).

3.2.6 MBOLOLO

Mbololo (03º18' S, 38º27 'E) is the largest and also the least disturbed forest fragment in the Taita Hills. According to Bytebier (2001: 24), Mbololo consists of 220 ha of moist forest while Beentje (1988: 26) claims the extent to be 168 ha and Brooks et al. (1998: 120) 200 ha. Mbololo (between 720 m and 1,779 m a.s.l.) lies on a ridge in a small hill complex to the northeast of Dabida and partly attached to it. Mbololo is surrounded by agricultural land. It has a large pinus plantation in the north, and, on the steep north-east flank of the massif an undisturbed forest runs further down the hill (Brooks et al. 1998: 121).

Because Mbololo is the most remote and inaccessible forest in the Taita Hills, it has remained more undisturbed than the other areas. There has not been much logging although there are some old pit-saw sites (Imboma 1997). It is obvious, though, that Mbololo was not able to escape from firewood collecting and selective logging in the past. Mbololo is almost incomparable with the other forests in the Taita Hills as it has more biomass, higher stem densities, more tree species, higher diversity, higher equitability, greater canopy cover, more open shrub layer, higher leaf litter cover and less herbaceous cover than Ngangao and Chawia (Bytebier 2001). Furthermore, waters flowing from Mbololo serve the main settlement areas including the nearby Voi Town (Conservation Profile of Taita-Taveta 2001: 5).

The most common trees in Mbololo include *Tabernaemontana stapfiana*, *Albizia gummifera*, *Cola greenwayi*, *Phoenix reclinata*, *Macaranga conglomerata*, *Newtonia buchananii* and *Strombosia scheffleri*. *Tabernaemontana stapfiana*, *Phoenix reclinata* and *Maesa lanceolata* are present particularly in the more disturbed parts of the forest. Some of the most common undergrowth includes *Culcasia falcifolia*, *Pauridiantha pauciflora*, *Blotiella stipitata*, *Dracaena steudneri* and *Asplenium holstii* (Beentje 1988). Mwangangi and Mwaura (1993) estimate that the Mbololo forest has an upper canopy of 45%, a middle canopy of 60%, a lower canopy of 80%, a shrub cover of 70% and a herbaceous cover of 36%.

3.2.7 NGANGAO

The second largest forest in the Taita Hills is Ngangao (03º22’ S, 38º20’ E) (Figure 11). It is situated quite in the middle of the main hill complex between 1,700 m and 1,952 m a.s.l. The extent of the forest differs in different sources. According to Bytebier (2001: 24) and Beentje (1988: 24), it comprises 92 ha, while Run (1995: 18) claims it to consist of 113 ha of indigenous forest, 29 ha of forest plantation and 5 ha of bare rock. The forest is surrounded by agricultural land and to the west, by steep cliffs. Outside the main forest, there are also very small patches of natural and planted forest intermixed with agricultural land.

Ngangao has suffered an intermediate level of disturbance, although it is one of the best forests in the Taita Hills. There are lots of old pit-saw sites, which were used to saw the logged trees. Most of the logging stopped after the Presidential Ban of 1977 which prohibited the cutting of indigenous trees without a licence (Beentje 1988: 25; Tetlow 1987). Nowadays even collecting of wood waste is controlled by the forest guard (Mwandoe 2004). According to the forest guard of Ngangao Mr. Mwandoe (2004), one of the greatest threats to the Ngangao forest in these days is fire, although there have not been any big fires in recent years. Furthermore, the collection of firewood and timber, both under licence and illegally, continues on a small scale in Ngangao as in other forests too (Brooks et al. 1998: 122).

Figure 11. The western side of the forest of Ngangao (22.1.2005, Petri Pellikka).

Plantations in Ngangao began in 1955, when 0.78 ha of pines were planted on the western edge of the forest. Since then, there has been several plantations including *Cupressus lusitanica* and *Pinus patula* in 1971 and 1973 to prevent erosion, and *Acacia* and *Maesopsis eminii* in 1976 (Tetlow 1987). Most of the plantations in Ngangao have been accomplished in areas that had already been cleared before or where no forest had been growing (Mwan'gombe 2004). Furthermore, these plantations replaced the original forest where it has disappeared due to forest fires (Beentje 1988: 25). An exception is an area near the local Mwarangu Youth Polytechnic, which was cleared for exotic plantations in mid-1980s (Brooks et al. 1998; Beentje 1988). The plantations separate a small indigenous forest area in the north; the plantations in the central part almost cut the main part of the forest into two. There has been an intention to replace the exotic species with indigenous species but this action has never been put into effect (Mwan'gombe 2004).

Ngangao has a wide range of trees from pioneer species to forest interior ones. Common pioneer species include *Phoenix* sp., *Bridelia micrantha*, *Maesa lanceolata*, *Celtis* sp. and *Ficus* sp. (Imboma 1997: 8). Other common trees include *Tabernaemontana stapfiana*, *Aningeria adolfi-friedericii*, *Albizia gummifera*, *Cola greenwayi*, *Macaranga conglomerata*, *Craibia zimmermannii*, *Syzygium sclerophyllum*, *Milletia oblate* ssp. *teitensis*, *Strombosia scheffleri* and *Newtonia buchananii* (Bytebier 2001: 79–80; Beentje 1988). Two of these, *Tabernaemontana stapfiana* and *Albizia gummifera* are broadly distributed species that are known to occur in disturbed forests. *Podocarpus latifolia* and *Ocotea usambaresis* are reported to have been common but are now almost absent as a result of extraction (Bytebier

2001: 17). There are lots of trees that are quite small but Ngangao holds some very large trees too (Wilder et al. 1998: 183). In 1993 Mwangangi & Mwaura estimated that Ngangao forest had an upper canopy of 40%, a middle canopy of 50%, a lower canopy of 60%, a shrub cover of 75% and an herb cover of 40%.

3.2.8 CHAWIA

Chawia (03º29' S, 38º20' E) lies in the south-western part of the hills, on top of the Bura Bluffs between 1,460 m and 1,587 m a.s.l. (Figure 12). According to Bytebier (2001: 24) and Brooks et al. (1998: 121), it comprises approximately 50 ha, while Beentje (1988: 28) claims that it only comprises 17 ha and Run (1995: 18) that it comprises as much as 100 ha of indigenous forest, with 4 ha of forest plantation along the edges. The forest is surrounded by agricultural land and, to the west and south, by very steep cliffs.

The Chawia forest is heavily disturbed. One of the reasons for this is that there was a way through the forest which enabled the local people to enter the forest for various purposes; nowadays there is a road going to a transmission tower. Moreover, the forest has been degraded by grazing and planting of the exotic trees (Flora of Taita Taveta District 2002: 5). These include *Cupressus lusitanica* and *Eucalyptus* sp., which surround the natural forest and partly spread into it, thus degrading the forest even more (Imboma 1997). Chawia is actually demarcated with *Eucalyptus* sp. Outside this border, cutting trees was allowed thus resulting in the diminution of the forest area. In Chawia, plantations have not only occurred in non-forested parts of the area. Here the Forest Department has also cleared the original forest to make way for exotic trees (Beentje 1988: 25).

Figure 12. The forest of Chawia photographed from the transmission tower (25.1.2005 Petri Pellikka).

The forest is dominated by two indigenous trees, *Albizia gummifera* and *Tabernaemontana stapfiana*. Underneath their canopy there are exotic planted trees and also a lot of wild coffee (Imboma 1997; Beentje 1988: 28). In the central valley of the forest there is some disturbed remnant forest dominated by *Albizia* and *Tabernaemontana*, with *Polyscids fulva* and *Cyathea manniana* as common species (Beentje 1988: 25). The heavy selective logging of easily-transported small trees has prevented regeneration, which is indicated by the low number of small trees, high mean size and low canopy cover of the forest (Wilder et al. 1998: 183).

3.2.9 OTHER FORESTS IN THE TAITA HILLS

Sagalla (03º30' S, 38º35' E), 1,350–1,450 m a.s.l. is a narrow strip of disturbed forest south-east of the Taita Hills. It comprises of approximately 4 ha of forest (Wilder et al. 1998). Epiphytes occur here in larger numbers than any of the other forests (Beentje 1988: 27).

Fururu (03º24' S, 38º20' E), 1,400 m a.sl. lies on the ridge crest north of Chawia. It is partly disturbed small fragment (5 ha), surrounded by agricultural land. It has been interplanted with *Eucalyptus* sp. (Bytebier 2001: 24; Brooks et al. 1998: 121).

Mwachora (03º25' S, 38º22' E), highest point 1,627 m a.s.l., is a small fragment (2 ha) on a hilltop. This disturbed, open forest type fragment without closed upper canopy is surrounded by agricultural land (Bytebier s.a.: 16; Brooks et al. 1998: 121; Bytebier 2001: 24). West of Mwachora is Mwacha (2 ha, highest point 1653 m a.s.l.) which is also disturbed and surrounded by plantations and agricultural land (Bytebier 2001: 24)

Vuria (03º25' S, 38º17' E), is the forest situated on the highest peak of the Taita Hills (2,208 m a.s.l.). Once, very densely forested mount Vuria is nowadays dominated by forest plantations (Run 1995: 18; Beentje 1988: 24). Remaining is only a small fragment (1 ha) of closed canopy forest on the western slope while the rest is heavily disturbed and has a lot of secondary vegetation (Bytebier 2001: 24, Bytebier s.a.: 16).

Yale (03º24' S, 38º18' E) is a high (2,104 m a.s.l.) rocky outcrop that has only two small fragments of indigenous forest (1 ha) left on the northern and eastern side of the rock-face (Bytebier 2001: 24), although Beentje reported in 1988 that the forests of Yale, Wesu and Susu had been totally disappeared. The forest is disturbed and intermixed with plantations.

Kichuchenyi (03º26' S, 38º22' E, 1,500 m a.s.l.) and Ndiwenyi (03º26' S, 38º21' E, 1,600 m) are small fragments (1 ha or less) of open forest type. They are disturbed and largely surrounded by agricultural land (Bytebier 2001: 24, Bytebier s.a.: 16).

Mwambirwa (03º21’S, 38º26’E, 1400 m a.s.l.) is actually an extensive plantation of *Pinus patula*, and it is managed mainly for sap production (Brooks et al. 1998). In addition, there are small patches (1 ha or less) of indigenous forest scattered within the agricultural areas (Bytebier 2001: 24).

4 REMOTE SENSING

4.1 MAIN PRINCIPLES OF REMOTE SENSING

Remote sensing can broadly be defined as gathering of information at a distance (Campbell 2002: 4). More precisely it can be defined as *a science or art of deriving information about an object, area or phenomenon through the analysis of data acquired by a device that is not in contact with the object, area or phenomenon under investigation* (Lillesand & Kiefer 2000: 1).

Remote sensing may be divided into passive and active remote sensing systems. Passive systems measure the intensity of the reflected or emitted electromagnetic radiation from the surface, originally coming from the sun. Active systems, instead, generate the electromagnetic radiation themselves and measure the intensity of the radiation scattering back to the sensor. These active sensors include e.g. microwave (radar) and laser (lidar) sensors, whereas cameras, multispectral scanners, linear and area arrays and spectroradiometers are examples of passive sensors implemented most often in satellites or aeroplanes.

All radiation detected in the sensors has passed through some distance of atmosphere. The effect of the atmosphere varies not only depending on this distance, also known as *path length*, but also on the intensity of the signal being sensed, the atmospheric conditions and the wavelengths involved (Lillesand & Kiefer 2000: 9). While passing through the atmosphere, solar radiation is subject to numerous physical processes, including scattering, absorption and refraction (Campbell 2002: 32–33). Scattering is the unpredictable redirection of electromagnetic radiation. The most common scattering types are Rayleigh, Mie and Non-selective scattering (Jensen 1999: 41–42; Richards & Jia 1999: 41–42; Campbell 2002: 33–35). Absorption may take place in the atmosphere or on the terrain. The gases of the atmosphere selectively absorb the energy at given wavelengths. The wavelength ranges in which the atmosphere transmits the energy relatively easily are referred to as the *atmospheric windows* (Gibson & Power 2000: 2; Lillesand & Kiefer 2000: 10; Campbell 2002: 38–39).

The interactions between the electromagnetic radiation and the terrain can be described with the radiation budget equation:

$$\Phi_{i_\lambda} = r_\lambda + \tau_\lambda + \alpha_\lambda. \qquad (1)$$

The total amount of radiant flux in specific wavelengths (λ) incident to the terrain (Φ_{i_λ}) must be counted for by evaluating the amount of reflected energy from the surface (r_λ), the amount of absorbed energy by the surface (α_λ) and the amount of transmitted radiant energy through the surface (τ_λ) (Jensen 1999: 44; Lillesand & Kiefer 2000: 12–13). The proportions of electromagnetic radiation reflected, absorbed and transmitted vary for different terrains depending on the material type and condition (Lillesand & Kiefer 2000: 12–13). These characteristics enable the distinguishing of different features on a remote sensing image. The spectral reflectance characteristics of three different land surface types are represented in Figure 13.

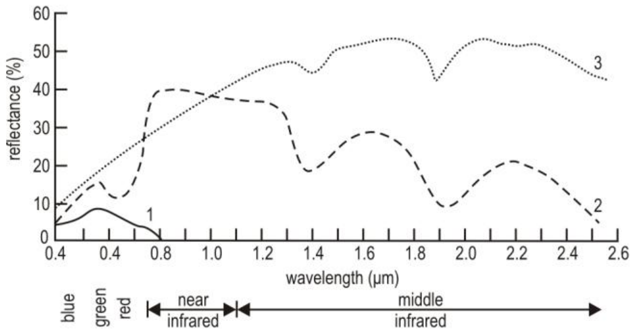

Figure 13. Spectral reflectance curves of water (1), vegetation (2) and soil (3) (modified after Richards & Jia 1999: 3).

4.2 RESOLUTION ISSUES

The major characteristics of a remote sensing system are described with its spectral, spatial, radiometric and temporal resolution. These four different resolution types define the accuracy that can be achieved with the system in question.

Spectral resolution refers to the width and number of spectral bands to which the remote sensing instrument is sensitive (Jensen 2000: 12; Mather 2001: 33–34). An instrument with many narrow bands averages less than an instrument with only a few wide bands. Thus, selecting the appropriate sensor for a certain assignment is important for its success.

The fineness of the spatial detail visible in an image refers to spatial resolution. Commonly used measures of spatial resolution are *instantaneous field of view* (IFOV) of a sensor and the pixel size of an image (Mather 2001: 30; Longley et al. 2005: 202).

Radiometric resolution refers to the number of digital levels used to express the data collected by the sensor. The number of these levels is expressed with the number of binary digits (bits) needed to store the value of the maximum level. Consequently, 8-bit data have 256 possible levels that are represented by the integer values 0–255 (Mather 2001: 34–35).

Temporal resolution, for its part, describes the frequency with which images are collected for a particular area.

Choosing a proper RS data for the phenomenon under research is not an easy task. Besides the resolution aspect, availability is often a restrictive factor. Most phenomena do not have one right resolution to study them with. Rather, studying complex issues at various scales and understanding how processes operate at these scales is more important (Marceau 1999). In addition, ambition for increasingly high resolution in all four resolution categories is not necessarily the answer. Data with coarser resolution have their advantages when balancing between the level of detail needed and the manageability of the data (Toivonen 2006: 27). The most important thing is to recognise and understand the special characteristics and limitations introduced by the resolution in all RS data.

4.3 DIGITAL AERIAL PHOTOGRAPHY

Previously, digital remote sensing has often referred almost exclusively to satellite images as digital aerial photography has been in its infancy. At the moment, digital aerial photography is becoming more and more important in the field of aerial photography.

The biggest difference between a traditional aerial camera and a digital aerial camera is in how they record the data. Whereas a traditional aerial camera has a layer of light-sensitive film at the film plane, a digital camera has solid-state CCD (charge-coupled-device) -detectors instead of the film. The CCD consists of metallic electrode on a silicon semiconductor that is separated by an oxide insulator (Figure 14) (Campbell 2002: 95; Konecny 2003: 31). The incoming photons charge the electrodes while the semiconductor acts as a capacitor. This charge is directly related to the amount of photons arriving at the electrode (Jensen 2000: 95; Konecny 2003: 31).

The detectors are arranged to form a two-dimensional (raster) array. Moreover, there are sensors with detectors arranged as a line (CCD-line sensors). These sensors scan the ground area with at least three sensors at different angles (forward, nadir and backward) (Kheiri 2006). The analogue signal detected in the electrodes is sampled electronically and furthermore converted into a digital brightness value number from 8-bit to 10-bit (Jensen 2000: 95). Digital aerial cameras can produce e.g. black and white or colour (visible bands) images. Moreover, there are also detectors that are sensitive to the near infrared wavelength.

The spatial resolution of CCD-sensors is determined by the sensor area and the distance between the sensor elements (Konecny 2003: 32). At the moment, the size of the array of detectors varies from one Megapixel to more than 36 Megapixels (Kheiri 2006). Other characteristics of digital aerial cameras are determined by the characteristics of e.g. the lens, the view angle, the focal length (*f*) and the exposure time.

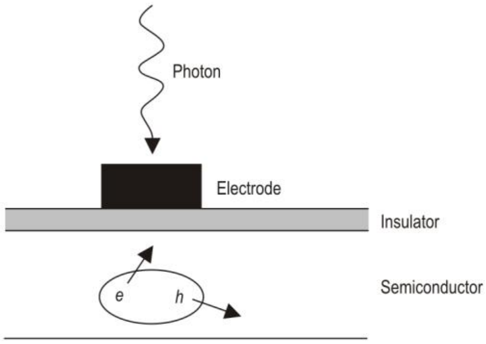

Figure 14. CCD Detector. (Schenk 1999: 161; Konecny 2003: 31).

The advantages of digital airborne camera data compared to traditional airborne camera data are in end-to-end digital flow line. In addition, automation and integration of the GPS-system to the camera give more accuracy to the aerial photographing. According to Pellikka (2003), the digital airborne imaging does not need as much light as traditional aerial photographing. Also, the absorption bands of the images can be defined in more detail. Furthermore, important advantages are digital data storage, manipulation, transmission and even easier display. The quality of the data increases when steps like chemical film, processing and scanning become unnecessary. On the other hand, the disadvantages of digital aerial photographs include unstable geometry and so called dead pixels (Pellikka 2003).

4.4 REMOTE SENSING OF FORESTS

4.4.1 REMOTE SENSING IN FOREST STUDIES

Forests have traditionally been studied with a lot of field work and sampling. In recent times, the role of remote sensing in forest studies has become more and more important. The use of remote sensing data began with black and white aerial photographs (Tokola et al. 1998: 2). Currently, colour (red, green, blue) and colour infrared (CIR) aerial photographs as well as satellite images and radars are used (see e.g. Holopainen 1998: 8; Uuttera et al. 1998; Trisurati et al. 2000; Gemmell et al. 2001; Drake et al. 2002; Næsset 2002). With recent improvements in digital cameras, digital aerial photographs also have potential in vegetation studies (Dean et al. 2000).

Remote sensing has many advantages in vegetation studies. One of the most important is the potentially lower-cost alternative to field-based assessment (Tokola et al. 1998: 2; Pouliot et al. 2002; Kangas et al. 2003: 121). Furthermore, the possibility to study large areas easily is very significant. The choice of the most appropriate data depends on the project aim and also on the available imagery's resolution and extent (Key et al. 2001: 100). The subjectivity of image interpretation decreases while more and more effort is put into digital and automatic image processing instead of visual interpretation methods (Tokola et al. 1998: 2). Despite the many advantages, remote sensing techniques still need the development of methods in order to easily and accurately extract the required information (Pouliot et al. 2002).

Lately, remote sensing techniques have been used successfully for example in forest inventories (e.g. Halme & Tomppo 2001), vegetation classifications (e.g. Trisurati et al. 2000; Key et al. 2001), tree crown detection (e.g. Uuttera et al. 1998; Pouliot et al. 2002), determining stand characteristics (e.g. Næsset 2002) and in estimating biomass (Drake et al. 2002; Heiskanen 2006). Other applications include planning of reforestation and mapping of vegetation disturbances such as fire, insect outbreaks, landslides and avalanches (Barrett & Curtis 1999: 335). The forest studies using RS data can utilise either the textural (Wulder et al. 1998) or spectral properties of the forest vegetation (Rautiainen 2005) or both (Tuominen & Pekkarinen 2005). The use of remote sensing techniques has also remarkable advantages in non-easily reachable areas such as tropical forests (Kangas et al. 2003: 121). This use of remote sensing has made it possible to put more effort into studying and mapping of tropical forests (see for example Trisurati et al. 2000; Drake et al. 2002; de Wasseige & Defourny 2002).

4.4.2 REFLECTANCE FROM VEGETATED SURFACES

Vegetated surfaces consist of individual leaves and other parts of the plants that are all organised in a particular manner. The reflectance from vegetated surfaces is thus determined by not only the leaf characteristics but also the structure of the entire vegetation. Also soil type, solar angle and climatic conditions affect the reflectance (Barrett & Curtis 1999: 326).

A healthy green leaf captures direct and scattered incident radiant flux (Φ_i). This incident electromagnetic energy then interacts with the pigments, water and intercellular air spaces within the leaf. The general equation for this interaction of spectral (λ) radiant flux on and within the leaf is

$$\Phi_{i_\lambda} = \Phi_{r_\lambda} + \Phi_{\alpha_\lambda} + \Phi_{\tau_\lambda} \cdot, \quad (2)$$

where Φ_{r_λ} = the amount of radiant flux reflected from the leaf
Φ_{α_λ} = the amount of radiant flux absorbed by the leaf and
Φ_{τ_λ} = the amount of radiant flux transmitted through the leaf (Jensen 2000: 334).

The interaction of energy in plant leaves is highly determined by the leaf structure (Figure 15). The outermost cell layer is formed by the cuticle and epidermis. These, as well as the lower epidermis with openings called stomata, are translucent and therefore can be penetrated by electromagnetic radiation. The palisade cells, just below the upper epidermis, contain chloroplasts with chlorophyll. This green pigment strongly absorbs energy in the wavelength bands centred at about 0.45 and 0.67 µm. Because of this very high absorption of blue and red energy and strong reflection of green energy healthy vegetation appears green in the visible range. Below the palisade layer are the spongy mesophyll cells that reflect about 60% of the near-infrared (NIR) irradiation back from the leaf. Thus, the peak reflectance of living vegetation is not in the green but in the NIR (Figure 16). This behaviour explains the usefulness of NIR in vegetation studies. Also differences between plant species are often more distinct in the NIR than in the visible green (Barrett & Curtis 1999: 326–327; Gibson & Power 2000: 111–112; Lillesand & Kiefer 2000: 18; Campbell 2002: 460; Kocecny 2003: 21).

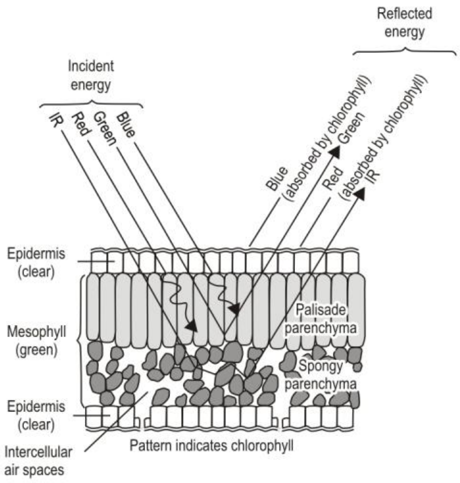

Figure 15. Cross-section of a leaf (modified after Kocecny 2003: 22).

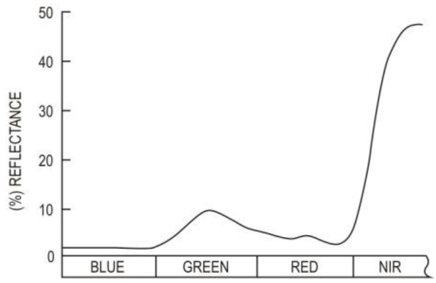

Figure 16. Typical spectral reflectance of a living leaf (modified after Campbell 2002: 462).

Spectral characteristics of a leaf or vegetation change when a plant senesces or becomes stressed or diseased. During leaf senescence, other pigments than chlorophyll begin to dominate thus causing the leaf to lose it greenness (Mather 2001: 20). Leaf senescence leads also to a decrease in infrared reflectance (Barrett & Curtis 1999: 327). Stress that caused by water shortage or other environmental factors can lead to a spectral response similar to senescence.

Reflection from a canopy is much more complicated than reflection from a single leaf. Vegetation canopies are always compiled of many layers of branches and leaves of different size, shape and orientation. Therefore, the overall reflectance of a vegetation canopy is a combination of leaf reflection, re-reflection of different layers and shadow. These re-reflection and shadows cause the reflectance values of a canopy to be lower than in an individual leaf (Gibson & Power 2000: 113; Campbell 2002: 463–464). The relative decrease in the NIR region is significantly lower than in visible region. This bright infrared reflectance of a canopy is due to reflection and retransmission in lower layers of the canopy (Figure 17). The reflectance from a canopy is also affected by background soil reflectance and phenology that is the variation of the vegetation due to the seasons (Gibson & Power 2000: 114; Jensen 2000: 352–353; Campbell 2002: 468–476).

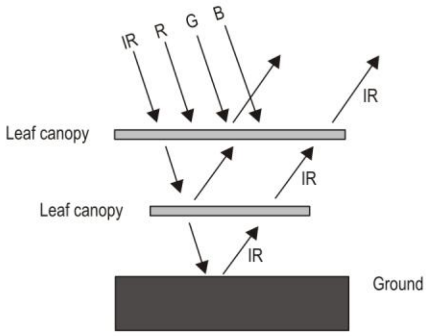

Figure 17. Simplified cross-sectional view of behaviour of energy interacting with a vegetation canopy (Campbell 2002: 464).

4.4.3 VEGETATION INDICES

Vegetation indices are empirical formulas that are calculated from combinations of several spectral values that are either added, divided or multiplied in order to get a single value. This single value is further used to measure vitality of vegetation in one pixel. The higher the value of a pixel is, the higher is the probability of the area studied having healthy vegetation (Gibson & Power 2000: 115; Campbell 2002: 465). Vegetation indices are also used as indicators of e.g. leaf area index (LAI), chlorophyll content and green biomass (Jensen 2000: 361).

The simplest form of vegetation indices is rationing of two values from different bands (Mather 2001: 118). Ratios as well as more complicated vegetation indices can reveal hidden information at least when two different spectral bands show inverse response from the same surface. In case of vegetation, this happens particularly in the ratios of red and NIR regions: red light is effectively absorbed while NIR is strongly reflected by the vegetation (Gibson & Power 2000: 115; Campbell 2002: 465). This NIR/R ratio is also called the *Simple Ratio* (SR) (Jensen 2000: 361). The green/red (G/R) ratio is also used but it is not as effective as the Simple ratio. One of the most utilized vegetation indices is the *normalised difference vegetation index* (NDVI):

$$NDVI = \frac{NIR - R}{NIR + R}. \tag{3}$$

NIR is a variable used widely also in other vegetation indices. These include e.g. Perpendicular Vegetation Index (PVI), Difference Vegetation Index (DVI), Soil Adjusted Vegetation Index (SAVI) and Modified Soil Adjusted Vegetation Index (MSAVI), Infrared Index (II), Moisture Stress Index (MSI) and Enhanced Vegetation Index (EVI). These and other vegetation indices are compiled for example in Gibson & Power 2000: 115–119 and Jensen 2000: 361–365.

5 DATA

5.1 REMOTE SENSING AND GIS DATA

The main data used in this study is airborne digital camera data from January 2004 covering the area of Ngangao and Chawia forests and their neighbourhood. This airborne digital camera data was acquired using a custom true-colour NIKON D1X digital camera system along with a GPS navigation system and accompanying software from the University of Helsinki. In addition, airborne remote sensing data from 1955 is used for change detection purposes. The characteristics of these two datasets are presented in Table 8.

Table 8. Characteristics of the airborne remote sensing data. APC stands for Aerial Photographic Camera and DC for Digital Camera.

Year	**1955**	**2004**
Sensor	APC	NIKON DIX
Date	Jan - Feb	Jan 26
Mode	Black & White	R, G, B
Camera focal length	152.3 mm	14 mm
Scale	~1:30,000	-
Scan resolution	14 µm	-
Ground resolution	~0.46 m	~0.33 m
Resampled resolution	1.0 m	0.5 m

The digital airborne data was photographed in 26th of January between 06:03 and 06:22 (Chawia) and between 06:29 and 06:55 (Ngangao) GMT in a cloudless weather. Altogether, nine flight lines were flown in Ngangao and seven in Chawia with 166 and 125 photographs taken, respectively. The flying altitude was approximately 600 meters above ground, 2,450 m a.s.l. in Ngangao and 2,170 m a.s.l. in Chawia, resulting in ground resolution of 0.33 meters. The ground resolution is calculated as follows; at first the half width of the image on ground in metres (*d*) is solved from:

$$d = h * \tan \beta \, , \tag{4}$$

where d = half width of the image on ground in metres
h = flight altitude to ground
β = half of the opening angle of the camera in degrees.

Then, the width of the image in pixels (*w*) is solved from:

$$\frac{d}{h} = \frac{w}{f} \Rightarrow w = \frac{df}{h} \, . \tag{5}$$

The final ground resolution is then solved from:

$$resolution = \frac{d}{w}. \tag{6}$$

The sidelap (side overlap) of the photographs varies between 50% (Ngangao) and 30% (Chawia) while overlap (forward overlap) is 60% in both cases (Table 9). The opening angle of the camera used is 78º. The produced digital airborne mosaics cover the area of 30.31 km² (Ngangao) and 27.03 km² (Chawia). However, for the purposes of this study, these mosaics as well as the aerial photographs from 1955 were further subset in order to reduce the processing times. The subsets cover the forests of Ngangao and Chawia and their surroundings and they constitute the actual study areas of this study (Figure 18). These study areas cover the area of 5.29 km² (Ngangao) and 4.03 km² (Chawia).

Table 9. Characteristics of the digital airborne data.

	Ngangao	**Chawia**
Flying altitude (above ground)	600 m	600 m
Flight lines	9	7
Images	166	125
Overlap (%) / Sidelap (%)	60 / 50	60 / 30
Resampled pixel size (m)	0.5	0.5

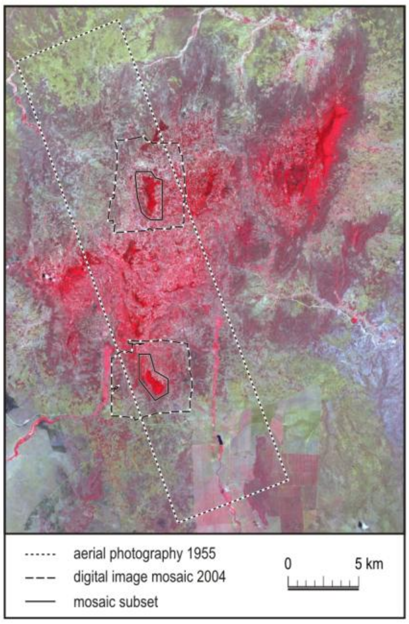

Figure 18. The extent of RS data used in this study overlayed on SPOT image from 2003. Topographic and atmospheric corrections for the SPOT image are done by Barnaby Clark.

Other data sources include the *Kenya 1:50 000 Topographic Map*, Sheet 189/4 Taita Hills (1991) and the vectors digitised using this map (Broberg & Keskinen 2004). Furthermore, the digital elevation model (DEM) automatically created in the mosaicking process of the 2004 images in *EnsoMOSAIC* was used for the ortho-correction of the 2004 images (see chapter 6.1.2.1). While in the field, parts of the forest borders were recorded with a GPS device. All the data used and produced in this study is reprojected to be in the same projection (Table 10).

Table 10. Projection properties.

Projection	Transverse Mercator
Spheroid	Clarke 1880
Datum	Arc 1960
Scale factor at central meridian	0.999600
Longitude of central meridian	39:00:00.00 E
Latitude of origin of projection	0:00:00.00 N
False easting	500,000.00 m
False northing	10,000,000.00 m

5.2 CANOPY AND FOREST HEALTH MONITORING (FHM) DATA

The forests in the Eastern Arc Mountains (EAM) have been studied earlier by the forest health monitoring program (FHM) developed by the USDA Forest Service and the National Association of State Foresters (Ward et al. 2002; Hertel et al. 2000). The main objective of the research made by the USDA Forest Service with its partners in co-operation was to study the current trends in forest condition of the EAM through forest health monitoring and remote sensing technology and techniques (Hertel et al. 2000: 5). This project was started in the year 2000. In this thesis, it was possible to combine the data collected by FHM with the data collected for this study.

In FHM, forest health conditions were examined through the establishment of a series of permanent plots. Altogether forty-four health monitoring plots were established in the area of EAM during the years 2000–2001 (Ward et al. 2002; USDA Forest Service 2006). Eleven of these plots were established in Ngangao forest and six in Chawia forest, in the Taita Hills. These core plots consist of four subplots, each of which has one microplot (Figure 19). The subplots were used to collect data on trees with a diameter at breast height (DBH) of 12.7 m or greater and the microplots were used to collect data on saplings and seedlings (EAMICFG 2000: 2). Information on the status and trend of the ecosystem's health was determined by measuring several indicators such as growth, crown condition, damage indicators and ecosystem disturbance (Table 11) (EAMICFG 2000; Ward et al. 2002). Altogether, there are 199 tree level samples from Chawia and 673 from Ngangao. The amount of samples for other indicators varies. The sample sizes of these indicators are given when discussing these indicators in more detail.

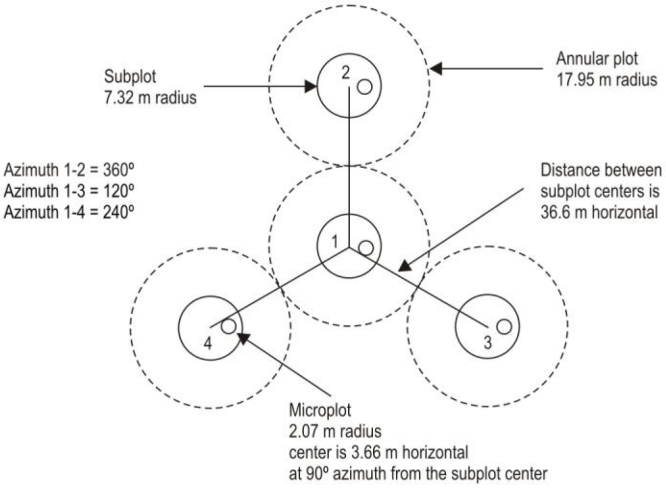

Figure 19. The core plot structure. Numbers 1–4 indicate the subplot number (modified after EAMICFG 2000: 4).

Table 11. Examples of data items collected in FHM (EAMICFG 2000).

Forest condition data	Subplot level data	Tree & sapling data *	Crown measurement data
predominant stand size class	slope	location of trees in subplots	uncompacted live crown ratio / compacted crown ratio
predominant stand age	aspect	location of saplings in microplots	crown light exposure
presence of disturbance type	species	tree status	crown position
disturbance year		diameter at breast height (DBH)	crown density
presence of treatment type		total / actual length of a tree	foliage transparency
treatment year		damage type & severity	crown dieback
		damage location	vigor class

* tree = saplings with diameter 2.54 cm to < 12.7 cm and trees with diameter > 12.7
seedling = trees with diameter < 2.54 and > 15 cm in length (conifers) or > 30 cm in length (hardwoods)

During the field study, conducted in February 2004, all 17 sample plots in the Taita Hills were studied: 11 sample plots in Ngangao and 6 sample plots in Chawia. The plots were located with the help of the forest guards in both forests. There were three plots in Chawia and one plot in Ngangao where the location of the plot was not possible to identify for certain. In each core plot, hemispherical upward photographs were taken in the subplot 1. Moreover, the coordinates of the plots were identified with GPS and the declination and the exposure of the slope were measured. In February 2005, additional hemispherical photographs were taken by Professor Petri Pellikka. These photographs were taken in the subplot 2 of 9 sample plots in

Ngangao and of 2 sample plots in Chawia. In addition, hemispherical photographs were taken in some randomly selected locations in years 2004–2006 (Table 12). The IDs and coordinates used for the plots where the hemispherical photographs were taken are presented in Appendix 1.

Table 12. The hemispherical photographs were taken in 2004–2006. The first set in 2004 was taken by the author, the second set in 2005 by Professor Petri Pellikka and the third set in 2006 by Nina Himberg.

	Year	Date	Photos taken in FHM plots	Additional photos	Total number of photos
Ngangao	2004	24.1. - 7.2.	11	8	19
	2005	26.1.	7	-	7
	2006	21.2. - 26.2.	-	17	17
Chawia	2004	10.2.	6	3	9
	2005	25.1.	3	7	10
	2006	17. - 18.2.	-	16	16

5.3 ADDITIONAL DATA

Besides the remote sensing (RS), GIS and FHM data, additional data was collected and used; some of it in the Taita Hills. Additional data includes interviews and conversations with the local specialists and forest guards, field notes, photographs and literature.

The time spent in the Taita Hills can also be thought as additional data; for the classification purposes of the RS data it is very important to be familiar with the environment and the conditions prevailing in the study area.

6 METHODOLOGY & ANALYSIS

6.1 PRE-PROCESSING OF AERIAL PHOTOGRAPHS

The original remotely sensed data contain distortions that are created through several means. These distortions can be divided into internal and external distortions. Whereas internal distortions are systematic and stationary and created by the sensor itself, external distortions are unsystematic and due to platform perturbation and the modulation of atmospheric and scene characteristics (Jensen 1996: 107). The most common of these distortions are spectral and geometric.

6.1.1 SPECTRAL DISTORTIONS

Spectral distortions refer to distortions in the measured brightness values of the pixels. These distortions can originate from the sensor, the atmosphere or the illumination conditions as expressed by position of the sun, topography and wavelength region (Holopainen 1998: 9; Richards & Jia 1999: 39). For aerial photographs, the two most important effects leading to inaccuracy in brightness values are the light fall-off effect (also known as exposure fall-off) and the bidirectional reflectance distribution function (BRDF) (Holopainen 1998: 9; Pellikka et al. 2000a). The correction methods needed depend greatly on how the aerial photographs are used. In this study, spectral corrections were made only for the 2004 digital aerial photographs. No spectral corrections were needed for the 1955 aerial photographs, because they were interpreted only visually.

6.1.1.1 LIGHT FALL-OFF

The light fall-off effect is a combination of vignetting and a $\cos^4$ Law of Illuminence that describes a variety of geometrical and optical factors occurring in the camera (Pellikka 1998: 12). This effect can be seen as a decline in light intensity away from the centre of the frame. Often, the fall-off is minimized at the time of photographing by using anti-vignetting filters (Holopainen & Wang 1998: 677). Also, correction methods that are implemented after the flight, during the pre-processing of the data, are often used (see e.g. Pellikka 1998; Dean et al. 2000; Brandtberg et al. 2003).

In this study, images were corrected for light fall-off effect by a method created by Pellikka (1998). The method was first implemented in *Erdas Imagine* by Petri Pellikka and Janne Heiskanen, and further modified by Pekka Hurskainen and Pertti Parviainen in the

Department of Geography, University of Helsinki (see Hurskainen 2005: 54–55). The method includes two parts: modelling the intensity of the light fall-off effect and correcting this effect.

The strength of the effect is dependent on the angle between the optical axis and the ray to the off-axis pixel (Figure 20). Therefore, this zenith view angle (θ) was determined for each pixel with:

$$\theta = \arctan\left(\frac{r}{f}\right), \tag{7}$$

where θ = viewing angle between the optical axis and the ray to the off-axis point
f = focal length
r = distance between the pixel in the off-axis position and that at the optical axis (Pellikka 1998: 40).

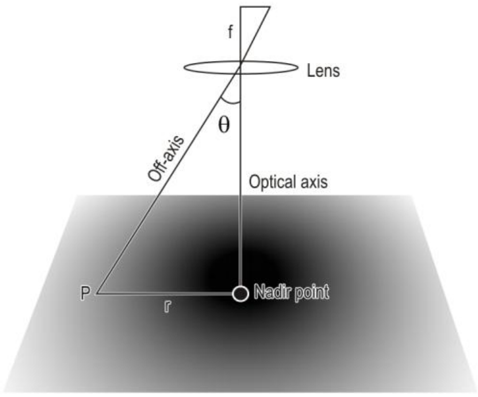

Figure 20. The strength of the light fall-off effect is dependent on θ, which is the viewing angle between optical axis and off-axis to the pixel P (modified after Pellikka 1998: 41).

As a result, a zenith view angle image was produced (Figure 21). The light fall-off effect is a systematic lens-related effect and therefore the same zenith view angle image applies for all the images taken with the same camera. Thus, the effect could be removed in a batch process created by Hurskainen (2005) which reduced the processing time.

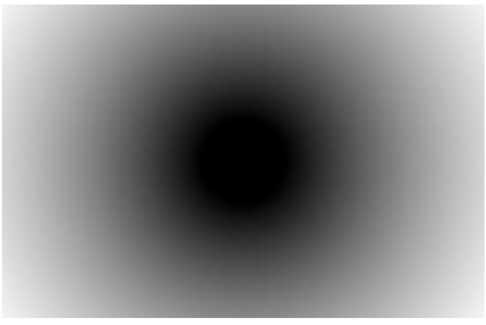

Figure 21. A zenith view angle image for 2004 digital aerial photographs. This image models how the light fall-off effect increases from the centre to the corners.

The actual removal of the effect was done for each 2004 digital aerial photograph in a batch. The correction algorithm for normalising the digital number (DN) of each pixel in each image is

$$E_0 = \frac{E_\theta}{\cos^4 \theta}, \tag{8}$$

where E_θ = DN of the pixel in the off-axis position
E_0 = DN that would have resulted if the pixel was located at the optical axis
$\cos^4$ = correction factor for the different aperture settings (Pellikka 1998: 41; Lillesand & Kiefer 2000: 68).

According to Lillesand & Kiefer (2000: 68), the cameras used at the moment have less severe fall-off characteristics than the theoretical $\cos^4$ fall-off, usually ranging from 1.5 to 4. In this case, the correction factors *n* were derived with regression by Hurskainen (2005). These correction values could be used because the same photographing equipment was used in the study of Hurskainen and this study. In order to determine the *n* factors, 10–15 clusters of pixels were evenly selected from spectrally homogenous land use areas from one image. The mean DN values and zenith angles were the computed. In order to remove the correlation between the zenith angles and the DN values in each band, a trial and error method was used to test different values for the *n* factor (Hurskainen 2005: 54–55). After this testing, correction values of 0.63, 0.29 and 0 were selected for R, G and B bands, respectively. These values minimized the effect of light fall-off over the image.

6.1.1.2 BIDIRECTIONAL REFLECTANCE

Land surface types reflect radiation differently depending on their properties (Figure 22). An ideal, totally diffuse surface that reflects energy equally in all directions is called a Lambertian surface. In a natural environment, this kind of surface does not exist. A specular reflection occurs from smooth surfaces, like water. However, most of all the land surfaces are anisotropic thus reflecting the energy unequally (Pellikka 1998: 13; Holopainen et al. 2000: 18–19).

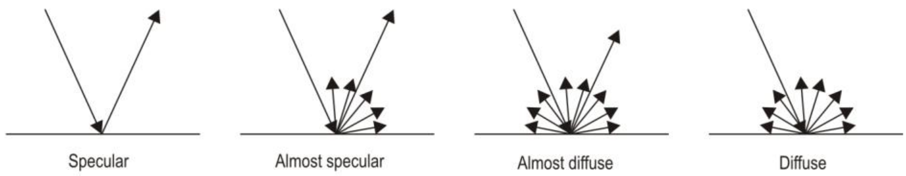

Figure 22. Specular and diffuse reflectance (modified after Kangas et al. 2003: 159).

Reflection from these anisotropic surfaces causes bidirectional reflectance distribution function (BRDF) effects on satellite and aerial images. Especially on low to medium altitude imaging, the BRDF is a significant disturbing factor (Pellikka et al. 2000a: 2). Bidirectional effects are governed by the sun-object-sensor geometry (Figure 23).The magnitude of the effect is also dependent on land surface optical characteristics, atmospheric conditions and microtopography of the soil (Pellikka 1998: 13–14; Pellikka et al. 2000a: 2; Mikkola & Pellikka 2002: 4720).

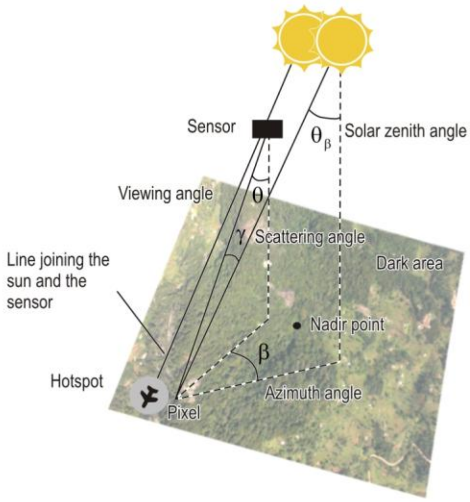

Figure 23. Bidirectional effects are governed by the sun-object-sensor geometry (modified after Pellikka et al. 2000a: 3).

The BRDF causes the spectral characteristics of a similar object to be different depending on the object's location in the image. This can induce severe problems particularly in spectral analyses and land use classifications (Pellikka et al. 2000a: 2). The BRDF is visible in the image as variations in brightness: objects in the direction of incoming solar radiation expose their shady sides to the sensor while objects in other direction expose their bright sides to the sensor (Figure 24; Holopainen & Wang 1998: 678; Tuominen & Pekkarinen 2005: 257). The most illuminated location in the image is called the hot spot (Deering et al. 1994). It is an area where sun and sensor view zenith angles are identical and the relative azimuth angle between the sun and sensor is zero. This causes the scattering angle γ to be 0° (Pellikka et al. 2000a: 3).

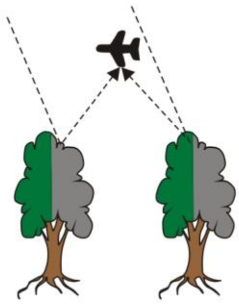

Figure 24. Trees in the direction of incoming solar radiation expose their shady sides to the sensor while trees in other direction expose their bright sides to the sensor (modified after Kangas et al. 2003: 160).

The BRDF for different kind of surfaces can be estimated by measuring the bidirectional reflectance factors (BRF) for a limited set of geometries (Pellikka et al. 2000a: 4). The BRF is the ratio of reflected radiance, L, in one viewing direction to the total downwelling irradiance, E:

$$BRF = \frac{L_\pi}{E}. \quad (9)$$

The methods used for removal of the BRDF can be divided into methods based on physical or empirical modelling. While physical models concentrate on theoretical modelling of the mechanism of the BRDF (see e.g. Chen & Leblanc 1997; Leblanc et al. 1999), empirical or semi-empirical models try to correct the effects caused by several factors simultaneously with a single correction model (see e.g. Holopainen & Wang 1998; Pellikka 1998; Tuominen & Pekkarinen 2004).

In this study, BRDF correction was carried out in the context of mosaicking the digital aerial photographs with *EnsoMOSAIC* software. A better result would probably have been obtained by correcting each image frame individually but, because of the large amount of aerial photographs and the ability to correct the BRDF in *EnsoMOSAIC*, this possibility was discarded. A BRDF correction method created by Pellikka (1998: 42–49) is implemented in *EnsoMOSAIC* (StoraEnso 2003). In order to accomplish the correction, a factor f has to be determined for all three channels. This correction factor takes into account the land surface reflectance properties and atmospheric condition and it should be chosen so that the DN values are not dependent on the size of the scattering angle (Pellikka 1998: 46–49; Mikkola & Pellikka 2002: 4727). For both study areas, Chawia and Ngangao, f values determined for Kenya were used. These correction values were 1.20, 1.00 and 0.80 for red, green and blue channels, respectively (Stora Enso 2003).

6.1.1.3 ATMOSPHERIC EFFECTS

One component affecting the DN number of each pixel is the atmosphere. As solar radiation passes through the atmosphere it is selectively scattered and absorbed (see chapter 4.1). These two processes together are called the atmospheric attenuation (Jensen 1996: 109). Whether these interactions of solar radiation with the atmosphere are treated as noise or not, depends on the focus of the study. If wanted, the noise caused by the atmospheric attenuation can be removed with several methods (see for example Jensen 1996: 108–122; Campbell 2002: 297–299).

The atmospheric effects are one of the main disturbing factors in satellite imagery (Song et al. 2001). This is a consequence of solar electromagnetic radiation passing through the full thickness of the earth's atmosphere twice on its journey from source to sensor. In the case of aerial photography, only a short atmospheric path length is involved and thus the atmospheric effects are minor (Lillesand & Kiefer 2000: 9; Kangas et al. 2003: 158). For this reason, no atmospheric corrections were made for the digital aerial photographs used in this study.

6.1.1.4 TOPOGRAPHICAL EFFECTS

Besides the viewing geometry and the atmospheric attenuation, also topography can cause spectral distortion. The characteristics of slope and aspect of the study area are responsible for the illumination variation. These topographic effects are significant especially in the mountainous areas where slope and aspect can vary a lot (Jensen 1996: 122).

There are several methods to correct the topographic effects (see for example Jensen 1996: 122–124; Mather 2001: 94–95). In this study, however, no topographic corrections were made. Although the study forests are situated in a mountainous area, the difference in altitude inside the forests is considered not to cause significant topographic effects.

6.1.2 GEOMETRIC DISTORTIONS

The geometry of a remotely sensed image is always distorted. This is due to the imaging geometry of the sensor, the sensor orientation and the displacements of the three-dimensional scene that is transformed into two-dimensional image (Kocecny 2003: 84). A part of these geometric distortions can be corrected using internal sensor distortion while a part of the distortions need a sufficient number of ground control points (GCPs) to obtain an acceptable accuracy (Jensen 1996: 124). These points are places that can be accurately located both in the remote sensing imagery and reference data (Lillesand & Kiefer 2000: 474). Thus, both image coordinates (measured in rows and columns) and map coordinates (measured in degrees of latitude and longitude, meters, etc.) have to identifiable in GCPs (Jensen 1996: 124). Airborne data, in particular, suffers also scale and location distortions caused by aircraft roll, yaw and pitch and decrease of pixel size from frame nadir point to the edges and off-axis areas (Pellikka 1998: 5). However, the correction of these distortions was impossible in this study.

Two different geometric correction methods were used to correct the aerial photographs used in this study. A bundle block adjustment method was used for the 2004 images while an image-to-image rectification was used for 1955 images.

6.1.2.1 GEOMETRIC CORRECTION OF 2004 DIGITAL AERIAL PHOTOGRAPHS

The geometric correction of 2004 aerial photographs was done in *EnsoMOSAIC* software, developed by StoraEnso Forest Consulting Oy Ltd and the Technical Research Centre of Finland (VTT) (StoraEnso 2003: 1). This software is meant to cover the whole processing chain of digital aerial photographs from flight planning to producing geo-referenced and ortho-rectified images and image mosaics. Thus, also geometric correction is implemented into the software. The mosaicking procedure is discussed in chapter 6.2.1.

The first part in rectifying the digital aerial photographs in *EnsoMOSAIC* is the image linking. These links are used to provide initial orientation of the images in relation to each other (StoraEnso 2003: 27–28). The image frames (166 in Ngangao and 125 in Chawia) were manually linked with their adjacent images using three objects indicated in both images. The triangle formed by these links was kept as wide as possible thus easing the further processing.

After linking the images, more precise tie points are searched and identified in order to connect separate images together. The image coordinates of these tie points are then used for block adjustment which finally rectifies the images (EnsoMosaic 2003: 19). In this study, the search for tie points was done automatically. The automatic search finds the tie points on neighbouring images by using correlation, standard deviation, sharpness and peak/mean ratio of the DN values as well as point shift as search and acceptance criteria (EnsoMosaic 2003: 25). The search runs on one to three rounds depending on the selection by user which, in this case, was three rounds. This means that on the first round all image pairs that are linked together on reduced resolution images were searched. On the second round full resolution images were used in order to re-evaluate all the points found before. On the third round, all the points found in rounds one or two were transferred from one image to all the other images that have overlapping the first image (Figure 25) (EnsoMosaic 2003: 25).

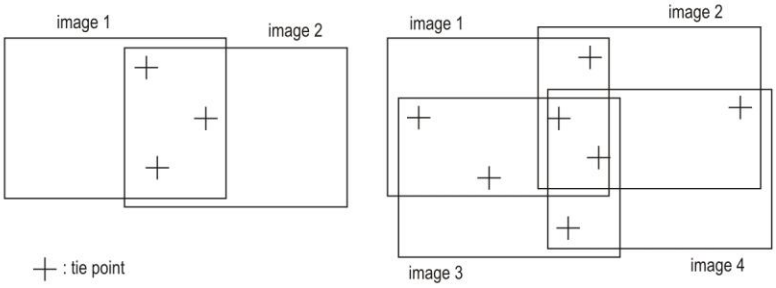

Figure 25. An example of measuring tie points: a) two images and three tie points (notice the geometry of the points), b) four images, seven tie points. All image pairs have at least three common points except pairs 1–4 and 2–3 that have two tie points (modified after EnsoMosaic 2003: 4).

The parameters for the automatic tie point search are selected by the user. Figure 26 shows the parameters used for the 2004 digital aerial photographs both in Ngangao and in Chawia. These quite tight computing parameters were used although they caused the processing time to be long.

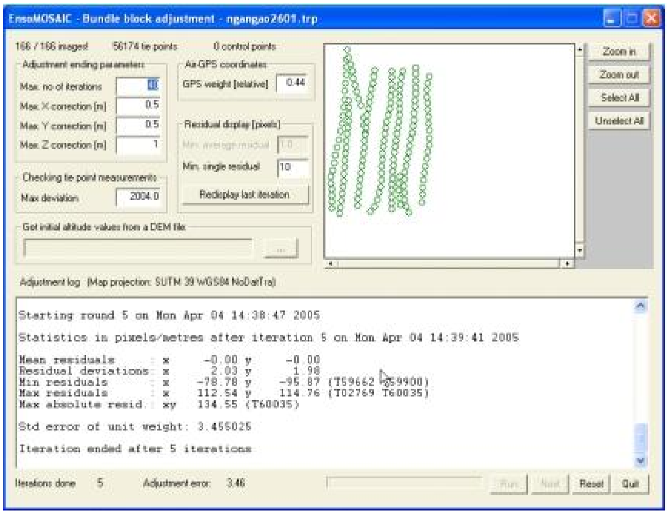

Figure 26. The parameters used for the automatic tie point search.

After the automatic tie point search, certain areas in some images were still missing enough tie points. Therefore, more tie points were added manually to these areas where the automatic search had failed (Figure 27).

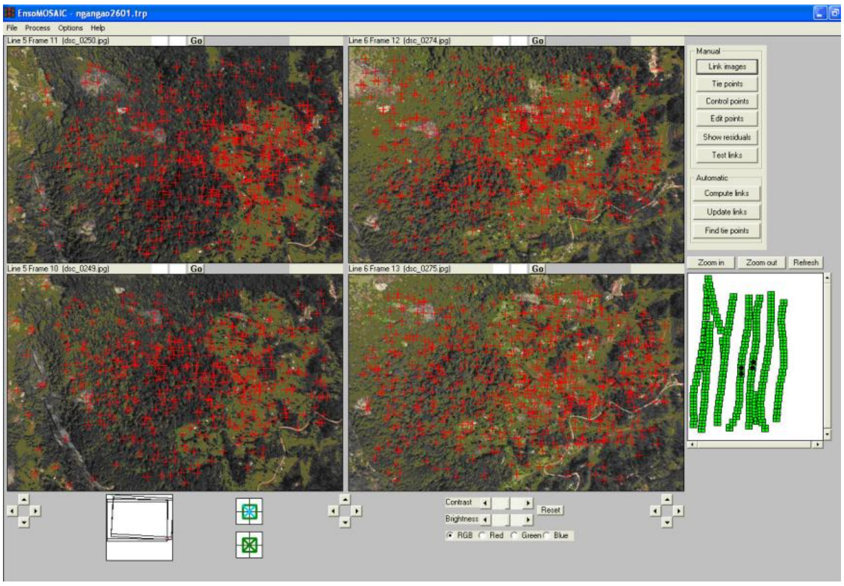

Figure 27. The user interface of EnsoMosaic with throughout the images distributed tie points. Also the flight lines for Ngangao can be seen in the right bottom corner.

An iterative mathematical process, *Bundle Block Adjustment* (BBA), is the process which eventually solves the geometrical orientation of the images and the location of the perspective centres simultaneously for a large image block. Geometrically, this mathematical model states the condition where the point in object space, the perspective centre of a camera and the projection of the point on the image plane are on a straight line (Amer 1962; StoraEnso 2003: 2). According to this method, a group of these lines running through the perspective centre comprise a virtual bundle of light rays for each image. These bundles of neighbouring images are then further combined through the common object points on these images (StoraEnso 2003: 2).

The BBA was run with parameters shown in Figure 28. Max. X, Y and Z corrections define for their part the accuracy of the correction. The smaller these values are the longer the iteration will continue (StoraEnso 2003: 36). Another important value is the air-GPS weight that affects the computing time of the procedure. The air-GPS weight used is dependent on the accuracy of the GPS used in the flight. The GPS weight value can be calculated as follows:

$$air - GPS = \frac{1}{\sqrt{a}}, \qquad (10)$$

where a = the position accuracy of the GPS on the airplane.

In this study, an air-GPS value of 0.44 was used. This corresponds to having an accuracy of 5 meters of the GPS on the airplane.

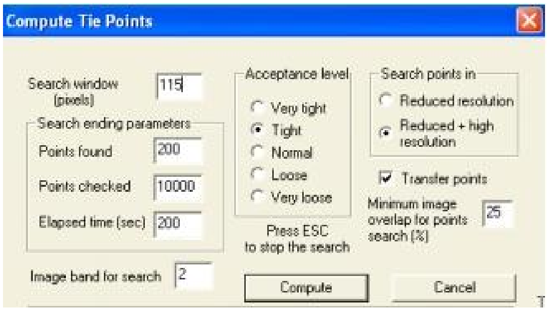

Figure 28. The parameters used for BBA of Ngangao and Chawia.

After each iteration of BBA, an estimate on the overall accuracy of the image rectification is provided. This adjustment error is the mean error of unit weight, a function of all the residuals and all the weights (EnsoMosaic 2003: 37). Adjustment error was used to remove the tie points of low quality after each round of BBA. After removing the erroneous tie points with large residuals the BBA was run again. This was carried on until the accuracy of the mosaic was considered good enough, which in this study took 10 iteration rounds (Table 13).

Table 13. The iteration rounds and the residuals of the tie points removed after each iteration round for digital aerial photographs of Ngangao and Chawia.

	Residuals of the tie points removed
Round 1	> 20
Round 2	> 10
Round 3	> 7
Round 4	> 5
Round 5	> 4
Round 6	> 3
Round 7	> 2.5
Round 8	> 2
Round 9	> 1.5
Round 10	BBA completed

6.1.2.2 GEOMETRIC CORRECTION OF 1955 AERIAL PHOTOGRAPHS

A more traditional approach was taken when correcting the geometry of the 1955 aerial photographs. The metadata of these photographs was very poor; only information on focal length of the camera was available and furthermore the aerial photographs had no fiducial marks. This affected significantly the correction procedure of the 1955 photographs.

The geometric correction of 1955 photographs was accomplished with an image-to-image registration using an image mosaic compiled of digital aerial photographs as a reference data.

When correcting an image to another image, it has to be taken into account that the uncorrected image will inherit all the geometric distortion that the reference image has. In this case, however, the geometric distortions of the reference image are very well corrected and thus this inheritance problem is insignificant.

Image registration is a polynomial transformation of an image, to a set of control points, GCPs. Polynomial transformation is a mathematical equation with which it is possible to link the uncorrected image to data already georeferenced (Gibson & Power 2000: 22). This polynomial transformation is based on CGPs and thus choosing the control points is a very important part of the correction procedure. Polynomial equations can be of any order but often equations of first-order to third-order are used. The amount of distortion and the degree of topographic relief displacement in the area define the order of the function needed. Even higher orders than third may be needed in some cases (Jensen 1996: 128). Polynomial corrections are not able to correct relief distortions completely and therefore separate ortho-rectification is often needed.

The areas of the two study forests, Chawia and Ngangao are well covered with the 1955 aerial photographs. The forests appear in several images in the 1955 aerial photograph transect but in the case of Chawia only one photograph was needed as it covers the whole forest area. The forest of Ngangao is visible in the borders of altogether seven photographs. Two photographs of same spatial resolution were selected to cover the area of Ngangao. These aerial photographs were further subset in order to reduce the processing time. The geometric correction was completed separately for these three subsets, named Chawia_1955, Ngangao_west_1955 and Ngangao_east_1955, in *Erdas Imagine*.

Finding suitable GCPs was exceptionally hard as the landscape has changed significantly between the years 1955 and 2004. Only a few GCPs were able to locate in distinct locations, such as road crossings. Instead, bare rocks and other not that obvious locations had to be used. In particular, finding the GCPs inside the forest was hard as the trees cannot be used as control points. Apparently, this had an effect on the quality of the geometric correction. Several combinations of GCPs and differently ordered polynomial functions were tested until the best possible combinations were achieved. The GCPs were tried to situate evenly and especially around and inside the forests thus emphasising the geometric correction in the forest area instead of the more remote areas (Figures 29–32).

This proved to be especially important in the area of Ngangao as a fifth-ordered polynomial function was needed in order to achieve the best possible result. When using this high-ordered polynomial functions, significant errors and thus image distortions can be introduced in areas outside the range of the GCPs (Richards & Jia 1999: 61). Despite this, it was decided to use high-order functions and image distortions were minimised with a large amount of GCPs inside and near the study forests.

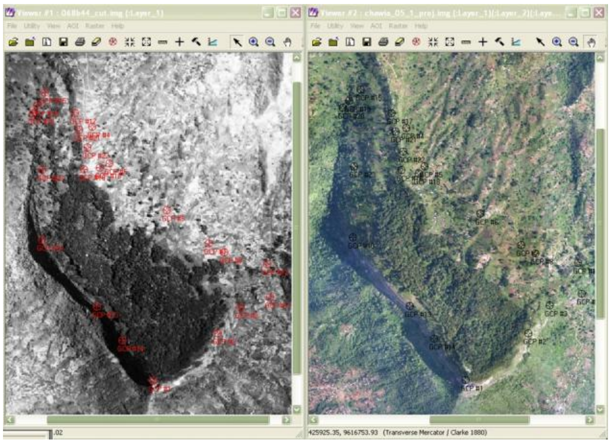

Figure 29. The locations of GCPs in Chawia_1955 and Chawia_2004.

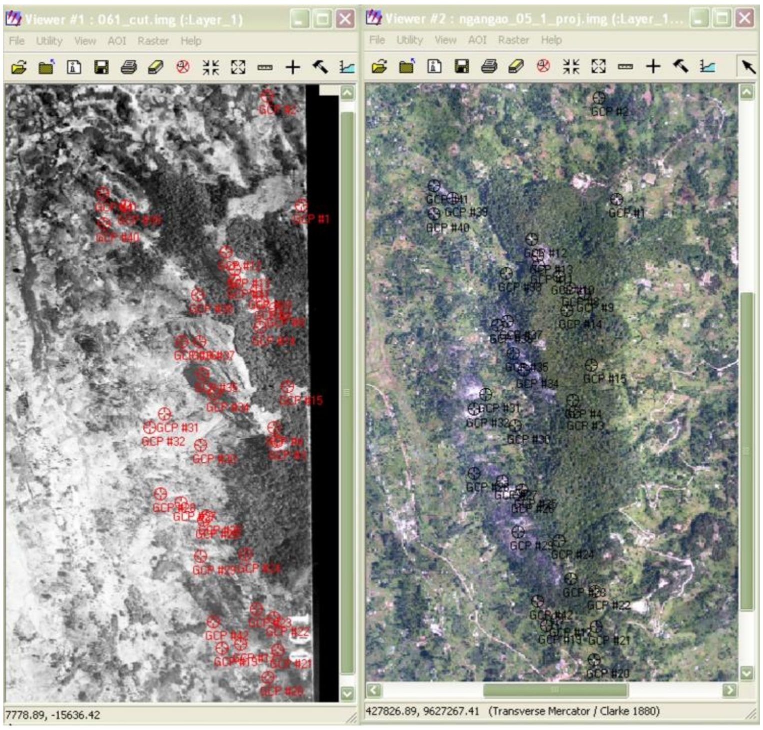

Figure 30. The locations of GCPs in Ngangao_north_west_1955 and Ngangao _2004.

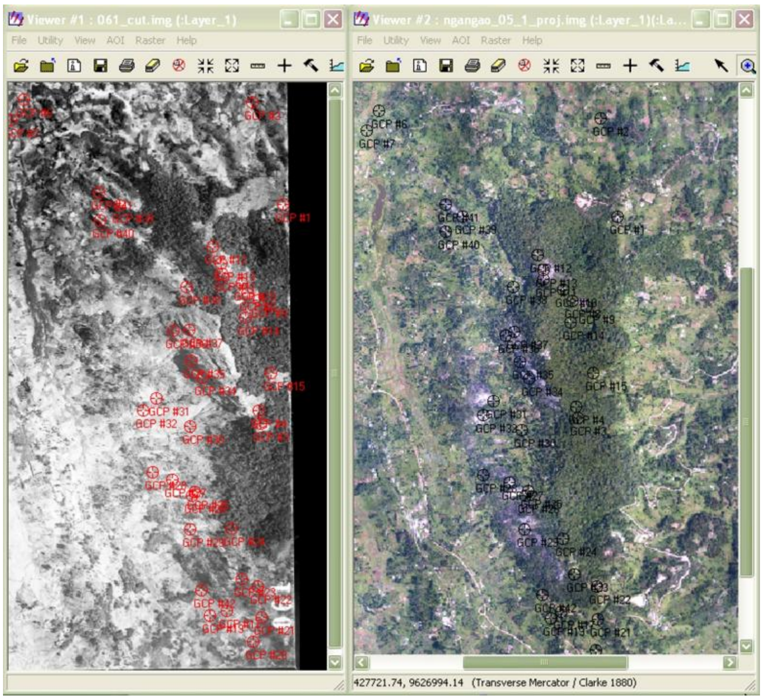

Figure 31. The locations of GCPs in Ngangao_south_west_1955 and Ngangao _2004.

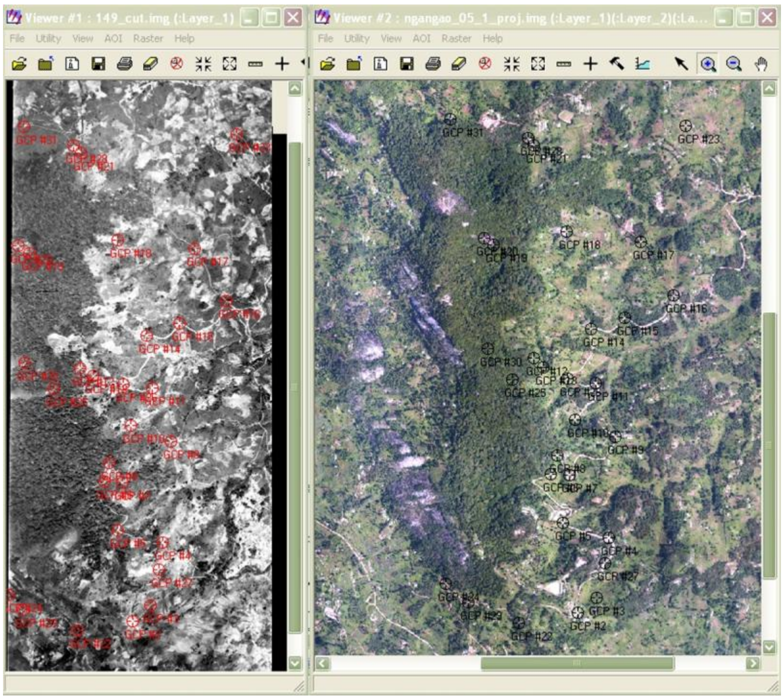

Figure 32. The locations of GCPs in Ngangao_east_1955 and Ngangao_2004.

The geometric correction of the aerial photographs of Ngangao proved to be very difficult and a special decision had to be made: the north and south parts of ngangao_west_1955 were compiled from two different results of geometric corrections. These were named Ngangao_north_west_1955 and Ngangao_south_west_1955. This decision was made because the north and south parts of western Ngangao were not possible to correct with satisfying result at the same time. Thus, finally, a fourth-order polynomial function for Chawia_1955 and for Ngangao_north_west_1955, and a fifth-order polynomial function for Ngangao_south_west_1955 and for Ngangao_east_1955 were used.

The number of GCPs needed is dependent on the order of the transformation. While a third-order transformation needs a minimum of 10 GCPs, a fifth-order transform needs a minimum of as much as 22 GCPs (Tokola et al. 1998: 69; Gibson & Power 2000: 22). The total number of GCPs used can be seen in Table 34, page 115. A root means square (RMS) error value is calculated automatically for each GCP in *Erdas Imagine*. It is a statistical measure of the error between the calculated co-ordinates of a GCP and the co-ordinates of the GCP in the georectified image (Gibson & Power 2000: 22).The RMS Error for each GCP is calculated with a distance formula:

$$RMS = \sqrt{(x_r - x_i) + (y_r - y_i)}, \tag{11}$$

where x_i and y_i = the input source coordinates
x_r and y_r = the retransformed coordinated (Erdas Imagine 2003: 356).

Usually, all the GCPs having an RMS error larger than the set value are not used for the transformation. In this case, however, it was impossible to use a limit as many RMS error values were very large. The limitations in choosing the GCPs are one of the main reasons for these large RMS errors. With better metadata for the aerial photographs, a different method could have been used with an implemented orthographic correction. Given the circumstances, however, it was attempted to correct all the topographic distortions as well as possible with the polynomial transformations. In addition to individual RMS errors, also the total RMS error, T was calculated as follows:

$$T = \sqrt{R_x^2 + R_y^2} = \sqrt{\tfrac{1}{n}\sum_{i=1}^{n} XR_i^2 + YR_i^2}, \tag{12}$$

where T = total RMS error
R_x = x RMS error
R_y = y RMS error
n = the number of GCPs
i = GCP number
XR_x = the x residual for GCP_i
YR_y = the y residual for GCP_i (Erdas Imagine 2003: 356–357).

In order to complete the rectification process of 1955 aerial photographs, new DN values have to be assigned for the rectified image. There are several different approaches to calculate the new values. The most commonly used are *nearest neighbour*, *bilinear interpolation* and *cubic convolution* methods.

The simplest method from a computational perspective is the nearest neighbour. In this method, the pixel of a corrected image takes its new value from the pixel in the input image that is closest to the rectified pixel (Mather et al. 2001: 85; Campbell 2002: 305–306; Erdas Imagine 2003: 360–361). This method is the fastest and it transfers the values without averaging them as the other methods do. On the other hand, some of the pixel values may be duplicated while some are dropped causing disjointed appearance in the image (Lillesand & Kiefer 2000: 474). Because it maintains the original DN values, this method is used particularly in studies where the spectral values are important, such as vegetation studies (Jensen 1996: 129). As the 1955 photographs are used only for visual interpretation, maintaining the original DN values is not as important as classification purposes. Nevertheless, this method was chosen to finalise the rectification process of the 1955 aerial photographs. The photographs were resampled to have 1.0 meter spatial resolution.

6.2 MOSAICKING

Mosaicking is a procedure where single remotely sensed images are combined together in order to create one cohesive image from a larger area. In this study, two different approaches were used in order to mosaic the two datasets (1955 and 2004) of aerial photographs.

6.2.1 MOSAICKING OF 2004 DIGITAL AERIAL PHOTOGRAPHS

The mosaicking of 2004 aerial photographs was done in *EnsoMOSAIC*. Its main function is to create a mosaic of a group of images consisting of several flight lines, although the software is designed to cover the processing chain of digital aerial photographs beginning from the flight planning. In order to function properly, the software needs certain parameters. These include the focal distance and the principal point of the camera and the lens-CCD distortion (EnsoMosaic 2003: 1).

The acquirement of the digital images has to be performed with adequate overlap (forward overlap) and sidelap (side overlap). In this case, the overlap for both areas, Ngangao and Chawia, is 60%. The sidelap for Ngangao is 50% while the sidelap for Chawia is 30%. The bigger sidelap of Ngangao was due to the greater difference in height: the higher sidelap value assured proper acquirement of the top of the hill in the area of Ngangao. The flight lines of the two areas can be seen in Figure 33. During the flight, GPS data was collected for each image providing three-dimensional coordinates for the centre of each image. These coordinates enable the software to create mosaic from individual images.

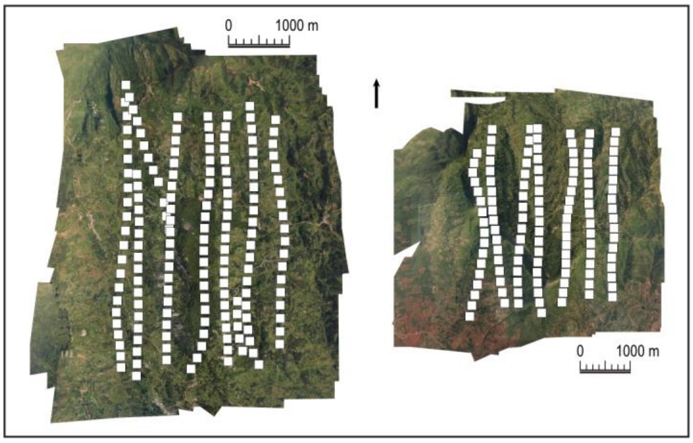

Figure 33. The flight lines in Ngangao and Chawia. The white boxes represent the locations where the images were taken during the flight.

The creation of a mosaic begins with defining the properties of a new block (EnsoMosaic 2003: 12); e.g. the coordinate system and the spheroid used were defined as well as the camera calibration file. The first phases of the mosaicking procedure, image linking and tie point measurements for bundle block adjustment (BBA) were discussed in chapter 6.1.2.1. Especially the tie points have an important role in mosaic formation. The extensive distribution of these points is essential for achieving an accurate mosaic (Sarmento & Sarkeala 2005: 5–6). Tie points are used also for creating the digital elevation model (DEM).

In order to create an ortho-corrected mosaic, a DEM is calculated in *EnsoMOSAIC* after the block adjustment. Ortho-correction removes the effects of topographic relief distortions and camera altitude variations. During the correction, the centre-projected image is transformed to an image having the viewing perspective modelled as being an infinite distance from the ground (Tokola et al. 1998: 71; Jensen 2000: 164). For both mosaic areas, Ngangao and Chawia, a DEM with a 1.0 meter resolution was calculated. For constructing the DEM, *EnsoMOSAIC* uses the elevation values generated for each tie point during the BBA (StoraEnso 2003: 42). Thus, the amount and distribution of the tie points define the accuracy of the DEM. All the tie points are not situated on the ground but also on the top of the trees or rocks. Therefore, the digital elevation model created should rather be called as the digital surface model. The same kind of problem can be seen in urban areas where the top of the buildings alter the DEM (Konecny 2003: 179). In this study, the elevation model created is still called DEM but the special characteristics of it are kept in mind.

After creating the DEM, the ortho-mosaics were created from the original aerial photographs (Figure 34). The mosaics of Ngangao and Chawia were created to have a pixel size of 0.5 m. A correction for BRDF-effects is implemented within this final stage of mosaics creation (see chapter 6.1.1.2). For the two areas, both BRDF-corrected and uncorrected mosaics were created using histogram matching between three images and nearest neighbours methods (see StoraEnso 2003: 49). The properties of the mosaics can be seen in Table 14.

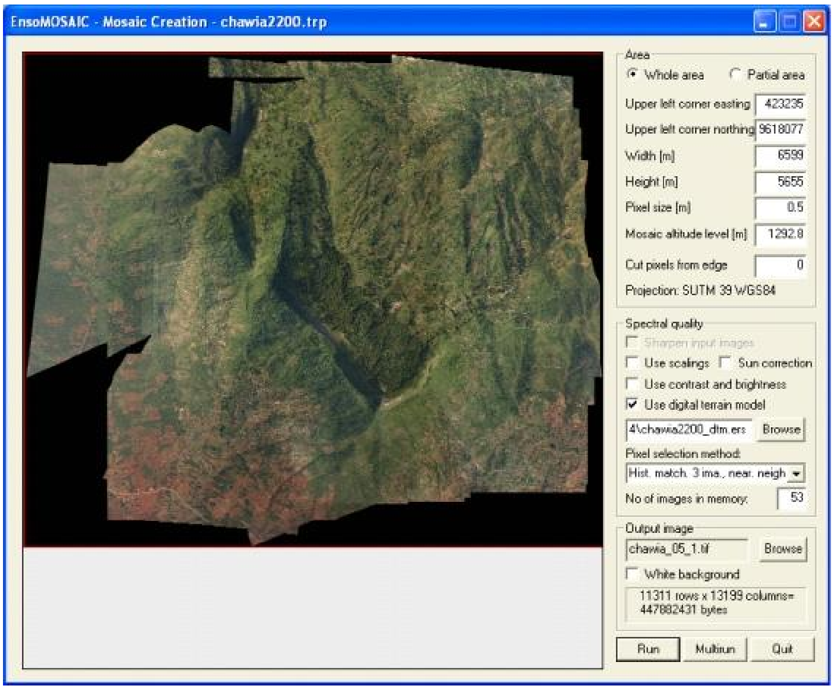

Figure 34. Mosaic formation of Chawia.

Table 14. The properties of the mosaics.

Mosaic	Number of images	Number of tie points	DEM resolution (m)	Radiometric corrections	Mosaic resolution (m)
Chawia	125	28,150	1 m	Light fall-off	0.5
Chawia_BRDF	125	28,150	1 m	Light fall-off & BRDF	0.5
Ngangao	166	43,995	1 m	Light fall-off	0.5
Ngangao_BRDF	166	43,995	1 m	Light fall-off & BRDF	0.5

After finishing the mosaicking in *EnsoMOSAIC*, the mosaics were imported to *Erdas Imagine*, where the mosaics were projected to the same coordinate system as other data.

6.2.2 MOSAICKING OF THE 1955 AERIAL PHOTOGRAPHS

The mosaicking of the 1955 aerial photographs was done with the mosaicking function implemented in *Erdas Imagine*. As the forest of Chawia is covered within one aerial photograph, no mosaicking was needed for that area. The forest of Ngangao, instead, had to be compiled from three different aerial photographs, named Ngangao_north_west_1955, Ngangao_south_west_1955 and Ngangao_east_1955. Originally, the first two were identical subsets of the same aerial photograph but different geometric corrections were applied to these images. Otherwise, the north and south parts of western Ngangao would not have been able to correct with satisfying results.

Therefore, the mosaicking of the area of Ngangao had to be done in two parts: first, Ngangao_north_west_1955 and Ngangao_south_west_1955 where combined and then the resulting image was further combined with Ngangao_east_1955. The mosaicking procedure starts with drawing a cut line. This cut line determines the intersection line of the images to be mosaicked. In the case of Ngangao_north_west_1955 and Ngangao_south_west_1955 the best option to insert the cut line was the centre part of these images (Figure 35).

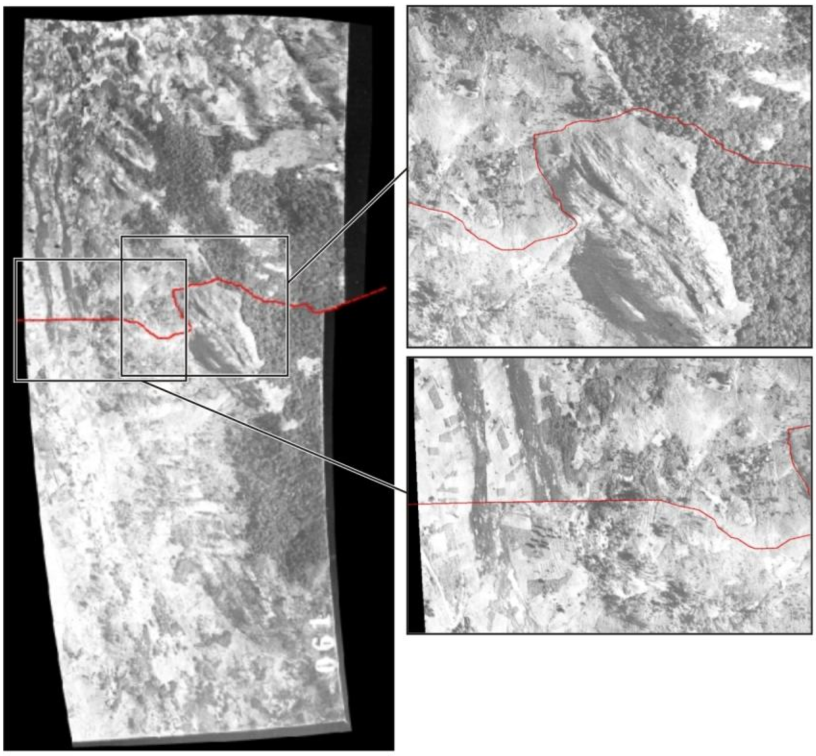

Figure 35. Mosaicking of Ngangao_north _west_1955 and Ngangao_south_west_1955.

After this, the mosaicking procedure of the western part of Ngangao could be finished. The final mosaicking was done for this resulting image and Ngangao_east_1955. The cut line determining this mosaicking can be seen in Figure 36. Improving the visual quality of the mosaics by histogram matching and colour balancing would also have been possible. However, these functions were not applied as the mosaics were interpreted only visually. The final images of Ngangao and Chawia from 1955 have the same projection as the 2004 mosaics. The flow line of the pre-processing of the 1955 and 2004 aerial photographs is presented in Figure 37.

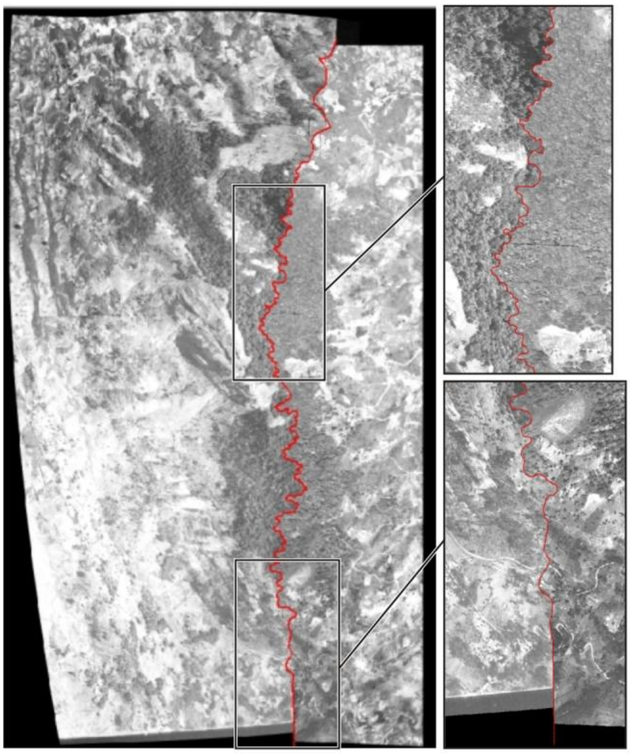

Figure 36. Final mosaicking of Ngangao_1955.

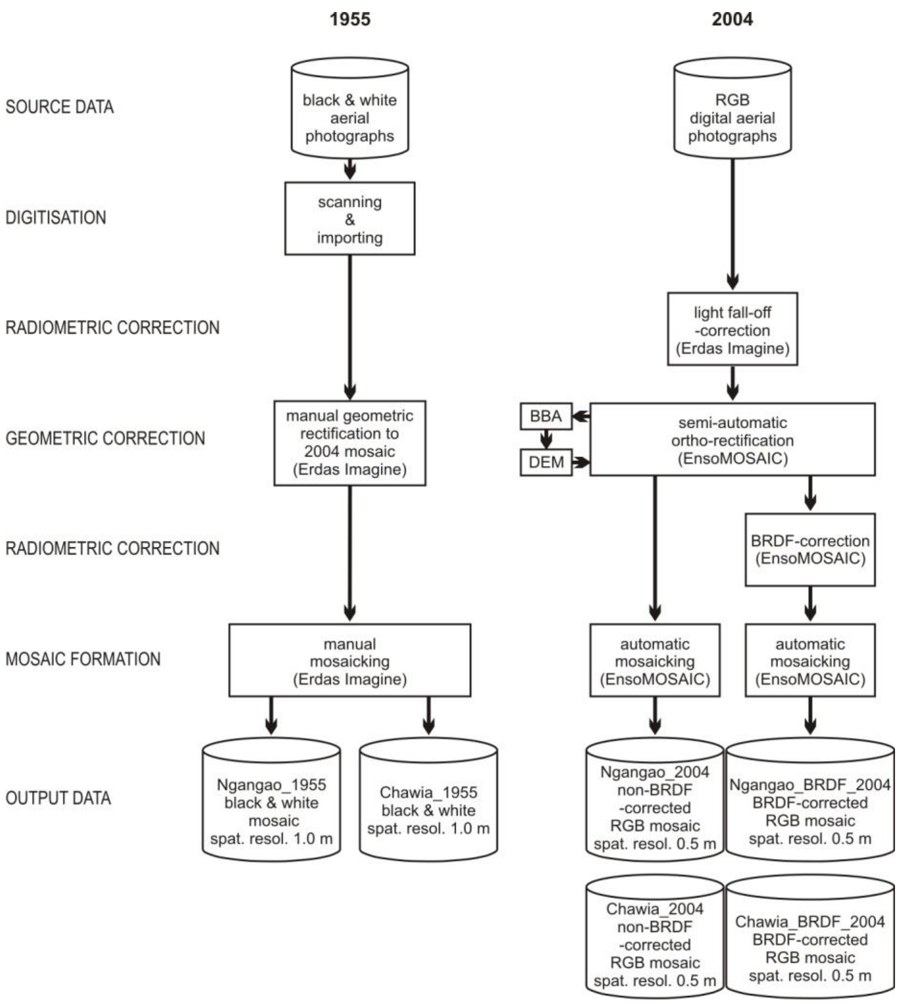

Figure 37. The flow line of pre-processing the aerial photographs from 1955 and 2004.

6.3 CLASSIFICATION

In order to interpret the image mosaics produced in this study, three different methods are used. The image mosaics from 1955 are interpreted visually and the mosaics from 2004 are interpreted both visually and using two different digital image classification techniques. For these interpretations, the non-BRDF-corrected image mosaics are considered to be better. The BRDF-correction implemented in *EnsoMOSAIC* produced saw-edged patterns in the mosaics thus making digital image classification much harder. This theme is discussed in more detail in chapter 7.1.1.

6.3.1 VISUAL INTERPRETATION

Visual interpretation is the simplest and most straight-forward but also time-consuming method to extract meaningful information from remotely sensed images. Although this method is nowadays more and more replaced by digital image classification techniques, visual interpretation is still used especially when other techniques prove to be inaccurate for some reason.

In order to perform a good visual interpretation of a certain area by using remotely sensed images, the interpreter has to familiarise oneself with the area. This can be done by studying maps and other material or visiting the location. This is important because every area has its own special characteristics.

The principles of visual image interpretation have been developed through empirical experience for more than 150 years (Jensen 2000: 121). The most essential of these principles are the elements of image interpretation. These elements include e.g. location, size, shape, shadow, tone and colour, texture, pattern, height and depth, site, situation, association and resolution (Jensen 2000: 121; Lillesand & Kiefer 2000: 192). By using a general impression made up of these elements, the interpreter constructs the interpretation of a certain area.

Some basic principles have to be chosen before doing the interpretation. These include for example the *minimum mapping unit* (MMU). This refers to the smallest size areal entity to be mapped as a discrete area (Lillesand & Kiefer 2000: 199). In this study, MMU is approximately 4 m (Figure 38). Another principle is that separate trees are not classified as woodland although their crown has a diameter bigger than 4 m. The trunks are in most cases smaller than the MMU. Shadows give a special character to every image. Sometimes they can obscure other objects that could otherwise be identified (Jensen 2000: 125). In these cases, the objects covered by shadows are interpreted as well as possible. *Relief displacement* also causes problems in interpretation. It is a geometric distortion that occurs because of the central projection of aerial photographs and elevation differences in the terrain. This feature causes high objects that are not situated directly on the principal point of the image to lean outward from the central perspective of the camera (Campbell 2002: 76). Thus, only the base of these high objects, such as trees or buildings are in their proper planimetric location in an ortho-rectified image (Jensen 2000: 172). In visual interpretation, the problem caused by relief displacement can be taken into account by carefully estimating the right places of the trees and the real land cover class under the “fallen” trees.

Figure 38. Part of Ngangao 2004 mosaic with visual classification.

Furthermore, the interpreter has to pay attention to the amount of generalisation. Especially with this kind of high-resolution aerial mosaics that are used in this study generalisation is very important. Defining of the borders between different land cover types can also be difficult. Land cover seldom changes with sharp boundaries but rather gradually.

Visual interpretation of the mosaics Ngangao_1955, Chawia_1955, Ngangao_2004 and Chawia_2004 was done by digitising in *ArcMap*. The visual interpretation of the land cover was accomplished by interpreting the spectral and textural properties of the images as well as other previously mentioned elements of visual classification. A general impression of the land cover was reached from the experiences in the field combined with the experiences of the aerial mosaics.

While the land cover polygons were digitised, attribute information including the land cover class was added manually to these polygons. A two-level class structure was chosen to meet the needs of all three classification techniques as well as black and white and RGB mosaics (Figure 39). The class structure is kept as simple as possible for the purposes of this study. In visual interpretation though, subclasses (level II) with more detail are recorded. While doing the digital classifications, the four main classes (level I) are used. Thus, the visual classification of 2004 mosaics has the most specific classes in this study. The classification made from 1955 mosaics are using level I classes, *woodland*, *bushland*, *agricultural land* and *open area* with the *open area* is further classified as *road*, *yard* and *rock* (level II). Distinguishing different agricultural types from the black and white 1955 mosaic is considered almost impossible. Division of exotic and indigenous woodland is also considered meaningless as there were not many exotic trees in 1955 and delineating them is extremely hard with the imagery in use.

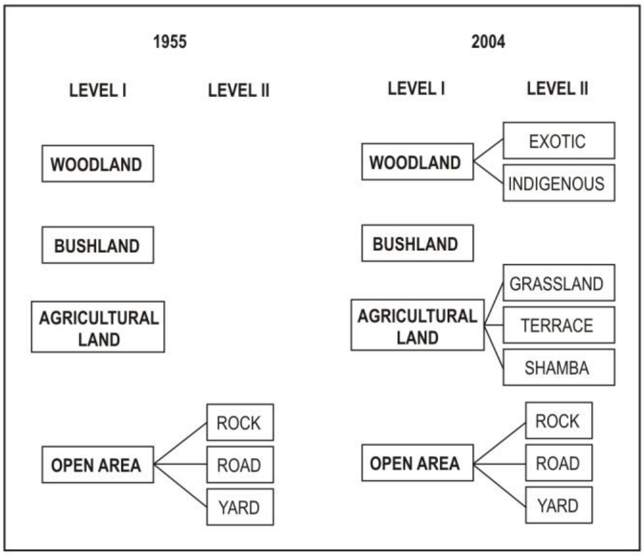

Figure 39. Class structure used in classifications.

In this study, *woodland* comprises all the trees approximately over two metres high. Single trees are not classified as *woodland* in visual classifications. The 2004 visual classification further differentiates *indigenous* and *exotic woodland*. *Indigenous woodland* consists of species discussed in chapters 3.2.7 and 3.2.8 while *exotic woodland* consists mainly of pine, sypress, eucalyptus and grevillea. *Bushland* is a land cover class that is hard to define. However, in this study, it comprises all the bushy vegetation that is approximately less than two metres high. *Agricultural land* consists of grassland, terraced agricultural land and shambas that are differentiated in 2004 visual classification as level II –classes. *Open area* can be divided to *rock*, *road* and *yard*. Examples of the used land cover classes are presented in Figure 40.

Figure 40. Examples of land cover classes: 1. *Indigenous woodland* (on the lower part of the image) and *exotic woodland* (on the upper part of the image), 2. mostly *bushland*, 3. mostly *agricultural land* (*grassland, terrace* and *shamba*), 4. some *open area* features (*road*, *rock* and *yard*).

The class structure chosen for this study is also recorded with *Land Cover Classification System* (LCCS, software version 2) by UNEP and FAO (LCCS 2005). LCCS is a comprehensive, standardized classification system that enables a comparison of land cover classes regardless of data source, thematic discipline or country. The class characteristics determined with LCCS can be seen in Table 15.

Table 15. The class characteristics determined with LCCS.

Own Classification		LCC Label	LCC Code	LCC Level
Level I	Level II			
Woodland	Indigenous	Broadleaved Deciduous Trees, Single Layer	20642	A3A10B2C1D1E2F1
	Exotic	Needleleaved Evergreen Trees, Floristic Aspect: Cypress	20092-Zt1	A3A10B2XXD2E1-Zt1
		Broadleaved Deciduous Trees, Floristic Aspect: Eucalyptus	20090-Zt2	A3A10B2XXD1E2-Zt2
		Needleleaved Evergreen Trees, Floristic Aspect: Pine	20092-Zt3	A3A10B2XXD2E1-Zt3
		Needleleaved Evergreen Trees, Floristic Aspect: Grevillea	20092-Zt4	A3A10B2XXD2E1-Zt4
Bushland	Bushland	Closed to Open (100-40)% Thicket, Single Layer	21600-121340	A4A20B3XXXXXXF1-A21
Agricultural land	Grassland	Closed Grassland, Single Layer	21299	A6A10B4XXE5F1
	Shamba	Small Sized Field(s) Of Rainfed Herbaceous Crop(s)	11251	A3B2XXC2D1
	Terrace	Small Sized Field(s) Of Rainfed Herbaceous Crop(s)	11251	A3B2XXC2D1
Open area	Rock	Bare Rock(s)	6002-1	A3-A7
	Road	Linear Built Up Area(s)	5002	A3
	Yard	Urban Area(s)	5003-9	A4-A13

6.3.2 IMAGE SEGMENTATION AND CLASSIFICATION

The first of the digital classification techniques used in this study is object-oriented segmentation and classification of the segments. In order to classify high-resolution remote sensing data like aerial photographs or other VHR (very high spatial resolution) data segmentation has proven to be a good method, especially when classifying vegetation (Pekkarinen 2002a; Riley et al. 2002; Flanders et al. 2003; Rego & Koch 2003). The spatial resolution of VHR or aerial photograph data is that high that a pixel may cover only a small part of the object of interest (Pekkarinen 2002b). Thus, information important for the understanding of a RS image is not represented in single pixels but in meaningful objects and in their relation (Blaschke 2004: 114). These objects cannot be recognised in pixel-based approaches, but with segmentation techniques recognition is possible. Furthermore, segmentation utilises the shape and context information present in the image better than pixel-based image analysis methods (Schneider & Steinwendner 1999; Blaschke & Strobl 2001; Pekkarinen 2002a: 2818).

Segmentation can be defined as division of an image into spatially continuous, disjointed and homogenous regions. In other words, neighbouring pixels are grouped into segments (objects) based on similarity criteria that can be based on DN value or texture (Ryherd & Woodcock 1998: 181; Hay et al. 2001; Pekkarinen 2002a: 2818). In an ideal case, within-segment object characteristics are homogenous, adjacent segments have significantly different values and boundaries of segments are simple and spatially accurate (Haralick & Shapiro 1985: 100; Pekkarinen 2002b: 350). Technically, segmentation is not a new method, but it is still quite rarely used in image processing of remotely sensed data (Burnett & Blaschke 2003). There are several methods for segmentation that can be grouped into clustering, edge detection and region extraction methods (see e.g. Schneider & Steinwendner 1999; Pekkarinen 2002a: 2818).

The segmentation software chosen for this study is *eCognition* that uses a region-merging technique, multi-resolution segmentation and fuzzy logic in classification of the segments (Baatz et al. 2004). This software has obtained good results when compared to other segmentation programs although it sometimes creates irregular or ragged delineated segments (Neubert & Meinel 2003).

The multi-resolution segmentation is one solution for the *modifiable areal unit problem* (MAUP) that is present in all RS data. The MAUP results from the fact that a RS image can be divided into meaningful, non-lapping units by numerous ways (Hay et al. 2001: 473). Different land cover types form different size of units and on the other hand the size and content of the units can differ according to the purpose of the interpretation.

In *eCognition*, objects are formed in every scale level according to certain parameters that the user can define. These include *scale parameter*, *segmentation mode* and *composition of homogeneity criterion* consisting of *shape factor* and *compactness-smoothness* variable. The scale parameter does not define a rigid constraint on the size of the resulting segments but is rather a relative guide (Burnett et al. 2003). In this study, the scale parameters were determined with the help of *scale parameter analysis* (Baatz et al. 2004: 207). The segmentation modes used are *normal mode* and *spectral difference*. While the normal mode creates segments based on the composition of homogeneity criterion the spectral difference segmentation is used to merge neighbouring objects according to their difference in spectral difference (Baatz et al. 2004: 201). The shape factor determines whether shape or spectral information is more important while doing the segmentation. This value can range between 0 (spectral information is most important factor) and 1 (shape is the most important factor).

Compactness-smoothness ranges also from 0 to 1. The parameters used in this study can be seen in Table 16. The values emphasise spectral information and smoothness. With the latter, it is determined that the object size can vary. For both Ngangao and Chawia, the same parameters are used. This is possible because the properties of the data and the land cover are similar.

Table 16. Parameters used in segmentation procedure.

Level	Segmentation mode	Scale parameter	Shape factor	Compactness - smoothness
I	normal	12	0.1	0.1 : 0.9
II	spectral difference	5	-	-
III	normal	27	0.1	0.1 : 0.9
IV	normal	58	0.1	0.1 : 0.9

In this study, multi-resolution segmentation is started with an over-fine level (Level I). The neighbouring pixels are joined to initial segments and the process is continued until a threshold determined by the segmentation parameters is reached. These parameters have to be set so that resulting segments consist of only one land cover class type. The Level I –segments are then further segmented with *spectral difference* –mode thus forming the segments of Level II. Levels III and IV are done with normal segmentation mode and they are the final levels used for classification. The differences of segments in all four levels can be seen in Figure 41.

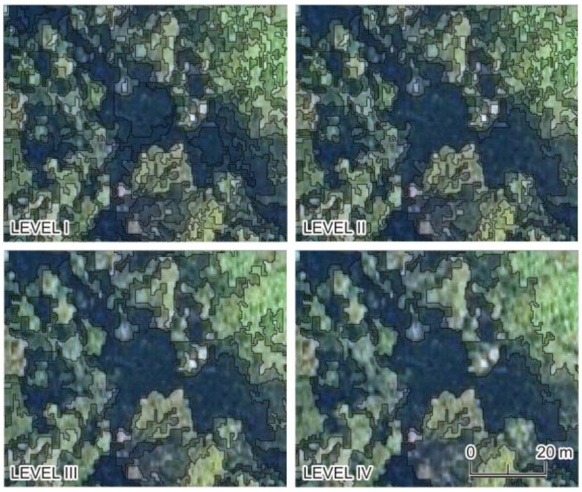

Figure 41. A part of Chawia with segments of levels I, II, III and IV. At level I, trees and other objects are divided into several segments. At levels II, III and IV, segments having similar properties are combined according to segmentation parameters.

The classification of objects in *eCognition* is conducted by fuzzy logic and the frame of *eCognition's* knowledge base for classification is the class hierarchy (Baatz et al. 2004: 223). It contains all the classes and their specific class descriptions. Whereas classic hard classifiers in RS (for example maximum-likelihood or minimum-distance) express whether an object (or pixel) belong to a certain class or not (giving a value of 1 or 0, respectively), soft fuzzy classifiers use a degree of membership probability in order to express an object's assignment to all considered classes (Baatz et al 2004: 68). The membership value can usually range between 0.0 (totally ambiguous) and 1.0 (totally unambiguous) (Flanders et al. 2003: 444). The set of membership degree of class assignment μ of the considered object *obj* to the *n* considered classes can be set as follows:

$$f_{class,obj} = \left[\mu_{class\_1}(obj), \mu_{class\_2}(obj), \ldots \mu_{class\_n}(obj)\right] \text{ (Benz et al. 2004: 251).} \qquad (13)$$

In *eCognition*, fuzzy rules are based either on one-dimensional membership functions or on nearest neighbour –classifier which operates on a multidimensional feature space (Baatz et al. 2004: 230). Both of these types are supervised classification methods. In this study, both nearest neighbour –classifier and membership functions were tested. Because classes could not be separated from other classes by a few features, standard nearest neighbour was selected to be the classification method used as is recommended in *eCognition*'s UserGuide (Baatze et al. 2004: 99). The feature space where NN-classifier acts contains the mean values of the three spectral bands (red, green and blue).

The classes were selected so that they can be compared with the classes of the visual classification and pixel-based classification. The class structure is kept simple with four level I –classes: *woodland*, *bushland*, *agricultural land* and *open area*. As the separation of different types of *open area*s or *agricultural area*s was discovered very difficult, only the main classes of these two were classified. This study is focusing on classifying woodland and thus the classification of these land cover types was considered unnecessary. Moreover, building extraction with the use of *eCognition* in the area of the Taita Hills is studied by Hurskainen (2005). Unfortunately, also differentiating exotic and indigenous woodland was discovered impossible after many classification trials. This may be because the lack of a NIR band in the data. Therefore, also woodland is classified only with level I –class.

The class hierarchy was compiled as in Figure 42. The hierarchy is based on two basic principles: both levels III and IV are used for the classification and furthermore the objects are first divided into *open area*, *shadow area* and *other area*. Level III is the level used for the final classification but (super-) objects in level IV are used also. An ideal situation is that objects are as big as possible but do not contain pixels from more than one land cover class.

This situation comes true with *open area* –class in level IV. Thus, classes that are used in level IV are *open area_4*, *shadow_4* and *no shadow_4*. The division of objects into three auxiliary classes was discovered a fairly good method after trying other different class hierarchies. *Open area*s can be quite easily detected even in level IV. In this level IV, other objects besides the *open area* –objects are then divided into *shadow_4* and *no shadow_4*. In this case, *no shadow_4* can only include objects that do not contain shadow at all (Figure 43). This separation is done in order to ease the classification in level III. Objects belonging to the same land cover class in reality can have very different spectral values whether they are in shadow or not. Thus, it was considered easier to separate all the objects having shadow from each other and all the objects not having shadow from each other.

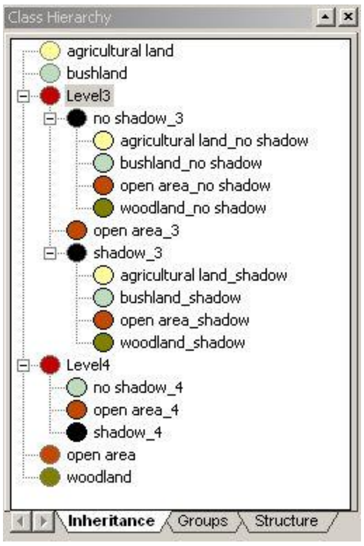

Figure 42. Class hierarchy in eCognition.

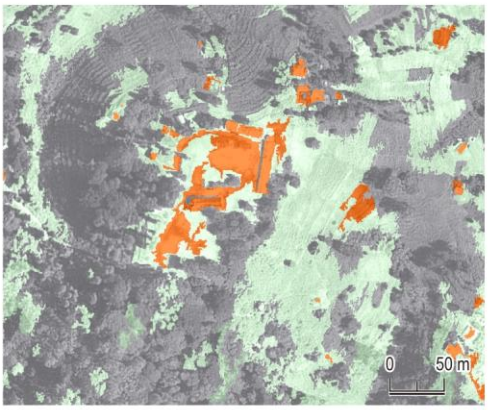

Figure 43. Classification at level IV. The grey areas represent class *shadow_4*, green areas *no shadow_4* and the red areas *open area_4*.

In the classification procedure of *eCognition*, it is possible to use class-related features. In this case, level IV was used as an auxiliary level and thus class-related features were added to parent classes *no shadow_3*, *shadow_3* and *open area_3* (Figure 44). In these features it was determined that all the objects in level III that are part of the objects belonging to class *no shadow_4* in level IV belong to class *no shadow_3*. This kind of feature was added to all three main classes in level III.

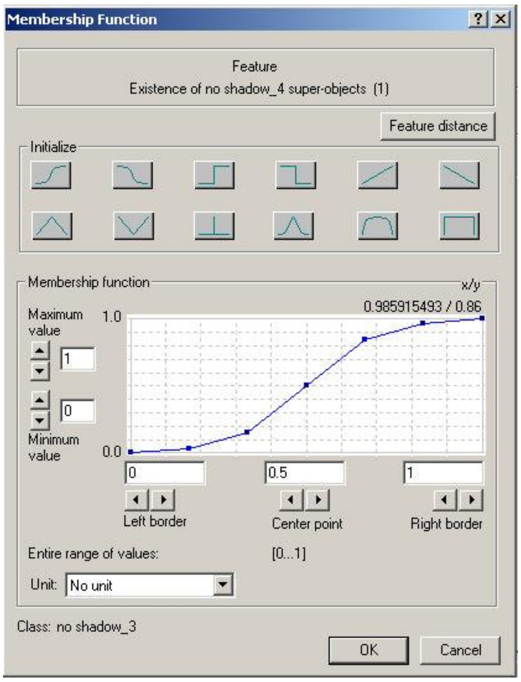

Figure 44. A class-related feature of existence of super-objects was added to all classes in level III. For example, to be classified to class *no shadow_3* an object needs to belong to an object in level IV that is classified as *no shadow_4*.

At first, the classification was done in level IV with samples that were assigned to each class in that level. The number of samples can be seen in Table 17. Samples were collected throughout the image in order to get a representative collection of sample objects (Figure 45). At first, just a few samples per class were collected and then the classification was run. Then, some misclassified objects were added as samples of the correct class and classification was run again. This was done until the best possible result was achieved. After the classification of level IV, samples were collected for all the subclasses of *shadow_3* and *no shadow_3*, namely *woodland_shadow*, *bushland_shadow*, *agricultural land_shadow*, *open area_shadow*, *woodland_no shadow*, *bushland_no shadow*, *agricultural land_no shadow* and *open area_no shadow*. These classes inherit the features given to their parent classes which are assigned to classify only objects from level III.

Table 17. The number of samples collected for each class in *eCognition*.

		Chawia	Ngangao
Level IV	shadow_4	33	28
	no shadow_4	21	34
	open area_4	18	31
	total	72	93
Level III	woodland_shadow	119	96
	bushland_shadow	63	33
	agricultural land_shadow	78	23
	open area_shadow	-	15
	woodland_no shadow	53	58
	bushland_no shadow	33	38
	agricultural land_no shadow	72	52
	open area_no shadow	9	21
	total	427	336

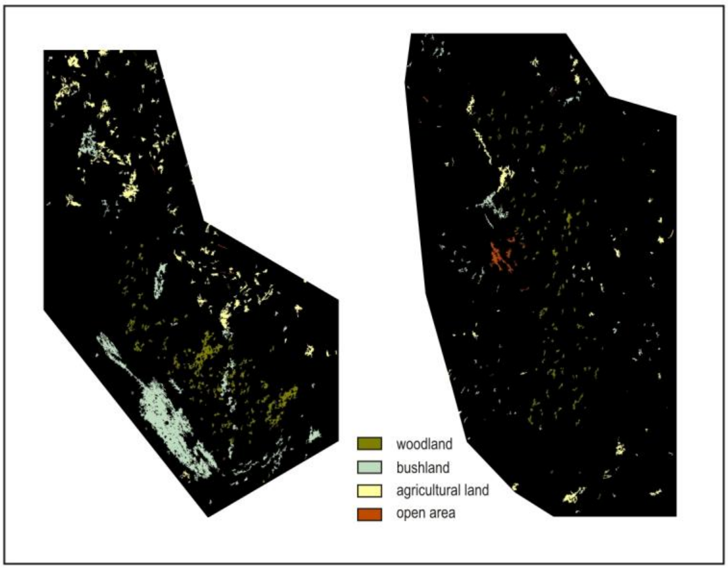

Figure 45. The samples used for classification in *eCognition*.

In the classification procedure, each object is given a membership value to all classes available. The minimum membership value was set to 0.5 meaning that in order to be classified an object needs to have a membership value of at least 0.5 to a class. Each object is classified based on the samples. The membership values are determined in a multi-dimensional feature space; the closer an object is located in the feature space to a sample of class A, the higher the membership value to this class. In *eCognition*, this distance is calculated as follows:

$$d = \sqrt{\sum_f \left(\frac{v_f^{(s)} - v_f^{(o)}}{\sigma_f} \right)^2} \;, \tag{14}$$

where d = the distance between sample object s and image object o

$v_f^{(s)}$ = the feature value of sample object for feature f

$v_f^{(o)}$ = the feature value of image object for feature f

σ_f = the standard deviation of the feature values for feature f (Baatz et al. 2004: 97).

For the classification, the class hierarchy is as given in Figure 42. In *eCognition*, there can be several class hierarchies. The one used for classification is called *Inheritance hierarchy* while the other one used in this study is the *Groups hierarchy*. The latter allows the grouping of classes to a superior class of common semantic meaning. Hence, after the classification the classes of level III were grouped in *Groups hierarchy* (Figure 46).

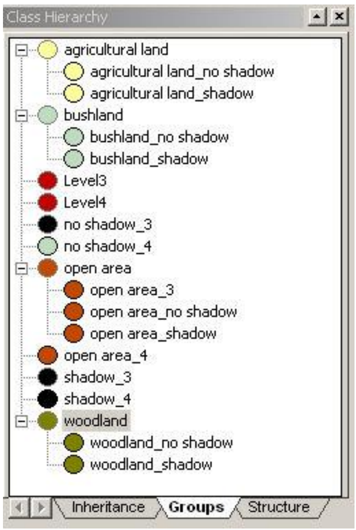

Figure 46. The groups hierarchy of the classes. All the classes in level III are grouped in final classes: *woodland, bushland, agricultural land* and *open area*.

The final classification was exported to *ArcGIS* for further analysis. In order to produce a map from these classifications, the fuzzy results need to be translated back to crisp values (Benz et al. 2004: 254). For this crisp class assignment, the maximum membership degree of each object is used.

6.3.3 PIXEL-BASED APPROACH

The second of the digital classification techniques used in this study is pixel-based supervised classification. Pixel-based approaches are traditional digital classification techniques widely used in RS studies. They consider each pixel individually without any knowledge of neighbourhood properties. Both in supervised and unsupervised classification methods, pixels are designated to classes by their spectral characteristics. While unsupervised classification groups the pixels into clusters based only upon the distribution of the DNs in the image, supervised classification uses external information given by *training sites* or *samples* (Gibson & Power 2000: 77). The pixel-based method chosen for this study is supervised classification realised in *Erdas Imagine*.

Training sites are samples of each land cover class to be classified from a RS image. The multivariate statistical parameters of samples' spectral characteristics (means, standard deviations, covariance matrices, correlation matrices, etc.) are used as reference when assigning each pixel to a class of which it has the highest likelihood of being member (Jensen 1996: 197). The information needed for the training samples can be obtained through fieldwork, maps or aerial photographs. In this study, a method of on-screen sampling was realised. According to Campbell (2002: 334–336) each class should be represented by a minimum of 5 to 10 samples and the total amount of pixels in samples of one class should be at least 100. In this study, 10 sample areas for each class were selected. The class structure used for this classification includes the level I –classes (*woodland*, *bushland*, *agricultural land* and *open area*). The sample areas consist of 20 x 20 pixel squares with the exception of the *open area* –class that has samples of 10 x 20 pixels. The samples were distributed over the entire image mosaic.

In order to classify all the pixels of an image to classes according to the samples, a proper supervised classification algorithm needs to be chosen. The most frequently used algorithms are the parallelepiped, minimum distance and maximum likelihood decision rules (Jensen 1996: 225–231). For the purposes of this study, the maximum likelihood classification was chosen because it is a powerful and the most common supervised classification method (Richards & Jia 1999: 182). All these different methods of pixel-based classification are not tested as more emphasis is put on the comparison between segmentation and one pixel-based approach.

The maximum likelihood classifier is based on a probability that a pixel belongs to a certain class. In order to calculate this probability, statistics computed from the training data like mean measurement vector and covariance matrix are used (Jensen 1996: 229; Campbell 2002: 343). This method is based on the assumption that the training data for each class is normally distributed.

One disadvantage of pixel-based approaches is that the classification result can have a so called salt-and-pepper pattern here and there. This is due to the spectral variability encountered by the classifier in pixel-based methods (Lillesand & Kiefer 2000: 566). Different post-classification smoothing operations have been developed in order to avoid the salt-and-pepper pattern in the final product. The smoothing method used in this study is the use of a majority filter. This majority filtering technique is based on spatial auto-correlation; the pixels near to each other are likely to be more similar than pixels further away. In this method, a moving window is passed through the image and the pixel at the centre of the window is reassigned with majority class of all the pixels in the window (Liu & Moore 1991: 2204). In this study, a 5 x 5 -window was used for the pixel-based classifications and the majority of the classes in the window was assigned to be the new value of the pixel at the centre of the window. This procedure was accomplished in *Erdas Imagine*. Finally, the classifications were exported to *ArcGIS* for further analysis.

6.4 CHANGE DETECTION

Change detection in remote sensing studies focuses on change between at least two images and thus at least two points in time. Therefore, change detection often studies the change between two snapshots of a time rather than the actual change that is continuously happening in e.g. landscape.

Change detection is often realised digitally on pixel-by-pixel basis. Ideally, in order to this kind of comparison to succeed, the spatial resolution as well as the spectral resolution and radiometric resolution of the images need to be comparable (Jensen 1996: 259–260). Furthermore, atmospheric and soil moisture conditions as well as phenological cycle can introduce special characteristics in the images under consideration thus hardening the comparison between them.

In this study, however, the change detection is realised using the visual interpretations of Chawia and Ngangao from 1955 and 2004. The comparisons were made in *ArcMap* by using GIS methods instead of pixel-by-pixel comparison. Thus, the previously mentioned requirements for successful change detection are less strict. However, the classifications that were compared are based on images or image mosaics all taken in the same time of a year. Also the spatial resolution of the images is similar enough for the comparison to succeed. Furthermore, the same spatial extent as well as projection was used.

The method used can de defined as *post-classification comparison*. The change detection is based on classifications made separately for years 1955 and 2004. As the class structure was also designed to meet the needs of change detection, the changes in land cover are straight-forward to detect.

For the comparison purposes, the spatial data sets of visual classification of Ngangao (1955 and 2004) and Chawia (1955 and 2004) were merged with union function in *ArcMap*. In consequence, each new polygon holds the information of the land cover in 1955 and 2004. Further analyses were made in order to find out where and how the land cover had changed.

6.5 STUDYING THE CANOPY

This part of the thesis concentrates also on the structure of the Ngangao and Chawia forests, but from another point of view: the structure of the canopy of these forests is studied combining the information of hemispherical photographs and digital aerial photographs.

6.5.1 FOREST CANOPY & HEMISPHERICAL PHOTOGRAPHS

The canopy defines the upper portion of a single tree crown or the entire upper portion of forest ecosystems (Nadkarni 1988: 190). However, the canopy has a great importance to the entire forest. Many processes that are essential to tropical forest maintenance and regeneration take place in the canopy (Nadkarni 1988). Moreover, the canopy structure controls the amount of solar radiation and therefore also the microclimate in the forest (Whitmore 1998: 110–113). Thus the quantity and spectral quality of this incident solar energy affects the development, structure and species composition of the canopy trees (Frazer et al. 1999: 1). Canopy gaps in tropical closed canopy forests can be created as a result of natural disturbances but also as a result of human action. As indigenous species growing in these closed canopy montane forests normally grow under relatively dark conditions during the early stages, better-lighted conditions due to a gap in canopy create improved growing conditions to other, non-indigenous species.

The research of forest structure is traditionally achieved through ground surveys. Lately, the use of remote sensing techniques has proven to be potential also in forest canopy structure studies (Hall et al. 1995; Pellikka et al. 2000b) and in estimating leaf area index (LAI) (Roy et al. 1996; Wulder et al. 1998; Broge & Leblanc 2000; Chen et al. 2002). In this study, digital aerial photographs are used to analyse the spectral characteristics of the forest canopy. This data is then compared with hemispherical (fisheye) photographs that are used as a reference data (see Pellikka et al. 2000b).

Hemispherical photography is a technique for characterising plant canopies using upward looking photographs taken through an extremely wide-angle lens (Walter et al. 2003; Leblanc et al. 2005). Typically, the viewing angle approaches or equals 180º. Consequently, the hemispherical photographs are circular images that record the size, shape and location of gaps in the forest overstory (Frazer et al. 1999: 1). If an analogue camera is used, images are further converted into bitmaps with a digital scanner in order to analyze them with specialized image analysis software.

The resulting hemispherical photographs record the geometry of canopy openings (Hardy et al. 2004: 259). Parameters that can be derived from the hemispherical photographs include LAI, effective LAI (LAI_e), gap fraction and canopy openness (Trichon et al. 1998; Walter et al. 2003; Leblanc et al. 2005). LAI is a dimensionless variable that is defined as the one-sided or hemisurface (half of total) green leaf area per unit area of ground (Monteith 1990: 73; Chen & Black 1992). The LAI_e differs from LAI as it is calculated from the gap probability in a given direction. For comparing LAI values of different types of forests, LAI_e is often used because it assumes a random spatial distribution of leaves instead of the clumped pattern that is observed in reality (Rautiainen 2005: 28).

6.5.2 PHOTOGRAPHIC DATA ACQUISITION

Hemispherical photographs were taken in the forests of Ngangao and Chawia during the years 2004–2006 both in FHM plots and other locations (Figure 47). Hemispherical photographs were taken with a Canon AE1 analogue camera equipped with an 8 mm Sigma F4 EX Circular Fisheye lens (180° viewing angle, equisolid angle projection). The camera was fixed on a tripod, approximately 1 m above the ground. Moreover, it was levelled horizontally using a bubble level and oriented so that the magnetic north corresponded with the top of the photograph. Optimal weather condition for hemispherical photographing, overcast sky, was not fulfilled in case of every photograph. Inaccuracy due to a very sunny or on the other hand foggy weather was later taken into account while processing and analysing the photographs. In order to digitally analyse the photographs, the negatives were scanned to JPG format.

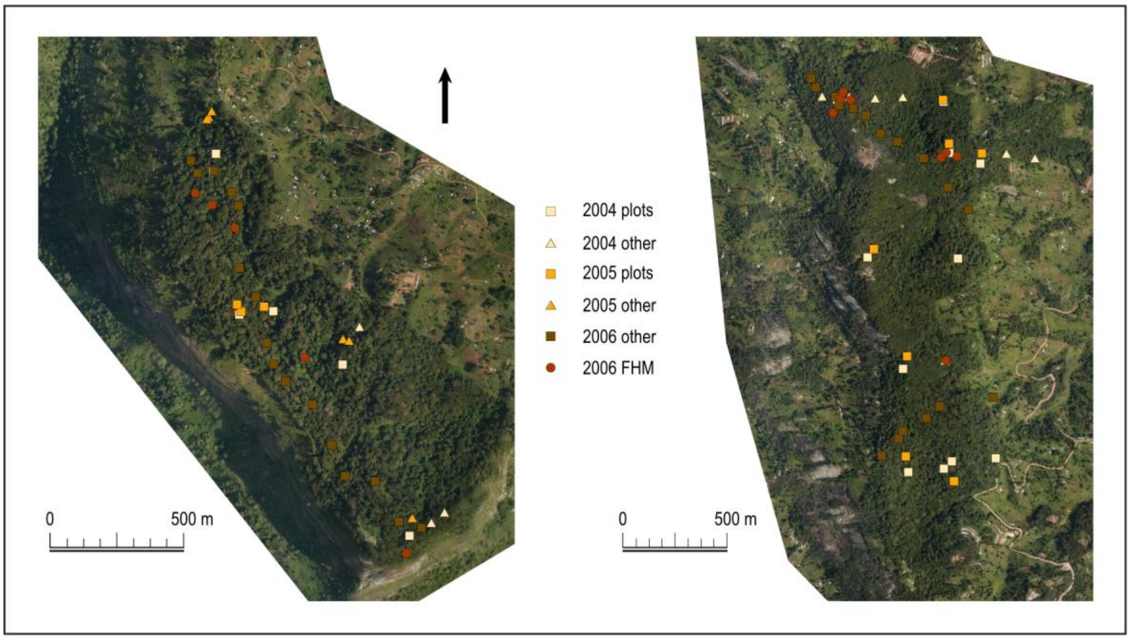

Figure 47. The locations of hemispherical photographs taken in Chawia (left) and Ngangao (right). Plots and other refer to these locations while 2006 FHM refers to the actual locations of FHM plots checked in 2006 (see chapter 6.5.6).

6.5.3 PROCESSING AND ANALYSIS OF THE HEMISPHERICAL PHOTOGRAPHS

Processing and analysis of the hemispherical photographs was done with the scientific image processing software, *Gap Light Analyzer* (GLA) version 2.0 developed by Frazer et al. (1999). With this software it is possible to calculate canopy and site openness, effective LAI, sunfleck-frequency distribution and daily duration as well as the amount of above- and below-canopy direct, diffuse and total solar radiation incident on a horizontal or arbitrarily inclined receiving surface.

At first, each image was registered in order to identify both the orientation and circular extent of the exposure. Furthermore, configuration settings were edited for each image. These configuration settings include information on the site position and orientation (Table 18). The orientation information, the slope and the aspect, were added to each image site separately in order to correspond the conditions in the field. However, a topographic masking of photographs was not performed during the analysis as the images were not considerably affected by topographic shading. Also information on growing-season length and atmospheric conditions could be added to the configuration settings, but these attributes were not needed in this analysis.

Table 18. The configuration settings used for hemispherical photographs taken in Ngangao and Chawia. The same average location settings were used to all the sites in the same forest.

Attribute	Ngangao	Chawia
Registration	Magnetic North	Magnetic North
Magnetic Correction	00º44’ W	00º46’W
Projection Distortion	Polar	Polar
Location / Latitude	03:21:50 S	03:28:58 S
Location / Longitude	038:20:30 E	038:20:38 E
Location / Elevation	1,850 m	1,570 m

Image classification is done in this software by using a threshold function that separates pixels within the image array into sky (white) and canopy (black) classes (Figure 48). The thresholding technique is subjective and therefore it has a possibility to be inaccurate. Nevertheless, a sensitivity analysis of this technique was accomplished by Hardy et al. (2004: 262) with satisfying results. The threshold values used in this study vary a lot depending mainly on the weather conditions: direct solar radiation and fog influenced the photographs to some extent. This influence was minimized using threshold values suitable for each photograph (Table 19). The output of image classification include canopy openness (the percentage of open sky seen from beneath a forest canopy), LAI 4 Ring (the effective LAI integrated over the zenith angles 0 to 60º, see Stenberg et al. 1994) and LAI 5 Ring (LAI 5 Ring is the effective LAI integrated over the zenith angle 0 to 75º, see Welles and Norman 1991). The parameters used in this study are *LAI 4 Ring*, *LAI 5 Ring* and *canopy closure* (%) (CLOSURE), which is calculated as follows:

CLOSURE (%) = 100 % - *canopy openness* (%).

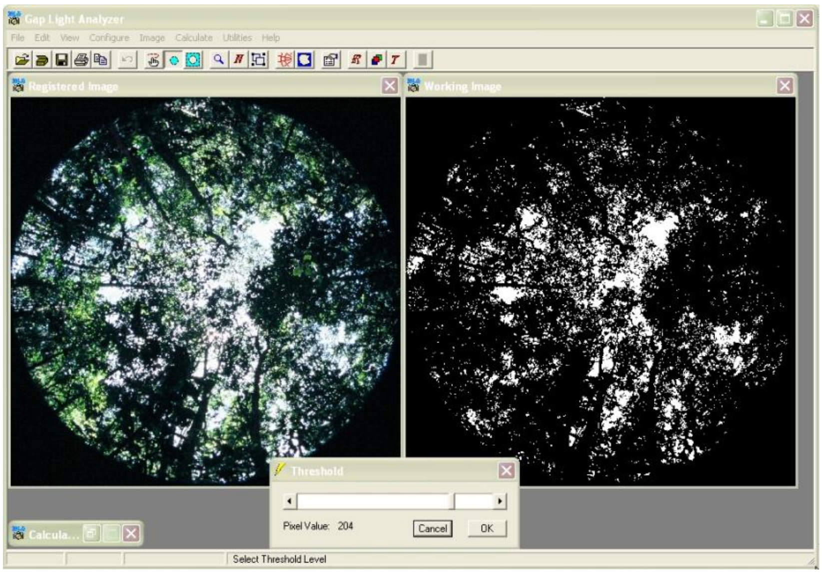

Figure 48. The user interface of GLA with registered and working image.

Table 19. The characteristics of the threshold values used for the hemispherical photographs.

	Year	Min	Max	Mean	Std. Dev.
Ngangao	2004	138	238	196.0	27.0
	2005	200	240	217.0	13.5
	2006	128	218	169.0	25.9
Chawia	2004	133	211	180.3	31.8
	2005	217	240	229.9	7.4
	2006	88	238	178.6	36.3

6.5.4 EXTRACTING THE TEXTURAL INFORMATION FROM THE DIGITAL AERIAL PHOTOGRAPHS

In recent times, there have been many attempts to derive LAI from remotely sensed data. Both satellite image (especially Landsat ETM+ data) (e.g. Eklundh et al. 2001; Asner et al. 2002; Chen et al. 2002) and aerial photograph data (e.g. Wulder et al. 1998; Pellikka et al. 2000b) have been used. The results vary depending on the method used. Many of these studies have used vegetation indices (e.g. NDVI) while a less utilized method is incorporating texture of the remotely sensed data in the estimation of LAI. This use of textural information has proven to improve the accuracy of deriving the LAI (Wulder et al. 1998; Asner et al. 2002).

Texture, in the context of digital image processing, is the spatial variability of image tones which describes the relationship between elements of surface cover. In the case of forest vegetation, the variation in texture is related to changes in the spatial distribution of the vegetation (Wulder et al. 1998: 66). The amount of textural information on forest structure is highly dependent on the spatial resolution of the remotely sensed data. Data with higher spatial resolution has more inter-pixel variation which in turn provides more structural information. Therefore, the use of low and high resolution data probably results in relationships different from each other (Wulder et al. 1998: 65).

Image texture may be defined by a variety of statistics which characterize the relationship between neighbouring pixels. In this study, the following parameters were used: average reflectance (MEAN), minimum reflectance (MIN), maximum reflectance (MAX), the range of reflectance results (RANGE) and standard deviation of reflectance (STD_DEV). These parameters were calculated from circular windows with the centre being the point where the hemispherical photograph was taken. Two different sized windows with diameters of 8 and 15 metres were created in *ArcMap* by buffering the GPS locations of the plots (Figure 49). The created polygon files were imported in *Erdas Imagine* where the Zonal Attributes function was used. With this function, the desired parameters were computed by intersecting the aerial photograph with the polygon Shapefiles. The intersection was done for each band (red, green and blue) in both BRDF-corrected and non-corrected mosaics.

Figure 49. Examples of buffers created in *ArcMap*. The inner buffer has a diameter of 8 m while the outer buffer has a diameter of 15 m.

6.5.5 COMPARISON OF HEMISPHERICAL PHOTOGRAPHS AND TEXTURAL INFORMATION

In order to find out whether the textural information derived from the mosaic can be used to model the canopy parameters in Ngangao and Chawia, the textural information was compared with the canopy parameters. All the data was normally distributed and no further transformations had to be made.

The linearity of relations between textural and canopy parameters was assessed with scatterplots made of each variable pair (appendices 2–7). Canopy parameters, *LAI 4 Ring*, LAI *5 Ring* and *CLOSURE* were plotted with textural parameters MAX, MIN, MEAN, RANGE and STD_DEV of polygons with diameters 8 m and 15 m of each band (1, 2, 3) of both normal and BRDF-corrected mosaic. The comparison was made for 1) Ngangao and Chawia 2004–2006 (n = 78), 2) Ngangao 2004–2006 (n = 43), 3) Chawia 2004–2006 (n = 35), 4) Ngangao and Chawia 2004 (n = 28), 5) Ngangao 2004 (n = 19), 6) Chawia 2004 (n = 9), although the sample size for most of the groups is very small. The optimal situation is that the hemispherical photographs are taken at the same time that the aerial photographs are acquired. In this study, the 2004 hemispherical photographs were taken within 15 days of the acquisition of aerial photographs. The 2005 and 2006 hemispherical photographs were taken in the same time of a year to avoid the phenological effects. Having canopy data from several years is taken into account by dividing the samples into the above-mentioned groups.

As can be seen in appendices 2–7, there is no linearity of relations between textural and canopy parameters. The situation is the same with all the variable pairs compared. Because no relationship can be expected according to the scatterplots, further statistical analysis was considered unnecessary.

6.5.6 COMPARISON WITH THE FOREST HEALTH MONITORING (FHM) DATA

One of the objectives of this study is to combine the canopy data acquired with the FHM data and study the relationships of these two data sets. A preliminary requirement for this kind of comparison is that the data sets are collected in the same locations. The locations of FHM plots were recorded only with very imprecise coordinates and some written instructions. Therefore, only the persons who did the first measurements know the exact locations of the plots. These persons include the forest guard of Ngangao, Jonam Mwandoe, who knew the locations of plots that he had been working with. As the plots were not marked very well, finding the exact locations proved to be extremely difficult.

In autumn 2006, the FHM measurements were repeated and this time also the coordinates were recorded with a GPS. Therefore, the locations where the hemispherical photographs were taken for this study and the original FHM plot locations could be compared. These locations can be seen in Figure 47 for Ngangao and Chawia. The distances between the original plot and the location visited for this study vary from 11 m to 480 m with the average of 150 m. The weak accuracy of the GPS coordinates in closed canopy forest can introduce some inaccuracy but can not explain all the errors. Thus, the most important reason for the inaccuracies is that the locations of the plots were not able to locate properly while in the field. Therefore, the data of FHM cannot be compared with the data acquired for this study by using plot level data. However, general findings of these two data sets are discussed in chapter 7.4.2.

7 RESULTS

7.1 MOSAICKING RESULTS

In this study, altogether four image mosaics were produced in the areas of Ngangao and Chawia using the digital aerial photographs from 2004. Furthermore, Ngangao was covered with a mosaic produced using aerial photographs from 1955. The area of Chawia was covered within one aerial photograph from 1955, thus mosaicking was unnecessary.

7.1.1 DIGITAL AERIAL MOSAICS FROM 2004

Digital aerial photographs from 2004 were used to create ortho-corrected aerial mosaics covering the areas of Chawia and Ngangao. Altogether four mosaics were produced; mosaics for both areas with and without using BRDF correction (Figures 50 and 51).

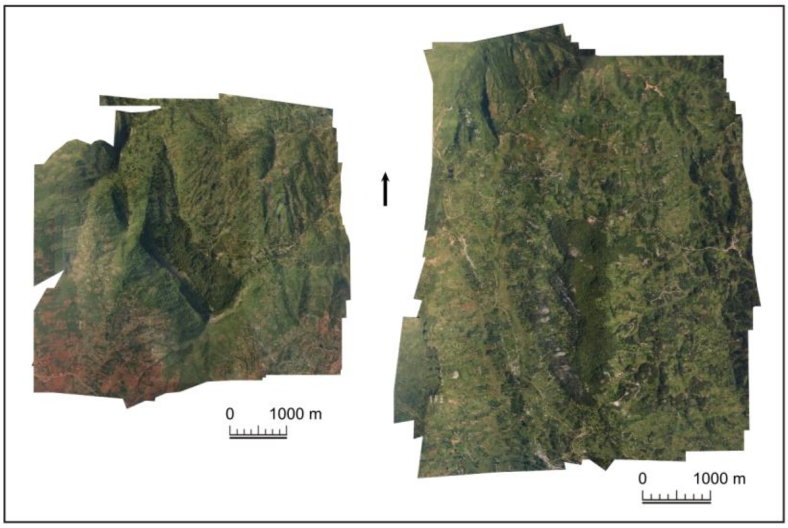

Figure 50. Mosaics of Chawia and Ngangao from 2004 without using BRDF correction.

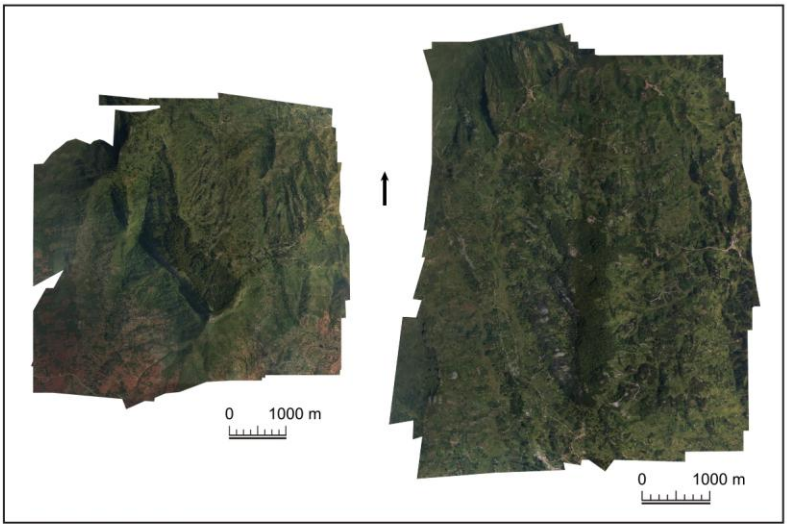

Figure 51. Mosaics of Chawia and Ngangao from 2004 with using BRDF correction.

Brightness variations introduced by BRDF are considered insignificant if noticeable at all in non-corrected mosaics. Conversely, mosaics with BRDF correction introduce saw-edged pattern between different flight lines together with clear brightness variations inside the forest areas. This phenomenon can be noticed especially in Ngangao (Figure 52). As the mosaics produced without the correction have significantly less brightness variations, these mosaics are considered better and thus used for further analysis. The spectral and geometric accuracies of the mosaics are discussed in chapter 7.5.1.

Figure 52. A small subset of BRDF-corrected mosaic (on the left) and non-corrected mosaic (on the right) from Ngangao. A north-south directed saw-edged pattern can be seen in the BRDF-corrected mosaic.

The mosaics produced were further subset for classification and canopy analysis. The same subset area was used also for the aerial mosaic and photograph from 1955. The final mosaics for analysis are presented in Figure 53 and Appendices 8 and 9.

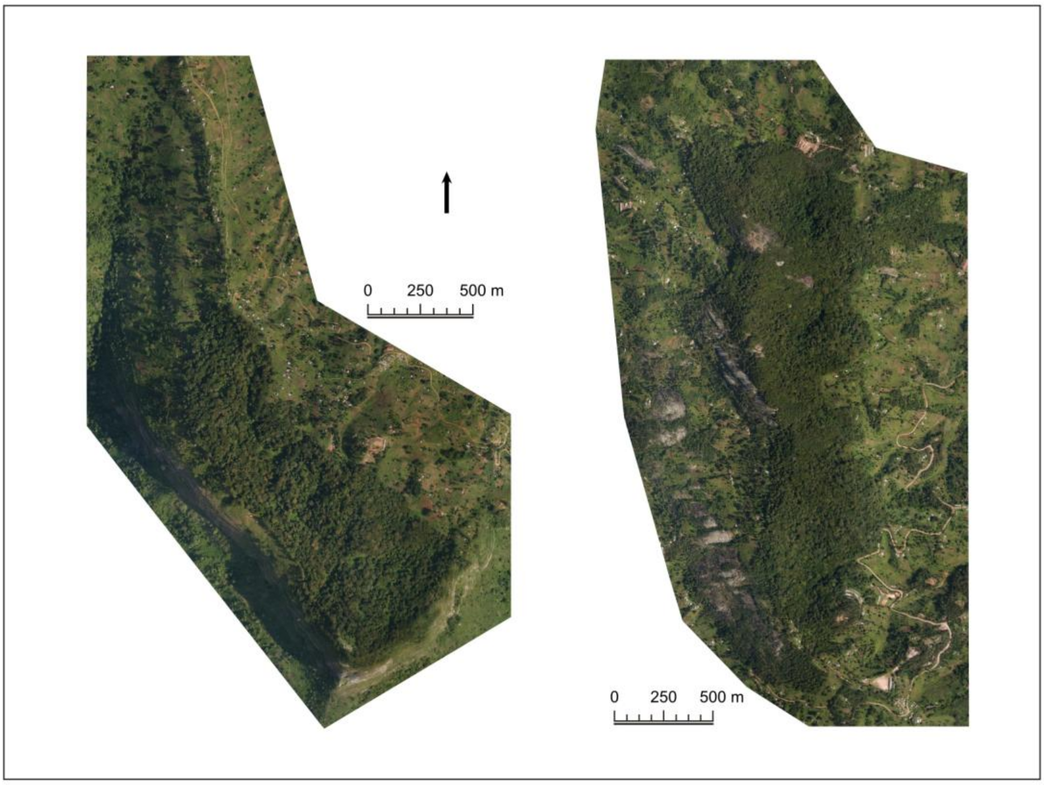

Figure 53. The mosaic subsets of Chawia (on the left) and Ngangao (on the right) without BRDF correction.

7.1.2 AERIAL MOSAIC AND PHOTOGRAPH FROM 1955

In order to study the change in the forests between 1955 and 2004, geometrically corrected aerial photograph for Chawia and mosaic from three aerial photographs for Ngangao were produced. The geometric accuracies of these products are discussed in chapter 7.5.1.2. No spectral corrections were needed as the mosaic and aerial photograph were used only for visual examination. The subsets made for classification purposes are presented in Figure 54 and Appendices 10 and 11 for Ngangao and Chawia.

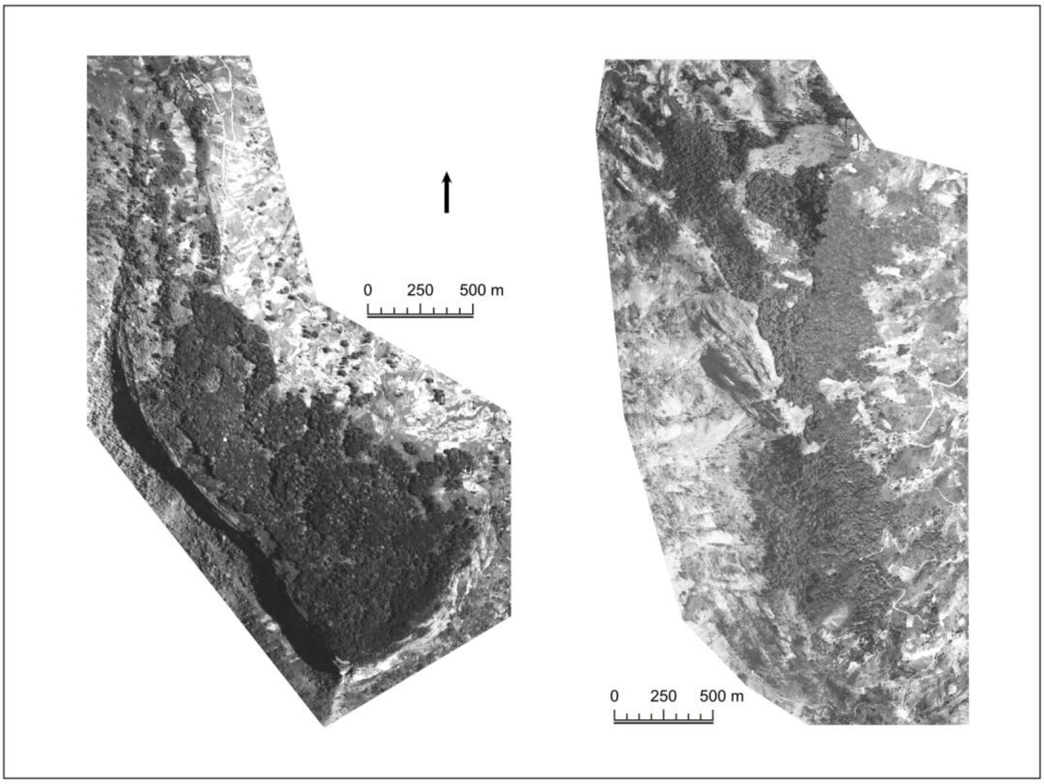

Figure 54. The mosaic subsets of Chawia (on the left) and Ngangao (on the right) from 1955.

7.2 CLASSIFICATION RESULTS

Altogether three different methods were used for classifications of the mosaics from 1955 and 2004. Visual classification made by digitising in *ArcMap* was done for all the mosaics from 1955 and 2004 while supervised classification based on segmentation made in *eCognition* and supervised classification made in *Erdas Imagine* were done for the mosaics from 2004.

7.2.1 RESULTS OF VISUAL CLASSIFICATION

Figure 55 and Appendices 12 and 13 represent the visual classifications of 1955 in Ngangao and Chawia, respectively. *Woodland* is covering 161.32 ha of the study area in Ngangao and 135.97 ha in Chawia while most of both study areas are classified as *agricultural land* (Table

20). Furthermore, *bushland* occupies a significant portion of the land in 1955. However, these proportions are highly dependent on the spatial extent of the area studied. The forest of Ngangao has a complex border but it is still connected almost everywhere. The border of Chawia is less complex and it has patches of *bushland* inside the forest. The forest of Chawia comprises of one larger fragment and a few smaller fragments in the north of the main part of the forest. In Ngangao, *bushland* and agricultural are surrounding the forest area from every direction although in the south-western and northern part of the area *bushland* dominates. In Chawia, on the other hand, agriculture is mainly found on the northern and north-eastern side of the forest while *bushland* and *rock* occupy the south-western part of the surroundings of the forest.

According to the 1955 mosaics, both forests are visually evaluated to be in good condition and without any exotic plantations. Anyhow, Ngangao is noticeably in better condition than Chawia where a road is entering to the forest from the north-eastern side of the forest thus introducing human impact to the forest.

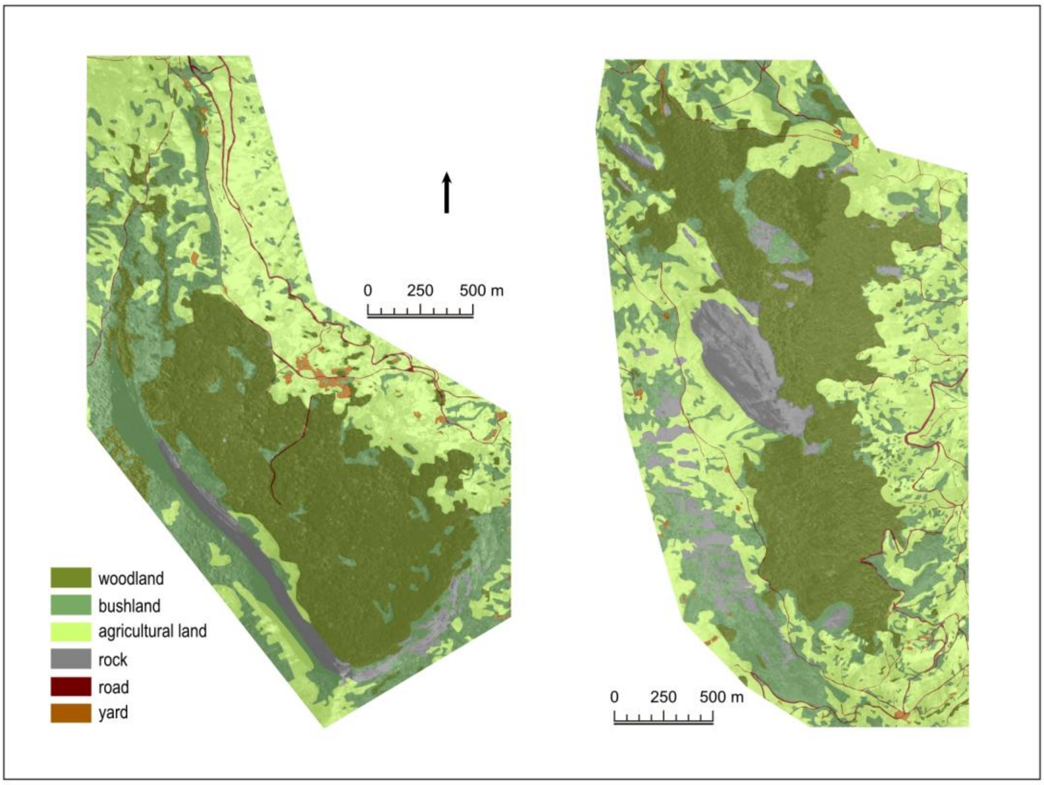

Figure 55. The 1955 visual classifications of Chawia (on the left) and Ngangao (on the right).

Table 20. Land cover classes and their areas in Ngangao and Chawia in 1955.

	Ngangao		Chawia	
	area (ha)	**%**	**area (ha)**	**%**
woodland	161.32	*30.48*	135.97	*33.77*
bushland	113.86	*21.52*	103.39	*25.68*
agricultural land	203.08	*38.38*	140.05	*34.79*
rock	40.93	*7.73*	14.68	*3.65*
yard	2.01	*0.38*	3.34	*0.83*
road	7.99	*1.51*	5.18	*1.29*

The visual classifications of Ngangao and Chawia in 2004 are presented in Figure 56 and Appendices 14 and 15. In Ngangao, *woodland* occupies most of the classified area with most of this *woodland* being indigenous (Table 21). The indigenous *woodland* in the study area comprises 140.74 ha. Furthermore, *agricultural land* and *bushland* occupy a significant proportion of the area. Most of the *agricultural land* is classified as *terrace*. In Chawia, *bushland* dominates the classified area with *agricultural land*. *Woodland* (both indigenous and exotic together) comprises 110.15 ha of the study area in Chawia.

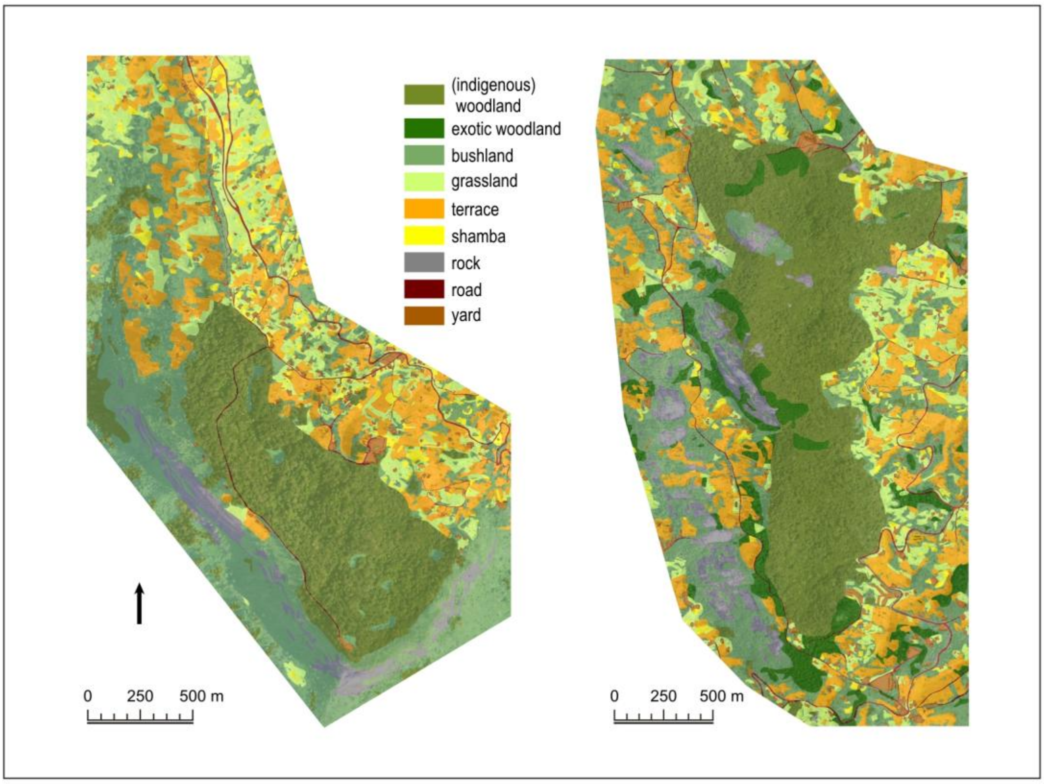

Figure 56. The 2004 visual classifications of Chawia (on the left) and Ngangao (on the right).

Table 21. Land cover classes and their areas in Ngangao and Chawia in 2004.

	Ngangao		Chawia	
	area (ha)	**%**	**area (ha)**	**%**
woodland	181.96	*34.38*	110.15	*27.36*
indigenous	140.74	*26.59*	-	-
exotic	41.22	*7.79*	-	-
bushland	137.99	*26.07*	133.41	*33.14*
agricultural land	159.73	*30.18*	130.07	*32.31*
shamba	9.91	*1.87*	12.80	*3.18*
terrace	95.21	*17.99*	64.72	*16.07*
grass	54.60	*10.32*	52.55	*13.05*
rock	25.00	*4.72*	14.56	*3.62*
yard	16.23	*3.07*	8.68	*2.16*
road	8.30	*1.57*	5.75	*1.43*

The land cover surrounding the forests is highly fragmented in both areas. In both Ngangao and Chawia, *bushland* and *rock* dominate in south-western part of the areas. In Ngangao, the exotic *woodland* areas are concentrated on the eastern and southern border of the forest.

Ngangao is visually evaluated to be in relatively good condition without any large openings in the crown cover. Anyhow, there are fairly large areas of exotic *woodland* disturbing the indigenous vegetation. Chawia is in poorer condition than Ngangao when observing the situation from aerial photographs. There are several openings in the crown cover as well as patches of *bushland* inside the forest. Furthermore, a road to the transmission tower is dividing the forest of Chawia. Yet, this road is different than the one entering the forest in 1955.

The borders of the main forest fragments of Chawia and Ngangao both in 1955 and 2004 were defined using the visual classifications (Figures 57 and 58). The forests are defined to include continuous forest areas with maximum of five metres gaps. These gaps are due to roads that divide the forest areas in Chawia and in the north part of Ngangao. In Ngangao, the area only includes *indigenous woodland* while in Chawia, the area includes *woodland* in general, as the indigenous and exotic species are very mixed. The areas of the main forest fragments in 1955 and 2004 are presented in Table 22. Between 1955 and 2004, the forest area of Ngangao has reduced by 20.33 ha while in Chawia the change has been even greater, 31.54 ha.

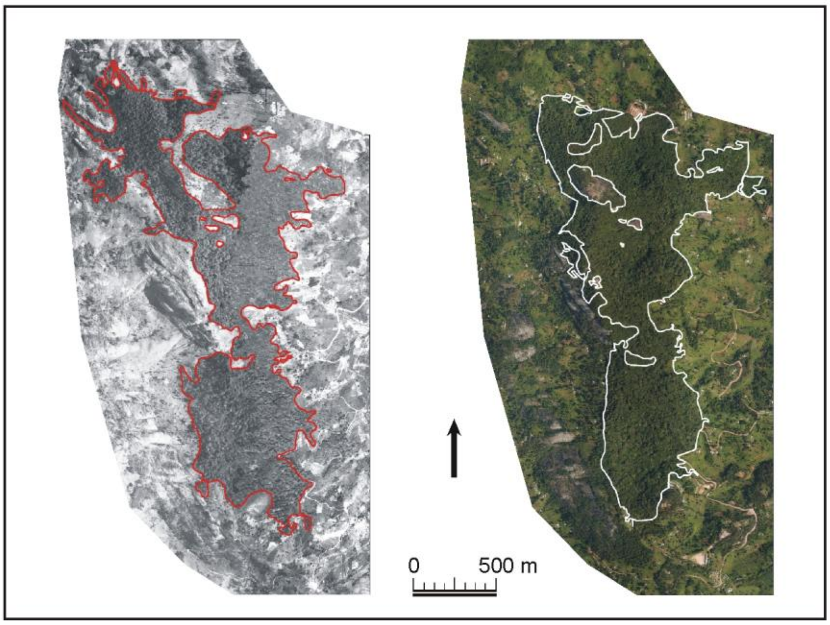

Figure 57. The main forest fragment of Ngangao in 1955 (on the left) and 2004 (on the right).

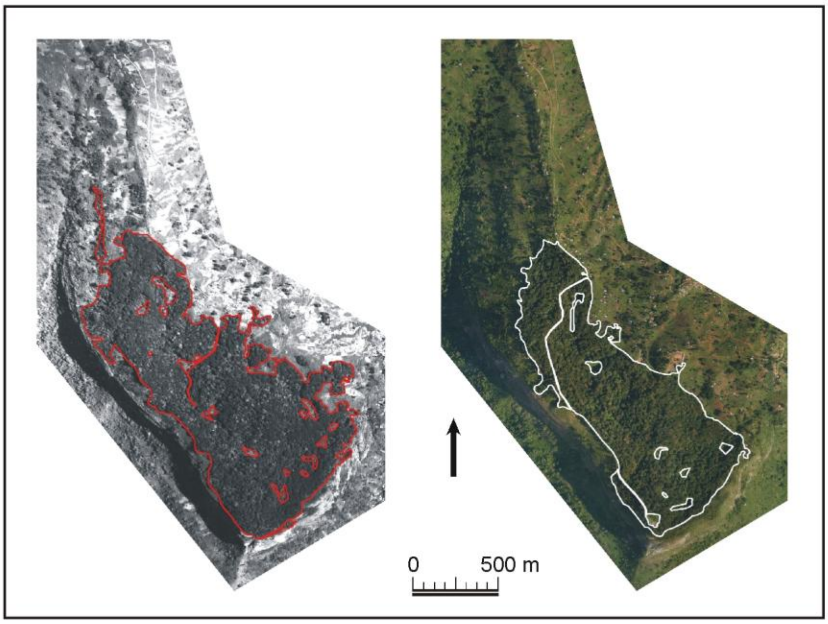

Figure 58. The main forest fragment of Chawia in 1955 (on the left) and 2004 (on the right).

Table 22. The areas of the main forest fragments of Ngangao and Chawia in 1955 and 2004.

	1955 area (ha)	2004 area (ha)
Ngangao	157.16	136.83
Chawia	122.92	91.38

7.2.2 RESULTS OF THE OBJECT-ORIENTED SUPERVISED CLASSIFICATION AND THE PIXEL-BASED SUPERVISED CLASSIFICATION

In addition to the visual classification, the mosaic subsets of Ngangao and Chawia from 2004 were classified in *eCognition* using object-oriented supervised classification based on segmentation and in *Erdas Imagine* using pixel-based supervised classification.

As the object-oriented supervised classification is based on the created segments, the segments themselves affect the final classification result significantly. The segmentation scheme created for this study is considered to be rather suitable for Ngangao and Chawia. The final classification of multi-resolution classification conducted in *eCognition* was done using segments from level III. The amount of segments created in different levels can be seen in Table 23. Level III holds segments that in general contain only one land cover class which is a necessary for a successful classification.

Table 23. The number of segments created in *eCognition*.

	Level I	Level II	Level III	Level IV
Ngangao	307,713	279,050	63,342	15,300
Chawia	196,735	168,354	37,797	9,820

The classification results of supervised classification based on segmentation is presented in Figure 59 and Appendices 16 and 17 for Ngangao and Chawia. According to this object-oriented classification, *woodland* comprises 240.37 ha of the study area in Ngangao and 136.24 ha in Chawia (Tables 24 and 25, page 96). Thus *woodland* is clearly over-emphasised. In the classification procedure, the most problematic was to differentiate *woodland*, *bushland* and *agricultural land*. All of these three land cover types vary a lot and they are spectrally very close to each other. Other problematic areas include the hillside areas and shadowed areas, especially the shadows of the terraces. The accuracy of this classification is discussed in more detail in chapter 7.5.4.2. Although the original pixel size of the mosaics is only 0.5 m, the classifications are visually clear and straight-forward. Thus, this object-oriented segmentation and classification of the segments seems to produce reasonable results. The results of the three different classifications are compared in chapter 7.2.3.

The results of the pixel-based supervised classification are presented in Figure 60 and Appendices 18 and 19 for Ngangao and Chawia. According to this supervised classification, *woodland* occupies 196.8 ha in Ngangao and 163.61 ha in Chawia (Tables 24 and 25, page 96).

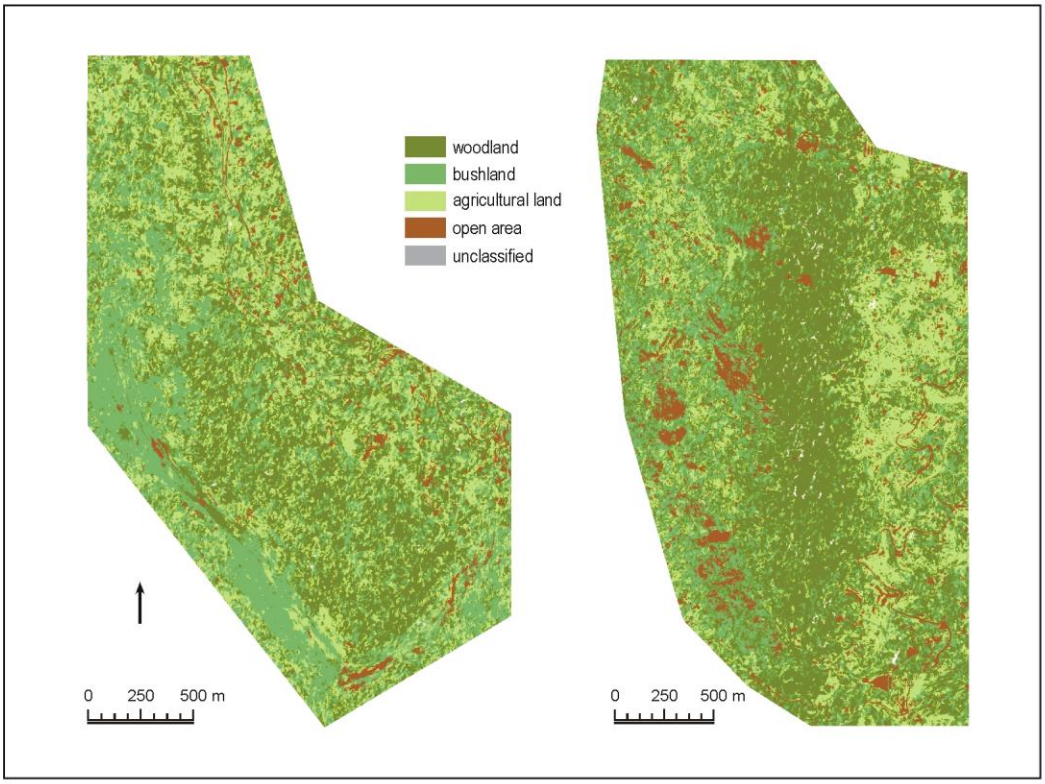

Figure 59. The object-oriented supervised classifications of Chawia (on the left) and Ngangao (on the right) in 2004.

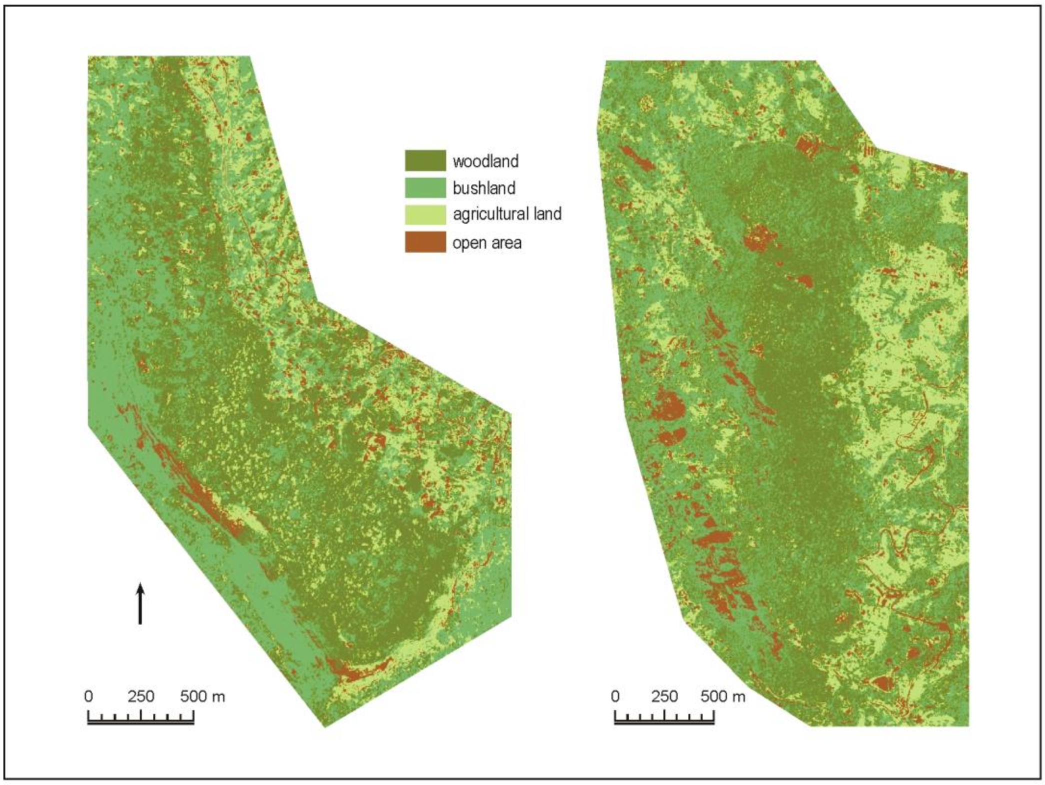

Figure 60. The pixel-based supervised classification of Chawia (on the left) and Ngangao (on the right) in 2004.

The most problematic areas are the same as in the object-oriented classification: *woodland*, *bushland* and *agricultural land* are easily mixed. *Woodland* and *bushland* are over-emphasised while the amount of *agricultural land* is notably smaller than in visual classification. Shadowed areas cause even more problems in this pixel-based classification than in object-oriented classification because the difficulty introduced by shadows could be handled to some extent in object-oriented process with the classification scheme.

Pixel-based classification produces a classification that is in some areas characterised by a "salt and pepper" pattern. This is because every pixel is classified separately without taking into account the properties of the neighbourhood. As these classifications are filtered with a 5x5 majority filter, the result is smoothed and is therefore visually more reasonable. The accuracies of the classifications are discussed in chapter 7.5.4.

7.2.3 COMPARISON OF THE CLASSIFICATIONS

Visual classification is considered to be the best of the three conducted classifications. Therefore, the visual classifications of Chawia and Ngangao are used as a basis when comparing the three classifications. It has to be remembered, though, that the visual classifications are generalised and thus they are not spatially as specific as the classifications of the other two methods.

The comparison is done here by different methods. First of all, the areas of the land cover classes are compared and thus an overall conception of the different classifications is achieved. Because this kind of comparison does not inform where the differences are geographically, the classifications are further compared by their regional differences. Furthermore, the differences in the classification of woodland areas are taken into deeper examination.

The areas of the land cover classes according to the classifications are presented in Table 24 for Ngangao and Table 25 for Chawia. In Ngangao and Chawia both object-oriented and pixel-based classification over-emphasise the amount of *woodland*. In Ngangao, 34.38% (181.96 ha) of the study area is classified as *woodland* by visual classification but object-oriented and pixel-based classifications produce the proportions of 45.42% (240.37 ha) and 37.19% (196.80 ha), respectively. In Chawia the amount of *woodland* is 27.36% (110.15 ha) according to the visual classification, 33.84% (136.24 ha) according to the object-oriented classification and 40.64% (163.61 ha) according to the pixel-based classification. Thus, it cannot be stated which one of the supervised classification methods over-emphasises more.

Table 24. Land cover classes and their areas in Ngangao in 2004 according to visual, supervised classification based on segmentation and supervised classification.

	Visual		**Object-oriented supervised**		**Pixel-based supervised**	
	area (ha)	**%**	**area (ha)**	**%**	**area (ha)**	**%**
woodland	181.96	*34.38*	240.37	*45.42*	196.80	*37.19*
indigenous	140.74	*26.59*	-	-	-	-
exotic	41.22	*7.79*	-	-	-	-
bushland	137.99	*26.07*	130.45	*24.65*	187.62	*35.45*
agricultural land	159.73	*30.18*	118.09	*22.32*	103.77	*19.61*
shamba	9.91	*1.87*	-	-	-	-
terrace	95.21	*17.99*	-	-	-	-
grass	54.60	*10.32*	-	-	-	-
open area	49.52	9.36	39.79	*7.52*	41.01	*7.75*
rock	25.00	*4.72*	-	-	-	-
yard	16.23	*3.07*	-	-	-	-
road	8.30	*1.57*	-	-	-	-
unclassified	-	-	0.49	*0.09*	-	-

Table 25. Land cover classes and their areas in Chawia in 2004 according to visual, supervised classification based on segmentation and supervised classification.

	Visual		**Object-oriented supervised**		**Pixel-based supervised**	
	area (ha)	**%**	**area (ha)**	**%**	**area (ha)**	**%**
woodland	110.15	*27.36*	136.24	*33.84*	163.61	*40.64*
bushland	133.41	*33.14*	137.01	*34.03*	145.83	*36.22*
agricultural land	130.07	*32.31*	113.65	*28.23*	69.86	*17.35*
shamba	12.80	*3.18*	-	-	-	-
terrace	64.72	*16.07*	-	-	-	-
grass	52.55	*13.05*	-	-	-	-
open area	28.99	7.20	15.53	*3.86*	23.31	*5.79*
rock	14.56	*3.62*	-	-	-	-
yard	8.68	*2.16*	-	-	-	-
road	5.75	*1.43*	-	-	-	-
unclassified	-	-	0.19	*0.05*	-	-

Both in Ngangao and Chawia, the amount of *bushland* is very similar according to the visual and object-oriented classifications. According to the pixel-based classification, *bushland* occupies 9.38% more of the study area in Ngangao and 3.08% more in Chawia than in the visual classification. The amount of *agricultural land* according to the supervised classifications is significantly less than according to the visual classifications; the biggest difference appears in Chawia where the pixel-based method classifies only 17.35% (69.86 ha) of the study area to be *agricultural land* while the proportion according to the visual classification is 32.31% (130.07 ha). In addition, the supervised methods classify smaller amount of areas to be open land than visual classification does in both Ngangao and Chawia.

Figure 61 and Appendix 20 represent the comparisons of *woodland* in visual, object-oriented supervised and pixel-based supervised classification in Ngangao and Chawia. Both supervised classifications are compared to the visual classification. In Ngangao as well as Chawia, a lot of both omission and commission errors occur in the study areas. Omission error means that a pixel is not classified as *woodland* in the supervised classifications although it is *woodland* in the visual classification. Commission error, on the other hand, means that a pixel is misclassified as *woodland* in the supervised classifications.

Figure 61. Comparisons of *woodland* in visual (*vis*), object-oriented supervised (*o-o*) and pixel-based supervised (*p-b*) classifications.

In Ngangao, 47.8% (86.92 ha) of the areas classified as *woodland* by the visual classification are also classified as *woodland* by the two supervised methods while in Chawia the proportion is only 39.1% (43.08 ha) (Table 26). The borders of the forests are classified tolerably well although errors are visible also in the borders. Both supervised classification techniques produce errors inside the main forest areas. Furthermore, there are no clear areas where one supervised method would perform better than the other. *Woodland* areas outside the main forest area are often misclassified by both supervised methods although in Chawia, the pixel-based method performs somewhat better. Shadowed areas are difficult for both supervised methods; in Ngangao, especially the pixel-based method classifies shadowed areas easily to *woodland*. In general, omission errors occur especially in the northern and southern parts of the study area in Ngangao and in the northern and eastern parts of the study area in Chawia. Commission errors occur constantly in the main forest areas as well as in the *woodland* areas outside them.

Table 26. Comparison of the classification of *woodland* by the three methods.

	Ngangao		**Chawia**	
	area (ha)	% of woodland (visual classification)	area (ha)	% of woodland (visual classification)
woodland in all	86.92	*47.77*	43.08	*39.11*
woodland in visual and object-oriented, other in pixel-based	40.59	*22.31*	15.01	*13.62*
woodland in visual and pixel-based, other in object-oriented	25.30	*13.90*	30.14	*27.36*
woodland in visual, other in object-oriented and pixel-based	29.15	*16.02*	21.92	*19.90*
other in visual, woodland in object-oriented and pixel-based	45.26		36.65	
other in visual and pixel-based, woodland in object-oriented	65.49		41.51	
other in visual and object-oriented, woodland in pixel-based	39.33		53.74	
other land cover	197.17		160.56	

The characteristics of the supervised classification results compared to the visual classification are presented in Figures 62 and 63 as well as in Appendices 21 and 22. In Ngangao, 70.1% (127.5 ha) and 61.7% (112.2 ha) of *woodland* according to the visual classification is classified as *woodland* by the object-oriented method and the pixel-based method, respectively. In Chawia, the proportion is 52.7% (58.1 ha) for the object-oriented method and 66.5% (73.2 ha) for the pixel-based method (Table 27). 34.3% (62.4 ha) of the *woodland* (visual classification) is classified as *bushland* in Ngangao according to the pixel-based method. The object-oriented method performs better with 20.3% (37.0 ha) misclassified as *bushland*. In Chawia, the proportions are approximately 25% according to both supervised methods. *Woodland* areas (visual classification) are constantly classified as *bushland* by both supervised methods and study areas; especially the pixel-based method misclassifies the *bushland* area in the steep of Chawia. Less than 10% of the *woodland* areas (visual classification) are classified as *agricultural land* by the supervised methods except the object-oriented method in Chawia that classifies 20.6% (22.7 ha) of the *woodland* (visual classification) to be *agricultural land*. The misclassification of *woodland* to *agricultural land* is a problem especially in the north-western and north-eastern parts (pixel-based method) and northern and southern parts (object-oriented method) of Ngangao while in Chawia these areas are constant all over the forest area.

As much as 42.3% (58.4 ha) of *bushland* areas (according to the visual classification) are classified as *woodland* in Ngangao by the object-oriented method while the proportion is 33.2% (45.8 ha) for the pixel-based method. In Chawia, conversely, the object-oriented method classifies less of the *bushland* areas to *woodland* than the pixel-based method that misclassifies *bushland* to *woodland* especially on the ridge area north of the main forest area. This area seems to be very problematic for the pixel-based method as also a lot of *agricultural land* is misclassified to *woodland* there. Object-oriented method classifies *agricultural land* as *woodland* constantly in all areas with agriculture. In Ngangao, the pixel-based method classifies *agricultural land* to *woodland* especially in the western and southern parts of the study area although there is much less agricultural activity than in the eastern part of the area.

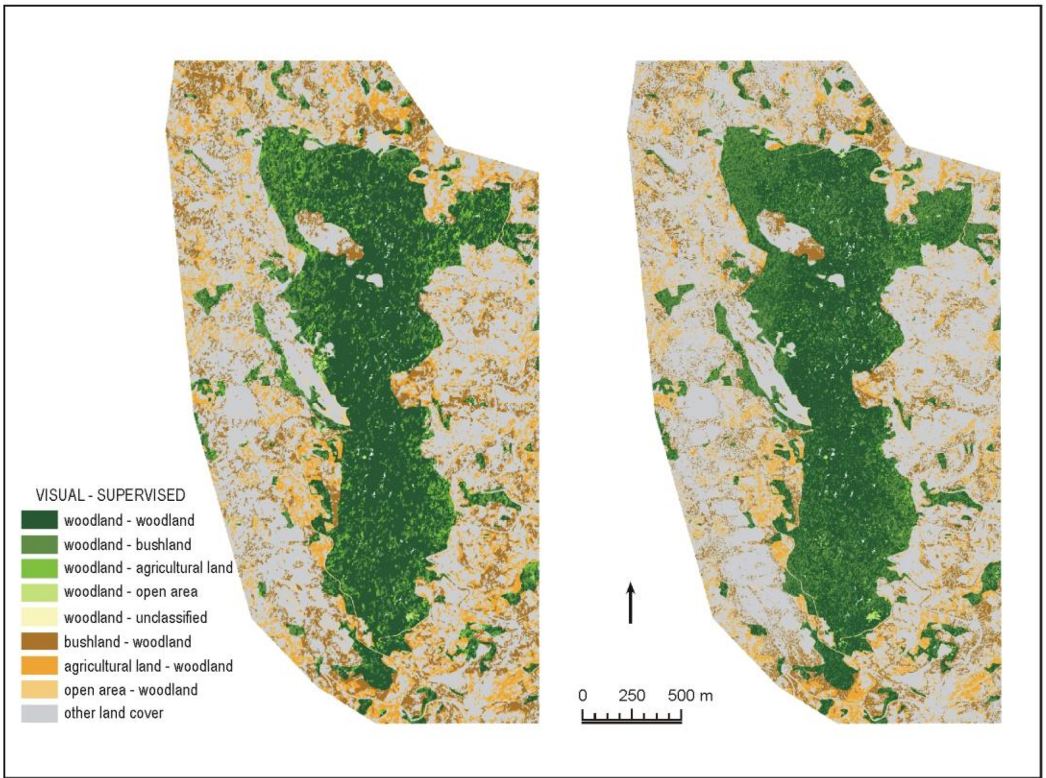

Figure 62. The object-oriented supervised classification (on the left) and the pixel-based supervised classification (on the right) compared to the visual classification in Ngangao.

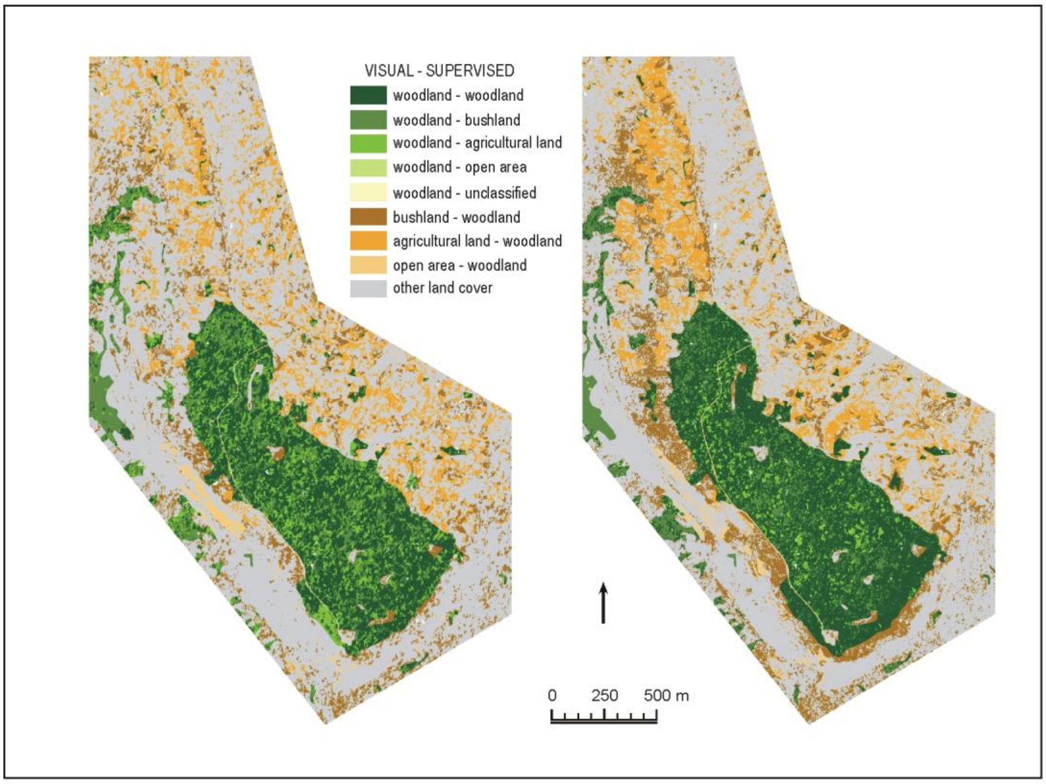

Figure 63. The object-oriented supervised classification (on the left) and the pixel-based supervised classification (on the right) compared to the visual classification in Chawia.

Table 27. The comparison matrices of the classifications in Ngangao and Chawia.

	NGANGAO	object-oriented supervised classification										pixel-based supervised classification								area (visual)
		woodland		bushland		agricultural land		open area		unclassified		woodland		bushland		agricultural land		open area		
		ha	%	ha	%	ha	%	ha	%	ha	%	ha	%	ha	%	ha	%	ha	%	
visual classification	**woodland**	127.5	*70.1*	37.0	*20.3*	15.9	*8.7*	1.5	*0.8*	*0.1*	*0.1*	112.2	*61.7*	62.4	*34.3*	5.9	*3.3*	1.4	*0.8*	182.0
	bushland	58.4	*42.3*	50.3	*36.5*	24.3	*17.6*	4.8	*3.4*	*0.2*	*0.1*	45.8	*33.2*	74.0	*53.6*	13.6	*9.8*	4.7	*3.4*	138.0
	agricultural land	47.7	*29.8*	31.6	*19.8*	72.9	*45.6*	7.5	*4.7*	*0.1*	*0.0*	34.4	*21.6*	41.4	*25.9*	77.4	*48.5*	6.5	*4.1*	159.7
	open area	6.8	*13.7*	11.5	*23.2*	5.0	*10.1*	26.1	*52.7*	*0.1*	*0.3*	4.4	*8.9*	9.9	*19.9*	6.9	*13.8*	28.4	*57.4*	49.5
	area (object-oriented)	240.4		130.5		118.1		39.8		0.5		196.8		187.6		103.8		41.0		529.2

	CHAWIA	object-oriented supervised classification										pixel-based supervised classification								area (visual)
		woodland		bushland		agricultural land		open area		unclassified		woodland		bushland		agricultural land		open area		
		ha	%	ha	%	ha	%	ha	%	ha	%	ha	%	ha	%	ha	%	ha	%	
visual classification	**woodland**	58.1	*52.7*	29.2	*26.5*	22.7	*20.6*	0.2	*0.2*	0.0	*0.0*	73.2	*66.5*	25.8	*23.5*	10.6	*9.6*	0.5	*0.4*	*110.2*
	bushland	33.7	*25.3*	66.5	*49.8*	32.5	*24.4*	0.6	*0.5*	0.0	*0.0*	45.5	*34.1*	76.5	*57.3*	9.8	*7.3*	1.6	*1.2*	*133.4*
	agricultural land	38.3	*29.4*	32.7	*25.1*	53.1	*40.8*	6.0	*4.6*	0.0	*0.0*	39.5	*30.4*	40.5	*31.1*	41.9	*32.2*	8.2	*6.3*	*130.1*
	open area	6.1	*21.2*	8.6	*29.8*	5.4	*18.5*	8.7	*30.1*	0.1	*0.4*	5.4	*18.5*	3.0	*10.4*	7.6	*26.2*	13.0	*45.0*	*29.0*
	area (object-oriented)	136.2		137.0		113.6		15.5		0.2		163.6		145.8		69.9		23.3		402.6

7.3 CHANGE DETECTION RESULTS

The changes of the land cover in the areas of Ngangao and Chawia were studied using the visual classifications from 1955 and 2004. Especially the changes in *woodland* are examined in more detail.

The areas of the land cover classes in the study areas in 1955 and 2004 are presented in Table 28 for Ngangao and Table 29 for Chawia. Furthermore, Figures 64 and 65 as well as Appendices 12 and 13 represent the comparable land cover classes according to the visual classifications of 1955 and 2004 in Ngangao and Chawia, respectively.

Table 28. Change in land cover in Ngangao between 1955 and 2004.

	1955		**2004**		**CHANGE 1955 - 2004**	
	area (ha)	**%**	**area (ha)**	**%**	**area (ha)**	**%**
woodland	161.32	*30.48*	181.96	*34.38*	**20.64**	***12.80***
indigenous	-	-	140.74	*26.59*	**-**	-
exotic	-	-	41.22	*7.79*	**-**	-
bushland	113.86	*21.52*	137.99	*26.07*	**24.12**	***21.19***
agricultural land	203.08	*38.38*	159.73	*30.18*	**-43.36**	***-21.35***
shamba	-	-	9.91	*1.87*	**-**	-
terrace	-	-	95.21	*17.99*	**-**	-
grass	-	-	54.60	*10.32*	**-**	-
rock	40.93	*7.73*	25.00	*4.72*	**-15.93**	***-38.93***
yard	2.01	*0.38*	16.23	*3.07*	**14.22**	***709.29***
road	7.99	*1.51*	8.30	*1.57*	**0.30**	***3.78***

Table 29. Change in land cover in Chawia between 1955 and 2004.

	1955		**2004**		**CHANGE 1955 - 2004**	
	area (ha)	**%**	**area (ha)**	**%**	**area (ha)**	**%**
woodland	135.97	*33.77*	110.15	*27.36*	**-25.82**	***-18.99***
bushland	103.39	*25.68*	133.41	*33.14*	**30.02**	***29.03***
agricultural land	140.05	*34.79*	130.07	*32.31*	**-9.98**	***-7.13***
shamba	-	-	12.80	*3.18*	-	-
terrace	-	-	64.72	*16.07*	-	-
grass	-	-	52.55	*13.05*	-	-
rock	14.68	*3.65*	14.56	*3.62*	**-0.12**	***-0.82***
yard	3.34	*0.83*	8.68	*2.16*	**5.34**	***159.97***
road	5.18	*1.29*	5.75	*1.43*	**0.57**	***10.92***

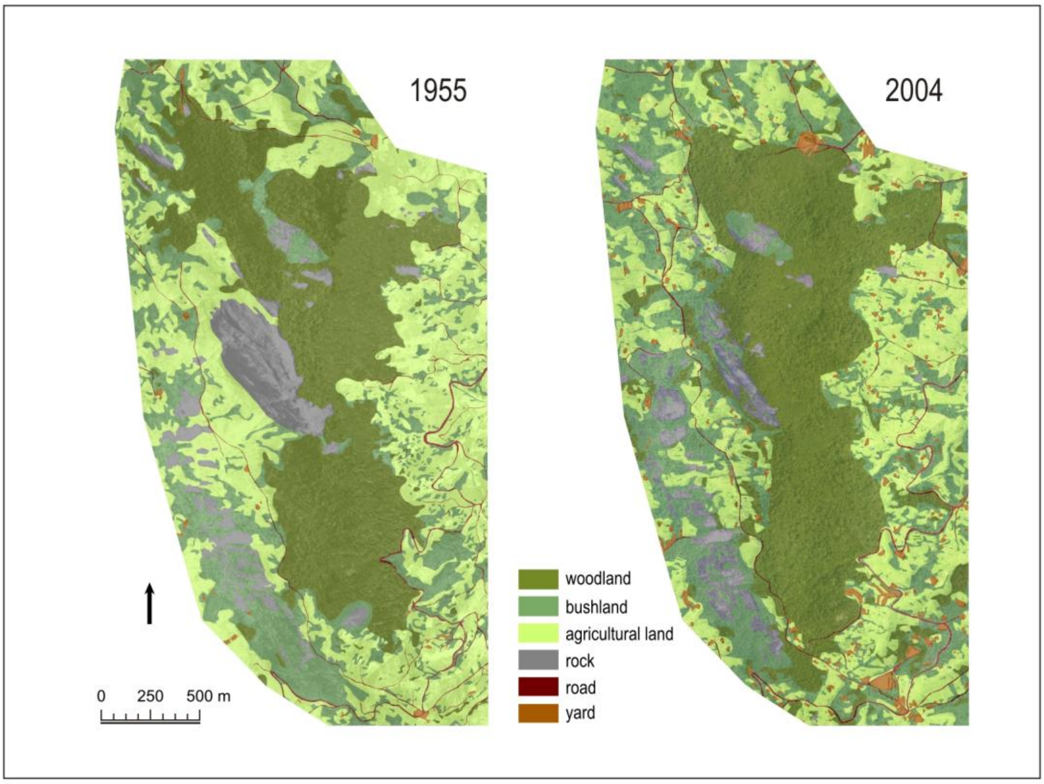

Figure 64. The comparable land cover classes (visual classification) in 1955 and 2004 in Ngangao.

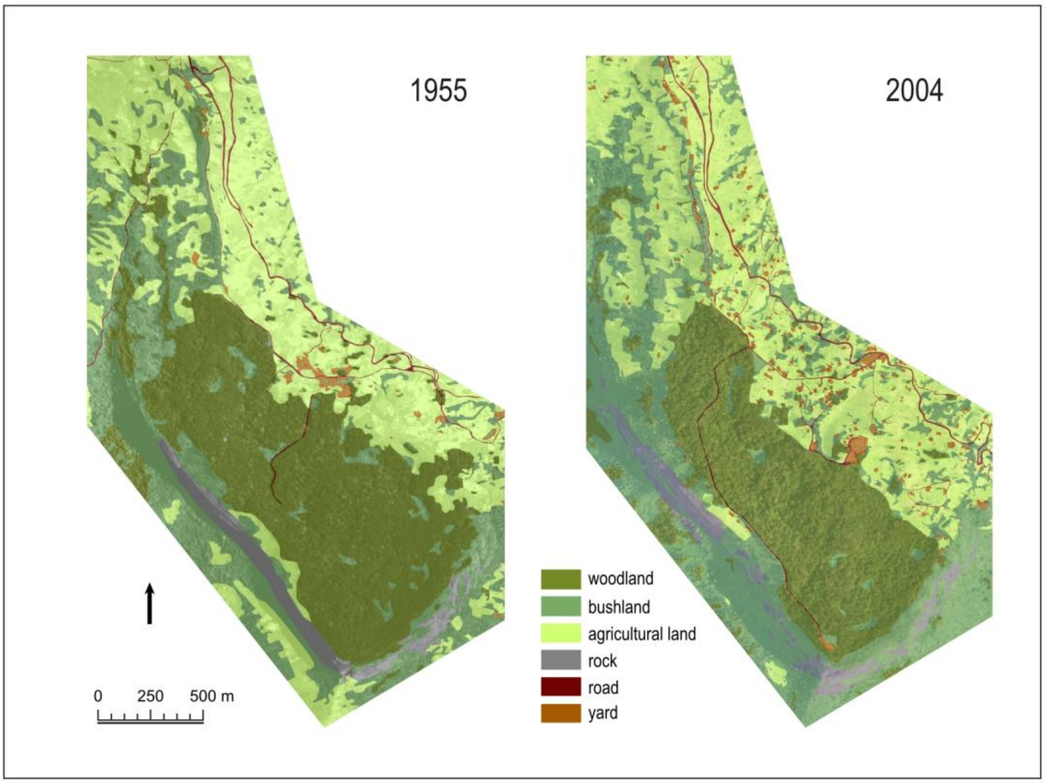

Figure 65. The comparable land cover classes (visual classification) in 1955 and 2004 in Chawia.

Between 1955 and 2004, the area of *woodland* in Ngangao has grown 12.80% (20.64 ha). However, this growth includes both indigenous and exotic *woodland*. In 1955, no exotic *woodland* was present and thus the change of indigenous *woodland* has been -12.76% (-20.58 ha). The increase in *woodland* cover is hence largely due to exotic plantations. In Chawia, the proportion of *woodland* in the study area has decreased 18.99% (25.82 ha). In 2004, the forest is largely a mixture of indigenous and exotic *woodland* and thus the decrease of indigenous *woodland* is even higher than the decrease of all *woodland*.

In both Ngangao and Chawia, the proportion of *bushland* has increased (21.19% in Ngangao and 29.03% in Chawia) while the proportion of *agricultural land* has decreased (21.35% in Ngangao and 7.13% in Chawia). In Ngangao, the amount of *rock* is decreased especially due to the plantations in the eastern side of the forest. Furthermore, the area occupied by human built structures such as roads and yards has increased significantly both in Ngangao and Chawia. It can be also noticed that the landscape is much more fragmented in 2004 than in 1955. This change relates to Ngangao as well as Chawia.

Figure 66 represents areas with changed land cover status between 1955 and 2004. In Ngangao, 51.1% of the study area has changed between the study periods while in Chawia 41.2% has changed. A minor part of these changes are unreal due to the differences between the geometries of the images in 1955 and 2004.

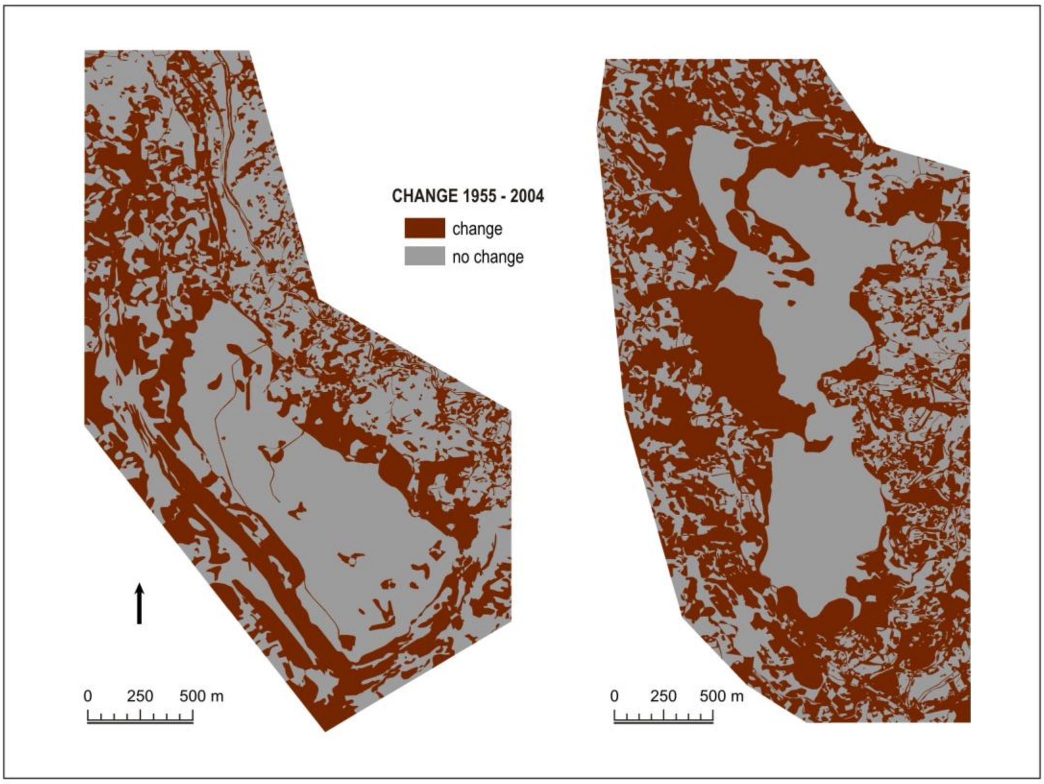

Figure 66. Areas with changed and persistent land cover in Chawia (on the left) and Ngangao (on the right) between 1955 and 2004.

The main forest areas of Ngangao and Chawia form the largest areas with persistent land cover types. In general, a lot of areas have changed their land cover status. This has led to more fragmented landscape in both study areas. In Ngangao, the changed areas are not concentrating to any part of the study area whereas in Chawia more change has happened in the western part of the study area.

The persistence, gain and loss of *woodland* areas are presented in Figure 67 for Ngangao and Chawia. In both study areas, approximately 20% of the *woodland* area in 1955 has remained *woodland* also in 2004 (Table 30). Most of the changes are situated in the forest border. In Ngangao, the areas with gained *woodland* cover 65.17 ha (12.32% of the study area). These areas are situated mainly in the northern and southern part as well as in the western slope of the forest and they are mainly areas with exotic plantations. In Chawia, most of the increase has happened in the borders of the study area and thus it is not increasing the area of the forest itself. The areas with extinct *woodland* cover comprise approximately 45 ha in both study areas. In Ngangao, the decrease is most noticeable in north-western and south-eastern part of the forest. In Chawia, *woodland* has been lost especially in northern and eastern parts of the forest.

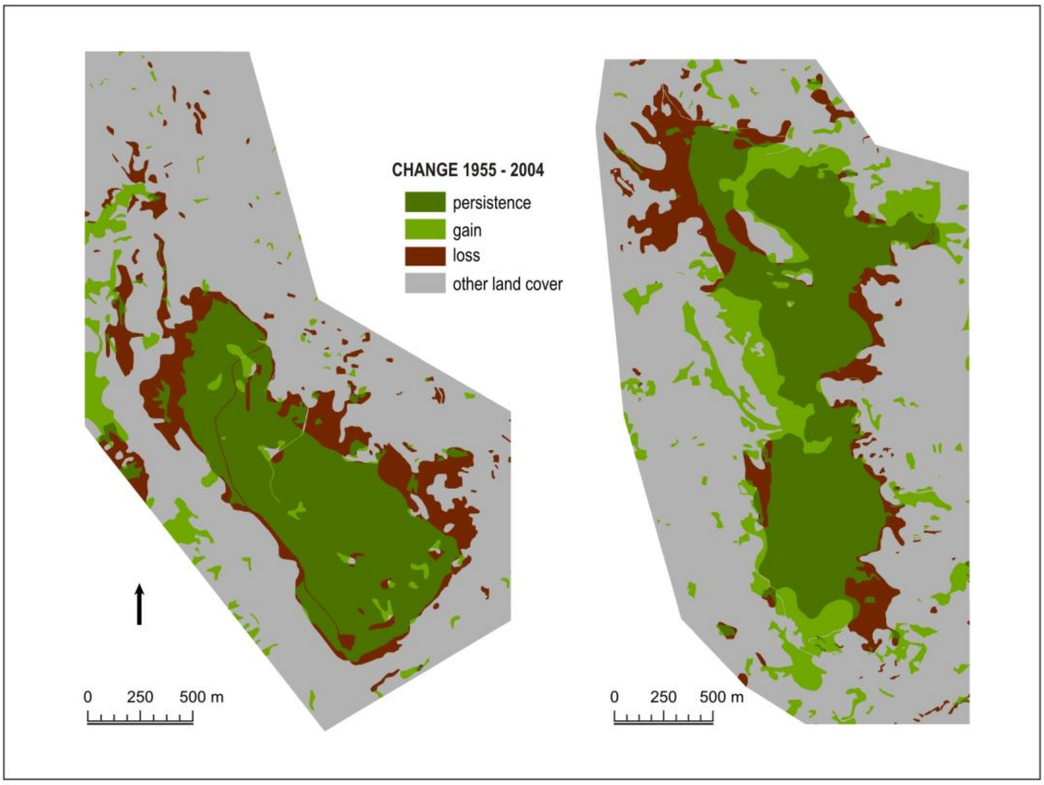

Figure 67. Persistence of *woodland* in Chawia (on the left) and Ngangao (on the right) between 1955 and 2004.

Table 30. Persistence of *woodland* in Ngangao and Chawia between 1955 and 2004.

	Ngangao		Chawia	
	area (ha)	**%**	**area (ha)**	**%**
persistence	116.79	*22.07*	91.05	*22.62*
gain	65.17	*12.32*	19.10	*4.74*
loss	44.53	*8.41*	44.92	*11.16*
other land cover	302.71	*57.20*	247.54	*61.48*

Figure 68 and Appendix 23 give a closer look to the *woodland* changes. In Ngangao, 72.4% (116.8 ha) of the *woodland* in 1955 was still *woodland* in 2004 while 10.8% (17.5 ha) has changed to *bushland* and 13.6% (21.9 ha) to *agricultural land*. In Chawia, only 67.0% (91.1 ha) of the *woodland* areas in 1955 are *woodland* in 2004. 17.3% (23.5 ha) has changed to *bushland* and 13.6% (18.5 ha) to *agricultural land*. Then again, 17.7% (20.1 ha) and 14.0% (14.5 ha) of the bushland areas in 1955 have changed to *woodland* in Ngangao and Chawia. In Ngangao, mainly the exotic plantations in the western slope have caused 38.1% (15.6 ha) of the *rock* to change to *woodland*. As much as 28.3 ha of *agricultural land* have changed to *woodland*. Table 31 represents the change matrices for both areas. In Ngangao, changes from *woodland* to certain land cover types are not concentrated to specific areas while in Chawia, the loss in the eastern and northern parts of the forest has mainly been due to the increase of *agricultural land*.

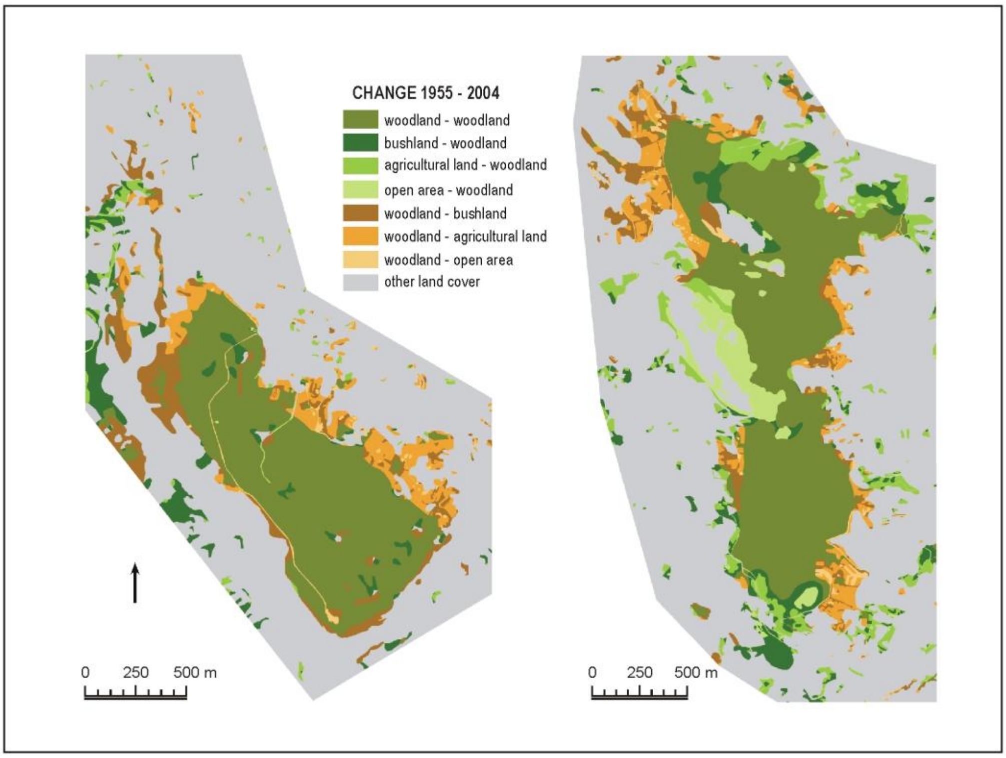

Figure 68. Change of *woodland* areas in Chawia (on the left) and Ngangao (on the right) between 1955 and 2004.

Table 31. The change matrices of Chawia and Ngangao between 1955 and 2004.

	NGANGAO	woodland		bushland		agricultural land		rock		yard		road		area 1955
		2004												
		ha	%	ha	%	ha	%	ha	%	ha	%	ha	%	ha
1955	**woodland**	116.8	*72.4*	17.5	*10.8*	21.9	*13.6*	1.2	*0.73*	2.9	*1.8*	1.1	*0.68*	161.3
	bushland	20.1	*17.7*	45.1	*39.6*	37.2	*32.7*	6.3	*5.5*	3.6	*3.2*	1.5	*1.3*	113.9
	agricultural land	28.3	*13.9*	62.8	*30.9*	96.0	*47.3*	2.3	*1.1*	9.0	*4.5*	4.7	*2.3*	203.1
	rock	15.6	*38.1*	9.2	*22.4*	0.91	*2.2*	15.1	*37.0*	0.04	*0.10*	0.06	*0.14*	40.9
	yard	0.23	*11.7*	0.62	*30.9*	0.8	*41.6*	0.02	*0.78*	0.19	*9.3*	0.12	*5.8*	2.0
	road	0.95	*11.8*	2.8	*35.1*	2.9	*36.1*	0.07	*0.92*	0.45	*5.6*	0.83	*10.4*	8.0
	area 2004	182.0		138.0		159.7		25.0		16.2		8.3		529.2

	CHAWIA	woodland		bushland		agricultural land		rock		yard		road		area 1955
		2004												
		ha	%	ha	%	ha	%	ha	%	ha	%	ha	%	ha
1955	**woodland**	91.1	*67.0*	23.5	*17.3*	18.5	*13.6*	0.03	*0.03*	1.5	*1.1*	1.4	*1.0*	136.0
	bushland	14.5	*14.0*	59.5	*57.5*	21.9	*21.2*	5.7	*5.5*	1.41	*1.4*	0.47	*0.46*	103.4
	agricultural land	4.1	*2.9*	42.2	*30.2*	84.9	*60.6*	1.0	*0.69*	5.0	*3.5*	2.9	*2.1*	140.1
	rock	0.03	*0.23*	6.7	*45.7*	0.04	*0.26*	7.9	*53.8*	0.00	*0.00*	0.00	*0.00*	14.7
	yard	0.01	*0.39*	0.58	*17.5*	2.1	*61.8*	0.01	*0.21*	0.54	*16.1*	0.13	*4.0*	3.3
	road	0.42	*8.1*	0.89	*17.3*	2.7	*52.5*	0.00	*0.00*	0.30	*5.8*	0.85	*16.3*	5.2
	area 2004	110.2		133.4		130.1		14.6		8.7		5.7		402.6

7.4 CANOPY RESULTS

7.4.1 COMPARISON OF CANOPY INFORMATION FROM HEMISPHERICAL PHOTOGRAPHS AND TEXTURAL INFORMATION FROM AERIAL MOSAICS

A summary of canopy parameters computed from the hemispherical photographs is given in Table 32. The variations between different years in all three canopy parameters are small thus indicating that significant differences in forest canopy because of phenology or other reasons do no appear. When comparing the canopy values from 2004–2006 in Ngangao and Chawia, only small differences exist in all three parameters, LAI 4 Ring, LAI 5 Ring and CLOSURE. Therefore, the forests are very uniform in canopy composition. Furthermore, although there are differences in species, the canopy is very closed in both forests. The overall variation that can be seen in RANGE and standard deviation (STD_DEV), of these three parameters is also quite small but a bit smaller in Chawia than in Ngangao.

Table 32. A summary of canopy parameters for test sites in Ngangao and Chawia during years 2004–2006.

		Ngangao			**Chawia**		
		LAI 4 Ring	**LAI 5 Ring**	**CLOSURE (%)**	**LAI 4 Ring**	**LAI 5 Ring**	**CLOSURE (%)**
2004	Mean	2.75	2.47	89.27	2.78	2.44	88.91
	Min	1.94	1.55	78.63	2.18	1.95	84.54
	Max	3.73	3.42	95.37	3.58	3.29	91.80
	Range	1.79	1.87	16.74	1.40	1.34	7.26
	Std_dev	0.50	0.46	4.04	0.50	0.44	2.75
2005	Mean	3.04	2.67	91.79	2.63	2.31	88.62
	Min	2.63	2.32	89.40	2.35	2.01	86.20
	Max	3.70	3.10	94.44	3.06	2.58	90.77
	Range	1.07	0.78	5.04	0.71	0.57	4.57
	Std_dev	0.39	0.27	1.92	0.22	0.20	1.82
2006	Mean	2.62	2.37	88.42	2.92	2.54	90.14
	Min	1.55	1.61	78.81	1.89	1.74	81.21
	Max	3.77	3.11	94.00	4.26	3.69	96.74
	Range	2.22	1.50	15.19	2.37	1.95	15.53
	Std_dev	0.57	0.41	4.18	0.55	0.46	3.64
2004 - 2006	Mean	2.74	2.46	89.34	2.80	2.45	89.39
	Min	1.55	1.55	78.63	1.89	1.74	81.21
	Max	3.77	3.42	95.37	4.26	3.69	96.74
	Range	2.22	1.87	16.74	2.37	1.95	15.53
	Std_dev	0.52	0.42	3.94	0.47	0.40	3.00

Figure 69 illustrates the differences in hemispherical photographs. Ng2004_1_1 has the minimum canopy closure, ng2004_3_1 has an average closure while ch2006_p has the maximum closure (Table 33). Differences can be seen in species composition but also in number of canopy layers in these three plots. The one that has the minimum canopy closure also has less canopy layers. This situation illustrates well that also the canopy structure has an impact on the canopy parameter values.

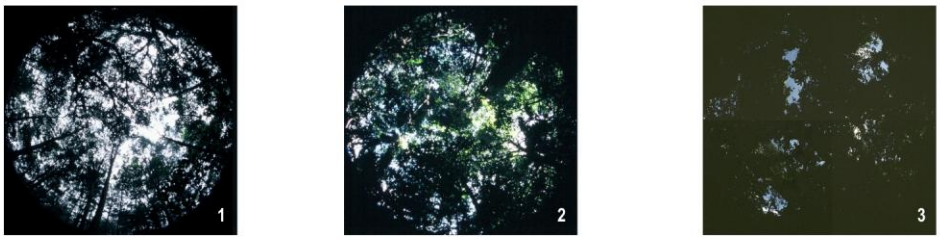

Figure 69. Hemispherical photographs of plots ng2004_1_1 (1), ng2004_3_1 (2) and ch2006_p (3).

Table 33. The parameters for sample plots ng2004_1_1, ng2004_3_1 and ch2006_p.

Plot	**LAI 4 Ring**	**LAI 5 Ring**	**CANOPY**
ng2004_1_1	1.94	1.55	78.63
ng2004_3_1	2.68	2.41	89.81
ch2006_p	4.26	3.69	96.74

7.4.2 COMPARISON WITH THE FOREST HEALTH MONITORING (FHM) DATA

Because the locations of the measurements made for this study and for FHM were not the same, as discussed in chapter 6.5.6, plot level comparisons cannot be made. Instead, some general comparisons are done between the forest structures of Ngangao and Chawia.

Forest disturbances and treatments have been recorded by FHM. Only one plot (including all the subplots), plot 20 in Chawia, of six plots in Chawia and eleven in Ngangao, had suffered from disturbance that was in this case human-caused damage in 2001. Treatments were also detected only in one plot, plot 23 in Chawia, where the trees of the subplots 1–3 have been cut in 1996.

The most common tree species in Ngangao and Chawia, according to FHM data, is *Tabernaemontana stapfiana* (Figure 70). This data shows also that the tree species composition is more complex in Ngangao than in Chawia; six most common species represent 37.1% of all trees measured in Ngangao while in Chawia this number is 75.8%. The height structure of the trees is quite similar in Ngangao and Chawia (Figure 71). The mean actual length is 14.4 m in Ngangao and 15.7 m in Chawia. The corresponding values for mean total length are 14.7 m and 16.2 m. *Actual length* refers to the length that a tree had at the recording moment. If a tree had a broken or missing top, the length of that tree with no missing part is estimated in *total length*.

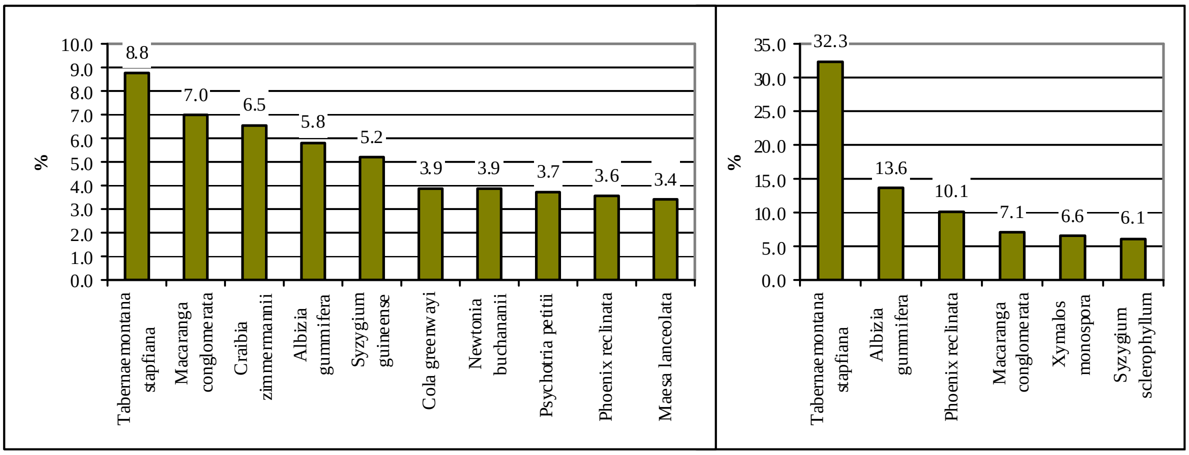

Figure 70. The most common tree species in Ngangao (on the left, n=673, other species conclude 48.3%) and in Chawia (on the right, n=198, other species conclude 24.2%).

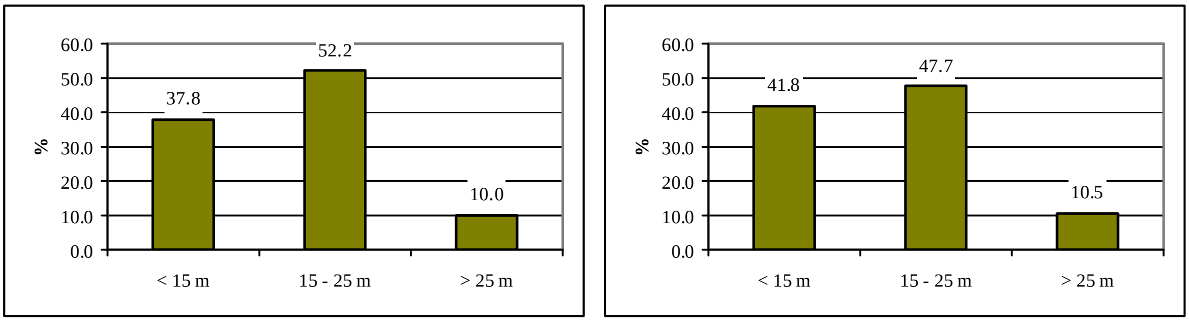

Figure 71. The height of trees in Ngangao (on the left, n=402) and in Chawia (on the right, n=153) divided into three height classes.

The DBH (diameter at breast height) varies quite a lot between Ngangao and Chawia (Figure 72). While in Ngangao, most trees belong to the smallest group (DBH < 28 cm), in Chawia most trees belong to the middle group (DBH = 28–50 cm). In Chawia the amount of the largest group (DBH > 50 cm) is also bigger than in Ngangao.

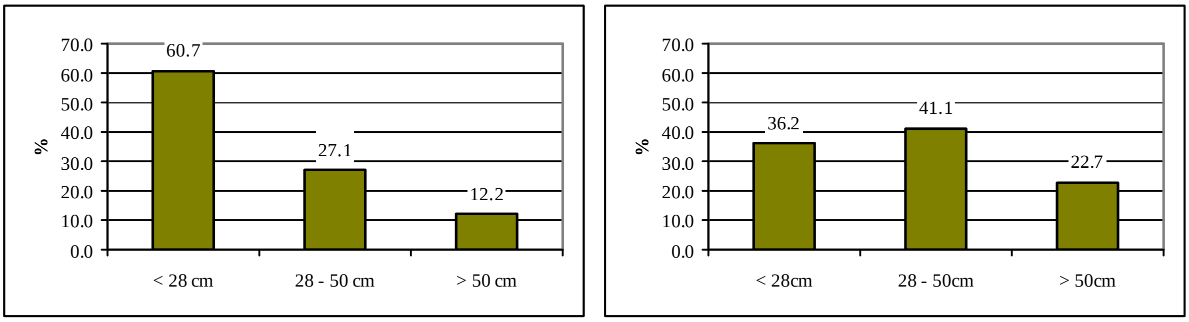

Figure 72. The DBH of trees in Ngangao (on the left, n=453) and in Chawia (on the right, n=153) divided into three DBH classes.

When comparing the condition of trees measured in Ngangao and Chawia, no significant difference can be seen (Figure 73). In both forests approximately 60% of trees have not suffered any damage and there are no trees having suffered from high damage. The amount of trees suffered from medium damage is higher in Ngangao than in Chawia.

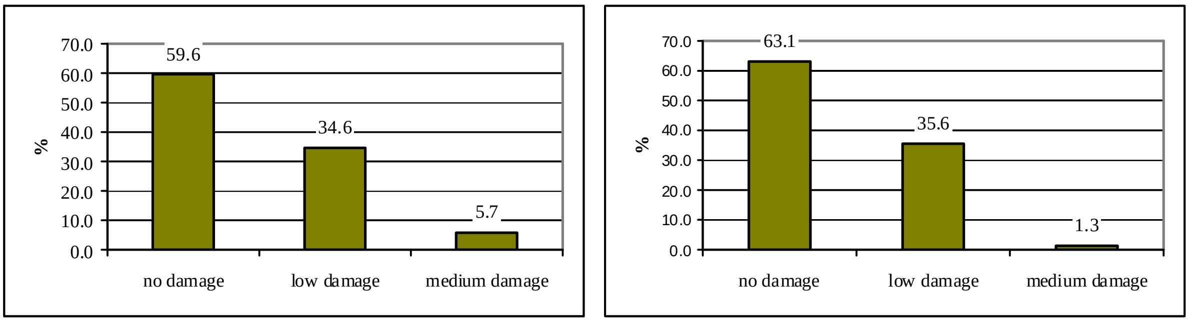

Figure 73. The condition of trees in Ngangao (on the left, n=436) and in Chawia (on the right, n=149).

Another measure of tree health is crown density. It is the amount of crown foliage, branches and reproductive structures that block visible light and it is used to assess the expected growth in the near future. The crown densities of Ngangao and Chawia are represented in Figure 74. Crown densities vary more in Ngangao, both in understory and overstory. In Ngangao, most of the measured trees fall in classes 41–45% (overstory) and 46–50% (understory) while in Chawia most of the trees in overstory and understory fall in class 41–45%.

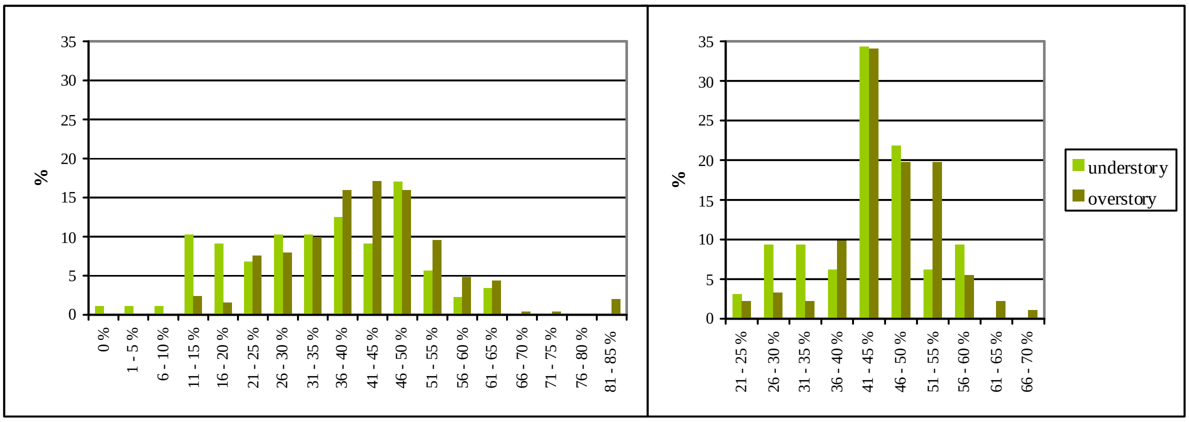

Figure 74. The crown densities of measured trees in Ngangao (on the left, n=339) and in Chawia (on the right, n=123).

The amount of foliage transparency, which is the amount of light that is visible through the live, normally foliated portion of the crown, varies more in Ngangao than in Chawia (Figure 75). In Ngangao, most of the understory trees have a foliage transparency of 21–35% while the amount of overstory trees in different classes is more evenly distributed. In Chawia, most of the understory trees have a foliage transparency of 16–20% while most of the overstory trees have that of 16–20%.

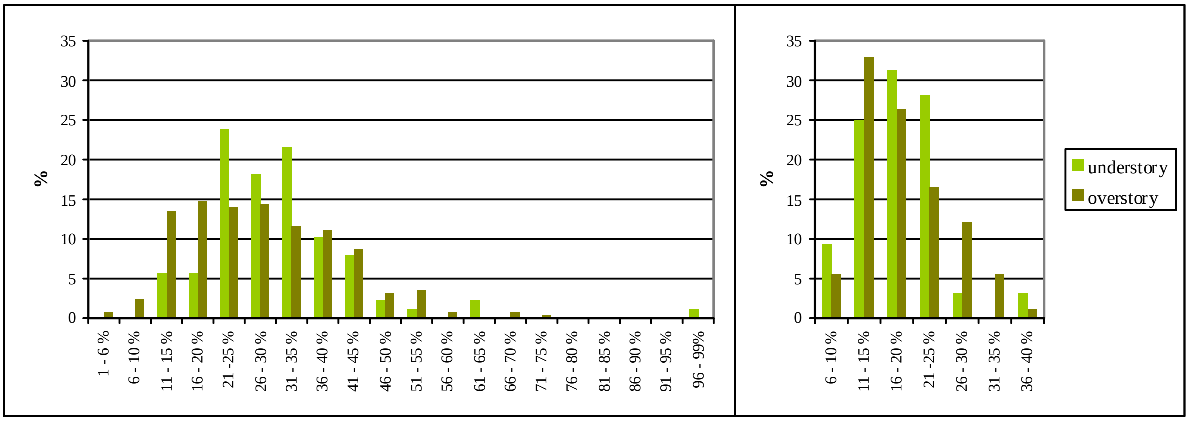

Figure 75. The foliage transparency in Ngangao (on the left, n=338) and in Chawia (on the right, n=123).

7.5 ACCURACY ASSESSMENT

In order to evaluate the reliability and quality of the results, accuracies of different stages of the study as well as the final results are analysed. In this chapter, each stage is analysed separately. However, it is important to notice that an error in the early stage of the study is transferred to all the later stages as well as the results.

7.5.1 ACCURACY OF PRE-PROCESSING

7.5.1.1 SPECTRAL ACCURACY

Before the mosaicking of the 2004 digital aerial photographs, each image was corrected for the light fall-off effect. The differences between uncorrected and corrected images were not compared and therefore the accuracy of the light fall-off correction is not assessed here.

The possibility for BRDF correction of the images is implemented in the mosaicking procedure in *EnsoMOSAIC* software. In this case, this possibility was used with correction factors determined for Kenya. As discussed earlier in chapter 7.1.1, BRDF-corrected mosaics introduced more brightness variation than the uncorrected mosaics. An optimum approach would have been to correct each image separately. This would have, in turn, required a lot of work as the correction parameters would have needed to be determined separately for each image.

The superiority of the uncorrected mosaic when comparing to the BRDF-corrected mosaic can be explained with two reasons. First of all, the mosaicking procedure of *EnsoMOSAIC* uses primarily the centre parts of the images where the brightness variations introduced by the

BRDF are the least. This may have a significant effect especially when the overlap of the images is wide as in the data used in this study. Secondly, the selections made in the final mosaic formation also affect the spectral values of the pixels in the mosaic. Thus, by using *histogram matching between three images* the brightness differences between images with varying land cover are smoothed.

7.5.1.2 GEOMETRIC ACCURACY

The geometric accuracy of the mosaics is dependent on the original images and the geometric corrections made to them. In this study, the corrections include ortho-rectification for 2004 mosaics and polynomial image-to-image rectification for the mosaic and aerial photograph from 1955. Besides the corrections, already the flight when the photographs are taken affects the quality of the mosaic. The movements of the aeroplane have an effect on the straightness of the flight lines both vertically and horizontally thus introducing differences in the images (Thurston 2002). These disturbances with the spectral differences due to illumination conditions between the flight lines can introduce seams to the mosaics.

In the mosaicking procedure of the 2004 photographs in *EnsoMOSAIC,* the Bundle Block Adjustment (BBA) is the process where the geometrical orientation of the images is adjusted. The quality of the rectification after each BBA round is evaluated with an overall adjustment error and specific residual values. In the mosaicking process of Ngangao and Chawia, all single residuals were less than 2 and the overall adjustment error was below 1 after the tenth and final BBA round. This result is considered to be excellent (EnsoMosaic 2003: 46).

In addition, the distribution of the tie points influences the accuracy of the geometric corrections in *EnsoMOSAIC* significantly (Sarmento & Sarkeala 2005: 5–6). The distributions of the tie points used in the mosaic creation of Ngangao and Chawia are presented in Figure 76. The tie points cover the study areas extensively except in the steep area on the south-western edge of the forest of Chawia. Furthermore, these tie points are used for the creation of the DEM and thus their distribution affects also the accuracy of it.

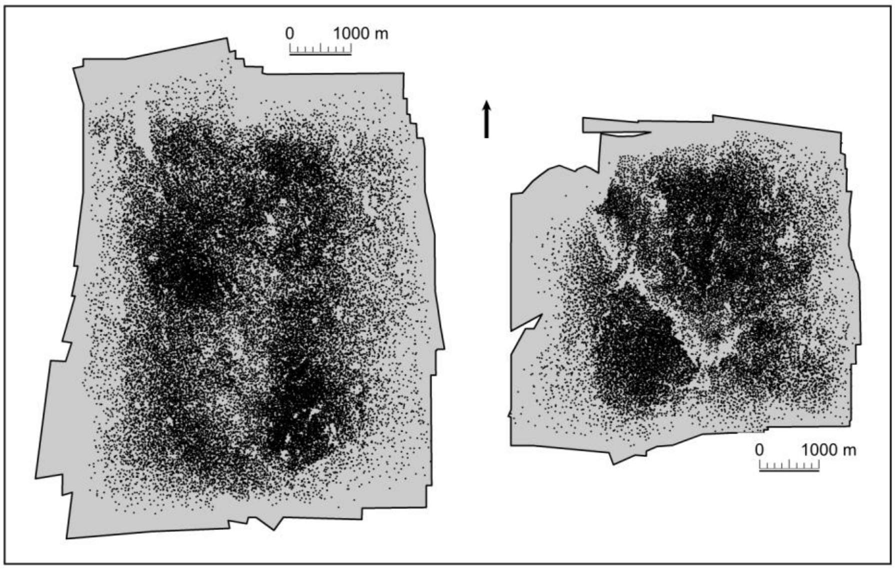

Figure 76. The tie points used in mosaic creation for Ngangao (on the left) and Chawia (on the right).

The geometric accuracies of the mosaics of Ngangao and Chawia were tested in field in February 2007 by Mika Siljander and Alemu Gonsamo. According to these tests realised by collecting several GPS points, the geometric accuracy of both mosaics is very good. In both study areas this accuracy is approximately 2 metres although in Chawia it is in places somewhat lower with a maximum error of 5 metres. The 2004 mosaics were also evaluated visually. The overall quality of the mosaics is very good; there are hardly any seam lines visible in the mosaics.

The geometric corrections of the 1955 aerial photographs were discovered extremely difficult due to the missing metadata. Ortho-corrections were impossible to realise and the corrections had to be made with image-to-image rectification technique. The RMS errors in four correction processes needed for Ngangao and Chawia in 1955 are presented in Table 34. The errors are exceptionally big because of the inappropriate correction method that needed to be used. The corrected 1955 images were evaluated also visually by comparing them to the 2004 mosaics. Under the circumstances, the correction is quite successful especially in the neighbourhood of the forest areas and the images can be well used for change detection purposes.

Table 34. Characteristics of the RMS errors in four correction processes.

Aerial photograph	Number of GCPs used	Min RMS error	Max RMS error	Average RMS error	Standard deviation of RMS error	Total RMS error
chawia_1955	22	3.70	57.32	28.91	12.26	31.62
ngangao_east_1955	30	18.90	319.04	96.70	75.46	121.88
ngangao_south_west_1955	37	15.42	156.49	72.93	38.60	78.75
ngangao_north_west_1955	36	2.45	231.34	66.20	56.77	205.62

A phenomenon of relief displacement needs also to be considered when evaluating the geometric accuracy of the mosaics. Relief displacement is a geometric distortion resulting from the object-sensor geometry (Jensen 2000: 172). It causes the tall objects to "lean" in large-scale aerial photographs. Thus, only the bases of the objects, such as buildings or tall trees, are in their proper planimetric (x, y) position. A traditional ortho-correction used in this study is not able to correct relief displacement. The distortions introduced by this phenomenon can be taken into account in visual classification but in supervised classifications of the mosaics, relief displacement introduces geometric inaccuracy to the results.

7.5.2 ACCURACY OF THE DEM

A digital elevation model (DEM) was created in the mosaicking procedure of the 2004 mosaics for Ngangao and Chawia. The DEMs were used for the ortho-correction of the mosaics and thus the quality of them affects also the quality of the mosaics. The DEM is created by using the tie points. Thus, when the tie points are located on top of trees or buildings the quality of the DEM decreases. As the overall tie point distribution in this study is good, this kind of a mislocation of the tie points is seen to be the main disturbing factor.

In order to evaluate the DEM created in *EnsoMOSAIC*, it was compared with a DEM created by using contour lines digitised from topographical maps. The height difference between these two DEMs varies between -78.5 m and 27.1 m in Ngangao with a mean value of -16.9 m and between -157.75 m and 126.15 m with a mean of -10.76 m in Chawia. Standard deviation of the differences is 15.7 in Ngangao and 25.83 in Chawia. The biggest differences occur in the steepest areas in both study areas. Thus, the DEM created in the mosaicking process is situated below the actual height. Although the differences are very big in some locations, generally the differences are relatively near to the mean difference. It has to be remembered, though, that this DEM is intended only for internal use of the ortho-correction procedure in *EnsoMOSAIC*.

7.5.3 SPECTRAL SEPARABILITY OF THE LAND COVER CLASSES IN SUPERVISED CLASSIFICATIONS

In both supervised classification methods, a nearest neighbour –algorithm is used. Because the NN-classifier uses the spectral properties of objects or pixels when classifying them, it is important to evaluate the separability of the classes according to their spectral properties. With this evaluation, it is possible to find out which classes are likely to produce errors of omission and commission in the classifications. The separability is calculated with methods implemented in *eCognition* and *Erdas Imagine*. Thus, the separability of the classes in object-oriented and pixel-based supervised classifications is assessed differently.

Table 35 represent the separability values for classes used in object-oriented supervised classification in Ngangao and Chawia. These values are calculated using the samples used for the classifications and all three spectral bands. The bigger the value is the better is the separability of the classes. Thus, all the separabilities between *woodland*, *bushland* and agrilcultural land classes are very poor regardless of whether they belong to *shadow* or *no shadow* group. However, the *no shadow* -classes show better separability values than the *shadow*-classes and in general, the values are better in Ngangao than in Chawia. The best separabilities are in Ngangao between *open area_no shadow* and other *no shadow* –classes.

The spectral separability of classes in pixel-based supervised classification is evaluated in *Erdas Imagine* by calculating *transformed divergence*, which is a common measurement for statistical separability. Transformed divergence ($TDiver_{cd}$) is calculated as follows:

$$TDiver_{cd} = 2{,}000\left[1 - \exp\left(\frac{-Diver_{cd}}{8}\right)\right], \qquad (15)$$

where c and d = all possible pairs of classes (Jensen 1996: 220).

Transformed divergence gives an exponentially decreasing weight to increasing distances between the classes. The divergence values are scaled between 0 and 2,000; a value of 2,000 suggests excellent separation, 1,900 provides good separation and under 1,700 poor separation (Jensen 1996: 225). The transformed divergence values for pixel-based classification in Ngangao and Chawia are presented in Tables 36 and 37. These values are calculated using the samples used for the classifications and all three spectral bands.

Table 35. Class separation of Ngangao and Chawia. The classes in shadowed areas (x_shadow) should not be compared with classes in non-shadowed areas (x_no shadow) as these cannot be mixed in the classification due to class related function –selections made in *eCognition*.

NGANGAO	**woodland_ shadow**	**bushland_ shadow**	**agricultural land_shadow**	**open area_ shadow**	**woodland_ no shadow**	**bushland_ no shadow**	**agricultural land_no shadow**	**open area _ no shadow**
woodland_shadow	*0*	*0.02303*	*0.01607*	*0.17203*	0.25301	0.43491	0.50269	1.55629
bushland_shadow	*0.02303*	*0*	*0.01971*	*0.13521*	0.18504	0.36544	0.49982	2.41378
agricultural land_shadow	*0.01607*	*0.01971*	*0*	*0.10979*	0.27476	0.55962	0.71587	3.34329
open area_shadow	*0.17203*	*0.13521*	*0.10979*	*0*	0.49204	0.82966	1.25093	4.18754
woodland_no shadow	0.25301	0.18504	0.27476	0.49204	*0*	*0.03208*	*0.02596*	*0.97340*
bushland_no shadow	0.43491	0.36544	0.55962	0.82966	*0.03208*	*0*	*0.03325*	*0.56558*
agricultural land_no shadow	0.50269	0.49982	0.71587	1.25093	*0.02596*	*0.03325*	*0*	*0.81915*
open area_no shadow	1.55629	2.41378	3.34329	4.18754	*0.97340*	*0.56558*	*0.81915*	*0*

CHAWIA	**woodland_ shadow**	**bushland_ shadow**	**agricultural land_shadow**	**woodland_no shadow**	**bushland_ no shadow**	**agricultural land_no shadow**	**open area _no shadow**
woodland_shadow	*0*	*0.01696*	*0.00676*	0.08510	0.15805	0.18558	0.88289
bushland_shadow	*0.01696*	*0*	*0.01497*	0.07108	0.12048	0.14221	0.94384
agricultural land_shadow	*0.00676*	*0.01497*	*0*	0.07752	0.16749	0.14694	0.80602
woodland_no shadow	0.08510	0.07108	0.07752	*0*	*0.04530*	*0.01987*	*0.39117*
bushland_no shadow	0.15805	0.12048	0.16749	*0.04530*	*0*	*0.03350*	*0.38140*
agricultural land_no shadow	0.18558	0.14221	0.14694	*0.01987*	*0.03350*	*0*	*0.36068*
open area_no shadow	0.88289	0.94384	0.80602	*0.39117*	*0.38140*	*0.36068*	*0*

Table 36. Transformed divergence of Ngangao.

	woodland	bushland	agricultural land	open area
woodland	*	508	1,675	1,987
bushland	508	*	1,791	1,993
agricultural land	1,675	1,791	*	1,946
open area	1,987	1,993	1,946	*

Table 37. Transformed divergence of Chawia.

	woodland	bushland	agricultural land	open area
woodland	*	412	798	1,928
bushland	412	*	1,334	1,996
agricultural land	798	1,334	*	1,767
open area	1,928	1,996	1,767	*

In Ngangao, only *open area* is separated well from *woodland*, *bushland* and *agricultural land*. *Woodland* is poorly separated from *agricultural land* while the separation from *bushland* is very weak. Chawia shows similar values although here *woodland* is very weakly separated also from *agricultural land*.

Separability evaluations for both object-oriented and pixel-based classifications show that the separabilities of *woodland*, *bushland* and *agricultural land* are poor. *Open area* is the only class that seems to be well separated from other classes.

7.5.4 CLASSIFICATION ACCURACY ASSESSMENT

In this study, three different kinds of classifications have been made: visual classification, object-oriented supervised classification using *eCognition* and pixel-based supervised classification using *Erdas Imagine*. The classifications are not complete until their accuracy is assessed. Therefore, the accuracies of the latter two are assessed by using error matrices, normalised error matrices and kappa coefficient while visual classification is evaluated with the knowledge achieved when doing the classification itself.

7.5.4.1 ACCURACY OF VISUAL INTERPRETATION

The classification made by visual interpretation is evaluated in a different manner than the other two classifications. The usefulness and the reliability of an error matrix in this case are considered poor because of several reasons. As the reference pixels are checked from the same aerial photograph mosaic that was used for the visual interpretation and these two procedures are made by the same person, there should be no difference. In reality, there are probably several differences originating from the interpretation technique rather than real errors.

Firstly, the visual interpretation is a generalised classification. Therefore, a pixel-based accuracy assessment does not meet the needs of this kind of classification. Secondly, the interpretation is made using the visual interpretation principles. Thus, for example, one pixel is classified as *woodland* in accuracy assessment as well as in supervised classification although it is visually interpreted to be agricultural land because of "leaning" trees a.k.a. relief displacement.

As the resolution of the aerial photograph mosaics is very good, 0.5 m, distinguishing different land cover classes is mainly not a problem. More complicated in some cases is to decide in which class a certain feature belongs to. This applies specially to little groups of bush and trees mixed together and grassland with some bushes. Usually the first one is classified as *bushland* and the second as *grassland*. Most of the area was easy to classify, this relates especially to *open area*s, *terrace*s and *shamba*s. Differentiating exotic and indigenous *woodland* is also rather straightforward: eucalyptus can be distinguished by its spectral characteristics whereas other exotic trees stand out mainly by their texture.

The accuracies of the visual classifications define also the accuracies of the change detections as the final products are only as good as the data it has been made from.

7.5.4.2 ACCURACIES OF THE OBJECT-ORIENTED AND PIXEL-BASED SUPERVISED CLASSIFICATIONS

Typically, the assessment of digital classification accuracy is based on an error matrix (Story & Congalton 1986). Although error matrices are informative, measures such as the percentage of cases correctly classified have been criticised (Foody 2002: 188). This criticism is focused on that some cases may have been allocated to the correct class by a pure chance (Congalton 1991). In order to accommodate the consequences of chance agreement, a kappa coefficient (K) is often used. Furthermore, all elements in the classification error matrix, rather than just the main diagonal, contribute to the calculation (Foody 1992: 1459). Two classifications can also be statistically compared by testing the significance of the difference between two kappa coefficients (Foody 2002: 188). Even the kappa coefficient is not without problems as it is said to overestimate the chance agreement thus resulting in an underestimation of classification accuracy (Foody 1992: 1460). Moreover, Stehman & Czaplewski (1998: 341) have criticised the kappa coefficient to be an inappropriate basis for accuracy assessment as it is a non-probability-based measure.

A normalised error matrix is a controversial way of assessing the accuracy. The error matrix is normalised by applying an iterative proportional fitting procedure that forces each row and column in the matrix to sum one. In this way, differences in sample sizes used to generate the matrices are eliminated and, therefore, individual cell values within the matrix are directly comparable (Congalton 1991: 37). On the other hand, normalised error matrix is said to lead to bias as it tries to condition simultaneously both the row and column marginal proportions thus equalising the user's and producer's accuracies that may differ significantly (Stehman & Czaplewski 1998: 340; Stehman 2004).

Because there is no established practice of which accuracy assessment method should be used it is often recommended that the accuracy is evaluated with several methods. Hence, the accuracies of the classifications in this study are assessed with both ordinary and normalised error matrices as well as kappa coefficient.

The object-oriented and pixel-based supervised classifications are first evaluated by using error matrices. In order to perform this kind of classification accuracy assessment, the remote-sensing-derived classification map is compared with reference test information. This reference information is assumed to be correct, although it can also contain errors.

The reference test information can be collected by ground truthing, in other words by visiting the locations of the determined test pixels in the field, or by checking these pixels from a good-resolution aerial photograph or other accurate data source. In this study, the latter option, checking the pixels from the digital aerial mosaics, was chosen. While it is impossible to compare the classification at every pixel with a reference source, a proper sampling method of the test pixels has to be selected. Furthermore, an adequate amount of test pixels has to be collected in order to get accurate results. It has been stated that a minimum of 50 samples for each class in vegetation and land use studies is a sufficient amount (Congalton 1988: 43–44).

In order to get enough reference pixels in every class, a stratified random sampling is considered to be the most appropriate for this study. Simple random sampling could have underestimated the smallest classes like *open area* in this case. Moreover, stratified random sampling has been widely used for this purpose and it is also discovered to perform well (Congalton 1988).

For all the four classifications, 250 random pixels were created in *Erdas Imagine*. The software uses a square window to select the reference pixels. In this case, a 3 x 3 -window where all the pixels belong to the same class was used. This way one single 0.5 m x 0.5 m pixel of *woodland* in the middle of agriculture, for example, cannot be chosen to be a reference pixel. The minimum amount of reference pixels in one class was set to be 50. Thus there were 50 extra pixels to be located randomly.

The ordinary error matrices for object-oriented and pixel-based classifications in Ngangao and Chawia present also the producer's and user's accuracies (Tables 1–4 of Appendix 24). The producer's accuracy indicates the probability of a reference pixel being correctly classified and is a measure of omission error while the user's accuracy indicates the probability that a pixel on a classification map actually represents that category on the ground (Story & Congalton 1986). The normalised error matrices are presented in Tables 1–4 of Appendix 25. They have to be treated with caution as they are said to under- or overestimate the accuracies (Stehman 2004: 748). In this study, however, normalised error matrices are used to compare the accuracy results in cell level.

Furthermore, while the true kappa value cannot be determined, a $\hat{K}$ statistics, which is the best estimate of the kappa, was calculated as follows:

$$\hat{K} = \frac{N\sum_{i=1}^{q} p_{ii} - \sum_{i=1}^{q} p_{i+}\, p_{+i}}{N^2 - \sum_{i=1}^{q} p_{i+}\, p_{+i}} \qquad (16)$$

where p_{ii} = the diagonal entries of the error matrix
p_{i+} = the sum of row i of the error matrix
p_{+i} = the sum of column i of the error matrix
N = the total number of observation in the error matrix
q = the number of rows in the error matrix (Bishop 1975 , cit. Stehman 1996: 401).

The $\hat{K}$ values of the classifications calculated from the ordinary error matrices are presented in Table 38. A summary of overall accuracy values in ordinary and normalised error matrices as well as kappa ($\hat{K}$) is given in Table 39.

Table 38. The kappa values ($\hat{K}$) and overall accuracy values according to the ordinary and normalised error matrices.

Classification		**Overall accuracy** ordinary error matrix	normalised error matrix	**Kappa**
Ngangao	object-oriented	52.40 %	54.67 %	0.36
	pixel-based	70.80 %	73.08 %	0.61
Chawia	object-oriented	54.40 %	56.93 %	0.39
	pixel-based	54.00 %	57.16 %	0.39

Table 39. The Kappa ($\hat{K}$) values of the classifications.

	Ngangao		**Chawia**	
	object-oriented	**pixel-based**	**object-oriented**	**pixel-based**
Woodland	0.39	0.57	0.34	0.35
Bushland	0.16	0.37	0.33	0.35
Agricultural land	0.47	0.78	0.19	0.30
Open area	0.44	0.80	0.75	0.58
Overall Kappa	**0.36**	**0.61**	**0.39**	**0.39**

When comparing the ordinary error matrices, it can be seen that the best overall accuracy was reached with pixel-based classification in Ngangao (70.80%) while the weakest overall accuracy was reached with the object-oriented classification also in Ngangao (52.40%). Both the object-oriented and pixel-based classifications in Chawia attained similar overall accuracies: 54.40% and 54.00%, respectively. In Ngangao, the pixel-based classification had better producer's and user's accuracies in all classes than the object-oriented classification. In the classification accuracy of *woodland*, the pixel-based method reached approximately 69% producer's accuracy in both study areas while the user's accuracy in this method was better in Ngangao (69.02%) than in Chawia (47.95%). Hence, the best accuracy of *woodland* was reached with pixel-based method except the user's accuracy in Chawia. The object-oriented classification reached there the accuracy of 48.53% while in Ngangao the user's accuracy with this method was 56.58%. The producer's accuracies with the object-oriented classification method were 58.90% in Ngangao and 60.00% in Chawia. The object-oriented method succeeds remarkably better than the pixel-based only with *open area* in Chawia in both producer's and user's accuracies. In general, the accuracy results are not very good. For instance Thomlinson et al. (1999:25) set the criteria of a successful classification to have an overall accuracy of minimum 85% with no class less than 70% accurate. The classifications of this study do not reach these requirements.

The comparison of normalised error matrices highlights similar results than the comparison of ordinary error matrices; the object-oriented classification in Ngangao performs the best with an overall accuracy of 73.08% and the pixel-best classification in Ngangao is the weakest (54.67%). Also with normalised matrices, both methods in Chawia attain similar overall results; 56.93% with object-oriented and 57.16% with pixel-based classification method. In normalised matrices, the accuracies of the classes are not assessed with producer's and user's accuracies but within cell level. Thus, it can be seen that in all classification methods both in Ngangao and Chawia, *open area* has been classified the most accurately. Also according to the normalised matrices, *woodland* has been classified the best with the pixel-based method in Ngangao (0.67) while the values for other methods are 0.56 (object-oriented in Ngangao), 0.57 (pixel-based in Chawia) and 0.60 (object-oriented in Chawia). *Bushland* has been misclassified to *woodland* the most with pixel-based method in Chawia (0.30) and the least with object-oriented method also in Chawia (0.23). On the other hand, *woodland* has been misclassified to *bushland* the most with object-oriented method in Ngangao and the least with both object-oriented (0.14) and pixel-based method (0.15) in Chawia. A remarkable amount of *woodland* has been misclassified as *agricultural land* in Chawia with both methods: 0.27 with object-oriented and 0.25 with pixel-based method.

Kappa ($\hat{K}$) has a value of 1 with perfect agreement and a value close to 0 when the observed agreement is approximately the same as would be expected by chance (Monserud & Leemans 1992: 283). Thus, the best overall kappa value of 0.61 with the pixel-based method in Ngangao means that the accuracy with this method is 61% better than would be expected from chance agreement of pixels to classes. According to Landis & Koch (1977: 165), this value indicates substantial agreement. Overall kappa values reached with other classification methods (0.36 with object-oriented in Ngangao and 0.39 with both object-oriented and pixel-based in Chawia) indicate fair agreement with the same grading system. The kappa values indicating the classification accuracy of *woodland* are similar than the overall results. The pixel-based method in Ngangao is the only method that reaches a moderate agreement while others indicate fair agreement.

The three different accuracy assessment methods used in this study give different values because these measures incorporate different information. Nonetheless, the accuracy results are very similar according to these three methods; the pixel-based method in Ngangao gives the best results while the object-oriented method in Ngangao performs the weakest. In

Chawia, both methods are equally accurate. However, only a statistical comparison of the accuracies reveals whether the accuracies differ significantly.

The use of following equations in studying the statistical significance of the accuracy differences assumes that the samples used for the accuracy assessment are independent; that is that the same samples have not been used for the classifications under comparison. In this study, independent samples have been used and thus these equations apply.

The significance of difference between two proportions of correctly allocated cases that is two overall accuracies is estimated from

$$z = \frac{\frac{x_1}{n_1} - \frac{x_2}{n_2}}{\sqrt{p(1-p)\left(\frac{1}{n_1} + \frac{1}{n_2}\right)}}, \qquad (17)$$

where x_1 and x_2 = the number of correctly classified cases in two independent samples
n_1 and n_2 = the sample sizes, respectively
p = $\frac{x_1 + x_2}{n_1 + n_2}$ (Foody 2004: 630).

Because a continuous distribution is being used to represent the discrete distribution of sample frequencies in the previous test, it is sometimes recommended to perform a continuity correction (Fleiss 1981 , cit. Foody 2004: 630). The continuity correction modifies equation 16 as follows:

$$z = \frac{\left|\frac{x_1}{n_1} - \frac{x_2}{n_2}\right| - \frac{1}{2}\left(\frac{1}{n_1} + \frac{1}{n_2}\right)}{\sqrt{p(1-p)\left(\frac{1}{n_1} + \frac{1}{n_2}\right)}} \text{ (Foody 2004: 630).} \qquad (18)$$

The significance of the difference between two independent $\hat{K}$-values is evaluated with the normal curve deviate:

$$z = \frac{\hat{K}_1 - \hat{K}_2}{\sqrt{\hat{\sigma}_{K_1}^2 + \hat{\sigma}_{K_2}^2}}, \qquad (19)$$

where $\hat{\sigma}^2_{K_1}$ and $\hat{\sigma}^2_{K_2}$ = the estimated variances of the derived coefficients (Congalton et al. 1983).

These variances are calculated with the equation for the approximate large sample variance of kappa:

$$\sigma^2\left[\hat{K}\right] = \frac{1}{N}\left[\frac{\theta_1(1-\theta_1)}{(1-\theta_2)^2} + \frac{2(1-\theta_1)(2\theta_1\theta_2-\theta_3)}{(1-\theta_2^3)} + \frac{(1-\theta_1)^2\left(\theta_4-4\theta_2^2\right)}{(1-\theta_2)^4}\right], \qquad (20)$$

where
$$\theta_1 = \sum_{i=1}^{q}\frac{p_{ii}}{N}$$
$$\theta_2 = \sum_{i=1}^{q}\frac{p_{i+}p_{+i}}{N^2}$$
$$\theta_3 = \sum_{i=1}^{q}\frac{p_{ii}\left(p_{i+}+p_{+i}\right)}{N^2}$$
$$\theta_4 = \sum_{\substack{i=1\\ j=1}}^{q}\frac{p_{ij}\left(p_{j+}+p_{+i}\right)^2}{N^3}$$
(Bishop et al. 1975, cit. Hudson & Ramm 1987: 421).

In this formula, p_{ij} is the number of counts in *ij*th cell.

The absolute values of *z* calculated with the previous equations are presented in Table 40. If the absolute value exceeds 1.96 ($|z| > 1.96$) in these tests, the difference is significant at the widely used 5% level of significance (Congalton & Green 1999). All the tests indicate the same three comparisons to be significant at this level. Thus, the pixel-based classification of Ngangao is significantly better than the object-oriented classifications of Ngangao and both the object-oriented and the pixel-based classifications of Chawia. The accuracies reached with pixel-based and object-oriented classifications in Chawia do not differ significantly.

Table 40. The absolute values of z ($|z|$). cc stands for continuity correction.

The compared classifications	Overall accuracy		Kappa
	normal	cc	
object-oriented (Ngangao) vs. pixel-based (Ngangao)	4.23*	4.14*	4.35*
object-oriented (Ngangao) vs. object-oriented (Chawia)	0.45	0.36	0.46
object-oriented (Ngangao) vs. pixel-based (Chawia)	0.36	0.27	0.46
pixel-based (Ngangao) vs. object-oriented (Chawia)	3.79*	3.70*	3.85*
pixel-based (Ngangao) vs. pixel-based (Chawia)	3.88*	3.79*	3.89*
object-oriented (Chawia) vs. pixel-based (Chawia)	0.09	0.00	0.00

* difference is significant at 5% level

The previous accuracy assessment methods do not reveal in which areas the classifications fail. The comparison of the classifications by using GIS overlay operations can evaluate also this aspect (Figure 61, page 91). The accuracy of the classifications is more likely to be better in the areas where all classification methods agree. However, it has to be taken into account that the supervised classifications are compared to the visual classification that is differing from the supervised classifications by the generalisation level.

Because the object-oriented classifications are conducted with fuzzy logic, their accuracy can be assessed also by studying the stability of the classifications. The stability is defined as the difference between the fuzzy score of the best class (highest fuzzy membership) and the fuzzy score of the second-best class (Flanders et al. 2003: 444). The fuzzy scores of the best object-oriented classifications in Ngangao and Chawia are presented in Tables 41 and 42. The best possible fuzzy score is 1 while the weakest is 0. In this study, the minimum membership value was set to 0.5. Thus objects with a fuzzy score under 0.5 to any classes were unclassified. *Agricultural land_shadow* in Ngangao has the best mean membership value. *Open area_3* cannot be taken into account as all the objects belonging to this class are sub-objects of *open area_4* and thus their membership value is set to 1. All the *woodland* classes have a mean membership value over 0.95.

Table 41. The best classification result in Ngangao.

Class	Objects	Mean	StdDev	Min	Max
woodland_shadow	17,743	0.990	0.020	0.501	1.000
woodland_no shadow	11,187	0.955	0.090	0.501	1.000
bushland_shadow	8,663	0.970	0.071	0.503	1.000
bushland_no shadow	6,777	0.983	0.026	0.564	1.000
agricultural land_shadow	1,563	0.993	0.009	0.909	1.000
agricultural land_no shadow	9,604	0.981	0.029	0.651	1.000
open area_3	4,261	1.000	0.000	1.000	1.000
open area_shadow	818	0.974	0.027	0.647	1.000
open area_no shadow	2,315	0.936	0.061	0.551	1.000

Table 42. The best classification result in Chawia.

Class	Objects	Mean	StdDev	Min	Max
woodland_shadow	9,601	0.978	0.046	0.504	1.000
woodland_no shadow	5,251	0.964	0.056	0.504	1.000
bushland_shadow	6,130	0.979	0.044	0.513	1.000
bushland_no shadow	4,277	0.964	0.050	0.537	1.000
agricultural land_shadow	4,186	0.988	0.024	0.652	1.000
agricultural land_no shadow	5,421	0.982	0.031	0.657	1.000
open area_3	1,792	1.000	0.000	1.000	1.000
open area_no shadow	940	0.896	0.109	0.500	1.000

The stabilities of the classifications are presented in Tables 43 and 44. All the classes except the *open area_no shadow* -classes have very vague mean stability values. Thus it can be stated that the object-oriented classifications of Ngangao and Chawia are not very stable.

Table 43. Classification stability in Ngangao.

Class	Objects	Mean	StdDev	Min	Max
woodland_shadow	17,743	0.012	0.018	0.000	0.557
woodland_no shadow	11,187	0.035	0.080	0.000	0.619
bushland_shadow	8,663	0.017	0.040	0.000	0.573
bushland_no shadow	6,777	0.012	0.016	0.000	0.123
agricultural land_shadow	1,563	0.003	0.005	0.000	0.041
agricultural land_no shadow	9,604	0.026	0.038	0.000	0.651
open area_3	4,261	1.000	0.000	1.000	1.000
open area_shadow	818	0.032	0.034	0.000	0.269
open area_no shadow	2,315	0.129	0.230	0.000	1.000

Table 44. Classification stability in Chawia.

Class	Objects	Mean	StdDev	Min	Max
woodland_shadow	9,601	0.015	0.033	0.000	0.689
woodland_no shadow	5,251	0.023	0.034	0.000	0.610
bushland_shadow	6,130	0.025	0.063	0.000	0.826
bushland_no shadow	4,277	0.027	0.035	0.000	0.220
agricultural land_shadow	4,186	0.006	0.009	0.000	0.100
agricultural land_no shadow	5,421	0.010	0.010	0.000	0.102
open area_3	1,792	1.000	0.000	1.000	1.000
open area_no shadow	940	0.219	0.272	0.000	0.974

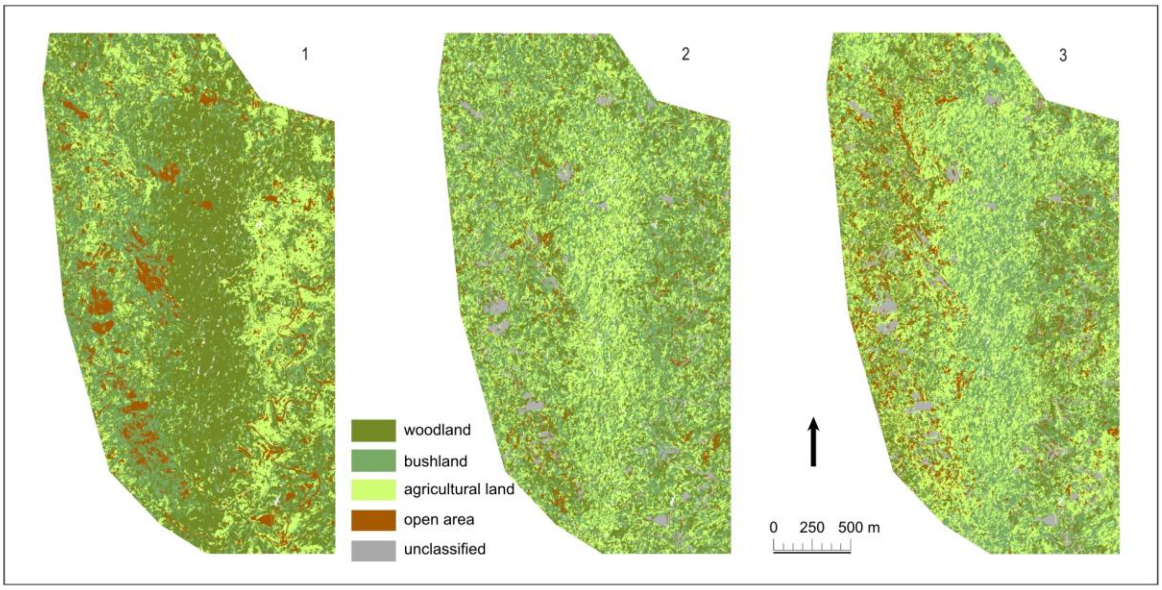

Figure 77. The three best classification results according to the object-oriented supervised classification of Ngangao in 2004.

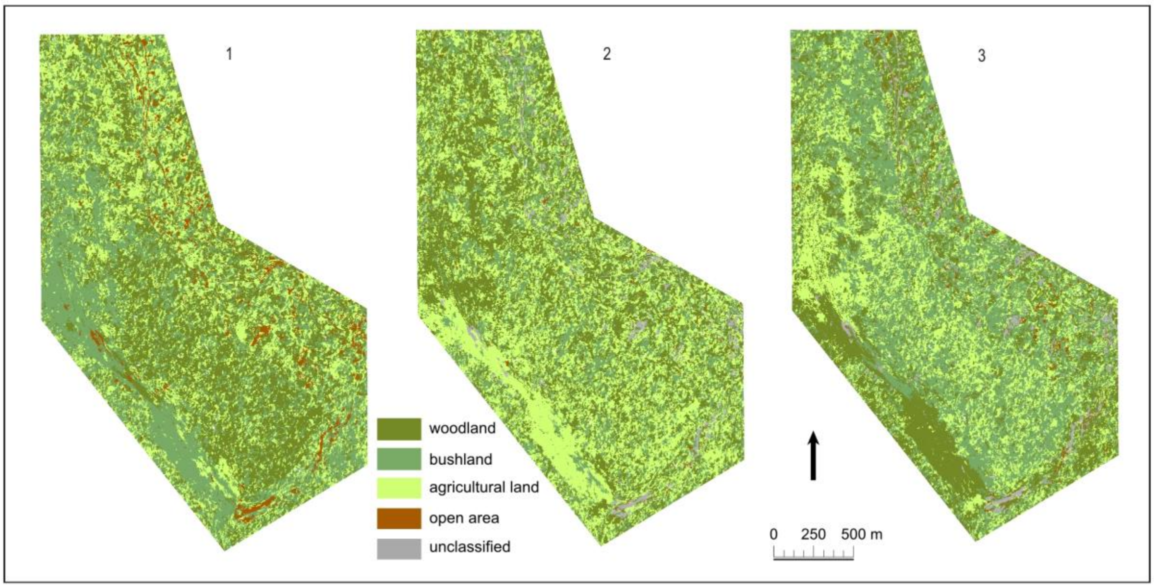

Figure 78. The three best classification results according to the object-oriented supervised classification of Chawia in 2004.

Figures 77 and 78 represent the three best object-oriented classification results for Ngangao and Chawia. The second- and third-best classification results represent very different classifications for both study areas. Also these figures show that nature classes of *woodland*, *bushland* and *agricultural land* are easily classified as another nature class.

7.5.5 ACCURACY OF CANOPY DATA

The accuracies of canopy data from hemispherical photographs and textural data from aerial mosaics are discussed in this chapter. Furthermore, the accuracy of FHM data is covered. As mentioned already in previous chapters, the inaccuracies in locations of these measurements caused problems. Therefore, the canopy data from hemispherical photographs and FHM data could not be compared with each other.

7.5.5.1 ACCURACY OF CANOPY DATA FROM HEMISPHERICAL PHOTOGRAPHS AND TEXTURAL DATA FROM AERIAL MOSAICS

The discussion about accuracies of canopy data and textural data can be divided into three influencing factors. These are location accuracy, accuracy in the analysis of hemispherical photographs and the overall characteristics of the data set.

Hemispherical photographs were supposed to take in the same plots that the FHM had used in order to compare these two data sets. These FHM plots were located with the help of forest guards and additional instructions written in FHM data sheets. Figure 47 (page 81) shows that most of the plots were not located correctly. In Ngangao, the forest guard had visited only part of the plots himself before and in Chawia, the forest guards had not visited the plots at all before. Also the marker ribbons left to the forest were not there anymore.

There are several factors that could have affected the results when comparing the canopy data from hemispherical photographs and textural data from aerial mosaics. One of these is the location accuracy of the two parameters. The geometric accuracy of the aerial mosaics is discussed in chapter 7.5.1.2. Even though the geometric accuracy is very good in general, there may still be some inaccuracies inside the forests although the differences in locations are most likely to be of similar size than elsewhere in the mosaic. The spectral accuracy is covered in chapter 7.5.1.1. The accuracy of locations where the hemispherical photographs were taken is dependent on the accuracy of the GPS coordinates recorded for the locations. The accuracy of the GPS coordinates in the forests could not be assessed when taking the photographs in 2004. However, in 2007 the same GPS devise was tested in Ngangao by using differential GPS device as a reference by Mika Siljander and Alemu Gonsamo. According to this test, the maximum error with the GPS device used in this study was 7 metres. Obviously, this kind of mislocation produces inaccuracy to the comparisons. However, the ordinary GPS device proved to be more accurate inside the forest areas than the differential GPS device.

The second factor affecting the overall accuracy of canopy data is the accuracy in the analysis of the hemispherical photographs. The software used for analyzing the photographs, *GLA*, uses a subjective approach when determining the threshold values for the photographs. In this study, however, all the photographs were analysed by the same person within a short time period. Thus, inaccuracy due to the subjective approach was minimized. Topography sometimes causes shading into hemispherical photographs (Figure 79). Yet, these shadings were not removed in this study. On the other hand, most of the photographs did not suffer from topographic effects. Because the canopy was very closed in all plots, the topographic shading did not affect as much as it would have in a less closed forest. Also the sun caused inaccuracy in the analysis; in some photos, there is an overexposed region around the sun and furthermore some leaves are very bright and thus could be considered as openings. Also fog complicated the thresholding of the images. The effect of these features was minimised when analysing the images one at a time.

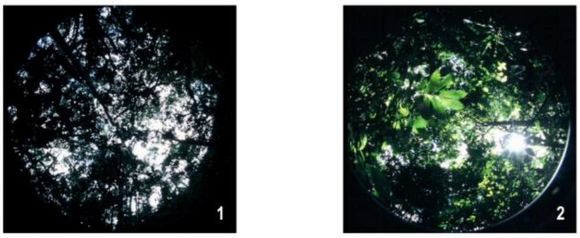

Figure 79. Shading in the hemispherical photograph ch2004_22_1 (1) and overexposed region around the sun and the leaves in the hemispherical photograph ng2004_b (2).

The third factor is the characteristics of the canopy data set. The sample size is small and the data is recorded in three different years. The sample sizes are however taken into consideration when discussing the results of the statistical analyses. The different times of data acquirement are taken into account by dividing the data set by years and studying the differences between year combinations.

7.5.5.2 ACCURACY OF THE FHM DATA

The accuracy of the FHM data is not assessed by the project itself in those reports that are used in this study (EAMICFG 2000; Hertel et al. 2000; Madoffe et al. 2005). Therefore, only general findings of the accuracy of the FHM data are discussed.

The measurements recorded in FHM are done by a group of people. This group varies in different forests and therefore there can be variation in the results. Anyhow, very in-depth instructions are given for all groups doing the measurements (EAMICFG 2000). In the data recorded in Ngangao and Chawia, all the information was not filled with every measured tree and thus the measurements could have been done more carefully. During years 2000 and 2001, the locations of the plots were not recorded with GPS. This was a severe weakness of the data. During year 2006, also the coordinates of the plots were recorded.

8 DISCUSSION

8.1 MOSAICKING

The mosaicking of 2004 digital aerial photographs succeeded well while the 1955 mosaic and aerial photograph suffered from some geometric inaccuracies due to the lack of metadata. Before the 2004 mosaics were done, the BRDF-corrected mosaic was assumed to be better than the mosaic without these corrections. But, this hypothesis was incorrect due to the artificial spectral differences introduced in the BRDF-corrected images. If the digital aerial photographs would have been individually corrected for this effect, the result would probably been much better. Furthermore, the BRDF correction values used in *EnsoMOSAIC* were general values for whole Kenya. Thus, by determining specific values for the study area and the data used, the quality of BRDF corrected mosaic could have been better.

However, the influence of a BRDF-corrected mosaic produced from individually corrected photographs on classification results as well as on canopy results could not be studied within the framework of this study.

8.2 CLASSIFICATION

The class structure design used in this study is considered to be good as it enables the comparison of different classifications very easily. The classes are always some kind of generalisations of the real land cover and thus a different land cover class scheme could also have been possible. The class structure could have been, for example, more complex with several classes for different woodland types. However, the properties of vegetation in tropical countries are usually very diverse, as also in the Taita Hills, and thus the class structure would have still been somewhat a compromise. Moreover, a better success of more complex classification is hardly likely.

The use of *eCognition* for object-oriented segmentation and classification brought many opportunities for the classifications. However, *eCognition* is quite user-dependent software although it is at the same time objective. Thus, the selection of different segmentation parameters and classification samples may have resulted in a different outcome. The possibility to use multi-resolution segmentation and classification is highly appreciated and it can certainly bring extra value to the classification if used correctly. Furthermore, the use of the fuzzy classification system enables more detailed interpretation of the classification results. A closer examination of the fuzzy results would have been very interesting but impossible to realise within the limits of this study. The multi-level class design in *eCognition* with *shadow* and *no shadow* –classes is only a one possible way to approach the classification assignment. Several other designs may also have been used.

If a NIR-band would have been within the band combination used in this study, the classification results would presumably have been better. This is because healthy vegetation has its peak reflectance in the spectral frequency of NIR and also the differences between different types of vegetation are clearer in these wavelengths. Furthermore, the presence of NIR might have enabled the use of membership functions within *eCognition*.

In general, the visual classifications from 1955 and 2004 succeeded well while the digital classifications suffered from various problems. The shadowed areas as well as the very similar spectral properties of *woodland*, *bushland* and *agricultural land* made the classifications difficult. As both digital classification techniques used in this study were supervised methods, the selection of samples holds a big role in the process. In this case, the sample selection is seen to affect the classification results perhaps even more than the chosen supervised method.

Rarely used comparison of different classification results realised with overlay-operations in *ArcGIS* is seen to bring additional value to the traditional classification comparison methods. However, there is no clear pattern in which kind of places one method succeeds better than the other. Both methods have problems with *woodland* as well inside the forest areas as elsewhere in the study areas. The fact that the supervised classifications are compared with generalised visual classifications brings some uncertainty to the comparisons. For instance, an agricultural area with single trees here and there is classified as *agricultural land* in visual classifications but the supervised classifications cannot make these kinds of generalisations. Nevertheless, the disadvantages of this method are recognised and they are rather due to the data used and not the method itself.

The visual classification technique is considered to be the most accurate of the three methods used both in Ngangao and Chawia. However, it differs noticeably from the supervised methods especially because of the generalisation level. Considering the accuracy assessment results, neither of the supervised succeeded well although the pixel-based method was significantly better in Ngangao than the object-oriented method. If only *woodland* is considered, the pixel-based classification is better from the producer's point of view while the situation is more even for the users. As a result, on the ground of this study, a clear recommendation on which supervised classification is better, cannot be given. The results achieved with the visual classification are good but the method is very time-consuming. On the other hand, visual interpretation method is the least dependent on the software and technical skills which is a profit especially in the developing world. Thus, the method to be chosen depends on the characteristics of the study area and the resources available.

8.2.1 COMPARISONS WITH PREVIOUS STUDIES

The forests of Ngangao and Chawia have been studied in several manners also before (Table 45). In these studies, the areas of the main fragments of the forests have been assessed with different methods. The differences between different years and studies may result also from other reasons than actual changes in forest area. These reasons include differences in the estimation methods and the forest definitions. Thus, the comparisons of the areas have to be treated with caution as there might be significant differences in the studying methods as well as in the interpretation of the results.

Table 45. The areas of the main forest fragments of Ngangao and Chawia according to Beentje 1988: 24, Run 1995: 17–18, Wilder et al. 1998: 182 and the results of this study (Lanne 2007).

	Ngangao (area / ha)	**Chawia (area / ha)**
Lanne 2007 (estimated based on visual interpretation of **1955** aerial photograph and mosaic)	157.16	122.92 ha
Beentje 1988 (estimated from the expeditions ground survey, covers indigenous forest only)	92	17
Run 1995 (estimated based on visual interpretation of **1993** aerial photographs, covers indigenous forest only)	113	100
Wilder et al. 1998 (no further details)	92	50
Lanne 2007 (estimated based on visual interpretation of **2004** digital aerial mosaics, Ngangao covers indigenous forest only, while Chawia covers both indigenous and exotic forest)	138.86	91.38

The area estimations of Beentje (1998: 24) and Wilder et al. (1998: 182) differ notably from the areas assessed in this study. Apart from the interpretation differences, the difference in Chawia may also be partly explained with the fact that both the indigenous and exotic species are taken into account in the calculations of this study. Still, the difference is remarkable, especially with Beentje's study where no kind of remote sensing data was used. However, Run (1995) assessed the area of the forest by visual interpretation of aerial photographs from 1993. Also the results of Run's study differ from the results of this study. Run estimates the area of Chawia to be 100 ha with only indigenous species while the area assessed in this study is approximately 91 ha with exotic species intermixed with indigenous species. It is hard to define whether these differences are due to real changes in forest areas or differences in interpretation and study methods. Unfortunately, spatial comparisons of the results from previous studies and this study are impossible as the forest maps in the previous studies are too imprecise.

Furthermore, Run (1995) studied the change in forests of Ngangao and Chawia in 1955–1993. Nevertheless, the change detection results are not comparable as the study areas as well as the class descriptions differ.

8.3 CHANGE DETECTION

This study, as many others, considers only so called hard changes from one land cover class to another. Although this kind of land cover conversion is an important aspect to study, it is just one part of the change. With the methods used in this study, it is impossible to evaluate subtle transformations like land cover modifications, in which the land cover may have been altered but not totally changed. Moreover, the change is studied here as a static change between two points in time. Therefore, it is not possible to assess information about the processes in land cover between these two time frames. With data from several other points in time, these processes could be studied in more detail.

In general, the landscape of Ngangao has changed more than the one of Chawia when considering changes from one land cover class to another. However, according to the aerial photographs, the study area of Chawia was more inhabited in 1955 and thus the landscape had experienced more human-caused changes already before the time period of this study. In the study area of Ngangao, on the other hand, the population grew intensively based on the interpretation of aerial photographs between 1955 and 2004 thus causing changes in landscapes during these years. Neither of the forests was unreachable even in 1955 and substantial changes in landscape had happened presumably for hundreds of years. Nowadays, the landscapes in both study areas are remarkably fragmented. Especially in Chawia, the topography has directed the sprawl of the settlements thus affecting also on the change of land cover.

Although the overall area of woodland has grown in Ngangao between 1955 and 2004, the amount of indigenous woodland has decreased between these times. This increase is mainly due to the exotic plantations in 1950s and 1970s. Fortunately, it seems that these exotic species have not dispersed and mixed with indigenous species as is the case in Chawia. The invasion of exotic species weakens the possibility of survival of other indigenous flora and fauna thus decreasing biodiversity. In Chawia, the amount of woodland in general has decreased substantially. Demarcating the forest with *Eucalyptus* sp. thus clearly allowing the cutting of trees outside the marked area has affected the diminution of Chawia. On the other hand, at the moment prevailing forbiddance of cutting the trees inside both the forest areas has improved the situation of Ngangao and Chawia. When taking into account that the forest of Chawia in 2004 has lots of individual exotic trees intermixed with the indigeneoud woodland, the decrease of indigenous woodland has been even more outstanding. Also the quality of the forest has been reducing.

The decrease of agricultural land especially in Ngangao is somewhat surprising as the need for land in the Taita Hills has grown all the time because of population growth. On the other hand, substantial amounts of woodland and bushland have changed to agricultural land during the study period. However, approximately 30% of the agricultural land in 1955 has been changed to bushland. Although the study time period is quite long and the change processes between 1955 and 2004 cannot be known, this might indicate problems with the use of land for agricultural purposes. These kinds of problems could be, for instance, decrease of productiveness of the land, drought or long-time uncommon weather conditions. However, a possibility of misclassifications has to be kept in mind although they are considered quite impropable.

8.4 TEXTURAL INFORMATION COMPARED TO THE CANOPY PARAMETERS

The textural information from the digital aerial mosaics and canopy parameters retrieved from the hemispherical photographs were compared in order to find out their relationship. As discussed in chapter 6.5.5, there is no linearity of relations according to the scatterplots. Even higher-degree linearity is absent. The hypothesis was that RANGE and MEAN would correlate the best. This is because RANGE was supposed to high if there is an opening in the canopy which should also be visible in the hemispherical photograph. MEAN, for one, was supposed to describe the spectral properties of the aerial mosaic that could have been correlating with hemispherical photograph of varying canopy.

Several reasons could have affected the lack of linearity between the textural information and the canopy parameters. One explanation for this result is the characteristic of the forests. The canopy of the forests is multi-level; therefore the canopy closure determined with the hemispherical photographs can be high even though the highest level of the canopy has openings that, for one, are visible in the aerial mosaics. Furthermore, the higher canopy level shed shadow over the lower canopy levels while in the hemispherical photographs the lowest canopy levels are the most visible. In some occasions, even high undergrowth may be visible in the hemispherical photographs but not in the aerial mosaics. Thus, it is likely that this kind of a study would be successful rather in forests with one-level canopy (see e.g. Pellikka et al. 2000b) than in tropical forests with multi-level canopy. Furthermore, the tree species of tropical forests like the forests of this study are spectrally more variable than for example coniferous forests due to the varying species composition.

The lack of NIR-band in the aerial mosaics may also affect to the result. On the other hand, the green band showed no difference when compared to the other two bands. Thus, the combination of the three bands (RGB) was used in this study. Moreover, the presence of NIR would have enabled the use of vegetation indices in the comparisons.

In addition, inaccuracies of the locations are likely to produce errors in the study. Although the geometric accuracy is estimated to be good in both forests, the accuracy of the locations where the hemispherical photographs were taken can be inexact. This is due to the weaker GPS reception inside the forest areas. This kind of a locational inaccuracy would affect the results significantly. Also inaccuracies in the interpretation process may affect the results.

8.5 THE HEALTH OF THE FORESTS

According to the FHM data, Ngangao is in better condition than Chawia although the condition of Ngangao is not perfect either. This is due to the varying structure of Ngangao; it has a more complex tree species composition and also the crown density and the foliage transparency vary more there. However, it seems that in general, the values of crown density and foliage transparency, both indicating the health of the forest, are better in Chawia than in Ngangao. Yet, based on the experience from the forests while on the field, the canopy and especially the upper canopy in Ngangao are more closed than the one in Chawia. The results originating from the FHM data are greatly affected by the locations of the study plots. This with the smaller sample size in Chawia could explain these contradictory experiences.

Furthermore, the regeneration of Ngangao seems to be more extensive as it holds relatively more trees with smallest DBH than Chawia. Both forests hold also some very large trees. The differences in height and DBH may be partly a result of selective logging in the past. Furthermore, the species composition and the location of the study sites affect the result. Disturbance was discovered only in one plot. Yet, it has to be remembered that in FHM, only those damages that could kill the tree or have the potential to affect the long-term survival of the tree are recorded (Hertel et al. 2000: 13). However, the disturbance of the forests is still evident: both forests have large proportions of *Tabernaemontana stapfiana* and *Albizia gummifera* that are known to occur in disturbed forests (Bytebier 2001: 80). Chawia has also a lot of *Phoenix reclinata*, a secondary successional species that also indicates disturbance in forests (Chege & Bytebier 2005: 233).

Generally, greater canopy closure means a healthier tree and healthier forest. However, the closure and also the foliage transparency vary somewhat between different species as some species exhibit higher canopy closure due to their leaf design or branch structure (Madoffe et al. 2006). According to the FHM data, Chawia seems to be more closed than Ngangao. However, Wilder et al (1998: 184) estimated the mean canopy cover to be 60% with a standard deviation of 32% in Ngangao and 51% with a standard deviation of 34% in Chawia. The mean canopy closure according to the hemispherical photographs of this study is approximately 89% in both forests with standard deviations of 3–4%. The differences these large are hardly due to a true change in the canopy closure. Rather, they can be reason of different study methods, study plot locations and phenology.

When comparing the results of the hemispherical photographs, it can be seen that not only the *canopy closure* but also the *LAI 4 Ring* as well as the *LAI 5 Ring* give very similar results to both Ngangao and Chawia with slightly higher values of *LAI 4 Ring* and *canopy closure* in Chawia. These results are somewhat surprising as the visual impression got in the forests was the opposite; the canopy of Ngangao is notably more closed than the canopy of Chawia. The disagreement of visual impression and the results gained with the hemispherical photographs can be a consequence of several factors. The sample size of the hemispherical photographs is relatively small and thus the photographs only represent a small portion of the forests. Also the locations where the photographs were taken have an effect to the results. Moreover, the hemispherical photographs are not able to differentiate between the canopy layers. Thus, also a closed lower canopy results in high *LAI* and *canopy closure* values. However, visual impression as well as textural parameters from aerial mosaics rather concentrate on the upper canopy.

Therefore, according to the results from the analysis of the hemispherical photographs, there is no notable difference between the forests.

In general, the studies suggest that both forests are somewhat disturbed, although Ngangao is in better condition than Chawia. Also visual interpretation supports this assumption. It has to be remembered that the sample size of these canopy studies is not large enough to make these results totally reliable. Furthermore, the samples are not gathered extensively in the forest areas. However, the results of this study can be considered suggestive.

8.6 THE PRESENT SITUATION OF THE FORESTS

The forests of Kenya have changed remarkably during the last hundreds of years both in terms of area and quality. Still in the 20th century, the loss rate was increasing but at the moment the situation is getting better. The remaining forests are, unfortunately, very fragmented. The administrative situation of the forests has been, in many cases somewhat unclear. Now, however, the forests are getting more and more attention and the management plans and the new forest policy are seen as a possibility to improve the situation of the forests. Especially the participation of communities to forest issues is considered as a good development.

The present situation of the forests in the Taita Hills is moderate considering the circumstances. The appreciation of forests has increased and much work has been done in order to preserve the maintaining forest areas. For instance, people are encouraged to plant indigenous species instead of the exotic ones.

The best-preserved forests of the Taita Hills are seen to have potential for eco-tourism in the future (Himberg 2006). However, any kind of tourism needs careful planning and realisation as well as resources in orders that no harm would be caused neither to the ecosystems of the forests nor to the people living in the area.

The future of the forests seems to be somewhat optimistic. It is extremely important for the whole Taita Hills area and its people, flora and fauna that the forests are valuated and preserved now and in the future.

9 CONCLUSIONS

This master's thesis has studied the present state of indigenous forests in Kenya in general level and in the Taita Hills in a more detailed level. In the Taita Hills, the situation of two study forests, Ngangao and Chawia, has been emphasised. Two high-resolution digital aerial mosaics were produced from the study areas for classification and change detection purposes. The land cover in Ngangao and Chawia has been classified using three different methods: visual classification method for 1955 and 2004 mosaics and object-oriented and pixel-based supervised classification methods for 2004 mosaics. The change in woodland between 1955 and 2004 in both study areas was assessed by examining the visual land cover classifications produced from 1955 and 2004 aerial mosaics. Furthermore, the present condition of these forests was evaluated by using hemispherical photographs and additional forest health monitoring data.

The visual classification method is the most accurate of the used classification techniques with the data used for this study. Neither of the supervised classification methods performed very well. Thus, no recommendations can be made on which supervised classification method should be used in similar classification tasks. The selection of proper classification technique depends greatly on the study area and the data used.

According to the change detection studies made, the overall woodland area grew in Ngangao and decreased in Chawia between 1955 and 2004. However, the area of indigenous woodland has decreased substantially in both study areas. Especially in Chawia, the exotic species are disturbing the growth of indigenous species thus weakening biodiversity of the forest. The present condition of Ngangao is seen to be better also according to the FHM data. The forests are even more fragmented which also affects the biodiversity. The decrease of indigenous forests appears to result from increasing need for land because of population growth. However, the situation of the forests is getting better due to the increasing appreciation of forest areas.

No relation between the canopy parameters retrieved from the hemispherical photographs and the textural information from digital aerial mosaics was found regardless of the prior good results achieved with this method. It seems that the canopy should be studied more carefully with different methods. This kind of study has already been started in the Taita Hills within the project TAITATOO.

This study is of value especially for the area of the Taita Hills and the research projects in that area. Especially the results and experiences reached with the land cover classifications and the change detection produced from high-resolution aerial photographs can be used in future for the purposes of other studies. Furthermore, the digital aerial mosaics as such have already been used for several purposes within the projects TAITA and TAITATOO. In the future, the research is focusing not only to the forests but also to the areas between them with, for instance, connectivity studies.

It is highly important for the whole area of the Taita Hills that the remaining forest fragments are preserved at least as they are now in their area and condition. That way they will serve as the lungs of the Taita Hills in the future as well.

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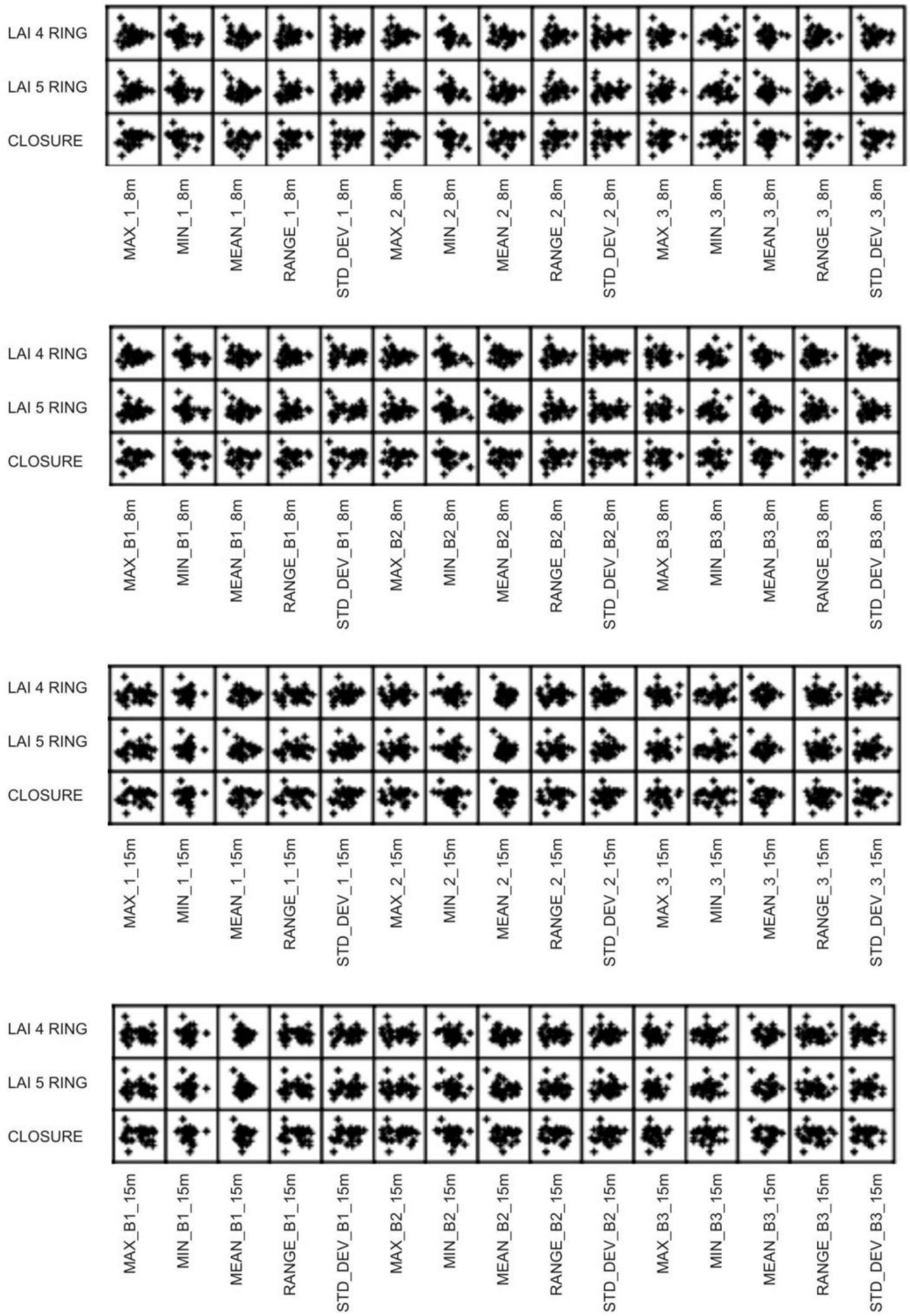
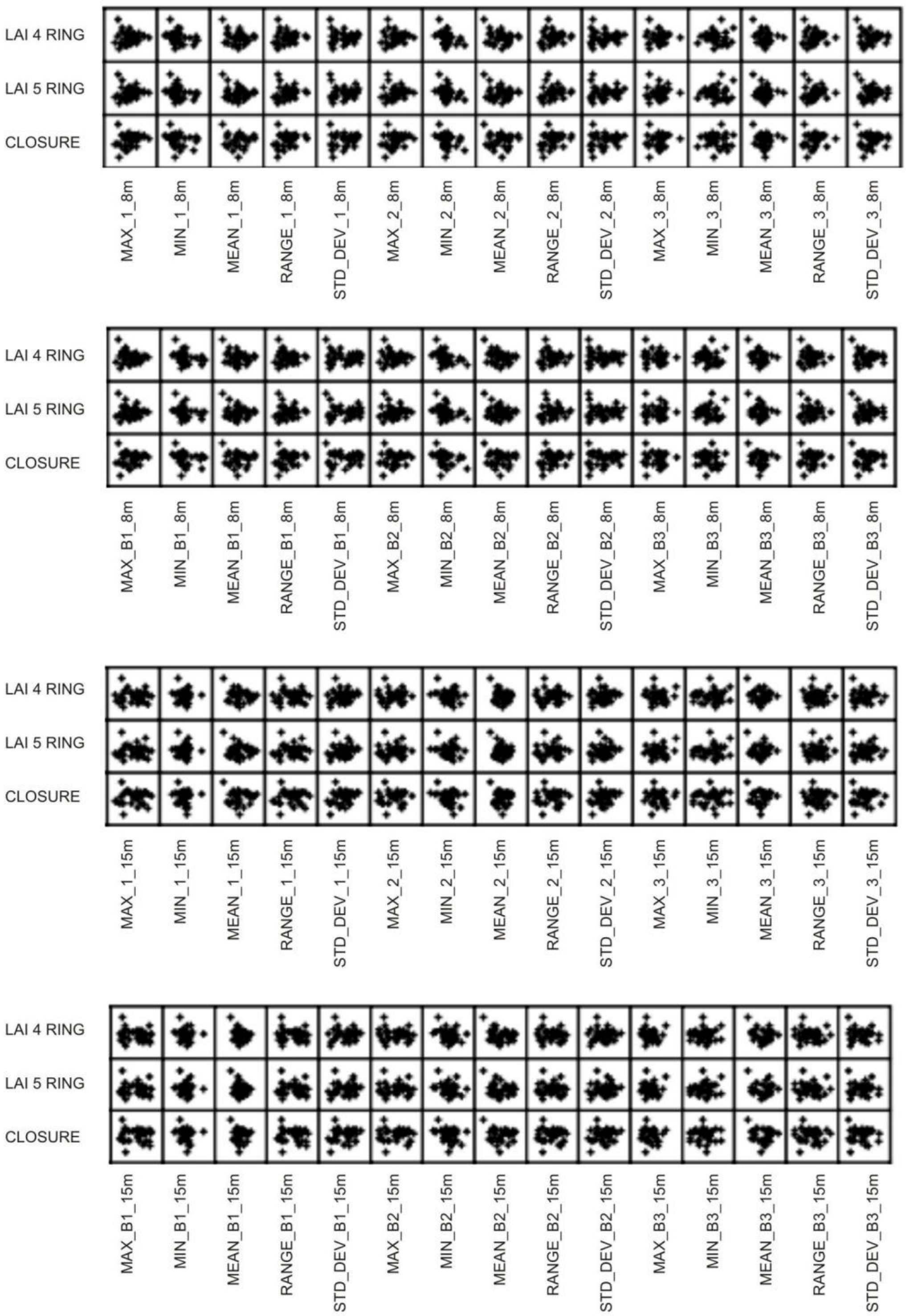
Appendix 1. The IDs and coordinates used for the plots where the hemispherical photographs were taken. The coordinates are in the projection defined in Table 10.

YEAR	FOREST	ID (this study)	ID (FHM)	PLOT	SUBPLOT	E	N	HEIGHT (m)
2004	Chawia	ch2004_20_1	1070020	20	1	426675	9615986	1593
2004	Chawia	ch2004_21_1	1070021	21	1	426892	9615391	-
2004	Chawia	ch2004_22_1	1070022	22	1	426763	9615378	-
2004	Chawia	ch2004_23_1	1070023	23	1	426665	9615921	-
2004	Chawia	ch2004_24_1	1070024	24	1	427405	9614543	1595
2004	Chawia	ch2004_25_1	1070025	25	1	427153	9615189	1604
2004	Chawia	ch2004_a	-	-	-	427488	9614591	1584
2004	Chawia	ch2004_b	-	-	-	427537	9614630	1584
2004	Chawia	ch2004_c	-	-	-	427217	9615332	1606
2005	Chawia	ch2005_21_2	1070021	21	2	426857	9615408	1577
2005	Chawia	ch2005_22_1	1070022	22	1	426770	9615390	1608
2005	Chawia	ch2005_22_2	1070022	22	2	426755	9615416	1609
2005	Chawia	ch2005_a	-	-	-	427154	9615285	1622
2005	Chawia	ch2005_b	-	-	-	427178	9615280	1630
2005	Chawia	ch2005_c	-	-	-	427416	9614609	1570
2005	Chawia	ch2005_d	-	-	-	426648	9616125	1608
2005	Chawia	ch2005_e	-	-	-	427448	9614574	1570
2005	Chawia	ch2005_f	-	-	-	426641	9616116	1581
2005	Chawia	ch2005_g	-	-	-	426659	9616147	1610
2006	Chawia	ch2006_a	-	-	-	426580	9615960	1582
2006	Chawia	ch2006_b	-	-	-	426606	9615913	1597
2006	Chawia	ch2006_c	-	-	-	426668	9615921	1604
2006	Chawia	ch2006_d	-	-	-	426736	9615842	1596
2006	Chawia	ch2006_e	-	-	-	426761	9615789	1605
2006	Chawia	ch2006_f	-	-	-	426763	9615555	1589
2006	Chawia	ch2006_g	-	-	-	426826	9615446	1559
2006	Chawia	ch2006_h	-	-	-	426867	9615271	1575
2006	Chawia	ch2006_i	-	-	-	426893	9615190	1586
2006	Chawia	ch2006_j	-	-	-	426939	9615125	1596
2006	Chawia	ch2006_k	-	-	-	427039	9615039	1596
2006	Chawia	ch2006_l	-	-	-	427112	9614885	1602
2006	Chawia	ch2006_m	-	-	-	427163	9614768	1596
2006	Chawia	ch2006_n	-	-	-	427276	9614749	1582
2006	Chawia	ch2006_o	-	-	-	427365	9614596	1591
2006	Chawia	ch2006_p	-	-	-	427451	9614572	1573
2004	Ngangao	ng2004_1_1	1070001	1	1	426756	9627738	-
2004	Ngangao	ng2004_2_1	1070002	2	1	426731	9628229	-
2004	Ngangao	ng2004_3_1	1070003	3	1	426562	9628759	-
2004	Ngangao	ng2004_4_1	1070004	4	1	426418	9629509	1843
2004	Ngangao	ng2004_5_1	1070005	5	1	427099	9629206	-
2004	Ngangao	ng2004_6_1	1070006	6	1	426926	9627755	-
2004	Ngangao	ng2004_7_1	1070007	7	1	426963	9627789	-
2004	Ngangao	ng2004_8_x	1070008	8	?	426993	9628754	-
2004	Ngangao	ng2004_9_1	1070009	9	1	426952	9629256	-
2004	Ngangao	ng2004_10_1	1070010	10	1	426924	9629500	1805
2004	Ngangao	ng2004_11_1	1070011	11	1	427172	9627804	-
2004	Ngangao	ng2004_a	-	-	-	426932	9628268	1809
2004	Ngangao	ng2004_b	-	-	-	426347	9629524	-
2004	Ngangao	ng2004_c	-	-	-	427358	9629230	1745
2004	Ngangao	ng2004_d	-	-	-	427223	9629252	1761
2004	Ngangao	ng2004_e	-	-	-	426475	9629523	-
2004	Ngangao	ng2004_f	-	-	-	426599	9629516	1789
2004	Ngangao	ng2004_g	-	-	-	426730	9629521	-
2004	Ngangao	ng2004_h	-	-	-	426710	9629308	-
2005	Ngangao	ng2005_1_2	1070001	1	2	426745	9627812	1824
2005	Ngangao	ng2005_2_2	1070002	2	2	426750	9628289	1924
2005	Ngangao	ng2005_3_2	1070003	3	2	426593	9628799	1932
2005	Ngangao	ng2005_5_2	1070005	5	2	427106	9629253	-
2005	Ngangao	ng2005_6_2	1070006	6	2	427963	9627828	1808
2005	Ngangao	ng2005_9_2	1070009	9	2	426950	9629300	1819
2005	Ngangao	ng2005_10_2	1070010	10	2	426921	9629508	1764
2005	Ngangao	ng2005_11_2	1070011	11	2	426973	9627695	1777
2006	Ngangao	ng2006_a	-	-	-	426630	9627817	1829
2006	Ngangao	ng2006_b	-	-	-	426710	9627898	1854
2006	Ngangao	ng2006_c	-	-	-	426730	9627933	1850
2006	Ngangao	ng2006_d	-	-	-	426843	9627995	1843
2006	Ngangao	ng2006_e	-	-	-	426905	9628050	1860
2006	Ngangao	ng2006_f	-	-	-	427033	9620086	1861
2006	Ngangao	ng2006_g	-	-	-	427033	9620086	1861
2006	Ngangao	ng2006_h	-	-	-	427160	9628094	1859
2006	Ngangao	ng2006_i	-	-	-	426296	9629610	1780
2006	Ngangao	ng2006_j	-	-	-	426317	9629568	1837
2006	Ngangao	ng2006_k	-	-	-	426410	9629523	1861
2006	Ngangao	ng2006_l	-	-	-	426494	9629468	1873
2006	Ngangao	ng2006_m	-	-	-	426427	9629483	1874
2006	Ngangao	ng2006_n	-	-	-	426554	9629435	1866
2006	Ngangao	ng2006_o	-	-	-	426626	9629349	1833
2006	Ngangao	ng2006_p	-	-	-	426705	9629309	1830
2006	Ngangao	ng2006_q	-	-	-	426831	9629230	1815

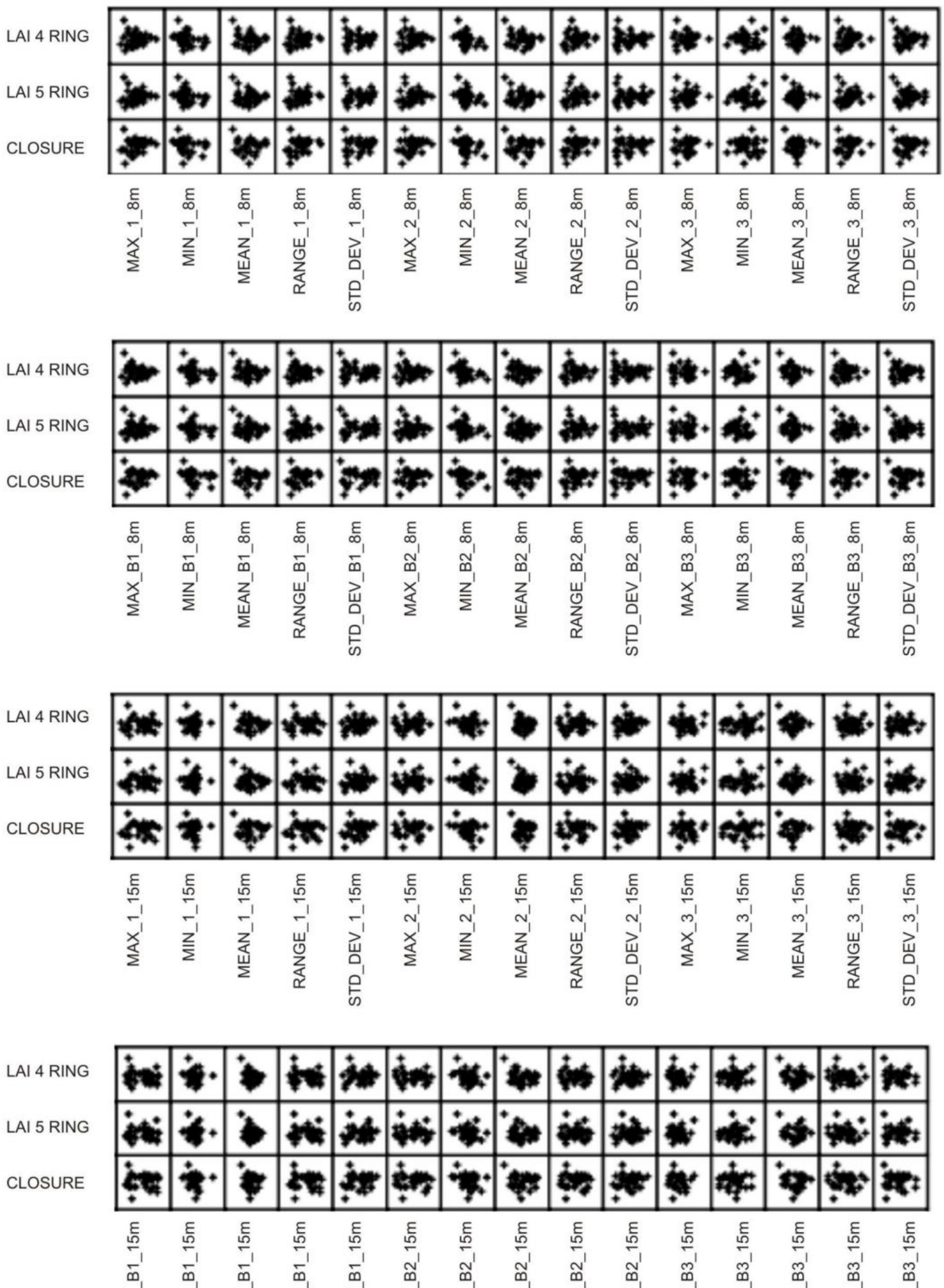


Appendix 2. Scatterplots for canopy parameters against textural parameters for dataset Ngangao and Chawia 2004–2006. The numbers 1, 2 and 3 refer to spectral bands 1, 2 and 3, respectively. B refers to BRDF corrected mosaic and 8m and 15m to diameters of the polygons used.

Appendix 3

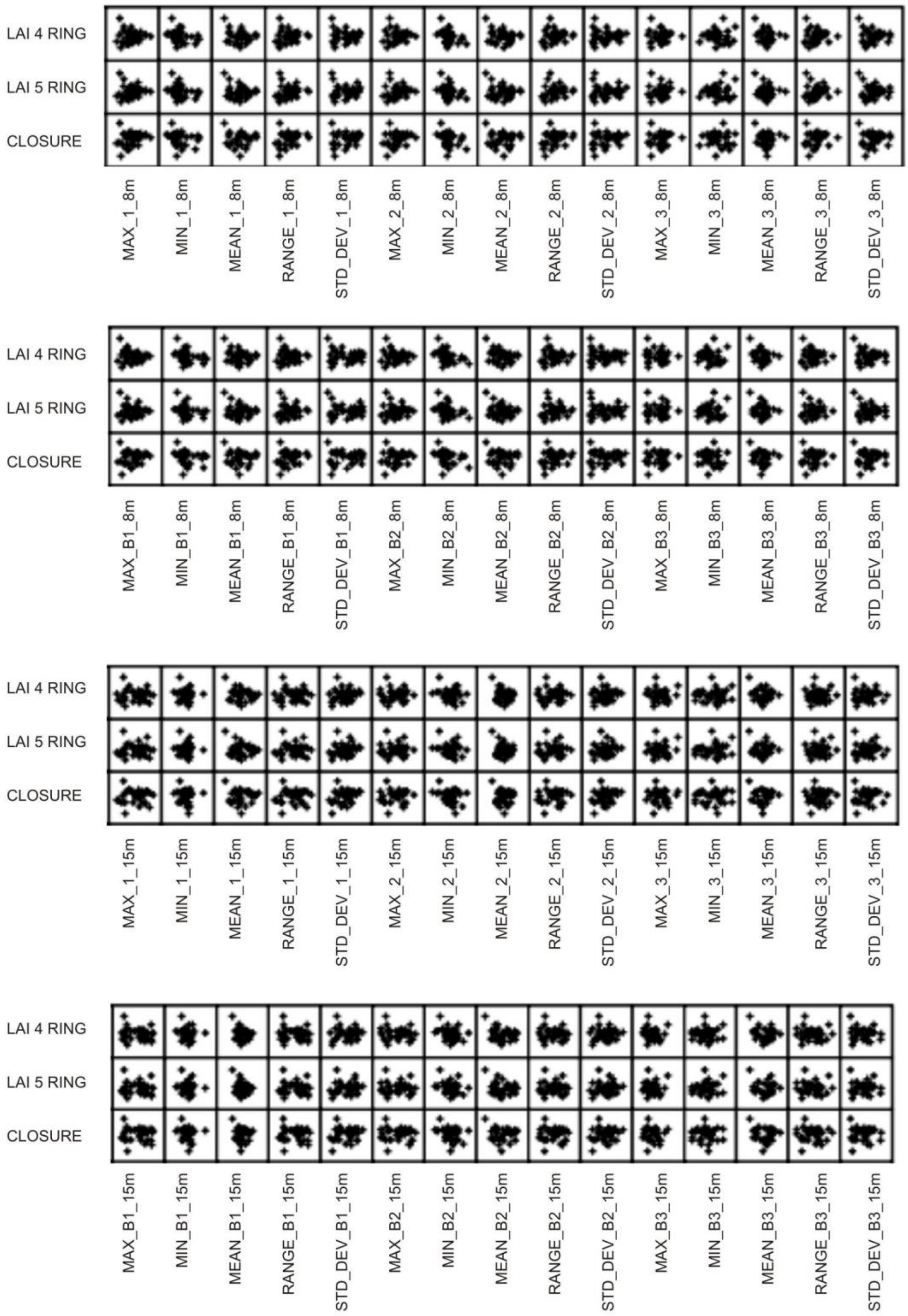


Appendix 3. Scatterplots for canopy parameters against textural parameters for dataset Ngangao 2004–2006. The numbers 1, 2 and 3 refer to spectral bands 1, 2 and 3, respectively. B refers to BRDF corrected mosaic and 8m and 15m to diameters of the polygons used.

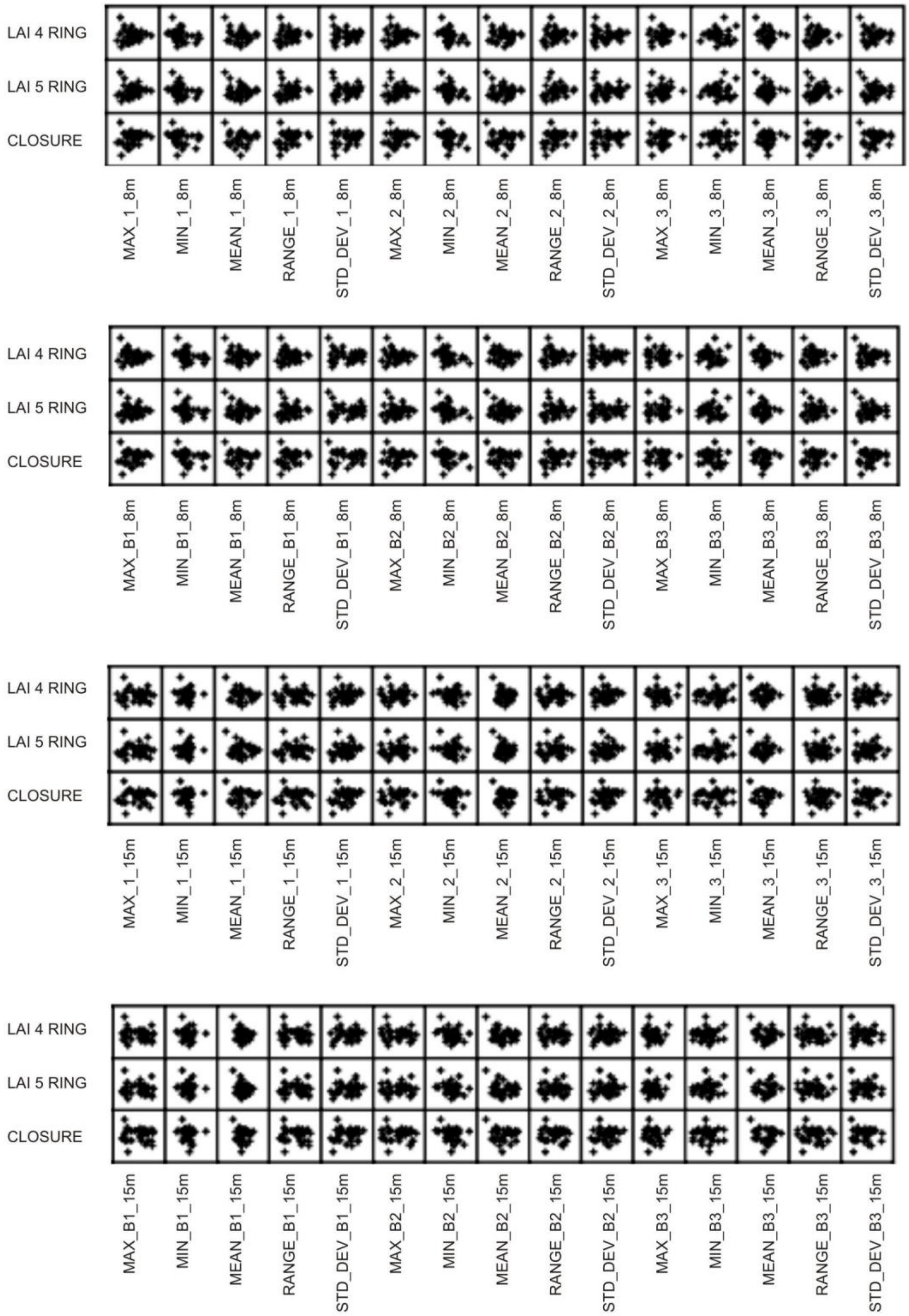


Appendix 4. Scatterplots for canopy parameters against textural parameters for dataset Chawia 2004–2006. The numbers 1, 2 and 3 refer to spectral bands 1, 2 and 3, respectively. B refers to BRDF corrected mosaic and 8m and 15m to diameters of the polygons used.

Appendix 5

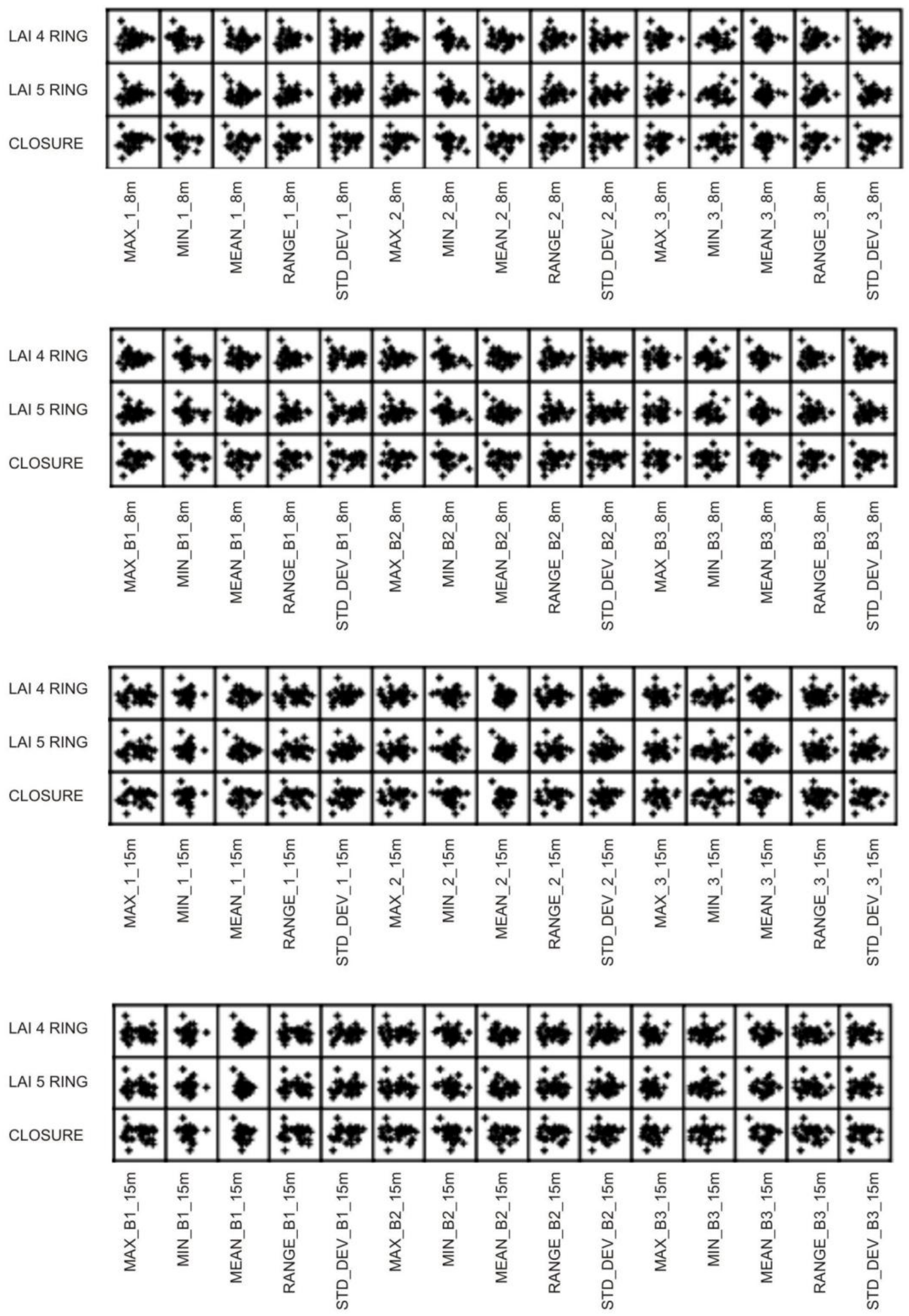


Appendix 5. Scatterplots for canopy parameters against textural parameters for dataset Ngangao and Chawia 2004. The numbers 1, 2 and 3 refer to spectral bands 1, 2 and 3, respectively. B refers to BRDF corrected mosaic and 8m and 15m to diameters of the polygons used.



Appendix 6. Scatterplots for canopy parameters against textural parameters for dataset Ngangao 2004. The numbers 1, 2 and 3 refer to spectral bands 1, 2 and 3, respectively. B refers to BRDF corrected mosaic and 8m and 15m to diameters of the polygons used.

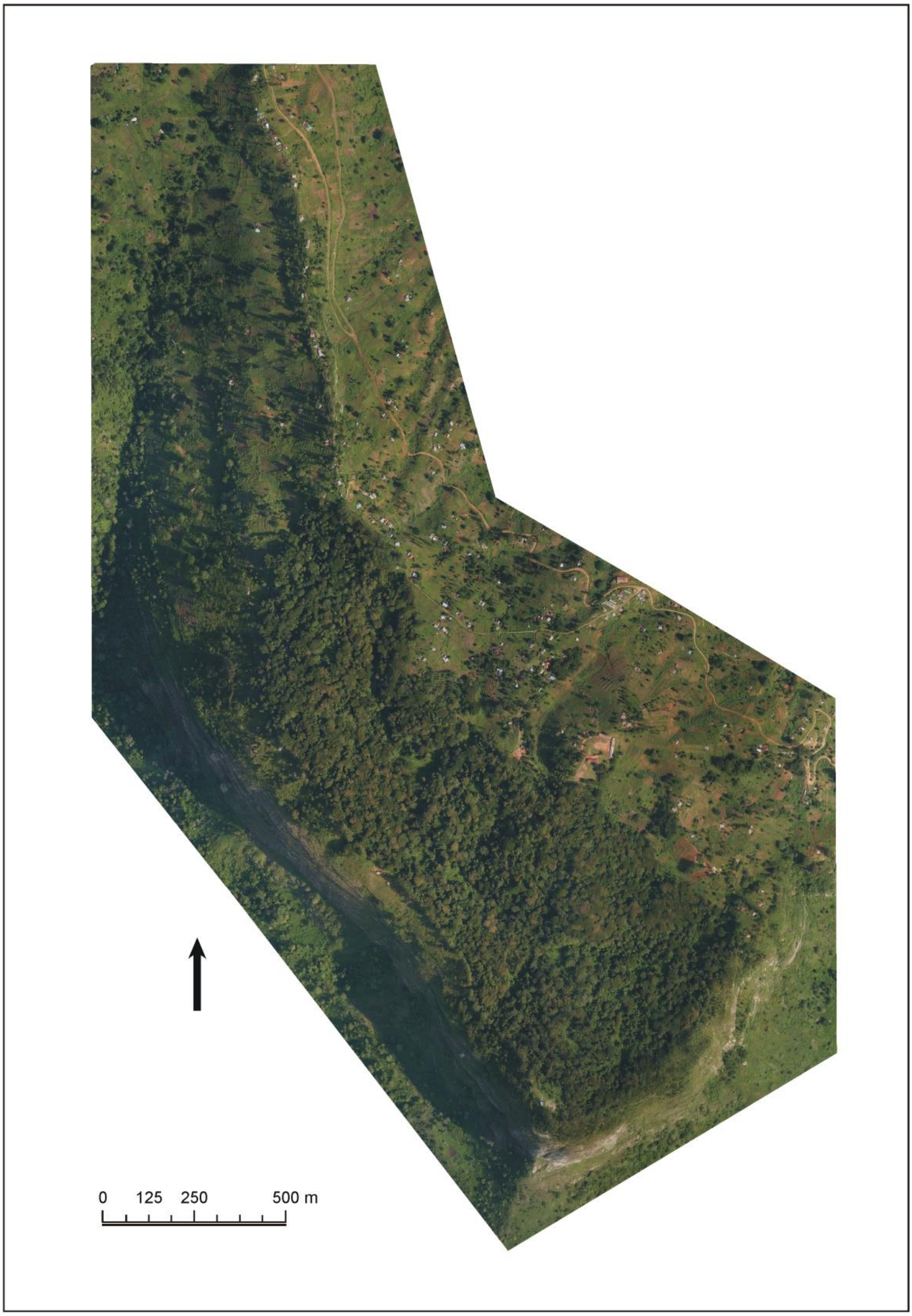
Appendix 7



Appendix 7. Scatterplots for canopy parameters against textural parameters for dataset Chawia 2004. The numbers 1, 2 and 3 refer to spectral bands 1, 2 and 3, respectively. B refers to BRDF corrected mosaic and 8m and 15m to diameters of the polygons used.

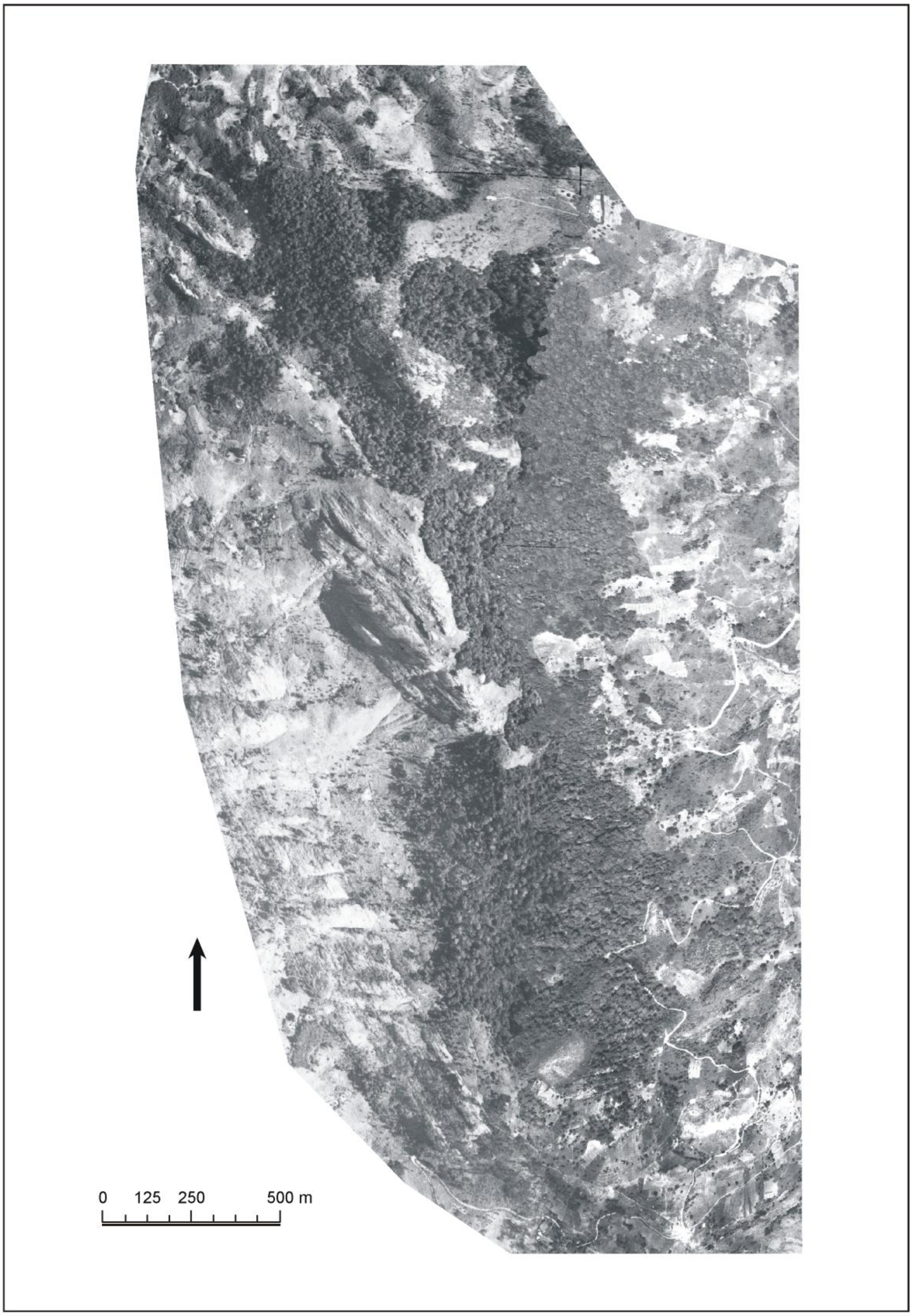
Appendix 8. The digital aerial mosaic subset of Ngangao in 2004.

Appendix 9

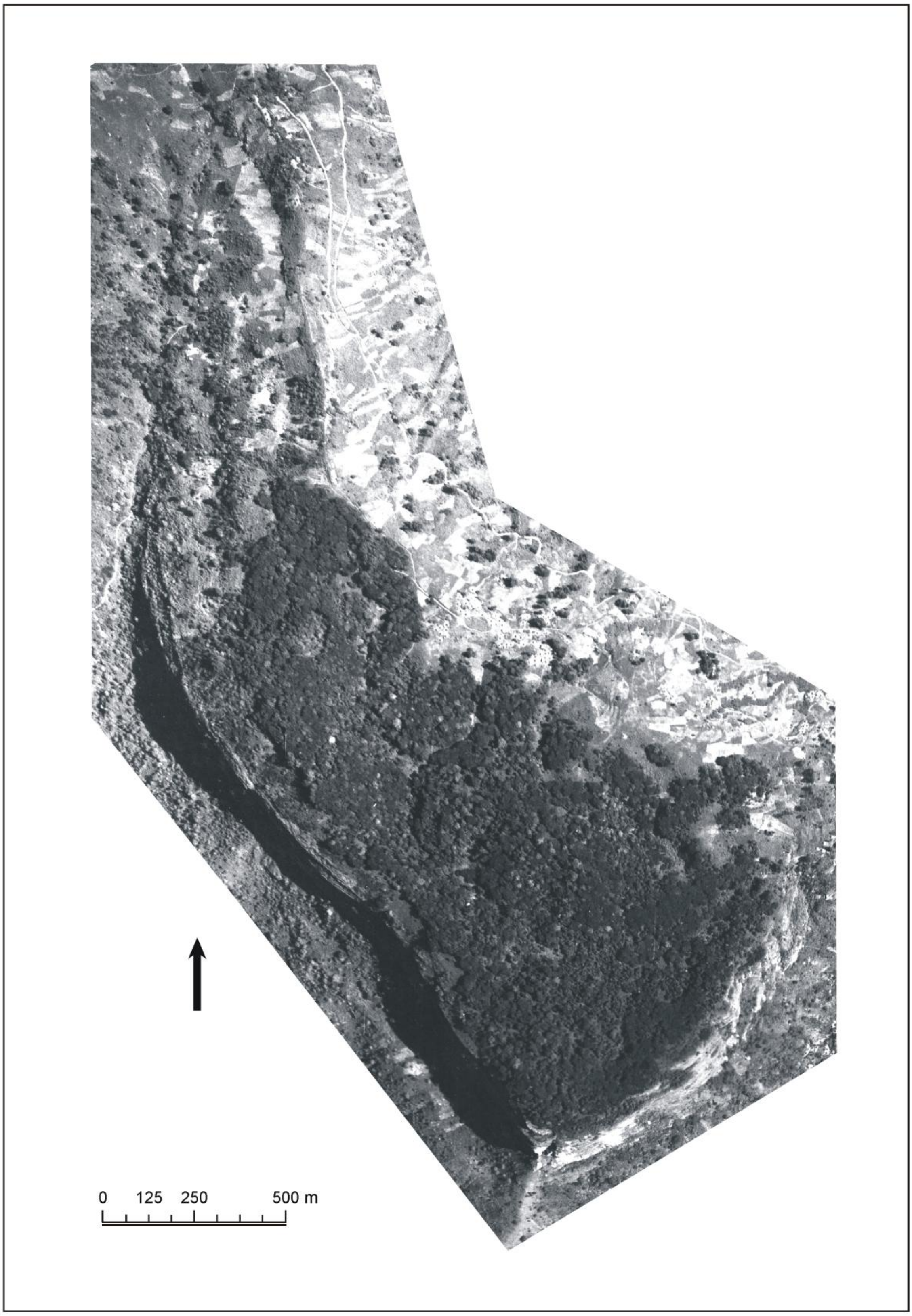


Appendix 9. The digital aerial mosaic subset of Chawia in 2004.

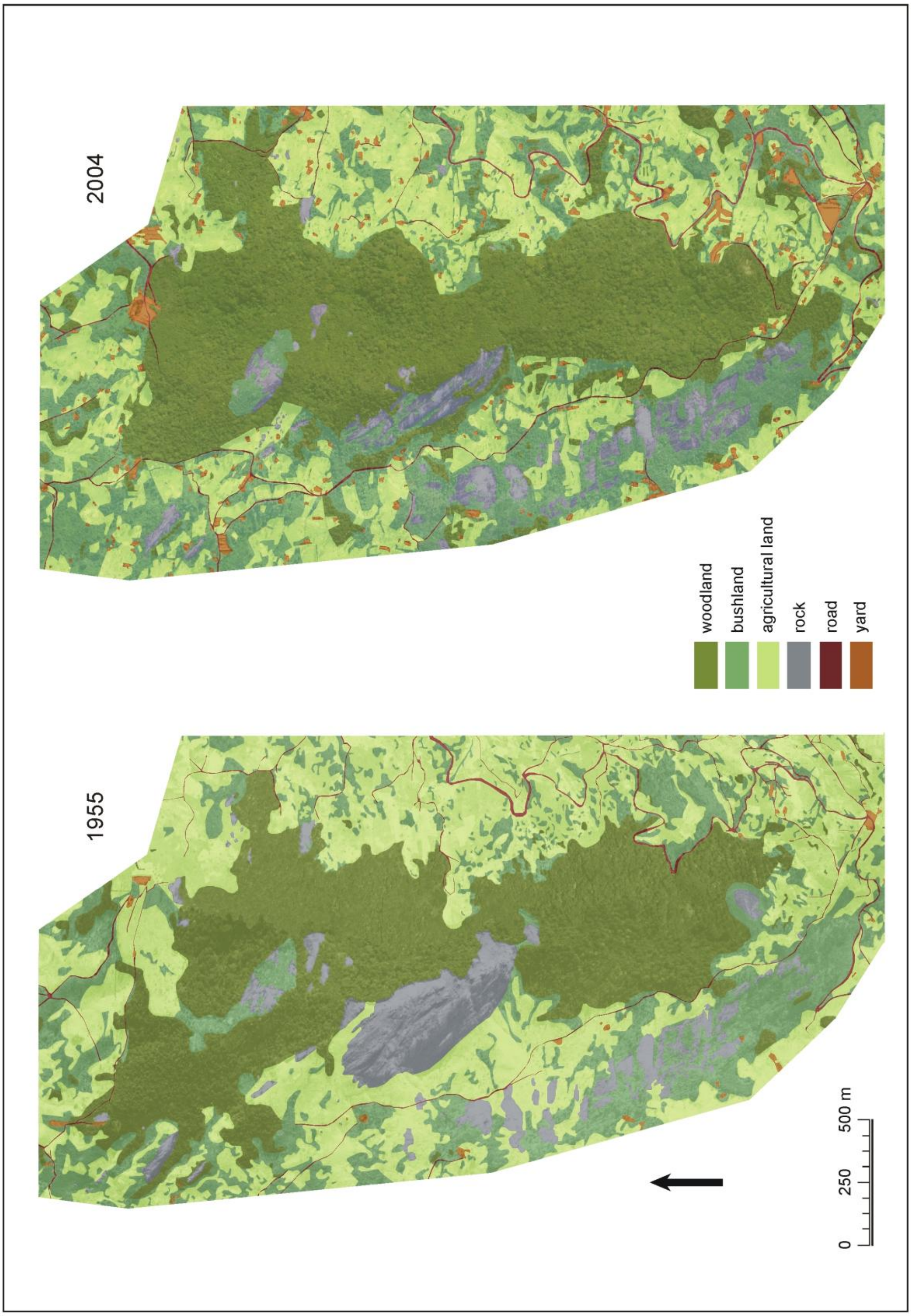
Appendix 10



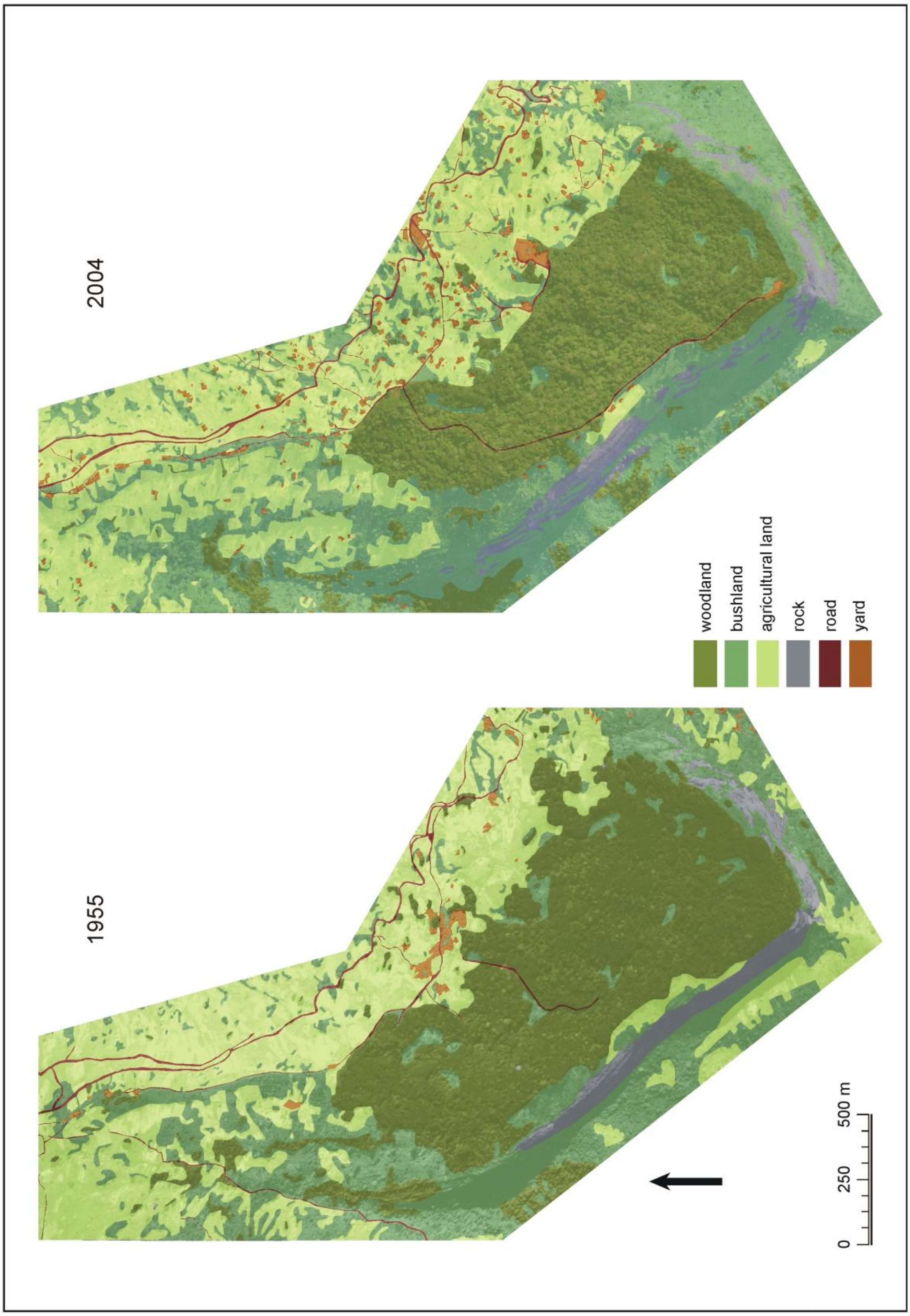
Appendix 10. The aerial mosaic subset of Ngangao in 1955.



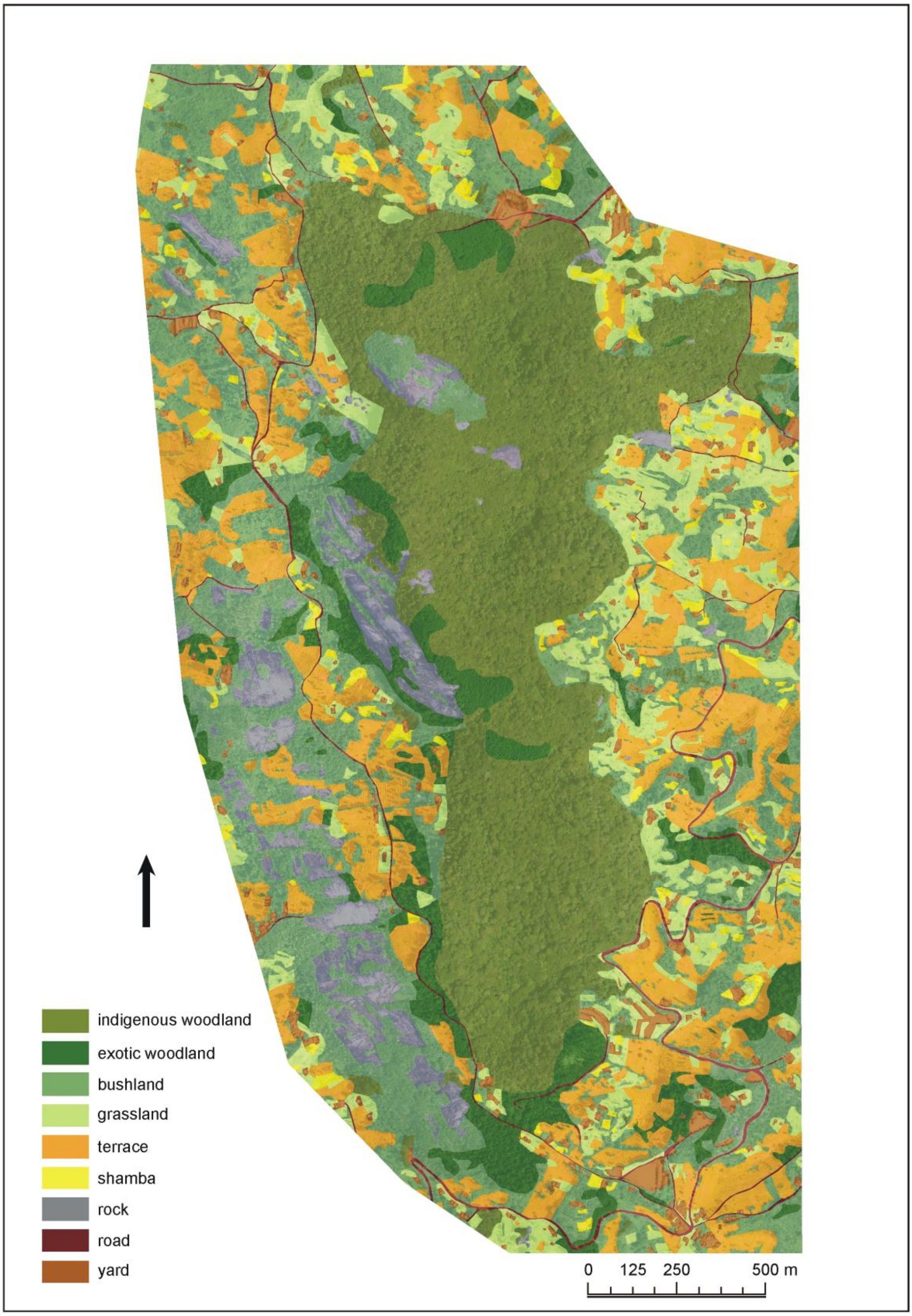
Appendix 11. The aerial photograph subset of Chawia in 1955.



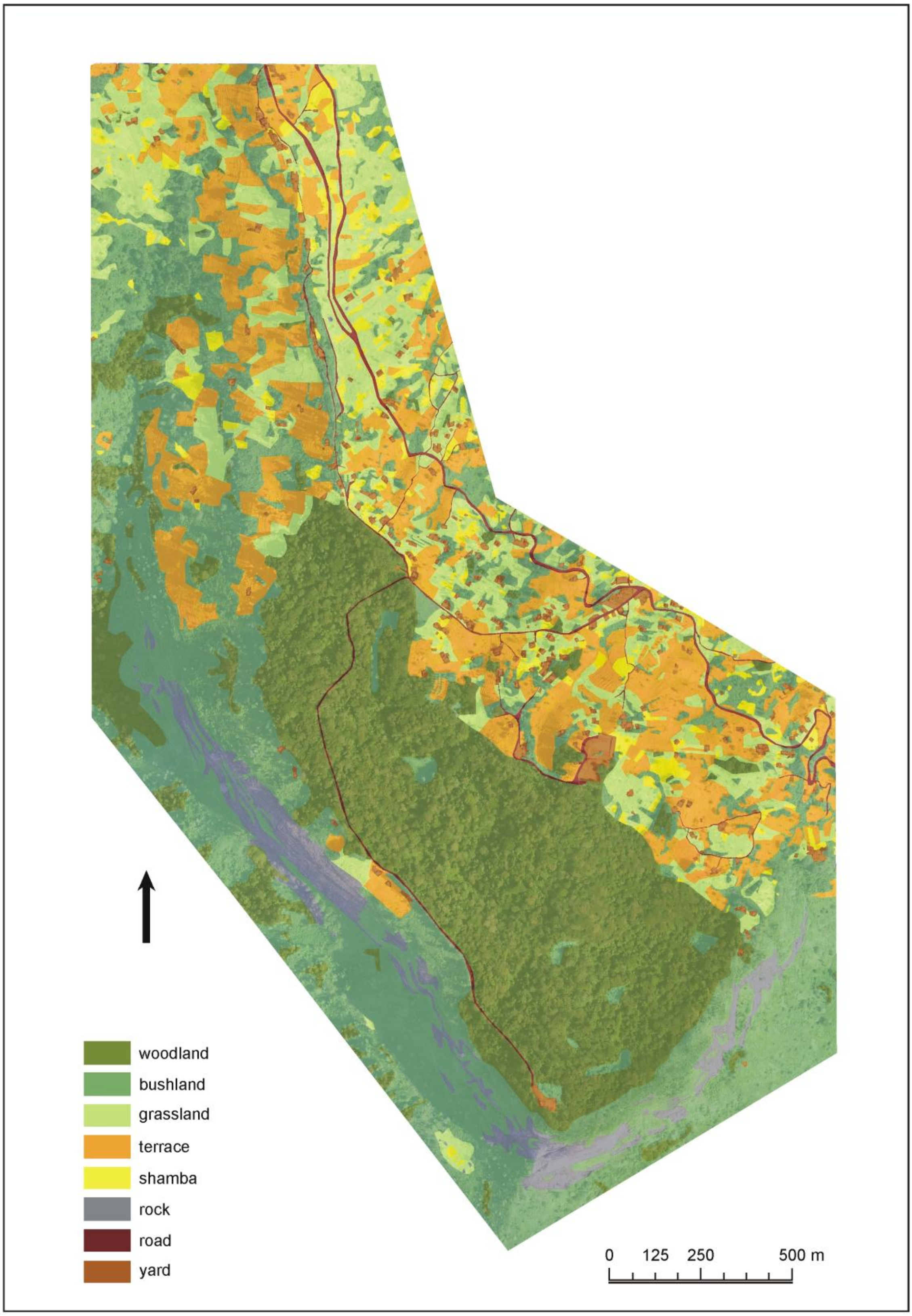
Appendix 12. The 1955 and 2004 visual classifications of Ngangao with comparable land cover classes.



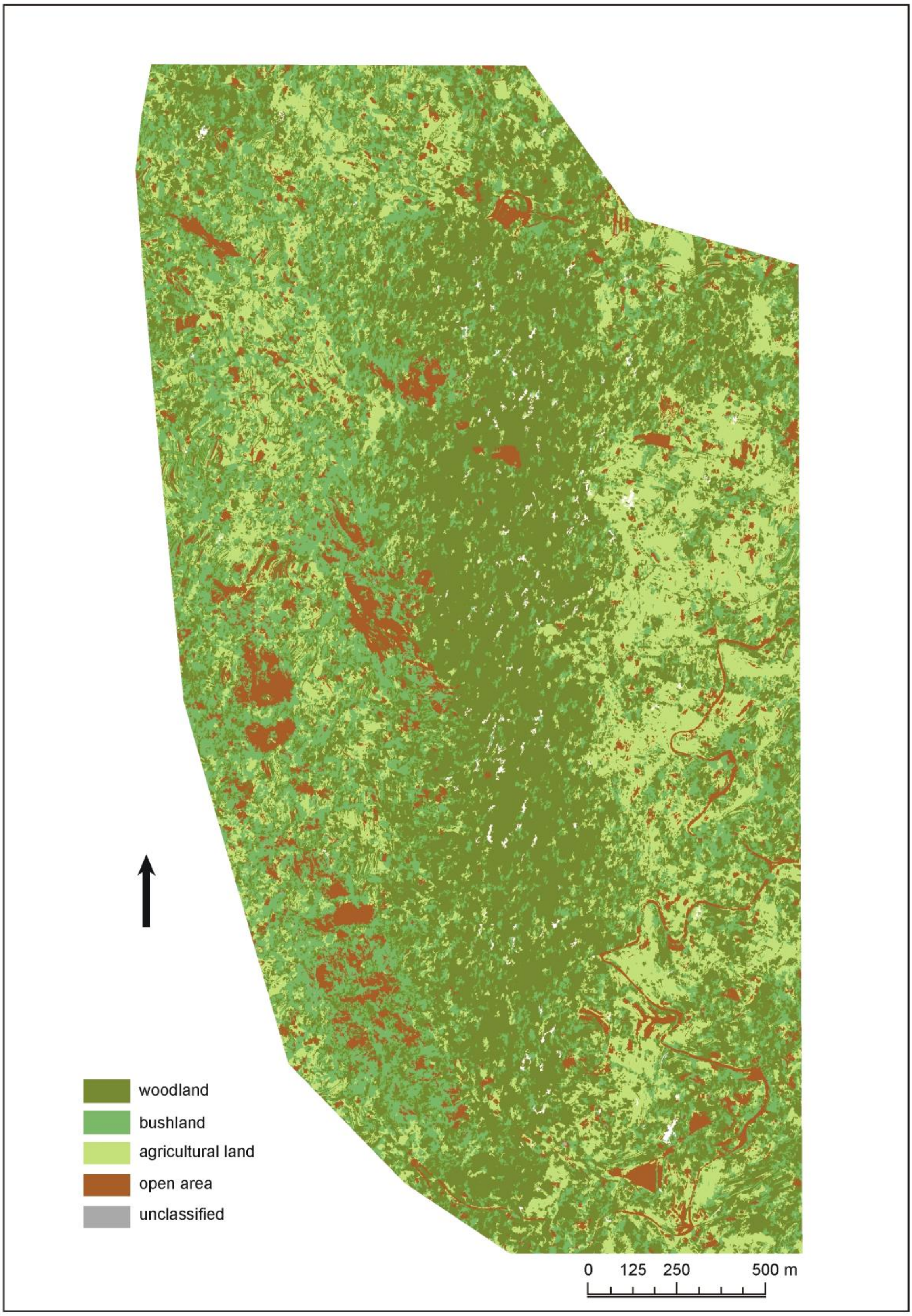
Appendix 13. The 1955 and 2004 visual classifications of Chawia with comparable land cover classes.



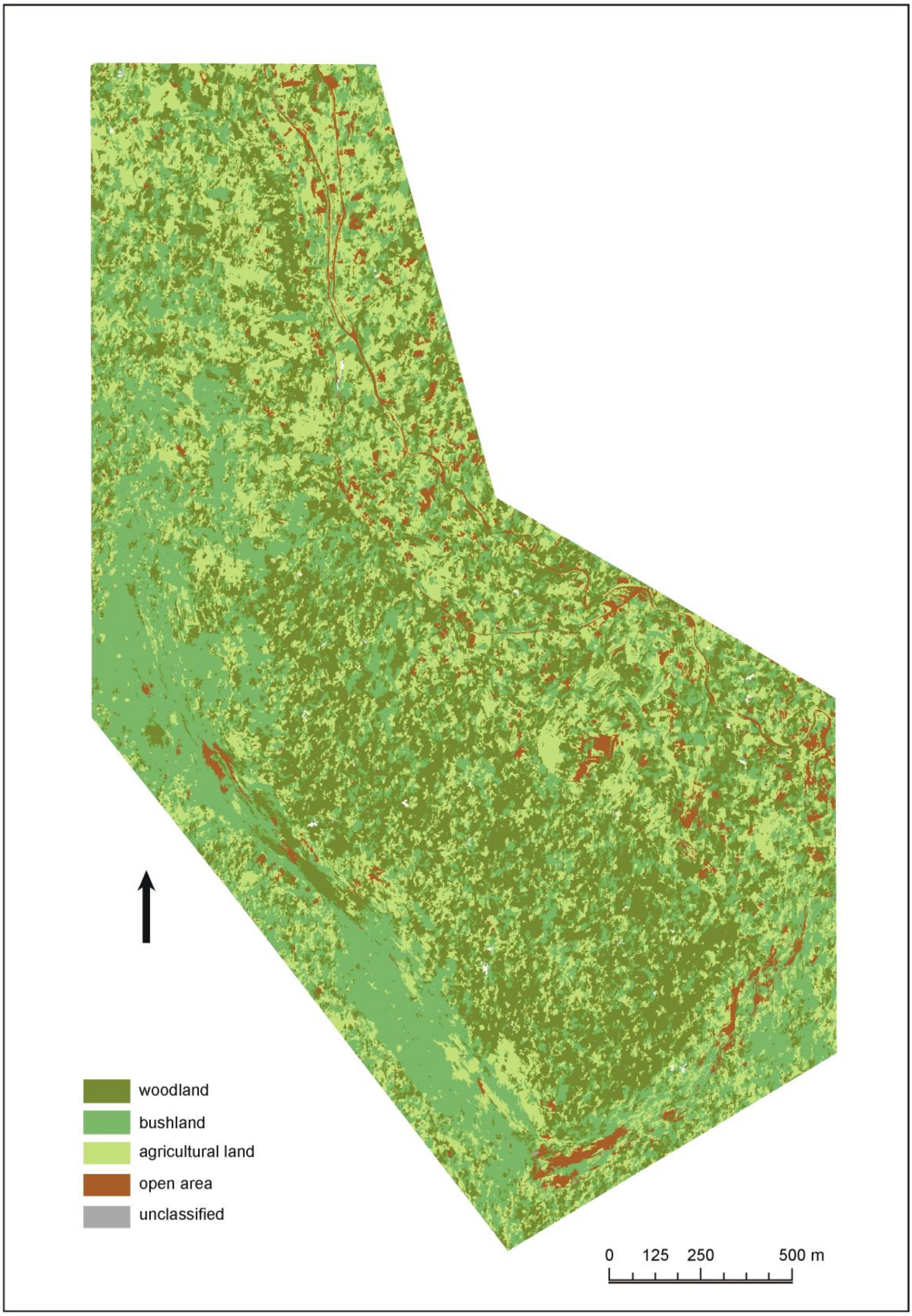
Appendix. 14. The 2004 visual classification of Ngangao.



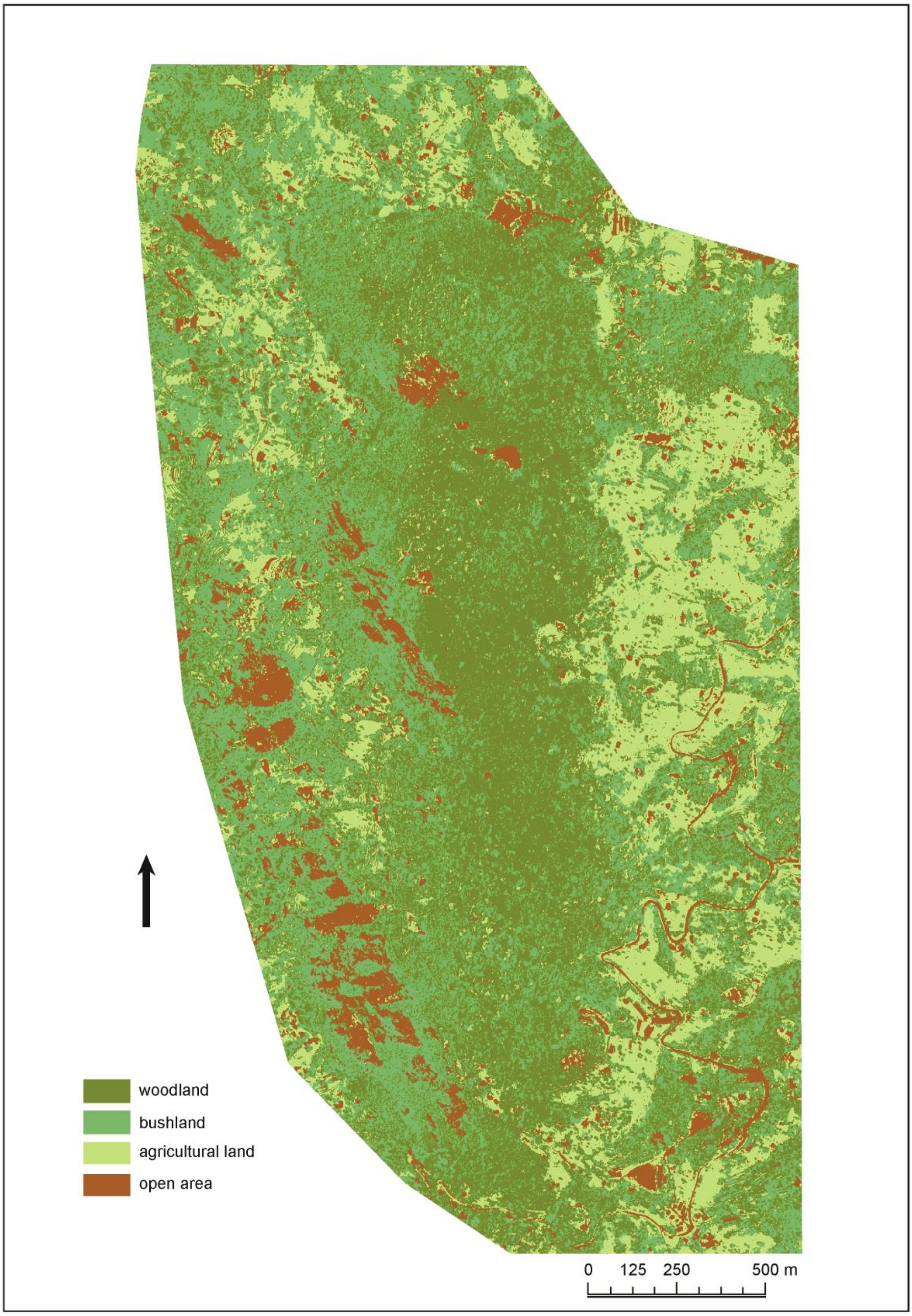
Appendix. 15. The 2004 visual classification of Chawia.



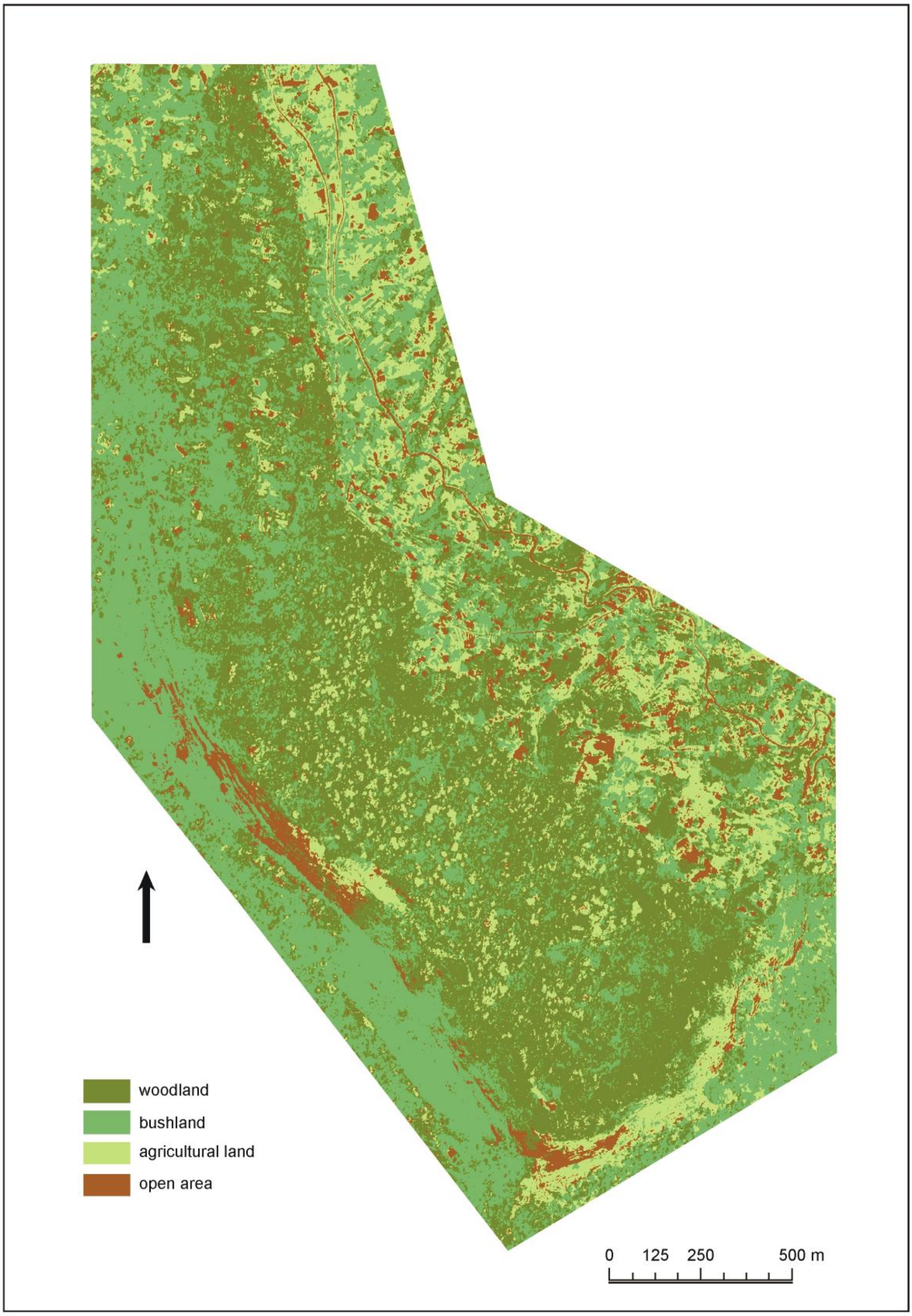
Appendix 16. The 2004 object-oriented supervised classification of Ngangao.



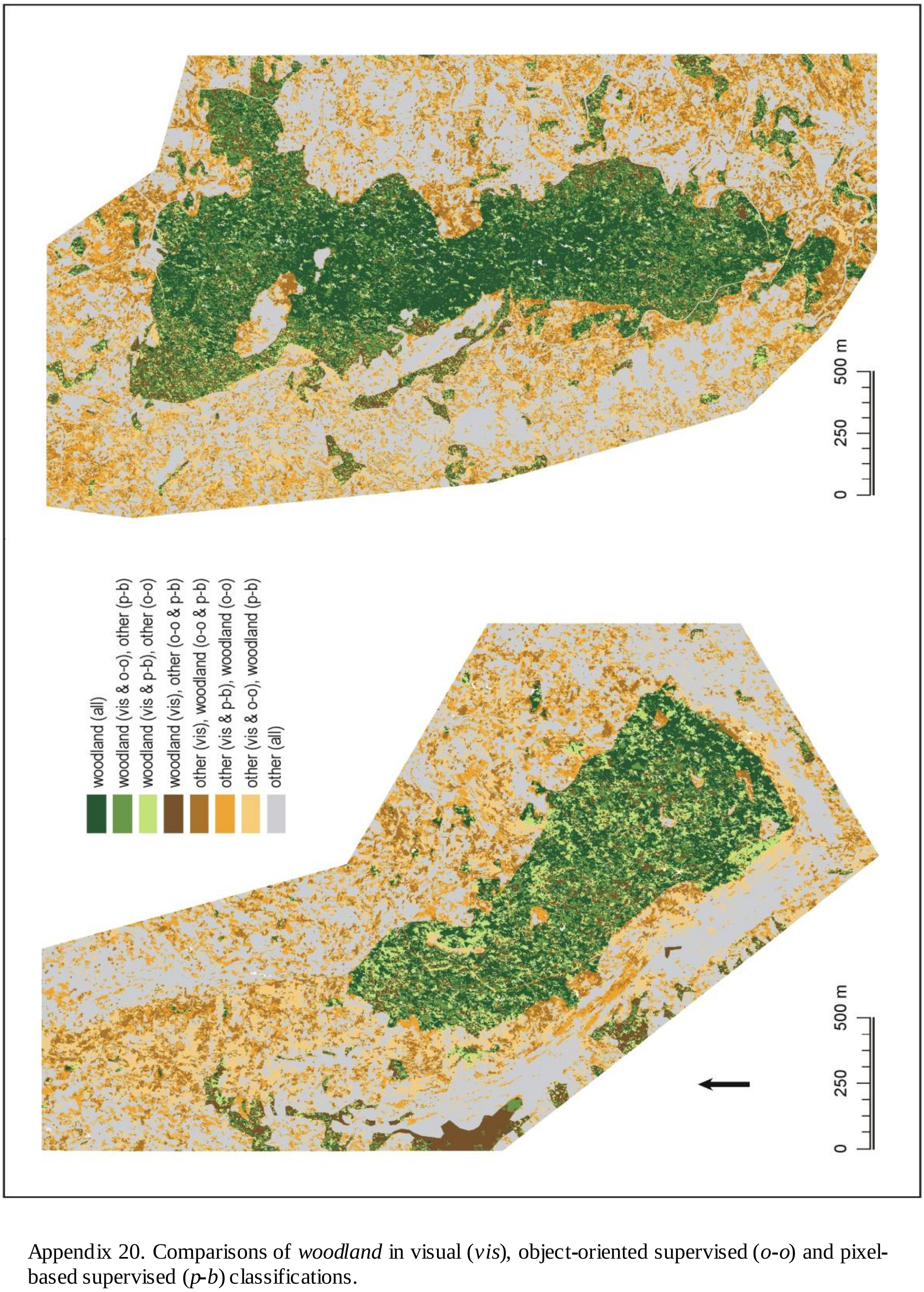
Appendix 17. The 2004 object-oriented supervised classification of Chawia.



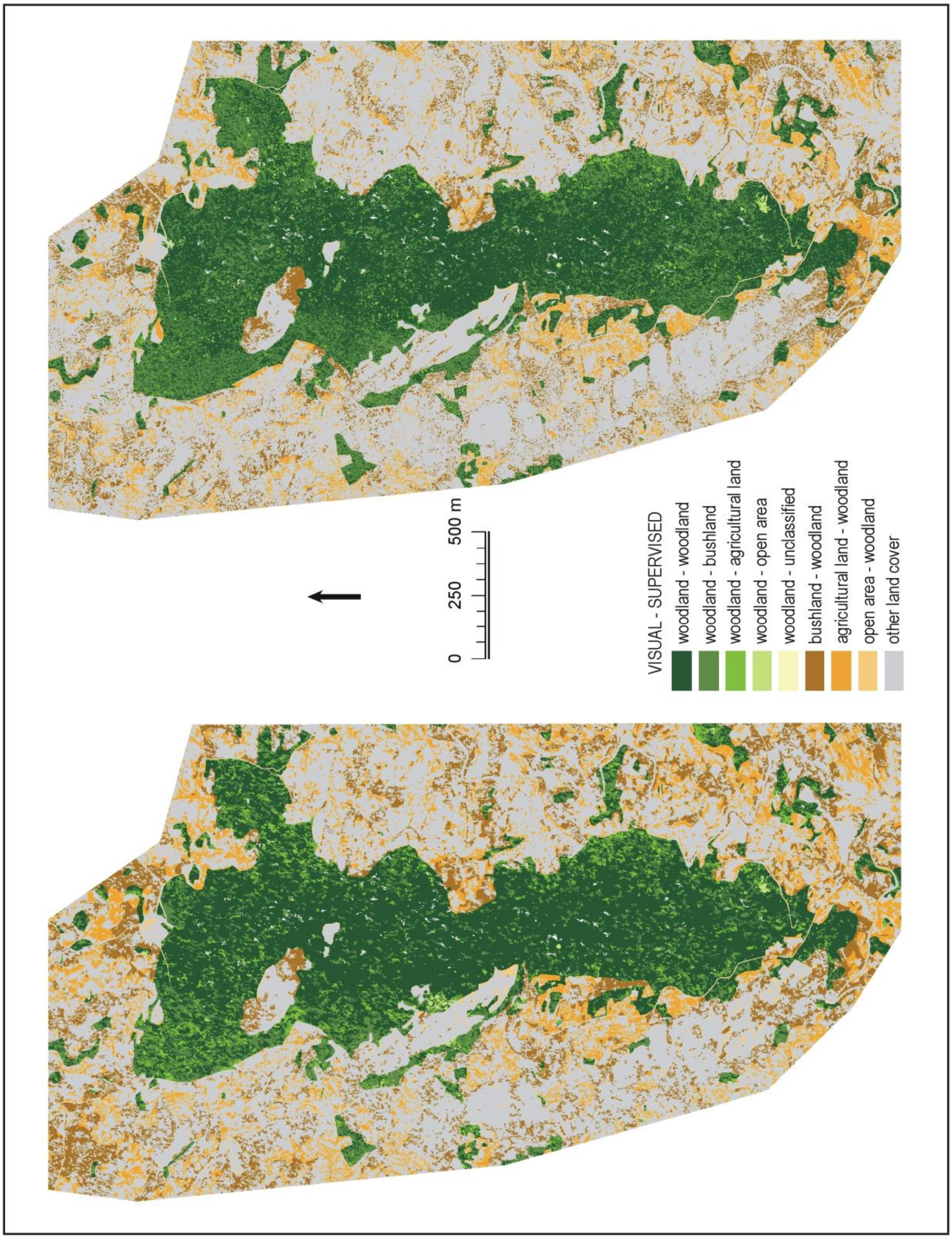
Appendix 18. The 2004 pixel-based supervised classification of Ngangao.



Appendix 19. The 2004 pixel-based supervised classification of Chawia.

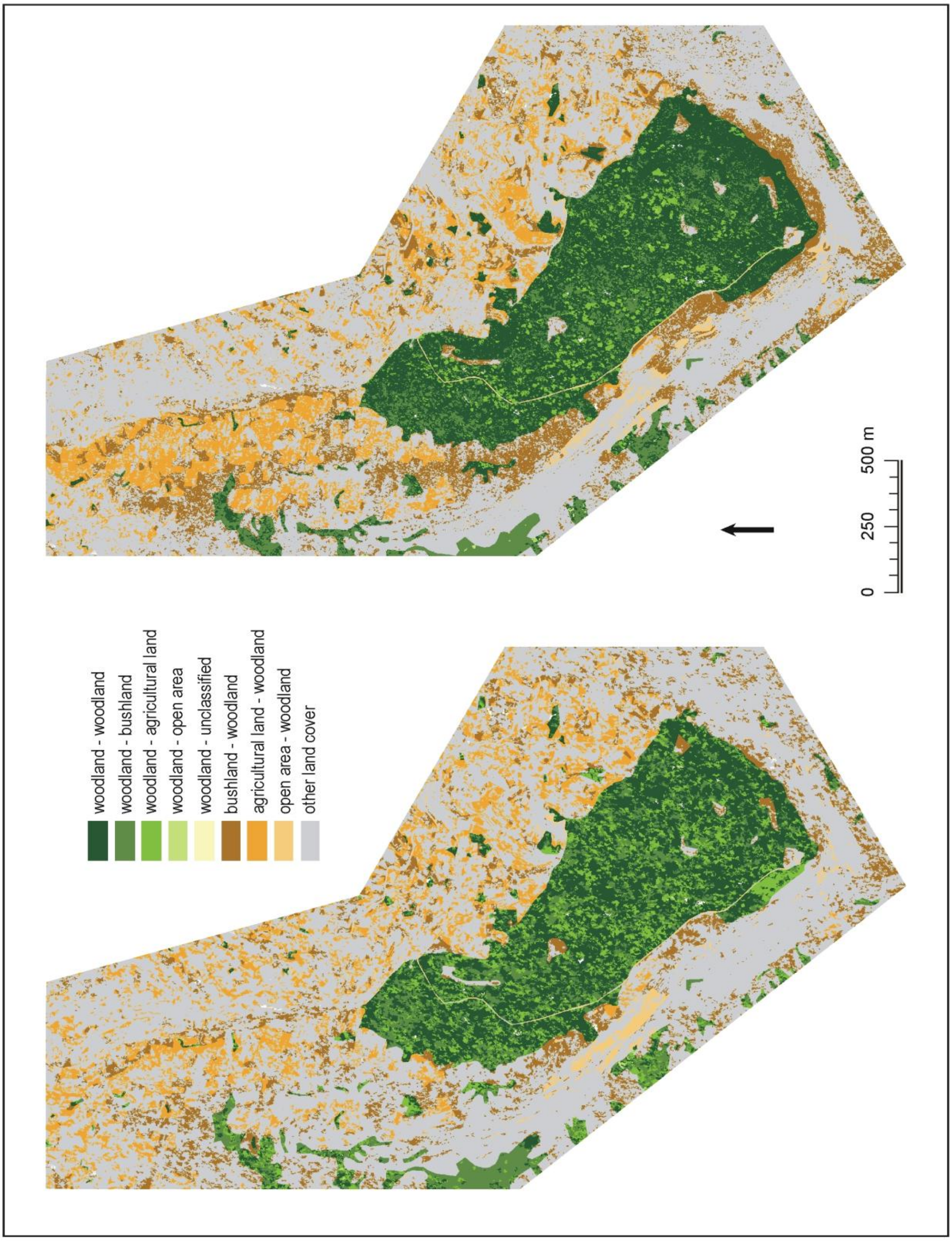


Appendix 20. Comparisons of *woodland* in visual (*vis*), object-oriented supervised (*o-o*) and pixel-based supervised (*p-b*) classifications.

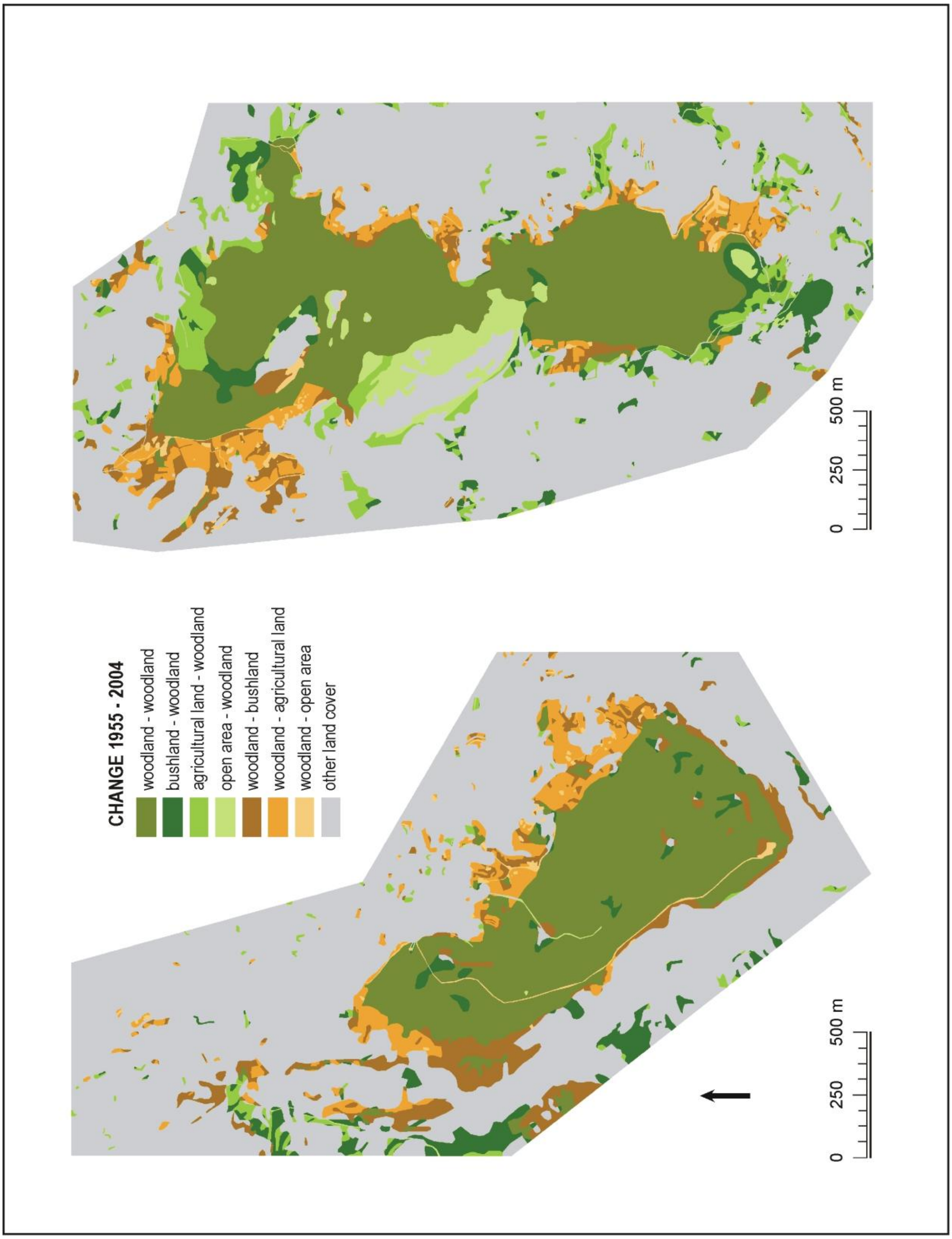


Appendix 21. The object-oriented supervised classification (on the left) and the pixel-based supervised classification (on the right) compared to the visual classification in Ngangao.

Appendix 22



Appendix 22. The object-oriented supervised classification (on the left) and the pixel-based supervised classification (on the right) compared to the visual classification in Chawia.



Appendix 23. Change of woodland areas in Chawia (on the left) and Ngangao (on the right) between 1955 and 2004.

Appendix 24. The ordinary error matrices of the supervised classifications in Ngangao and Chawia.

Table 1. Error matrix of object-oriented supervised classification in Ngangao.

	Reference data					**Producer's**	**User's**
	Woodland	Bushland	Agricultural land	Open area	Totals	**accuracy %**	**accuracy %**
Woodland	43	18	15	0	76	58,90 %	56,58 %
Bushland	20	23	14	6	63	37,70 %	36,51 %
Agricultural land	8	11	39	3	61	48,15 %	63,93 %
Open area	2	9	13	26	50	74,29 %	52,00 %
Totals	73	61	81	35	250		
Overall accuracy: 52.40%							

Table 2. Error matrix of pixel-based supervised classification in Ngangao.

	Reference data					**Producer's**	**User's**
	Woodland	Bushland	Agricultural land	Open area	Totals	**accuracy %**	**accuracy %**
Woodland	49	17	5	0	71	69.01 %	69.01 %
Bushland	19	36	15	0	70	63.16 %	51.43 %
Agricultural land	2	3	50	4	59	65.79 %	84.75 %
Open area	1	1	6	42	50	91.30 %	84.00 %
Totals	71	57	76	46	250		
Overall accuracy: 70.80%							

Table 3. Error matrix of object-oriented supervised classification in Chawia.

	Reference data					**Producer's**	**User's**
	Woodland	Bushland	Agricultural land	Open area	Totals	**accuracy %**	**accuracy %**
Woodland	33	20	15	0	68	60.00 %	48.53 %
Bushland	7	37	20	4	68	46.84 %	54.41 %
Agricultural land	14	19	26	5	64	38.81 %	40.63 %
Open area	1	3	6	40	50	81.63 %	80.00 %
Totals	55	79	67	49	250		
Overall accuracy: 54.40%							

Table 4. Error matrix of pixel-based supervised classification in Chawia.

	Reference data					**Producer's**	**User's**
	Woodland	Bushland	Agricultural land	Open area	Totals	**accuracy %**	**accuracy %**
Woodland	35	25	13	0	73	68.63 %	47.95 %
Bushland	7	37	24	2	70	53.62 %	52.86 %
Agricultural land	9	5	30	13	57	36.59 %	52.63 %
Open area	0	2	15	33	50	68.75 %	66.00 %
Totals	51	69	82	48	250		
Overall accuracy: 54.00%							

Appendix 25. The normalised error matrices of the supervised classifications in Ngangao and Chawia.

Table 1. Normalised error matrix of object-oriented supervised classification in Ngangao.

	Reference data				
	Woodland	Bushland	Agricultural land	Open area	Totals
Woodland	0.56	0.28	0.16	0.00	1
Bushland	0.28	0.38	0.16	0.18	1
Agricultural land	0.13	0.22	0.54	0.11	1
Open area	0.03	0.13	0.14	0.71	1
Totals	1	1	1	1	4
Overall accuracy (normalised): 54.67%					

Table 2. Normalised error matrix of pixel-based supervised classification in Ngangao.

	Reference data				
	Woodland	Bushland	Agricultural land	Open area	Totals
Woodland	0.67	0.28	0.04	0.00	1
Bushland	0.26	0.61	0.13	0.00	1
Agricultural land	0.05	0.09	0.76	0.11	1
Open area	0.02	0.02	0.07	0.89	1
Totals	1	1	1	1	4
Overall accuracy (normalised): 73.08%					

Table 3. Normalised error matrix of object-oriented supervised classification in Chawia.

	Reference data				
	Woodland	Bushland	Agricultural land	Open area	Totals
Woodland	0.57	0.23	0.20	0.00	1
Bushland	0.14	0.48	0.30	0.07	1
Agricultural land	0.27	0.24	0.39	0.09	1
Open area	0.02	0.04	0.10	0.84	1
Totals	1	1	1	1	4
Overall accuracy (normalised): 56.93%					

Table 4. Normalised error matrix of pixel-based supervised classification in Chawia.

	Reference data				
	Woodland	Bushland	Agricultural land	Open area	Totals
Woodland	0.60	0.30	0.11	0.00	1
Bushland	0.15	0.56	0.26	0.03	1
Agricultural land	0.25	0.10	0.40	0.25	1
Open area	0.00	0.04	0.23	0.72	1
Totals	1	1	1	1	4
Overall accuracy (normalised): 57.16%					