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Assessing processes of long-term land cover change and modelling their effects on tropical forest biodiversity patterns – a remote sensing and GIS-based approach for three landscapes in East Africa

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Erklärung des Promovenden

Die Übereinstimmung dieses Exemplars mit dem Original der Dissertation zum Thema:

„ Assessing processes of long-term land cover change and modelling their effects on tropical forest biodiversity patterns – a remote sensing and GIS-based approach for three landscapes in East Africa “

wird hiermit bestätigt.

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Preamble

This dissertation constitutes an integrative part of the research activities within the BIOTA East Africa project, funded by the German Ministry of Education and Research (BMBF). Three main parts of the thesis (Chapters 2 to 4) were prepared as stand-alone manuscripts and published in international peer-reviewed journals. The stand-alone manuscripts were written originally by the author of this thesis and subsequently revised by the co-author(s) and reviewers of the respective journal. The historical land cover data of 1965/67, 1948/(52) and 1912/13 as presented in Chapter 4 were made available by Nick Mitchell while the biological field data were provided by the co-authors and project colleagues Jun.-Prof. Dr. Nina Farwig and Dr. Marcell K. Peters. In close co-operation with the author of this thesis, M.K. Peters also conducted the statistical part of the analysis as described in Section 4.3 whereas the classification of field data on birds into groups of bird habitat guilds was done by N. Farwig. As each of the manuscripts follows the standard structure for a scientific publication (introduction, material and methods, results, discussion and conclusion), some limited material is recurring throughout the thesis. The contents of the pre-published articles have remained unchanged in this thesis and were published as follows:

Chapter 2: Lung, T. and Schaab, G. (2006). Assessing fragmentation and disturbance of west Kenyan rainforests by means of remotely sensed time series data and landscape metrics. *African Journal of Ecology*, 44(4), 491–506.

Chapter 3: Lung, T. and Schaab, G. (2010). A comparative assessment of land cover dynamics of three protected forest areas in tropical eastern Africa. *Environmental Monitoring and Assessment*, 161(1), 531–548.

Chapter 4: Lung, T., Peters, M.K., Farwig, N., Böhning-Gaese, K. and Schaab, G. (accepted). Combining long-term land-cover time series and field observations for spatially explicit predictions on changes in tropical forest biodiversity. *International Journal of Remote Sensing*.

Additional material presented in the appendices was published as follows:

Appendices A & B: Lung, T. and Schaab, G. (2008). Land cover change for Mabira Forest and Budongo Forest in Uganda - results of processing Landsat satellite imagery time series, 1972 to 2003. In: *Karlsruher Geowissenschaftliche Schriften,* D 9 (Ed. G. Schaab), Karlsruhe University of Applied Sciences, Karlsruhe, Germany.

Appendix C: Farwig, N., Lung, T., Schaab, G. and Böhning-Gaese, K. (submitted). Linking land use scenarios, remote sensing and monitoring to predict the impact of management decisions on bird diversity in a tropical forest. Biological Conservation.

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1. Introduction – tropical forest biodiversity and land change science

1.1 Background

Tropical forest biodiversity – value and threats

Already in the 18th and 19th century scientists began to realize the phenomenal diversity of plants and animals that tropical forests exhibit (Montagnini and Jordan, 2005). Among the terrestrial biomes of the earth, tropical and sub-tropical moist broadleaf forests stand out as reservoirs of exceptionally high biodiversity[1] with a total of around 20,000 amphibians, birds, mammals and reptiles and an endemism rate of approximately 40% (Millennium Ecosystem Assessment, 2005). The value of this immense biodiversity is not limited to ecological aspects but also includes economic and cultural components. Forest biodiversity plays a key role in underpinning ecosystem services that influence human well-being in a positive way, with direct and indirect links to be considered. The wide range of ecosystem services involves provisioning (e.g. wood, fibre, fuel), culture (e.g. recreation), support (e.g. water cycling, primary production) and regulation (e.g. climate regulation, seed dispersal, erosion regulation) (Millennium Ecosystem Assessment, 2005). However, tropical forests and their biodiversity are highly affected and threatened by global processes of habitat destruction (conversion) and alteration. Biodiversity loss is considered to be one of the few processes of global environmental change that are truly irreversible and one third of the existing species could disappear with the destruction of all tropical rainforests (Dirzo and Raven, 2003). While less than 50% of the potential global tropical forest cover still exists (Wright, 2005), deforestation[2] rates in Africa between 1990 and 2005 have been three times higher than the world average. In particular, eastern Africa has been identified as a hotspot of forest destruction with change rates from the last two decades almost five times higher compared to the global average (FAO, 2009). Given the high concentration of endangered species in tropical forests, a continued deforestation and fragmentation is expected to cause a tremendously high rate of extinctions (Chhabra, 2006).

Habitat destruction and alteration has two components almost always occurring in tandem, (a) the reduction of area covered by a certain habitat type and (b) a change in habitat configuration with the remaining habitat apportioned into smaller and more isolated patches, commonly referred to as habitat fragmentation (Noss et al., 2006). Both processes are triggered by a combination of proximate causes and underlying causal synergies among demographic, economic, institutional and socio-political factors. In tropical forest ecosystems, evidence indicates that the proximate causes of biodiversity loss are almost identical with those of deforestation (e.g. Van Laake and Sánchez-Azofeifa, 2004). Whereas other factors like climate change, invasive species or pollution are believed to play a minor role, habitat change coupled with overexploitation is considered the direct driver with strongest impact on biodiversity loss (Millennium Ecosystem Assessment, 2005). In sub-Saharan Africa, deforestation is mainly driven by

[1] "The sum total of all plants, animals, fungi, and micro organisms on earth; (…) and the communities and ecosystems of which they are a part" (Dirzo and Raven, 2003).

[2] "The conversion of forest to another land use or the long-term reduction of the tree canopy cover below the minimum 10 percent threshold", with forest being defined as an area of minimum 0.5 ha with trees of minimum 5 m height in situ (FAO, 2001).

an expansion of smallholder agriculture and wood extraction (both commercial and fuelwood for domestic usage), coupled with a range of interlinked underlying causes such as institutional weakness and low income growth (FAO, 2003; Lambin and Geist, 2003). In addition, deforestation processes are accelerated by a rapid population growth. For the future, population pressure on the remaining forest areas is likely to further increase as projections up to 2025 for eastern Africa reveal growth rates that are among the world's highest (UN-DESA, 2007).

The role of GIS and remote sensing

As the prime determinant of changes in tropical biodiversity, land use/cover changes have been studied for several decades in order to assess land resources, to analyse ongoing change trajectories and to identify hotspots of change. With the advent of remote sensing satellites in the 1970s and subsequent advances in remote sensing technology and in Geographical Information Systems (GIS), GI science has played a vital role in this context. Enhanced spatial, spectral and radiometric resolutions combined with progress in change detection techniques have increased the abilities for monitoring and mapping land use/cover of tropical forest ecosystems and for deriving other biodiversity-related information on e.g. landscape configuration or fragmentation (Boyd and Danson, 2005; Foody, 2008). However, up to the 1990s land use/cover has been mostly studied from a narrowed disciplinary perspective (Verburg et al., 2009). In the recent past, the need for interdisciplinary approaches uniting remote sensing/geographical information, human and environmental sciences to improve our understanding of the dynamics of land use/cover changes and its impacts and feedbacks on ecosystems and on humankind has lead to the emergence of an integrated land change science (Turner II et al., 2007). In regards to changes of (tropical) forest ecosystems, impacts on population dynamics

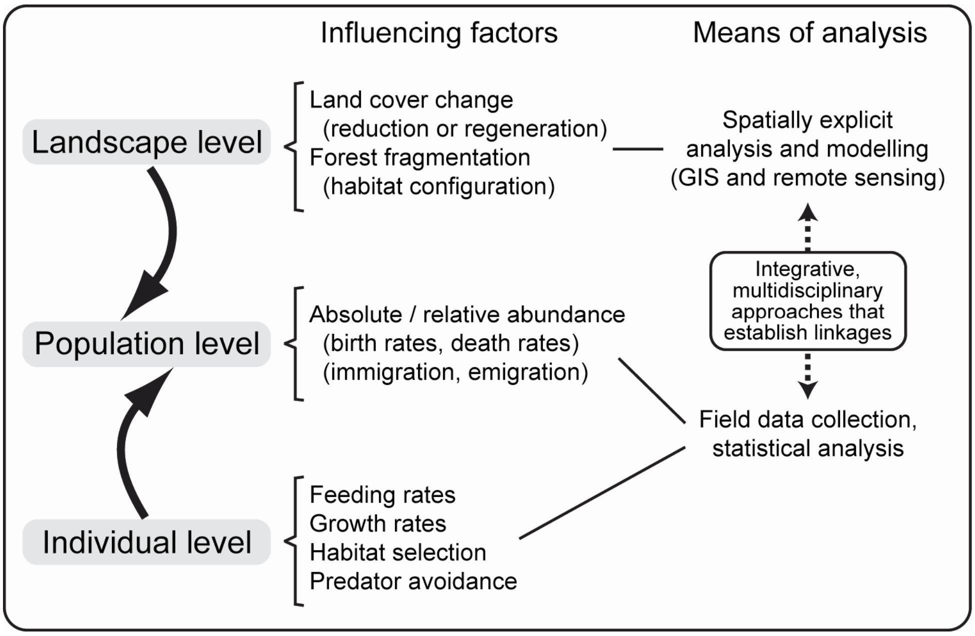


Figure 1.1: Hierarchy of levels affecting species population dynamics, their influencing factors and means of analysis (modified and extended from Dunning et al., 2006).

should be investigated considering a hierarchy of causation operating on three different levels: the individual level, the population level and the landscape level (see Figure 1.1). While influencing factors at the individual level and the population level are typically addressed by biological field data collection and subsequent analysis, landscape-level effects like changes in land cover or forest fragmentation require the analysis of spatially explicit geodata with GIS and remote sensing methodologies (Turner et al., 2003). In many instances, remote sensing data provides the only means of measuring landscape-scale characteristics of certain habitats across large scales (Kerr and Ostrovski, 2003).

Despite its potential for landscape-scale assessments, historically, remote sensing has been scarcely used for studies of biodiversity. A perception problem has prevented many from pursuing more integrated approaches combining GIS and remote sensing with traditional ecological field data: the belief that the spatial scales of remote sensing systems and those addressed by ecologists do not match (Turner et al., 2003). At the same time, predictions on the consequences of ecosystem changes on distributions and abundances of species at both the regional and the global scale had been identified as highest future research priority (Kerr and Ostrovski, 2003). Therefore, integrative, multidisciplinary GIS-based approaches linking remote sensing data with ecological field data (see Figure 1.1) are needed in order to derive more holistic assessments of the impact of environmental changes on tropical forest ecosystems. In the light of the globally vanishing natural ecosystems, numerous authors have pointed out the importance of integrated remote sensing – ecology approaches not only for an improved scientific understanding of ecosystem function, but also as an indispensable contribution to aid informed decision making towards the ultimate goal of biodiversity conservation (e.g. Foody, 2003; Leyequien et al., 2007). Indeed, in the last few years GIS and remote sensing have been increasingly applied for analysing and modelling biodiversity data, thus contributing to improved landscape-scale assessments (Gillespie et al., 2008). Typically, studies have focussed on mapping and modelling species richness, alpha diversity and beta diversity at the landscape scale, while limited attention has been given so far to species abundance and composition that require more comprehensive field data (*ibid*). Moreover, terrestrial vegetation diversity has been addressed more frequently than faunal diversity, since the latter is more complicated given several uncertainty-adding factors like size, mobility and habitat preferences of faunal species (Leyequien et al., 2007). Finally, only very few landscape-scale attempts have been made to map and model changes in terrestrial faunal biodiversity over prolonged periods of time.

The objectives and contribution of this study

This study has been conducted in the framework of the interdisciplinary research project BIOTA East Africa (Biodiversity Monitoring Transect Analysis in Eastern Africa) which is investigating the influence of fragmentation and anthropogenic use on the biodiversity of tropical rainforest ecosystems (Köhler, 2004 or http://www.biota-africa.de). Funded by the German Federal Ministry of Education and Research (BMBF) from 2001 to 2010, BIOTA research focuses on vegetation structure, certain animal groups emphasising invertebrates, some ecosystem functions and services (i.e. seed dispersal, pollination) and socio-economic aspects. The ultimate overall project aim is the implementation of instruments and the provision of recommendations for a sustainable use and conservation of the forests' biodiversity. Investigations are conducted along forest disturbance gradients of moderately disturbed near natural forest to secondary forest,

forest plantations, highly degraded bushland, and farmland. Three East African forest areas are studied: whereas two areas in Uganda are used for comparison purposes, the project activities focus on a study area in western Kenya.

In order to allow for landscape-scale assessments of biodiversity distribution and human impact patterns on the forest ecosystems and to support forest biodiversity management, the analysis of geo-spatial data by means of GIS and remote sensing plays a key role. In this context, the first objective of this thesis is:

(1) to derive truly comparative, detailed information on the development of land cover since the early 1970s for the three East African rainforest areas from Landsat satellite data.

To address this, an already existing time series for the Kenyan study area (Lung, 2004) is extended and satellite time series with comparable time steps for the two Ugandan reference areas are processed following a tailored image pre-processing and classification approach with an emphasis on distinguishing the same forest formations (see blue part of Figure 1.2). Based on the classification results, the second objective is:

(2) a comparative analysis of the three derived land cover change patterns over time.

This is achieved by a change detection analysis (see Figure 1.2) of the three areas considering both long-term trends and short-term fluctuations in forest composition over time. Based on the derived time series, this thesis also aims at assessing forest fragmentation[3] by making use of spatially explicit landscape metrics (see Figure 1.2). Further, the results from the change detection analysis and the forest fragmentation assessment are related to ancillary geo-spatial information (i.e. on accessibility by roads, population distribution) in order to assess the influence of driving factors underlying the observed change patterns. The third objective is:

(3) a spatially explicit quantitative landscape-scale assessment of the influence of forest cover change on selected keystone species/groups for the Kenyan focus area.

This is addressed by GIS-based extrapolation modelling approaches combining the land cover time series data and spatially explicit landscape metrics with biological field data in order to derive landscape-scale species abundance distributions (see Figure 1.2). The extrapolations also include the use of land cover data derived from aerial photography and old topographic maps to reach back in time as far as possible as well as the generation of possible future scenarios to simulate potential changes in forest biodiversity. A forth objective is:

(4) the visualisation of the derived patterns of change over time in land cover and species distribution addressing different user groups ranging from scientists to local people living adjacent to the studied forests.

Accomplishing this aim involves the use of a mix of different means of static and dynamic visualisations including e.g. forest cover change maps, maps of synthesised land

[3] Here defined as small-scale fragmentation measuring the proportion of forest edge within the forest landscape and calculated within a 3 x 3 pixel sized moving window from 30 x 30 m (Landsat TM and ETM+) or 60 x 60 m (Landsat MSS) resolved land cover data.

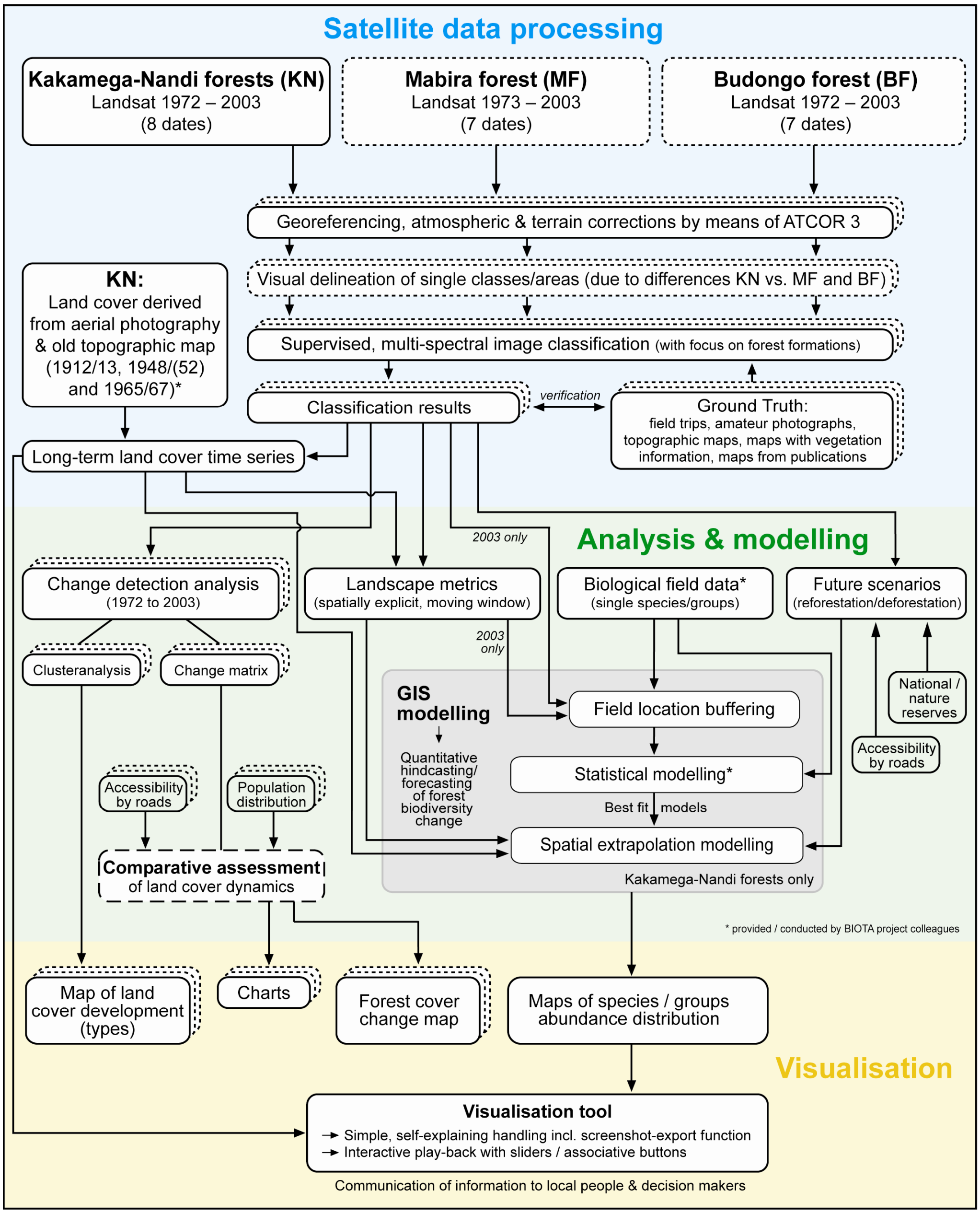


Figure 1.2: Outline of the methodology of the thesis encompassing satellite data processing, analysis and modelling, and visualisation.

cover development types[4] and an interactive visualisation tool (see yellow part of Figure 1.2).

[4] Relates to the term "Synthetische Karte" used in cartography in German-speaking countries. "Synthetische Karte" refers to a type of thematic map generated by synthesising multiple findings or variables considering

Structure of the thesis

Chapter 1 introduces the research subject of this thesis and presents a short overview of the state of the art regarding the use of GIS and remote sensing for change detection in the tropics in general, its specific use for measuring and modelling tropical forest biodiversity, and the visualisation of spatio-temporal data. Moreover, the BIOTA East project and its three study areas in Eastern Africa are presented. In Chapter 2, the focus is on the analysis of land cover changes and forest fragmentation in the Kenyan focus area based on an already existing time series (Lung, 2004). An accuracy assessment is conducted to ensure the reliability of the derived land cover data. Subsequently, forest fragmentation is assessed by deducing a quantitative, spatially explicit and biodiversity-relevant indicator from the land cover classification results. Furthermore, a cluster analysis is applied on the classification results and its suitability for a rapid visual assessment of distinct patterns of land cover development is discussed. Chapter 3 expands to all three study areas presenting a comparative satellite time series processing approach (i.e. satellite data pre-processing, classification and accuracy assessment) followed by a comprehensive land cover change analysis. In order to assess the influence of population pressure and forest management implications on deforestation processes, the observed changes are analysed and discussed in the context of population distribution and the protection status of the forests. Chapter 4, zooming back to the Kenyan study area, develops different approaches of combining spatially explicit GIS modelling with statistical modelling in order to use the land cover time series to derive landscape-scale, quantitative biodiversity assessments over time. Different sets of field observations on tropical fauna are employed for extrapolations in space (i.e. to the entire study area) and time (i.e. back to the early 20th century and into the future based on scenarios). Additionally, the value of the modelling results is discussed. Chapter 5 synthesises the derived results regarding satellite data processing, change detection analysis and extrapolation of biological field findings, and discusses differing visualisation options. A concluding discussion on implications of this work's results for forest management and conservation brings together the main aspects of the thesis. Finally, Chapter 6 gives an outline on possible future extensions of the study.

1.2 Efforts to analyse landscape-scale changes of tropical forest

Means and approaches for detecting patterns of land cover change from space

Global changes in land surface have increased dramatically in the 20th century with larger areas of forest clearings between 1950 and 1980 than in the 18th and 19th centuries combined (Ramankutty et al., 2006). Detecting these patterns of change, commonly referred to as change detection, constitutes the quantification of temporal phenomena from multi-date imagery (Coppin et al., 2004). For this purpose remote sensing has been used extensively as primary data source in the last decades (Lu et al., 2003). Particularly in regards to earth observation satellites operating in the optical spectrum (0.3 to 14 μm, Lillesand and Kiefer, 2000), there has been a marked increase in the last ten years with improvements in technical capabilities and performance, e.g. the emergence of numerous

their causal relationships in order to derive (landscape) types, usually accompanied with extended textual explanations (Bollmann and Koch, 2002). It can be translated into English as "Thematic map of synthetic representation" (Bill and Zehner, 2001).

Table 1.1: Earth observation satellites operating in the optical spectrum that have been in orbit for at least one decade including their spectral bands, spatial resolution, year of launch and revisit time (see Jensen, 2005; Lillesand and Kiefer, 2000)

Satellite	Sensor	Spectral bands	Spatial resolution [m]	Launched	Orbit [days]
Landsat 1-3	MSS	4 (G, R, 2x NIR)	60	1972	18
Landsat 4-7	TM/ETM+	7 (B, G, R, NIR, 2x MIR, TIR)	30, 120/60 (TIR)	1982	16
SPOT 1-3	HRV	3 (G, R, NIR)	20	1986	26
SPOT 4+5	HRVIR	4 (G, R, NIR, MIR)	20 (4), 10/20 (5)	1998	26
IRS-1A/B	LISS I+II	4 (B, G, R, NIR)	23, 72.5	1988/91	22
IRS-1C/D	LISS III	4 (G, R, NIR, MIR)	23, 70 (MIR)	1995/97	24
EOS	Aster	14 (G, R, NIR, 6xMIR, 5xTIR)	15 (VNIR), 30 (MIR), 90 (TIR)	1999	16
IKONOS	IKONOS	4 (B, G, R, NIR)	4	1999	1-5
NOAA	AVHRR	5 (R, NIR, MIR, 2x TIR)	1100	1979	0.5
SPOT	Vegetation	4 (B, R, NIR, MIR)	1150	1998	1
EOS	MODIS	36	250, 500, 1000	1999	2

B = blue; G = green; R = red; NIR = near infrared; MIR = mid infrared; TIR = thermal infrared; VNIR = visible and near infrared

high to very high resolution land satellites such as Quickbird, IKONOS, OrbView or EROS (Toutin, 2008). However, in a summary of the findings of the Millennium Ecosystem Assessment, Carpenter et al. (2006) have pointed out the essential role of long-term and uninterrupted time series data as key information for the understanding of linkages between ecosystems and their anthropogenic use. When aiming at change studies with a temporal scale considerably longer than one decade, the choice is limited to a few systems designed to provide long-term continuity of data collection. For local-to-regional scale studies, these are moderate to high resolution data of Landsat (first launched in 1972), SPOT (1986) and IRS (1988) while AVHRR (1979) data with its coarser spatial resolution is more suited for continental or global studies (see Table 1.1). Alternatively, data from disparate sensors can be used for change detection, but such multi-sensor approaches usually face difficulties in image processing and in the selection of an appropriate change detection technique (Lu et al., 2003). With more than 35 years of imaging, Landsat offers the longest-running time series of systematically collected remote sensing data and has therefore become the backbone of change detection studies (Ramankutty et al., 2006). Despite a higher percentage of cloud cover compared to other biomes (Ju and Roy, 2008) and the failure of the Landsat 7 scan line corrector (SLC) in May 2003 (Markham et al., 2004), Landsat has been and is still extensively used also in the humid tropics.

Studies dealing with the detection and analysis of changes in land surface commonly utilise two terms: land cover and land use. These terms refer to the different ways in which land surface is characterised and are important to distinguish. Land cover has been defined as the earth's surface and immediate subsurface including natural vegetation, crops and human built-up structures and hence, land cover change refers to the replacement of one cover type by another. In methodological terms, land cover is directly observable in remotely-sensed imagery (Lambin et al., 2006). In contrast, land use is usually not directly observable by satellite imagery although, in some cases, it may be inferred from observable activities (e.g. grazing). Land use is mainly gained through detailed field-based analysis and it refers to the purposes for which humans exploit land cover, including all land management practices (Lambin et al., 2006; Verburg et al., 2009). As this study focuses on changes as derived from remote sensing-based analysis, the term 'land cover (change)' will be used[5], which also serves as a general, overarching term for other, in parts overlapping aspects of change detection often found in the literature. Related to (forest) ecosystems these are for example "forest change", "vegetation change", "deforestation and regeneration" or changes due to selective logging (Lu et al., 2003). A variety of change detection algorithms and approaches have been developed and applied to detect tropical forest change. Therefore, the selection of a change detection method suitable for a given research purpose is an essential but challenging task (Lu et al., 2003). An important consideration in this context refers to the determination of change direction. While some approaches only provide "change/no-change" information, others allow for the extraction of a complete matrix of "from-to" change information such as postclassification comparison or change vector analysis (e.g. Buchroithner, 2009). The choice of the change detection approach also dictates as to whether the spectral information of the original images is used or a (certain type of) image classification has to be performed prior or during the change detection analysis (Jensen, 2005).

Analysing changes in landscape composition and configuration

For analysis of aspects of landscape composition and configuration based on remotely sensed land cover data, landscape metrics have become a standard tool (Huang et al., 2006). In particular, landscape metrics quantifying the spatial heterogeneity of a landscape to elucidate relationships between ecological processes and spatial patterns have received enormous attention in the field of landscape ecology in the recent past (Turner, 2005). According to McGarigal et al. (2002), the plethora of metrics developed can be grouped into three different levels, patch-level metrics, class-level metrics and landscape-level metrics. Whereas patch-level metrics characterise the spatial character and context of individual patches, the second group measures the configuration of each individual land cover type/class in the landscape mosaic, and the last group applies to the landscape as a whole, i.e. including all land cover classes. Other authors have classified landscape metrics according to the aspect of landscape pattern measured, e.g. Huang et al. (2006) distinguish between area/edge/density metrics, shape metrics, contagion/interspersion metrics and diversity metrics. Generally, the proliferation of metrics within the last two decades poses a serious challenge for the analyst to select relevant and representative components (Cushman et al., 2008). Several studies have shown that many of the metrics are highly redundant and that a parsimonious suite of (very) few independent metrics is therefore sufficient for deriving a representative picture of landscape structure (e.g. Linke and Franklin, 2006; Schindler et al., 2008).

An alternative way of grouping landscape metrics is to distinguish between those with a numerical, non-spatial output per land cover class or area and those with a spatially explicit output as derived when utilising a moving window-based approach. Most commonly applied are metrics of the former group with many examples of regional case

[5] An exception is Chapter 2 which uses the more general term "land use/cover change" (LUCC). It was written and published as a stand-alone manuscript before the authors were aware of the distinctive difference in terminology.

studies in the tropics making use of these metrics for assessing landscape heterogeneity and (forest) fragmentation as a supplement to change detection analyses based on remotely-sensed time series data (e.g. Kamusoko and Aniya, 2007 for an area in Zimbabwe, Reid et al., 2001 for a rainforest in Costa Rica, or Southworth et al., 2004 for a highly fragmented forest area in Honduras). In each of these studies, the calculated metrics are presented in tabular form in an aggregated manner for the entire study area or a subset of it. In contrast, moving window-based approaches provide a spatially explicit pattern of the calculated metrics, thus enabling to detect hotspots or areas less affected by the calculated metrics, but are still rarely applied. One of the few studies related to forest is the work of Wade et al. (2003) assessing global forest fragmentation by making use of a set of moving window-based forest fragmentation indices. While results form metrics calculations resulting in tabular, non-spatial outputs cannot be used for further spatially explicit analyses or modelling, this is a major advantage of approaches like that of Wade et al. (2003), whose results (i.e. maps of forest fragmentation) are highly suitable for linkages to other geo-spatial data.

Regardless of the approach chosen, a crucial factor is the scale sensitivity of landscape metrics. Numerous studies have shown that metrics values change with the resolution and the aggregation of the input data, particularly those metrics estimating forest fragmentation (García-Gigorro and Saura, 2005). However, the effect of changing the grain size on landscape metrics seems not to be clearly predictable. A study by Ferraz et al. (2006) testing eight spatial resolutions from 30 m to 270 m for an area of fragmented tropical forest in the Amazon, revealed a linear behaviour of edge measures in relation to pixel size with lower fragmentation at coarser resolution. Contrary, Wu et al. (2002) found power law relationships for edge measures. Additionally to the spatial scale, Huang et al. (2006) showed that edge metrics are also influenced by the detail of the land cover classification scheme (i.e. the number to classes distinguished) whereas land cover misclassifications do not appear to significantly amplify biases in landscape metrics (Wickham et al., 1997). Therefore, in order to warrant an appropriate and unbiased comparison of forest fragmentation metrics derived from satellite time series data, a consistent land cover classification scheme is indispensable.

1.3 Remote sensing for mapping and modelling forest biodiversity

Recently, studies employing remote sensing for monitoring, mapping and modelling biodiversity have become more prevalent (see also Section 1.1). While traditional ground based methods of inventorying are logistically and financially prohibitive to achieve at larger scales, remote sensing offers a means for deriving a complete spatial coverage of biodiversity-relevant information in a repeatable and consistent manner (Duro et al, 2007). Not only for change detection studies in general but also for biodiversity studies, Landsat is the most widely used of all earth observation satellite systems. Landsat data have played the most pivotal role in landscape ecology and conservation biology for applications and models on the state and temporal dynamics of ecosystems (Cohen and Goward, 2004). The popularity of Landsat for ecological research relies on a combination of advantages it offers compared to other satellite systems: long-term data continuity, a spatial resolution suited for a broad range of applications, spectral measurements covering all major portions of the electromagnetic spectrum, and an affordable price (*ibid*). A review of 179 articles published on conservation or biodiversity issues employing

Landsat data revealed that almost 40% of them cover tropical forest ecosystems (Leimgruber et al., 2005).

Generally, the different attempts and efforts (also including those utilising other than Landsat remote sensing data) can be divided into two groups: direct approaches and indirect approaches (Duro et al., 2007; Turner et al., 2003). Direct approaches use remotely sensed imagery to identify either land cover or species and directly map their distribution without considering any other variables. In contrast, indirect approaches measure environmental variables or indicators (e.g. different forest cover classes, measures of forest fragmentation or other geophysical parameters) that are believed to impact biodiversity and subsequently model the distribution of species and/or diversity based on these variables. The following two sections give an overview of the state of the art in regards to the two approaches.

Mapping and monitoring (direct approaches)

Direct approaches, also called first-order analysis of species occurrence (Turner et al., 2003), enable the direct quantification of aspects of biodiversity. As a surrogate for habitats and for composition and distribution of individual species or assemblages, mapping of land cover has received most attention (Foody, 2008). Satellite measurements of broad-scale trends in vegetation provide direct estimates of habitat losses or gains. However, land cover classifications have typically been limited to assemblages of several plant species, e.g. trees. The emergence of high to very high resolution satellites over the last decade has opened the door to new approaches directly mapping single species from remote sensing data. For example, data from IKONOS, Quickbird or other very high resolution satellites have enabled researchers to accurately identify single tree species in forest canopies (see Carleer and Wolf, 2004; Wang et al., 2004), to quantify tree mortality in tropical rainforest (Clark et al., 2004) or to study introduced or invasive species (Huang and Asner, 2009). The direct identification of faunal species from satellite data is difficult, since most species are too small to be captured even by very high resolution satellites. Additionally, satellite revisit times that are not frequent enough for meaningful comparisons of the spatio-temporal movements of animals currently impede any meaningful direct capture (Gillespie et al., 2008). However, the measurement of species movements via satellite tracking systems has become commonplace, mostly applied to large mammals (e.g. Ngene et al., 2009).

Modelling (indirect approaches)

Offering the possibility for more comprehensive assessments on the impact of multiple variables or indicators of environmental change on species distributions and abundance, the most common and intriguing approach for assessing and modelling biodiversity with remote sensing data is the use of indirect methods (Duro et al., 2007). In contrast to direct approaches, indirect methods are not limited to plant species, but main research attention is also given to assess the terrestrial faunal biodiversity (Leyequien et al., 2007). Species distribution modelling, also referred to as ecological niche modelling, has grown considerably within the last 10 to 20 years. Species distribution models, based on presence/absence or abundance data collected in the field or from museum archives or other secondary sources, employ certain environmental variables (predictors, usually spatially explicit GIS data) to generate maps of species distribution probabilities (Guisan and Thuiller, 2005).

The plethora of indicators and explanatory variables for modelling biodiversity has been grouped into four categories: (i) the physical environment such as climate and topography, (ii) vegetation production, (iii) habitat and (iv) metrics of fragmentation/ disturbance (Duro et al., 2007). Generally, the influence of climate on species distribution has received enormous attention (e.g. de Chazal and Rounsevell, 2009), but for the tropics climate is not considered the prime determinant of changes/loss of biodiversity (Sala et al., 2000). Instead, many diversity models (i.e. studies modelling species richness) have considered spatial heterogeneity based on measures of vegetation production such as the Normalized Difference Vegetation Index (NDVI) (e.g. Oindo and Skidmore, 2002; Pettorelli et al., 2005). While several studies have shown significant correlations between the NDVI and tropical plant species richness (e.g. Cayeula et al., 2006), the detection of the terrestrial fauna by means of the NDVI or other proxies for primary production remains challenging (Leyequien et al., 2007).

Habitat/land cover data as derived from remotely sensed imagery is considered a key variable for biodiversity modelling to extrapolate field survey data on species abundance, habitat use, characteristics of nesting, breeding etc. to cover a large area of interest. While until the 1990s remote sensing-based habitat maps were predominantly used as a proxy for modelling the distribution of plant species (Nagendra, 2001), land cover data is increasingly and successfully applied also for assessments of the terrestrial animal distribution including different taxa (Leyequien et al., 2007), especially mammals (e.g. Stickler and Southworth, 2008), the avifauna (Gottschalk et al., 2005) and also insects (e.g. Seto et al., 2004). In addition, there are an increasing number of studies utilising landscape metrics on landscape composition and configuration as derived from remote sensing data for biodiversity modelling and assessments at the landscape scale (e.g. Davis et al., 2007; Kumar et al., 2009).

Modelling forest biodiversity with remote sensing data inevitably focuses on the spatially explicit modelling of functional ecological relationships between biological field data and one or multiple explanatory variables. However, in recognition of the accelerating rate of global biodiversity loss, many of the efforts to model forest biodiversity with remote sensing data have also a strong emphasis on conservation. While studies linking biodiversity and remote sensing data generally have a major role to play in helping to identify conservation priorities (i.e. biodiversity hotspots) (Harris et al., 2005; Wiens et al., 2009), they are equally important for revealing areas where high human-induced threats coincide with high biodiversity and/or change over time. However, even for protected areas, it is widely recognised that officially gazetted reserves are often not exempted from human-induced destruction processes, particularly in the tropics (Nagendra et al., 2004; Wright et al., 2007). In this context, landscape-scale biodiversity studies based on remote sensing data can not only contribute with land cover change information but also with valuable insights of the biological effects of forest alterations to be used as a basis for developing sustainable strategies for forest conservation and use (Foody, 2003). However, some taxonometric groups have been scarcely related to conservation issues so far. For example, most studies on insects have considered them as pests and have therefore focussed on investigating their effects on e.g. crops (Leyequien et al., 2007).

Common to most of the models linking remotely-sensed imagery with biodiversity data is the lack of a temporal component actually revealing changes over time. Usually, studies modelling species richness or the distribution of single species have been limited to one point in time. Some exceptions relate to approaches of modelling changes in plant species richness (e.g. Fairbanks and McGwire, 2004), but hardly any attempts have been made so far to model changes in animal distribution and diversity over time based on remote sensing data.

1.4 The visualisation of spatio-temporal data

According to a general framework proposed by DiBiase (1990), geographic visualisation in the context of scientific research involves two types of maps, (i) maps acting as facilitators of visual thinking in the data exploration phase of the research and (ii) those serving for public visual communication of the final research results. Based on this as well as on other cartographic views on visualisation, MacEachren (1994) developed the cartography-cubed representation of how maps are used, contrasting visualisation with communication along three dimensions: private versus public, revealing unknowns versus presenting knowns, and the degree of human–map interaction. MacEachren (1994) stresses that there are no clear boundaries in the cube-space but only identifiable extremes at its outer ends. Similarly, the dividing line between visualisation and communication is not sharp but is meant to aid in identifying the primary map function(s) with corresponding differences in appropriate map design (*ibid*). In the recent years, in this context several issues have been identified as research priorities, amongst others the focus on representation of geographic phenomena (particularly spatio-temporal datasets) and on usability (i.e. assisting particular users/groups with particular geovisualisation approaches) (Dykes et al., 2005).

The visualisation of spatio-temporal data has been in the focus of cartography for several decades, e.g. Koussoulakou and Kraak (1992) proposed a comprehensive framework on spatio-temporal maps and cartographic communication. A conventional approach from traditional analogue cartography is the juxtaposition of multiple maps representing situations at different moments (see Figure 1.3), but such map series can be difficult to deal with for the user (Kraak, 2007). The suitability of juxtaposition of several maps as means of visualisation is inversely related to the number of time frames of a time series. The higher the number of time frames of a time series, the more difficult it gets for the user to grasp the spatio-temporal processes it depicts, and hence, such time series have to be investigated at a rather coarse temporal resolution, particularly if they are displayed digitally on the screen (Andrienko et al., 2003). An alternative approach is the use of change maps representing differences between situations at two (or multiple) moments in time (Slocum et al., 2009). With the development of computer cartography new approaches emerged, such as cartographic animations and dynamic maps, with various possibilities for user control (Kraak and Ormeling, 2003). It has been suggested that animations are particularly powerful when aiming to reveal detailed sequential information about changes (Blok, 2005). From the mid-1990s the interdisciplinary field of geovisualisation evolved, emphasising the integration of approaches from cartography with other disciplines, e.g. scientific visualisation, image analysis or exploratory data analysis (Kraak, 2008). Regarding the visualisation of spatio-temporal patterns this also included the expansion towards new methods such as space-time cubes, three-dimensional approaches where time is visualised as third dimension over a two-dimensional map (e.g. Turdukulov et al., 2007).

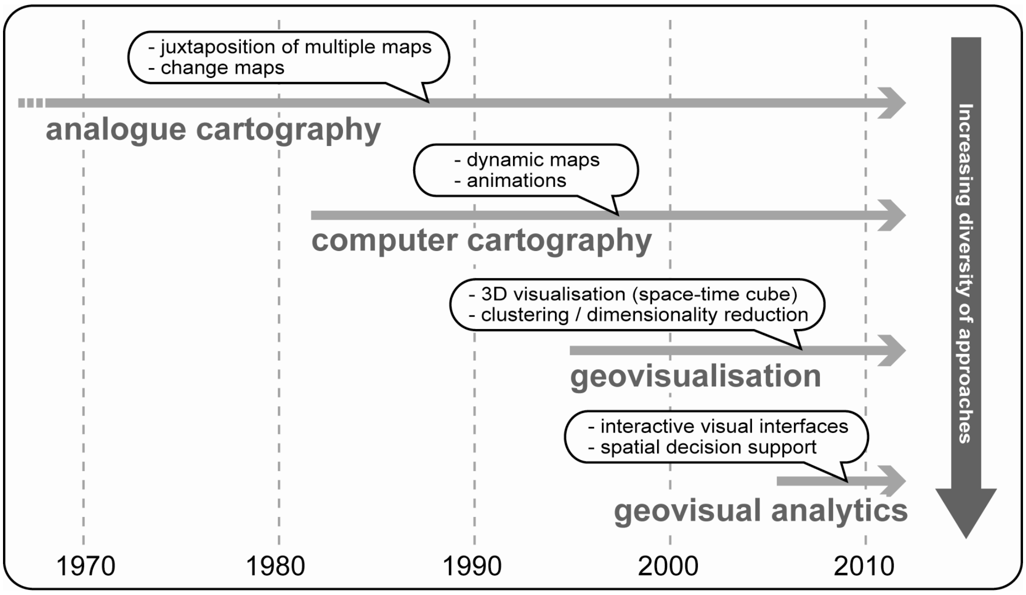


Figure 1.3: The development of cartography since the 1970s and corresponding concepts of spatio-temporal data visualisation (modified and extended from Kraak, 2008).

Another alternative concept addressing the problem of space-time data visualisation combines elements of clustering and dimensionality reduction. In this regard, the approach of self-organising maps (SOM), based on the technique of artificial neural networks (ANNs), has received considerable attention in recent years. The SOM algorithm employs an unsupervised neural network with competitive learning/training in an iterative process were the major topological relationships between the clusters are preserved (Skupin and Agarwal, 2008). This makes it a highly relevant concept for visually detecting patterns and relationships in a large volume of multivariate, geo-spatial data from different disciplines such as environmental, social, transportation or facilities data (Koua and Kraak, 2008). An interesting tool combining methods of data clustering and pattern searching with information visualisation and synthesis has been developed by Chen et al. (2008). Their integrated approach employs the SOM technique together with the parallel coordinate plot technique (PCP), resulting in the 'Visual Inquiry Toolkit' (VIT) which allows space-time-attribute data to be visualised both in a holistic overview and in detail views.

However, in a recent, comprehensive review of the ongoing research on geovisualisation, Andrienko et al. (2007) conclude that most current visualisation tools are inadequate to address spatial decision problems. Therefore, additional forms of information communication are needed. In this regard, interactive, dynamic visualisation tools are ascribed great potential to present complex processes in a tangible way. They are not only capable to reveal patterns or show trends, such tools also tell a story to the user that would not be clear from looking at a single map or a series of maps only (Kraak, 2007). According to Andrienko et al. (2007) a new generation of tools is needed, enabling to truly use the synergies between the power of computational techniques and human capacity of knowledge construction and representation. In this context, they advocate strong links with the emerging research discipline 'visual analytics', defined as "the science of analytical reasoning facilitated by interactive visual interfaces" (Thomas and Cook, 2005, p. 4). Visual analytics has been 'translated' into the GI science domain as 'geovisual analytics' (see Figure 1.3) and was proposed as the avenue of future research (Andrienko et al. 2007). In geovisual analytics, tools with interactive visual interfaces as means for effective information communication, "enabling a truly synergetic work of humans and computers" and supporting the needs of multiple actors in decision making processes are considered the essential key element (Andrienko et al., 2007, p. 840). Among the major research directions of geovisual analytics, Andrienko et al. (2007) point out visualisations of complex spatio-temporal processes in a manner appropriate to stimulate visual thinking about geo-spatial patterns and trends, and to provide the ground for human analysis and reasoning allowing for e.g. resource or impact assessments.

The described development of cartography entailed an enormous increase of approaches, techniques and concepts for visualising spatio-temporal data (see Figure 1.3). However, the evolvement of new methods does not necessarily mean that established techniques have become out-dated or inadequate. The choice of the right approach rather depends on needs and requirements of the users in order to move away from "one tool fits it all" approaches still dominant in contemporary geoinformation technology (Dykes et al., 2005, p. 8) Furthermore, data structure and characteristics play an important role. In this regard, Blok (2000) distinguishes between three basic types of spatio-temporal data related to the type of change, (i) existential changes (i.e. appearing/disappearing), (ii) changes of spatial properties (e.g. size, shape, location) and (iii) changes of thematic properties (i.e. values of attributes).

1.5 Study areas

Three areas in Eastern Africa comprising islands of tropical rainforest partially or fully surrounded by agricultural land are studied: the Kakamega-Nandi forests in western Kenya, Mabira Forest in south-eastern Uganda and Budongo Forest in western Uganda (see Figure 1.3). Each of the three areas is characterised by a larger main forest (three in the Kakamega-Nandi area) and a number of smaller forest fragments in their surrounding area. Whereas the study areas of the Kakamega-Nandi forests and Budongo Forest are of similar size, the study area of Mabira Forest is somewhat smaller. All three areas are located in the northern hemisphere close to the equator (the southernmost part of the Kakamega-Nandi area stretches across the equator to the southern hemisphere). Table 1.2 provides a comparative overview of the three study areas highlighting distinct differences in regards to the physical environment and human impact.

1.5.1 Kakamega-Nandi forests

Location, topography and climate

The study area comprises three larger forest blocks, namely Kakamega Forest (KF), North Nandi Forest (NN) and South Nandi Forest (SN), encompassing a gazetted total area of 52,067 ha (calculated from official forest boundaries as provided to BIOTA by UNEP, Nairobi). These blocks are surrounded by seven smaller forest fragments: Kisere Forest, Malava Forest, Bunyala Forest, Taresia Forest, Kapteroi Forest, Ururu Forest and Kaimosi Forest (see Figure 1.4) Kakamega Forest ranges between 1460 and 1,765 m a.s.l. whereas the Nandi Forests are placed about 200 to 300 m higher on the Nandi Escarpment. With 1165 m a.s.l. the lowest point of the study area is located south of the

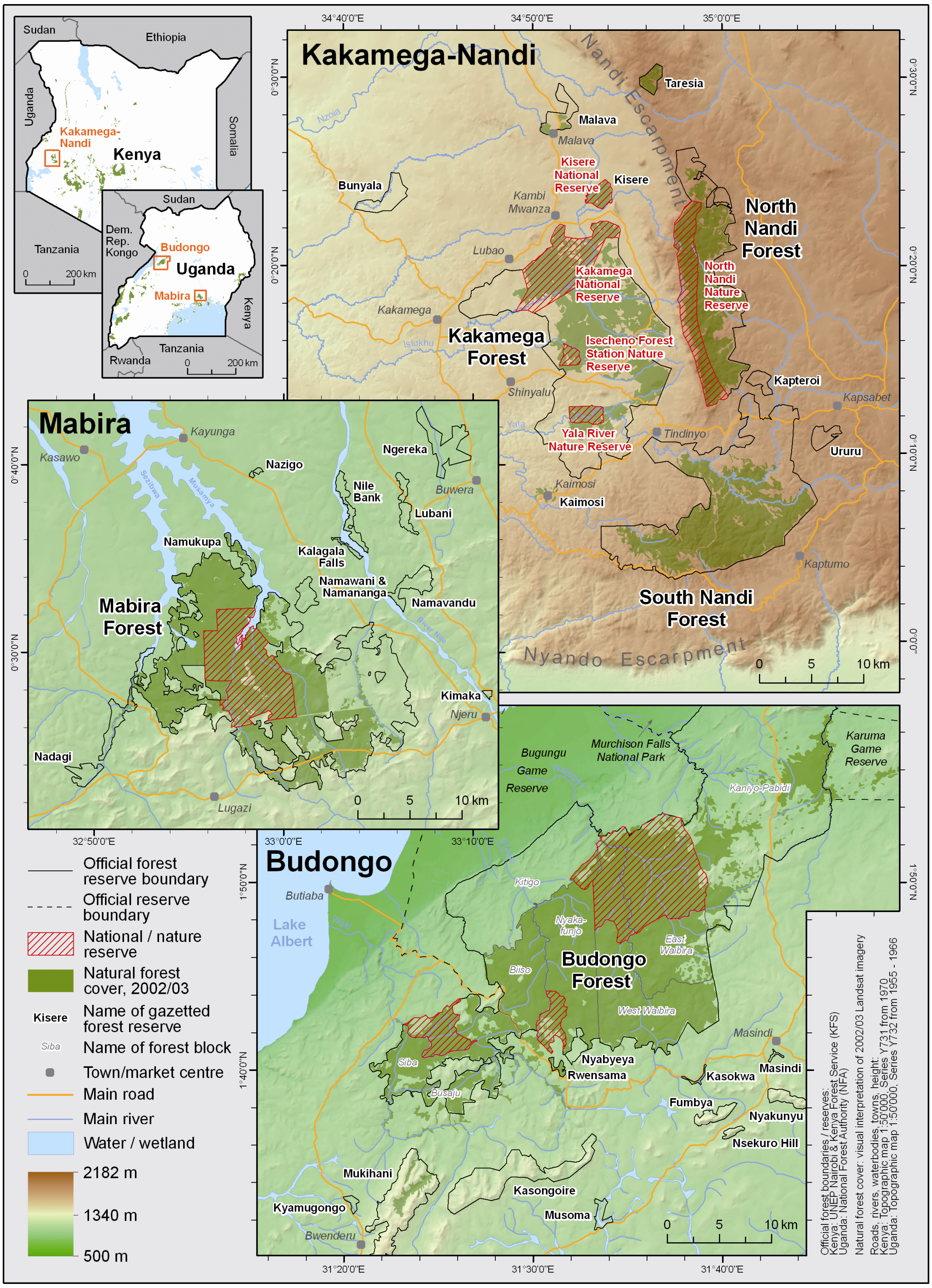


Figure 1.4: Overview map of the study areas (1) Kakamega-Nandi forests, (2) Mabira Forest, and (3) Budongo Forest and their location in Kenya/Uganda (see also Figure 3.1).

Nyando Escarpment whereas the highest elevation is 2180 m a.s.l. and found north-east of North Nandi Forest. All forests are important water catchment areas for the Lake Victoria basin (Kamugisha et al., 1997). Two major rivers are found in the area: the Isiukhu River with its source at the Nandi Escarpment passing through the northern part of Kakamega Forest, and the Yala River passing South Nandi Forest and the southern part of Kakamega Forest. Climatic conditions are influenced by the ITCZ (Intertropical Convergent Zone) with the movement of air masses between two temperature belts in the northern and southern hemisphere, and by the Lake Victoria with it own specific diurnal winds leading to frequent thunderstorms during afternoon and evening (Flohn and Frädrich, 1966). The driest months are December, January and February although the rainfall regime is well distributed throughout the year without a real dry gap (Jätzold and Schmidt, 1982). Highest rainfall levels occur from March to June (long rains) and from July to September (short rains) resulting in an annual average of 2,007 mm (year to year) at Isecheno Forest Station in Kakamega Forest (Farwig et al., 2006, averaged from Forest Department records, 1982 to 2001) while the Nandi Forests are believed to receive slightly less annual rainfall (Mitchell and Schaab, 2008). The temperature is influenced by altitude with slightly lower annual temperatures for the Nandi Forests ranging between a mean minimum of around 10°C to a mean maximum of around 25°C (Blackett, 1994b; Blackett, 1994c), whereas the mean values for the area around Kakamega Forest are between 15°C and 27°C (KIFCON, 1994).

Geology and soils

The underlying geology is of Precambrian origin with the oldest rock formations belonging to the Neoarchean Nyanzan System (Schlüter, 2008). It generally comprises metamorphosed volcanics, sediments and granites, while in the area around Kakamega a sequence of andesites to rhyolites is dominant (Schlüter, 1997). The southern part of Kakamega Forest as well as the area south-west of it are characterised by sediments of the Kavirondian System, which is made up of conglomerates intruded by granites (Schlüter, 2008). The Nandi Forests are mainly underlain by undifferentiated granitic and Basement System rocks on which humic Nitosols with moderate to high inherent fertility are found in the area of South Nandi Forest. The soils North Nandi Forest is growing on are defined as Acrisols with moderate to low natural fertility (Blackett, 1994b; Blackett, 1994c). In the area of Kakamega Forest, ferralo-orthic Acrisols, humic Arcisols, mollic Nitosols and humic Cambisols are found. Apart from Nitosols with moderate fertility they have low natural fertility (Jätzold and Schmidt, 1982). A recent soil survey in Kakamega Forest distinguished between Ferralsols being dominant in the north and Cambisols mostly present in the south (Musila, 2007).

Fauna and flora

The Kakamega-Nandi forests are regarded the easternmost relic of the Guineo-Congolian rainforest belt (Wagner et al., 2008), but with a species composition considered transitional between the lowland Congolian rainforests and the Afro-montane forests of the Kenyan highlands (Althof, 2005, Blackett, 1994c). While the fauna and flora of Kakamega Forest have been studied well over the past decades, the Nandi Forests have received far less scientific attention. Kakamega Forest is known for its large faunal diversity, especially related to birds and insects (KIFCON, 1994) and for its primate populations (e.g. Mammides et al., 2009). Consequently, Kakamega Forest but also the

Nandi Forests have the status of Important Bird Areas, with Kakamega Forest holding 488 bird species in total (Mitchell et al., 2009, for a comprehensive bird list provided by the BIOTA project see www.biota.de). While Turner's Eremomela (*Muscicapa lendu*) and Chapin's Flycatcher (*Muscicapa lendu*) are registered as globally threatened birds, a further 46 species are probably not found elsewhere in Kenya (Bennun and Njoroge, 1999). The forest flora has fairly low species diversity for a rainforest, but with 80 species restricted within Kenya to Kakamega Forest (among them two of which are endemic) the floristic mix is considered unique (Mitchell et al., 2009). Most of the forest is considered near primary forest or middle-aged secondary forest, dominated by *Deinbollia kilimandscharica* and *Markhamia lutea* in the north and *Celtis mildbraedii* and *Craibia brownie* in the south, often surrounded by young secondary forest (Althof, 2005). Additionally, three different types of forest plantations are found: mixed indigenous plantations, indigenous monocultures (e.g. *Maesopsis eminii*) and exotic monocultures (e.g. *Bischoffia javanica* or *Pinus patula*) (Farwig et al., 2008; Mitchell et al., 2009).

Management, administration and areas around the forest

The Kakamega-Nandi forests, still being one continuous area (Mitchell et al., 2006), were managed at the local scale on clan level until the early 1930s (Opole, 1991). At that time, the colonial government realized the economic importance of the forests and the Forest Department (FD) took over the management (Mitchell, 2004). Consequently, in 1933 Kakamega Forest was gazetted with 23,777 ha as Trust Forest under Proclamation No. 14, followed by South Nandi Forest (20,185 ha) and North Nandi Forest (11,845 ha) under Legal Notice No. 76 in 1936 (Blackett, 1994a). In 1967, three areas were declared as nature reserves: Yala and Forest Station, placed inside Kakamega Forest, and Kisere (*ibid*). As of today these are named Yala River Nature Reserve, Isecheno Forest Station Nature Reserve and Kisere National Reserve (see Figure 1.4). One year later, a nature reserve was also demarcated in North Nandi Forest (Blackett, 1994b). In 1985, a National Reserve was established in the northern part of Kakamega Forest (Blackett, 1994a), which is managed by Kenya Wildlife Service (KWS) under the name Kakamega National Reserve together with Kisere National Reserve, whereas all other gazetted forest areas are under jurisdiction of the KFS (Kenya Forest Service, former FD) (Mitchell et al., 2009). Due to re-gazettments and/or excisions the current area sizes are as follows: Kakamega Forest 23,841 ha, North Nandi forest 10,332 ha and South Nandi Forest 17,894 ha (calculated from official forest boundaries as provided to BIOTA by UNEP, Nairobi). All three forests have a long history of human encroachment and utilisation. Commercial exploitation of Kakamega Forest started with gold prospecting in the 1930s and has persisted until 1975 with extensive clear felling and selective logging as the major activities (Mitchell, 2004). Similarly, the Nandi Forests have experienced considerable logging operations (Blackett, 1994b; Blackett, 1994c). While commercial exploitation has been successfully banned, the forests have always been and still are an important resource for the local people to satisfy their daily needs (in respect to fire wood, house building material, etc.). Thus, cattle grazing, charcoal burning, illegal pit-sawing, hunting and collecting of medical plants are some of the threats the forests are exposed to (Mitchell, 2004). Kakamega Forest is placed in one of Kenya's most densely populated rural areas (643 inh./km^2), whereas population density in the area surrounding the Nandi Forests is much lower (371 inh/km^2; both figures calculated from Kenya National Bureau of Statistics (former CBS) 1999 census data for a 2 km-buffer around the gazetted forest areas). However, both forest surrounding areas are extensively used for subsistence agriculture with a continuously growing population. Therefore, the pressure from local forest use is expected to further increase in the future (Gibbon, 1991).

Table 1.2: A comparison of the geographic characteristics for the Kakamega-Nandi forests (Kenya), Mabira Forest and Budongo Forest (Uganda).

	Kakamega-Nandi forests	**Mabira Forest**	**Budongo Forest**
Study area size	60 x 65 km	46 x 42 km	65 x 54 km, excluding 10 x 34 km at south-eastern corner
Geographical location	34°37'5" to 35°9'25"E and 0°2'52"S to 0°32'24"N	32°46'34" to 33°11'22"E and 0°20'28" to 0°43'16"N	31°15'23" to 31°50'27"E and 1°29'56" to 1°59'14"N
Gazetted area (main forest blocks)	Kakamega Forest (KN), North Nandi Forest (NN) and South Nandi Forest (SN): total of 52,067 ha (from official boundaries provided by UNEP)	Mabira Central Forest Reserve (CFR): 29,974 ha (Karani et al., 1997b)	Budongo Central Forest Reserve (CFR): 82,530 ha (Karani et al., 1997a)
Elevation (main forest blocks)	KF: 1,460 to 1,765 m a.s.l.; Nandis: 1,695 to 2,145 m a.s.l.	1,030 to 1,355 m a.s.l.	900 to 1,440 m a.s.l.
Climate	annual mean temperature: KF: min. ~15°C, max. ~ 27°C (KIFCON, 1994); Nandi Forests: min. ~10°C, max. ~25°C (Blackett, 1994b,c) annual precipitation: 2,007 mm at Isecheno Forest Station; rainy seasons: March to June and July to September (Farwig et al., 2006)	annual mean temperature: min. 16 to 17°C, max. 28 to 29°C (Howard, 1991) annual precipitation: 1,250 to 1,400 mm; rainy seasons: April to May and October to November (Howard, 1991)	annual mean temperature: min. 17 to 20°C, max. 28 to 29°C (Howard, 1991) annual precipitation: 1,200 to 1,800 mm; rainy seasons: March to May and September to November (Sheil, 1997)
Geology	KF: Neoarchaen Nyanzian System and Kavirondian System (Schlüter, 2008); Nandi Forests: undifferentiated granitic and Basement System rocks (Blackett, 1994b,c)	Paleoproterozoic Buganda-Toro System (south-eastern part) and Mesoarchean Gneissic-Granulitic-Complex (north-western part) (Schlüter, 2008)	Mesoarchean Gneissic-Granulitic-Complex (largest part), Mesoproterozoic Karawagwe-Ankolean System (southeast) and Neoproterozoic Bunyoro-Kyoga Series (southern part of CFR) (Schlüter, 2008)
Soils	KF: ferralic-orthic and humic Acrisols, mollic Nitosols and humic Cambisols (Jätzold and Schmidt, 1982); NN: friable sandy clays (Acrisols) (Blackett, 1994b); SN: humic Nitosols (Blackett, 1994c)	ferrallitic sandy clay loams: mostly red Latosols, additionally grey sandy soils, grey clay soils along the rivers and shallow Lithosols on ridge crets (Karani et al., 1997b)	ferrallitic types: mostly leached Latosols (sandy clay loams), additionally murams on hilltops (Sheil, 1996)
Fauna	large species diversity, especially regarding birds and insects (KIFCON, 1994); home to the rare and threatened de Brazza's Monkey (Chism and Cords, 1997/98)	diversity above Ugandan average regarding birds and butterflies (Howard et al., 2000)	highly diverse, especially regarding butterflies, birds and moths, some endemic species (Forest Department, 1996), home to endangered chimpanzee populations (Plumptre, 2002)
Flora	botanically unique mix of Guineo-Congolian and Afro-montane species but no true primary forest (Althof, 2005), also found: three types of plantation forest (Farwig et al., 2008)	secondary forest with three distinct sub-climax communities (Baranga, 2007), also found: monocultures of *Broussonetia papyrifera* (Karani et al., 1997b)	known for its large tree diversity (e.g. Eilu et al., 2004), four distinct forest types with *Cynometra*-dominated climax community (Eggeling, 1947), no plantation forest (Lung and Schaab, 2008)

Continuation of Table 1.2

Management	gazetted as reserves, managed by KFS; KF: two national reserves managed by KWS and two nature reserves (KFS), 22% of area; NN: one nature reserve (KFS), 33% of area; SN: no reserves (Blackett, 1994a-c)	gazetted as central forest reserve, managed by NFA, four zones: nature reserve (21% of area), recreation zone, production–low impact, production–encroachment (Karani et al., 1997b)	gazetted as central forest reserve, managed by NFA, five zones: nature reserve (16% of area), recreation zone, protection zone, low impact harvesting, sawmill harvesting (Karani et al., 1997a)
Population density (surrounding area, within 2 km-buffer)	Kakamega Forest: 643 inh./km²; Nandi forests: 371 inh./km² (calculated from Central Bureau of Statistics 1999 census data)	302 inh./km² (calculated from Uganda Bureau of Statistics 2002 census data)	158 inh./km² (calculated from Uganda Bureau of Statistics 2002 census data)
Forest threats	pressure from growing population (local forest use); commercial exploitation since the 1930s (Mitchell, 2004)	mainly charcoal burning, timber cutting and agricultural encroachments (Baranga, 2007; Howard et al., 2000)	selective logging over the last 60 years (Plumptre, 1996; Howard, 1991)

1.5.2 Mabira Forest

Location, topography and climate

The area under investigation has been defined as a box of 46 km by 42 km around Mabira Forest, gazetted as central forest reserve (CFR) with an area of 29,974 ha (Karani et al., 1997b), and further includes ten smaller areas also gazetted as forest reserves (see Figure 1.4). The undulating terrain ranging from 1030 to 1355 m a.s.l. is divided into a north-eastern part and a larger western part by the river Nile. The western part contains three stretches of swamp connected with the Lake Kyoga drainage system further north: Matumbwe, Sezibwa and Musamya, the latter two reaching southwards into Mabira Forest. The climate is tropical, influenced by the proximity to the Lake Victoria with inland penetrations of the onshore lake breezes during the day (Karani et al., 1997b). The area receives an annual average precipitation of 1,250 to 1,400 mm with two rainfall peaks from April to May and October to November (Howard, 1991). Regarding the temperature, considerable diurnal changes of up to 13°C are common, but seasonal variations are relatively small (Karani et al., 1997b). The annual mean temperatures range from a minimum of 16–17°C to a maximum of 28 to 29°C (Howard, 1991).

Geology and soils

The rock formations underlying the south-eastern part of the study area are of the Paleoproterozoic Buganda-Toro System (Schlüter, 2008), which for that area is made up of granitic gneiss and granites and is covered by metamorphosed sediments such as schists, phyllites, quarzites and amphibolites (Karani et al., 1997b). The north-western part of the study area is characterised by high grade metamorphics named Gneissic-Granulitic-Complex of probably Mesoarchean age (Schlüter, 2008). Soils of the area can be summarised as ferrallitic sandy clay loams with dark clays in the valleys (Howard, 1991). More precisely, four different soil types are found: highly fertile red Latosols with a top soil of brownish-red clay covering the largest parts of the area, shallow Lithosols on the highest ridge crests, grey sandy soils at the base of slopes and grey clay soils along the rivers and swamps (Karani et al., 1997b).

Fauna and flora

Mabira Forest's fauna and flora is known to be relatively biodiverse compared to other Ugandan forests (Davenport et al., 1996) although the forest is dominated by secondary forest due to heavy human influence over the past decades (Baranga, 2007; Davenport et al., 1996). A comprehensive biological inventory programme of protected areas in Uganda between 1991 and 1995 revealed a diversity above average for birds and butterflies and an average diversity for the remaining taxa (Howard et al., 2000). In total, 287 bird species including the threatened Nahan's francolin (*Francolinus nahani*) and 218 butterfly species were found (Davenport et al., 1996). Characteristic vegetation types represent sub-climax communities (Baranga, 2007) of which three sub-types are found: young colonising forest dominated by *Maesopsis eminii*, mature mixed forest with 229 species occupying the largest part of the forest, and *Celtis* dominated forest. Additionally, extensive areas of the eastern and north-eastern part of Mabira Forest are colonised by exotic monocultures of *Broussonetia papyrifera* spreading rapidly to all areas where natural forest has been removed (Karani et al., 1997b).

Management, administration and areas around the forest

Mabira Forest is managed by the National Forest Authority (NFA) of Uganda and was first gazetted as a central forest reserve in 1932 under legal notice No. 87. In 1962 the area was re-gazetted with the area as stated above (Karani et al., 1997b). Mabira CFR is divided into four different zones according to forest working cycles: a strict nature reserve, a recreation/buffer zone, a production – low impact area and a production – encroachment area. Each zone is subdivided into compartments for forest management purposes (*ibid*). The forest has a long history of exploitation and human impact, culminating in massive agricultural encroachments and uncontrolled exploitation in the late 1970s and early 1980s that have considerably reduced the forest extent (Baranga, 2007). Although smallholder agriculture is widely practiced, the areas around the gazetted reserves are dominated by large scale sugar cane and tea plantations owned by state-run companies which function as important employers for several thousands of local people (Welch Devine, 2004). Despite a lower population density (302 inh./km^2; calculated from Uganda Bureau of Statistics 2002 census data, for the parishes adjacent to Mabira CFR) as compared to Kakamega Forest, the pressure on the forest is nevertheless high. Within the area of Mabira CFR, eleven demarcated human settlement enclaves with a continuously increasing number of inhabitants are found (Karani et al., 1997b). Thus, charcoal burning, illegal timber sawing as well as firewood extraction are still existent threats (Howard et al., 2000; Naidoo and Adamowicz, 2005) competing with forest conservation efforts.

1.5.3 Budongo Forest

Location, topography and climate

The study area comprises an area of 65 km by 54 km in western Uganda on the edge of the western Rift Valley, excluding 10 km by 34 km in the south-eastern corner (see Figure 1.4). Budongo Forest, placed on the escarpment east of Lake Albert, has been gazetted as central forest reserve with an area of 82,530 ha (Karani et al., 1997a). It is contiguous with two game reserves (GR), Bugungu GR at its north-western edge and Karuma GR in the north-east, and with Murchison Falls National Park in the north. South of Budongo Forest Reserve eleven smaller areas also gazetted as forest reserves are situated within the extent of the study area. The area on the escarpment is undulating at an altitude of about 900 to 1440 m a.s.l. with most of the ridges and hilltops located within the forest reserves, whereas the terrain around Lake Albert is placed some 200 to 250 m lower. Three main rivers, Waisoke, Waki and Sonso, each with numerous small contributory streams, drain the forest catchment to Lake Albert. The climate of the region is described as transitional between the Congo forest and savannah climates further east in Uganda and is influenced by incursions of westerlies causing afternoon thunderstorms (Karani et al., 1997a). Annual rainfall on the escarpment is between 1200 and 1800 mm with two rainy peaks from March to May and September to November, while the period January to March is considered to be the only genuine dry season (Sheil, 1997). The eastern and southern parts of the area receive more precipitation compared to the north and north-western area towards Lake Albert (Karani et al., 1997a). Annual mean temperatures on the escarpment range between a minimum of 17 to 20°C and a maximum of 28 to 29°C (Howard, 1991) while highest temperatures (max. 32°C) are found in the low lying areas around Lake Albert (Karani et al., 1997a).

Geology and soils

The geology underlying the largest part of Budongo CFR is of the Gneissic-Granulitic Complex whereas the area southeast of it is dominated by low grade meta-sediments of the Karagwe-Ankolean System (Schlüter, 2008). Some smaller southern parts of Budongo CFR are underlain by Bunyoro-Kyoga series rock types, which are made up of mudstones, shales, phylites, quartzites and conglomerates of pluvio-glacial origin (Karani et al., 1997a). The soils belong to ferrallitic types which represent the final stage of tropical weathering (Howard, 1991). Most common are heavily leached Latosols and murrams. Whereas the first represents clay loams with varying proportions of sand, the latter ranges from red loam with ironstone concretions to localised exposures of solid plinthite and mainly covers exposures like hill tops (Sheil, 1996).

Fauna and flora

Classified as a medium altitude, moist semi-deciduous forest (Langdale-Brown et al., 1964), its ecological importance is considered to be outstanding as it contains a large number of species not known elsewhere in Uganda or being even endemic (Forest Department, 1996; Plumptre, 2002). In an assessment of the 64 most important forest reserves in Uganda Budongo CFR was ranked third in overall biodiversity importance. While the comprehensive field surveys on which the assessment was based upon amongst others recorded 254 butterfly species, 359 bird species and 130 moth species (Howard et al., 2000), the fauna of Budongo Forest is also known for its well studied chimpanzee populations (e.g. Tweheyo et al., 2004). About 50% of the area of Budongo CFR is not covered by forest but characterised by grassland and woodland communities, the latter mostly *Terminalia*-dominated (Nangendo, 2007). According to Eggeling (1947), four types of forest are found: ironwood forest strongly dominated by *Cynometra alexandri*, mixed forest dominated by *Celtis mildbraedii* and *Khaya anthotheca*, colonising forest dominated by *Maesopsis eminii* and varied types of swamp forest along the rivers. The first three types are thought to form an ecological succession (*ibid*). Several studies revealed an exceptionally high overall diversity of tree species in Budongo Forest as compared to other forests in Uganda (e.g. Eilu et al., 2004, Howard et al., 2000).

Management, administration and areas around the forest

Budongo Forest was first gazetted under legal notice No. 87 in 1932 followed by some amalgamations with adjacent areas to reach a size of 82,530 ha in 1968 (Karani et al., 1997a) which makes it to Uganda's largest forest reserve (Langoya and Long, 1997). Budongo CFR is under jurisdiction of the NFA and its compartments are grouped into eight forest blocks (Karani et al., 1997a, see Figure 1.4). Similar to Mabira Forest, each compartment has been assigned one of the following management zones: nature reserve, recreation zone, protection (buffer) zone, low impact harvesting or sawmill harvesting. Being Uganda's most important timber forest it has experienced selective logging for over 60 years (Plumptre and Reynolds, 1994) and around 80% of the forest has been logged at least once (Howard, 1991). Attempts to abolish not marketable ironwood species (especially *Cynometra*) by treating the forest with arboricide have further altered the vegetation composition (Plumptre, 1996). The area north and west of Budongo CFR is dominated by grassland and woodland, whereas its eastern and southern boundaries are adjacent to agriculturally used land. Traditionally, subsistence farming is widely practiced but in recent time a governmental sugar mill has encouraged local landowners to grow sugar cane for commercial production. Consequently, the proportion of areas used to grow monocultures of sugarcane has increased sharply (Mwavu and Witkowski, 2008). Population density in the agricultural areas is still relatively low with about 158 inh./km^2 (calculated also from Uganda Bureau of Statistics 2002 census data). However, due to the very high population growth rate in Uganda (UN-DESA, 2007) and migration from more densely populated areas an increased population pressure on the forest in the future is expected (Langoya and Long, 1997).

2. Assessing fragmentation and disturbance of west Kenyan rainforests by means of remotely sensed time series data and landscape metrics

(ex AFR J ECOL, 44(4), 491–506)

2.1 Abstract

Biodiversity in tropical rainforests is heavily influenced by land use/cover change (LUCC), but so far there have been few LUCC studies conducted in Africa. We present several methods that make use of remotely sensed data and landscape metrics and allow for assessment of the development of land cover and thus forest fragmentation and disturbance over a substantial period of time. The study covers Kakamega Forest and its associated forest areas in western Kenya, over the last 30 years. The accuracy of a supervised multispectral classification of Landsat time series data encompassing seven time steps between 1972 and 2001 is numerically assessed using ground truth reference data considering the 2001 time step. Here, buffering the forest areas by 1 km, highest user's accuracies for the forest classes 'Near natural + old secondary forest' (87.50%), 'Secondary forest' (80.00%) and 'Bushland/shrubs' (81.08%) are revealed. Images of a spatially distributed fragmentation index derived from the land cover time series by applying a three by 3 pixel-sized moving window to determine forest pixels' adjacency highlight trends in forest fragmentation, e.g. the splitting into two separate forests along the Yala/Ikuywa corridor. Calculations of mean fragmentation indices for the Biodiversity Monitoring Transect Analysis in Eastern Africa (BIOTA-East Africa) focus research areas are used to evaluate the fragmentation index and to demonstrate its potential to extrapolate (e.g. biological) field findings in space and time. Here we argue for a correlation of the fragmentation indices results not only with forest management regimes, but with population distribution and accessibility (e.g. by roads). A cluster analysis applying the isodata-algorithm on the classification results of all seven times steps allows for a rapid visual assessment of the distinct pattern of typical land cover development trends since 1972. This reveals that parts of Kakamega Forest have experienced severe forest loss while others, especially in the north-east, show signs of succession.

2.2 Introduction

Modelled predictions for 2100 reveal that the largest impact on biodiversity is expected to be due to land use/cover change (LUCC), this being especially true for the tropics (Chapin et al., 2000; Sala and Chapin, 2000). Here, highest species numbers and concentrations are found in rainforests with 60–90% of the estimated total biological diversity encountered on just 7% of the total land surface (UNEP-CBD GBO, 2001). Global forest cover has shrunk by more than 20%, possibly up to 50%, since pre-agricultural times (UNEP-CBD, 2001). In Eastern Africa cropland has expanded by 200% between 1900 to 1990 (Klein Goldewijk, 2001). Typical causes of today's continuous deforestation of African rainforests are the expansion of smallholder agriculture for subsistence purposes and fuelwood extraction for domestic uses (Lambin and Geist, 2003). The conversion process is accelerated by a rapid population growth and thus high population pressure particularly in Kenya and Uganda (UNEP-DEWA WRCF, 2001). However, Geist and Lambin (2001) conclude in their global comparison of 152 subnational studies referencing drivers and causes of tropical deforestation, that too few studies on LUCC have been conducted within Africa. Of these only one is located in Eastern Africa.

The research framework of Biodiversity Monitoring Transect Analysis in Eastern Africa (BIOTA-East Africa) follows an integrated and interdisciplinary research approach with at present fifteen subprojects investigating the influence of fragmentation and anthropogenic use on the biodiversity of East African rainforests (Köhler, 2004 or http://www.biota-africa.org). Funded by the German Federal Ministry of Education and Research (BMBF) since 2001, research is related to vegetation structure, certain animal groups emphasizing invertebrates, ecological interactions (e.g. seed dispersal and pollination) and, since 2005, also including socio-economic issues. The focus area of research is the Kakamega Forest in Western Kenya. Petit et al. (2001) point out that field studies alone are not sufficient for assessing and quantifying human impact on forest biodiversity. An analysis of spatial patterns of LUCC is needed, also for predicting future changes. Various studies have shown that in this context geographic information systems (GIS) and remote sensing are valuable a means to this end (e.g. Fuller et al., 1998; Gottschalk, 2002; Mas et al., 2004; Roy and Tomar, 2000). Hence, the setting-up of a common geospatial data basis in a GIS including LUCC information derived by remote sensing is a prerequisite for integrating the interdisciplinary BIOTA-East project results and for extrapolating from or scaling-up the field-based findings in space and time effectively (Schaab et al., 2004) as the area coverage is large compared with sampling

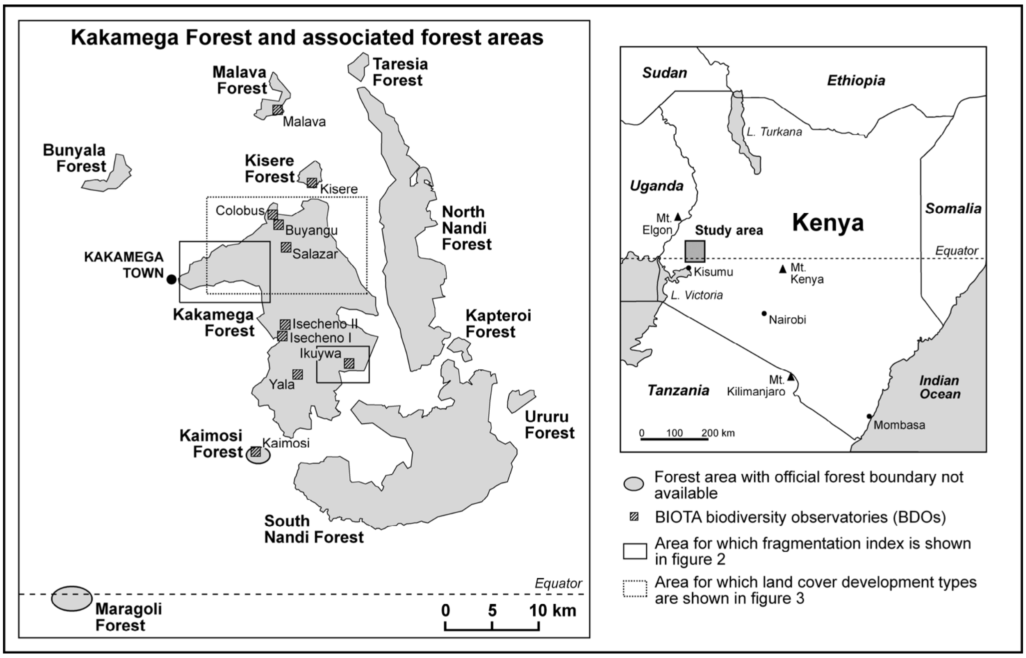


Figure 2.1: Map of Kakamega Forest and its associated forest areas in Western Kenya based on official forest boundaries; including information on focus areas of research within the BIOTA-East Africa project as well as on subset areas chosen for presenting results in Figures 2.2 and 2.3.

density and 'footprint'. Spatial LUCC patterns and their subsequent statistical analysis together with biological field survey data enable assessments of the relationship between biodiversity and forest fragmentation. Information as on the effects of forest fragmentation and disturbance appears to be missing. This is especially so regarding invertebrates which account for up to 80% of forest biodiversity [as Wass (1995) points out for Kenya] and which serve as the focus animal group of BIOTA-East.

It is this issue on providing information on forest fragmentation and disturbance to which our studies are aimed. While forest fragmentation describes the process of forest cover breaking or the state of being broken into separate patches, forest disturbance summarizes diverse human impacts which act locally, like for example selective logging. Often, both terms are mentioned together. Land cover classification results for Kakamega Forest and its associated forest areas over the last 30 years were derived using a supervised multispectral classification of Landsat time series data. These are described in Lung (2004) including extensive analyses of land cover change. In this paper, the accuracy assessment of the classification results is added for stronger confidence in using them for the further processing as described thereafter. Here, our landscape metrics calculations based on a moving window approach contribute to the much-needed quantification of forest fragmentation and, indirectly, disturbance. Finally, the outcome of a cluster analysis is presented summarizing the distinct trends in forest cover development for the area under investigation between 1972 and 2001.

2.3 Material and methods

Site description

The study site comprises an area of 60 km by 65 km. The site is located between longitudes 34°37'5" and 35°9'25" East and latitudes 0°32'24" North and 0°2'52" South in Western Kenya and encompasses the Kakamega Forest and its associated forest areas (Figure 2.1). Elevation ranges from an altitude of 1,165 m above sea level south of Nyando Escarpment to 2,180 m in the north-east of the Nandi Escarpment [topographic map East Africa 1:50,000 (Kenya), Sheets 88/3, 88/4, 89/3, 102/1, 102/2, 103/1, 102/3, 102/4, 103/3, Series Y731 (D.O.S. 423), Edition 6 (1970)]. Kakamega Forest, as defined by its official forest boundary, is placed between 1,520 m and 1,680 m elevation. Two major rivers are passing the area, the Isiukhu River in the northern part and Yala River in the southern part both making their way through Kakamega Forest. The forests in the area are important water catchment areas feeding into Lake Victoria basin (Kamugisha et al., 1997). The area around Kakamega Forest has one of the highest levels of annual rainfall in Kenya with an annual average of approximately 2,000 mm (Haupt, 2000). There are two rainy seasons with long rains from March to June and short rains from July to September. The weakly developed or totally missing dry season is in mid-year (Flohn and Frädrich, 1966).

Kakamega Forest is often described as the easternmost relic of the Guineo–Congolian rain forest (e.g. Kokwaro, 1988). It is considered to be botanically unique since it has many endemic plant species (Mutangah et al., 1992) and is known for its large species diversity (KIFCON, 1994). With a total of 254 recorded forest dependent bird species the Kakamega-Nandi Hills complex is the most bird-diverse area in Kenya. The number of threatened or scarce bird species is estimated to be approximately 45 species (Wass, 1995). Thus, Kakamega Forest and its associated forest areas have been identified as being of the highest priority for biodiversity conservation (Wass, 1995).

The forests are located in one of the world's most densely populated rural areas with an average population density of 600 people/km² (Blackett, 1994). A rapidly growing population occupies 57 forest-adjacent villages and thus places pressure upon Kakamega Forest (KIFCON, 1994). Population growth is leading to repeated sub-division of land parcels and has rendered the traditional agricultural system of fallow rotation almost unworkable as the pressure to continuously cultivate all available land increases. As a result, the forest has become an ever more important resource for satisfying the daily needs of the local people. Hunting, collecting of medical plants, charcoal burning, illegal pit-sawing, grazing, collecting of fuel wood and the agricultural shamba-system are some of the threats to which the forest is exposed (Mitchell, 2004). Additionally, the forest has been commercially exploited for gold mainly in the 1930s and for both clear-fell and selective logging. These factors have contributed to the recent appearance of the forest as a mosaic of dense forest, clearings, forest plantations, regenerating forest areas, cultivated land and grassy glades (Kamugisha et al., 1997). Many research studies have been conducted in Kakamega and Kisere Forests but the other associated forest areas have mostly been excluded.

Multispectral image classification

Landsat satellite data have been acquired for seven time steps between 1972 and 2001. The early time steps (1972/73, 1975 and 1979/80) have been detected by Landsat MSS (Multispectral Scanner) and have a spatial resolution of 60 m, while the Landsat TM/ETM+ (Thematic Mapper / Enhanced Thematic Mapper) imagery for 1984, 1989, 1994/95 and 2001 have an improved resolution of 30 m. Data preparation involved orthorectification by means of topographic map sheets (1.50,000 from 1970) and atmospheric correction with the help of the ATCOR three module based on a digital elevation model constructed from the topographic maps' contour lines. The supervised multispectral classification of the remotely sensed imagery has been performed in the software ERDAS Imagine 8.5 (Leica Geosystems, Atlanta, Georgia, USA). For classification, training areas were selected based upon ground truthing via (i) different maps with vegetation information (vegetation map 1 : 250,000 from 1966/69, forest cover in 1 : 50,000 topo maps from 1970, FD forest map 1 : 10,000 from 1972 with updates on planted species up to the 1990s, and KIFCON land cover map 1 : 25,000 from 1991), (ii) amateur photographs taken during a flight over Kakamega Forest in May 2001, and (iii) terrain references. Whenever available (1972/73, 1975, 1979/80, 1994/95 and 2001), two scenes, covering dry and rainy seasons, have been used and allow for seasonal variation in vegetation patterns. For the two remaining time steps, 1984 and 1989, only scenes from the dry season are available as rainy season imagery with severe cloud coverage was not purchased. Clouds and cloud shadows in the images have been manually masked via on-screen digitizing and filled by inserting the spectral values of the other scene available for the same time step. For Landsat-TM/ETM+ the bands 3, 4, 5, 7 and the ratio channel 7/2 have been considered in the multispectral classification applying the maximum likelihood classificator. The classifications of MSS-data are based on other spectral band combinations (bands 1, 2, 3, 4, no artificial channel) due to sensor differences. A detailed description of the classification procedure and the resulting classified time series is given by Lung (2004), for a summary see Lung and Schaab (2004). Here we simply point out that twelve land cover classes could be realized (see Table 2.1) on the basis of the available Landsat satellite imagery and the reference data for ground truth verification.

Accuracy assessment

Only the classification results for the year 2001 are considered in the accuracy assessment. Although the classification for 1994/95 has been judged via a visual assessment to have gained the best result (Lung, 2004), the time step of 2001 provides the best and broadest ground truth reference data due to the availability of the 2001 amateur photographs. In order to perform a statistically sound and practically accomplishable assessment, Congalton and Green (1998) suggest the generation of 50 random samples for each land cover class, which, for our 12 land cover classes, results in 600 sample pixels. The method of randomly distributing 50 pixels per classified land cover class area, as provided by ERDAS Imagine 8.5, is used here as the sampling scheme. The accuracy assessment is carried out by individually comparing the randomly selected classified pixels with the original Landsat image data, the amateur photographs of the forest taken from the air and the maps with vegetation information. This visual interpretation of the true land cover per random pixel is confronted with the land cover classes resulting from the multispectral image classification by means of an error matrix.

As it is the forest and not the surrounding farmland that is the focus of the BIOTA-East biodiversity research, three spatial levels have been applied for specifying the accuracy. While the first level comprises the total area under investigation (60 km by 65 km), the second level encompasses the forest areas buffered by 1 km in order to ensure that the full forest extent reaching across the official forest boundaries is included. The buffered area, as a subset of the 60 km by 65 km area, contains 302 of the total 600 sample pixels.

Table 2.1: Reclassification schemes applied to the land cover classes as distinguished in a supervised multispectral classification of Landsat satellite imagery of the wider Kakamega Forest area.

Value	Land cover classes	Reclassified to (for accuracy assessment, A)	Reclassified to (for accuracy assessment, B)	Reclassified to (for deriving a fragmentation index)	Reclassified to (for performing a cluster analysis)
1	Near natural + old secondary forest	1 Forest	1 Forest	1 Forest	1
2	Secondary forest	1 Forest	1 Forest	1 Forest	22
3	Bushland/shrubs	2 Bushland	1 Forest	2 Nonforest	43
4	Secondary Bushland–*Psidium guajava*	2 Bushland	1 Forest	2 Nonforest	55
5	Grassland with scattered trees	3 Grassland	2 Grassland	2 Nonforest	76
6	Grassland	3 Grassland	2 Grassland	2 Nonforest	82
7	Plantation forest–*Pinus patula*	1 Forest	1 Forest	2 Nonforest	116
8	Plantation forest–*Bischoffia javanica*	1 Forest	1 Forest	2 Nonforest	128
9	Tea plantation	4 Tea plantation	3 Tea plantation	2 Nonforest	149
10	Agricultural land	5 Agricultural land	4 Agricultural land	2 Nonforest	170
11	Water	6 Others	5 Others	2 Nonforest	191
12	Others	6 Others	5 Others	2 Nonforest	212

Performed for an accuracy assessment of the classification quality, for deriving a spatially distributed forest fragmentation index and for running a cluster analysis.

For a third level only those forests investigated in BIOTA-East (Malava Forest, Kisere Forest, Kakamega Forest and Kaimosi Forest) are considered, also buffered by 1 km, and result in 147 sample pixels.

Further, two reclassifications of the land cover classes as derived using the multispectral classification are performed in order to also allow an assessment of a less ambitious separation of some neighbouring land cover classes (see Table 2.1). In the first reclassification (A) the four forest classes, including plantation forest (classes 1, 2, 7 and 8), are merged to 'Forest'. 'Secondary bushland–*Psidium guajava*' (class 4) is combined with 'Bushland/shrubs' (class 3) to become 'Bushland', 'Grassland with scattered trees' (class 5) with 'Grassland' (class 6) to become 'Grassland' and the classes 'Water' and 'Others' merge to become 'Others'. The second reclassification (B) is the same as the first except that the bushland classes 3 and 4 are added to the class 'Forest' resulting in a classification scheme with five classes, one of these containing all six forest classes.

On the basis of the error matrix a calculation of four measures of accuracy have been performed for each of the three spatial levels as well as the three (re)classification schemes. While the overall classification accuracy specifies the percentage of correctly classified pixels in total, the user's accuracy provides the percentage of correctly classified pixels per land cover class. The producer's accuracy indicates the percentage of correctly classified pixels per reference class, that is the total number of pixels visually assigned to a certain land cover class. In the calculation of the Kappa index, both numerator and denominator are reduced by the same amount, i.e. by an estimate of the number of pixels correctly classified purely by chance (Longley et al., 2001). Thus, in comparison to the overall classification accuracy, the Kappa provides a more accurate but less readily apparent measure of classification success.

Landscape metrics making use of a moving window

In order to analyse forest fragmentation an index based on the satellite time series classification results proved useful. For this purpose the 12 land cover classes are reclassified for all seven time steps by distinguishing between 'Forest' (original classes 1 and 2) and 'Non-Forest' (all other classes, see Table 2.1). A tool developed in C++ and based on a moving window algorithm identifies edges between forest and non-forest pixels (compare Wade et al., 2003). An edge is defined as the line segment that separates any two adjacent pixels. The algorithm as applied here uses a window size of 3 x 3 pixels. The window is centred on each pixel of the input data. For these 9 pixels the algorithm counts the number of edges between forest and non-forest pixel pairs (used later as nominator) and between forest and any other pixel pairs, i.e. either forest or non-forest; (the denominator). From the two edge counts a fragmentation index is calculated and the resulting score assigned to the windows' mid-pixel. Then the window moves one pixel further to the right and again the index is calculated and assigned to the new mid-pixel. This process continues pixel by pixel until indices are determined for all pixels making up the input dataset except for the outermost pixel rows and columns. The output is a spatial distribution of the fragmentation index with values ranging from 0 to 1. Whereas 0 indicates no forest fragmentation, the level of fragmentation increases up to 1 indicating total fragmentation, i.e. no remaining adjacent forest pixels considering cardinal directions. Such images of fragmentation index distributions are generated for all seven time steps. Additionally, a mean fragmentation index is derived for the main focus areas of Biota-East research, i.e. for each of the 10 biodiversity observatories (BDOs, see Figure 2.1) applying zonal statistics in GIS, but considering the 2001 output only.

Cluster analysis

A cluster analysis is performed for the second spatial analysis level (all forest areas buffered by 1 km). The preparation of the data involves a weighted normalisation of the classification results for all time steps. This is done in order to create meaningful values that allow for a grouping in clusters. The normalisation process stretches the values 1 to 12 (see original land cover classes in Table 2.1) to a maximum range of 1–256 for unsigned 8-bit data. Additionally, a weighting of the land cover classes is applied to the stretching process, which takes similarities of the land cover classes into account. Four 'distances' are defined: very close (a value difference of 6), close (12), average (21) and far (34). The distance between classes 5 ('Grassland with scattered trees') and 6 ('Grassland') is defined as 'very close' whereas the distance between classes 3 ('Bushland/shrubs') and 4 ('Secondary bushland–*Psidium guajava*') and between 7 ('Plantation forest–*Pinus patula*') and 8 ('Plantation forest–*Bischoffia javanica*') is set to 'close'. The greatest distance ('far') is assigned between the classes 6 and 7. All the other distances are set to 'average'. After the weighted normalisation the values spread from 1 to 212 (see Table 2.1).

The resulting reclassified land cover data sets for the different years are merged in a layer stack as input to an unsupervised classification, i.e. a cluster analysis applying the isodata-algorithm (Iterative Self-Organizing Data Analysis Technique of the ERDAS Imagine 8.5 software, see LEICA, 2003). This algorithm arbitrarily locates the cluster centres in the seven-dimensional (due to seven time steps) feature space according to the number of clusters specified by the analyst. Next, each pixel is assigned to the cluster whose centre is closest. After all pixels have been classified, the mean for each cluster is determined and the revised cluster centres are used as the basis for repeated reassignment of the pixels. In order to stop the process the maximum number of iterations is set to 25 runs. As a second criterion for stopping the process a threshold of 97% is specified as the percentage of pixels which no longer change classes anymore, i.e. only 3% of the pixels still move between clusters. The number of clusters to be distinguished is set to 100. This proved to be a reasonable figure for use as the basis for a meaningful aggregation to regions that are alike, i.e. types, showing typical developments in land cover over time. Tests revealed that the generation of <100 clusters causes pixels of opposed trends to be assigned to the same cluster. A higher number of clusters did not result in an improved assignment of pixels to clusters. Instead clusters with less pixels were produced, and a high proportion of these were not spatially adjacent to each other thus failing to produce representative areas. It was not possible to aggregate those to meaningful development types. Test runs on modified distances between class values did not lead to significant improvements.

For the aggregation of the 100 clusters to meaningful types of land cover development about 10–50 pixels are randomly chosen from every cluster, if possible those uniformly distributed in space. The assigned land cover classes for the seven time steps are reviewed for each pixel individually. Figure 2.3 shows, upper left, an example of how the single pixels are viewed and examined on-screen. The pixel in the example has been assigned to the cluster valued 18 in the unsupervised classification process. For the first three time steps (i.e. 1972/73, 1975 and 1979/80) the value for the pixel is 1 (i.e. class 'Near natural

+ old secondary forest') whereas from 1984 to 2001 the value is 43 ('Bushland/shrubs', compare with Table 2.1). Therefore a clear trend of forest loss is obvious. If the other tested pixels for that cluster reveal a similar development, the main direction would be 'forest loss' as the original land cover class 1 is replaced by class 3 in 1984 and stays class 3 until 2001. In the manner demonstrated for the given example, the main direction of development from 1972 to 2001 is determined for each cluster. In a second step, these main trends are grouped into thirteen distinct types of development in land cover and supplemented by a description.

The aggregated types are visualised in a colour-coded map. Whereas negative trends in forest development depending on the degree of forest loss are assigned with red, orange or yellow, areas of more stable status are displayed in green colours. Regeneration and succession of forest formations are presented in mauve while agricultural land is shown in brown hues.

2.4 Results

Classification accuracy

Six hundred randomly selected pixels were assessed showing that user's accuracies are highest for the land cover classes 'Near natural + old secondary forest' (84%), 'Secondary Forest' and 'Bushland/shrubs' (80% each), 'Tea plantation' (94%) and 'Agricultural land' (88%). In contrast the classes 'Grassland with scattered trees' (58%), 'Grassland' (26%) and 'Plantation forest–*Pinus patula*' (24%) show lower values. Together they result in an overall classification accuracy of 58.17%. As the BIOTA-East Africa project concentrates on forest areas, we present classification accuracies based on those randomly chosen pixels that are found within the forest areas buffered by 1 km (second spatial level, see Table 2.2). These assessments are performed for every single land cover class as well as for an aggregation of these 12 land cover classes into 6 classes (reclassification A, see Table 2.1). Here, the overall classification accuracy considering the 12 original classes is 68.54% and the overall Kappa index is 0.64. Similar to the results for the total area under investigation, the highest user's accuracies of 80% and more have been achieved for the land cover classes 1, 2, 3, 9 and 10, which cover about 70% of the area. Lower user's accuracies can again be noticed for classes 5 (50%), 6 (36%) and especially 7 (28%). In general, the Kappa index is slightly lower compared to the user's accuracy but shows the same tendency when treating all 12 land cover classes. With a producer's accuracy of 100% for classes 8 and 4 all the areas classified as 'Plantation forest–*Bischoffia javanica*' or 'Secondary bushland–*Psidium guajava*' are likely to be correctly assigned.

The aggregation of the ambitiously separated twelve classes to six classes, grouping forest, bushland and grassland formations results in an increase of the overall classification accuracy from 68.54% to 81.41% (Kappa index of 0.70). This difference is mainly influenced by an increase of the user's accuracy for the classes with the highest classified totals (e.g. class 'Forest' with 182 of in total 302 pixels). Here, the aggregated forest classes show a user's accuracy of 87.36%. A combination of all six forest formations (including classes 3 and 4) into one class (reclassification B, see Table 2.1) leads to an increase of the user's accuracy for 'Forest' from 87.36% to 93.78% and a rise in the overall classification accuracy from 81.46% to 88.08%. When considering only the forests under investigation in BIOTA-East, the overall classification accuracy is 73.5% when

Table 2.2: Accuracies of the supervised multispectral classification results for Kakamega Forest and its associated forest areas buffered by 1 km (time step 2001), based on a random visual comparison of classified pixels with the original satellite image as well as photographs and maps.

	Pixels			Percent			
Land cover class	Reference totals	Classified totals	Number correct	Producer's accuracy	User's accuracy	Overall classification accuracy	Kappa index
Near natural + old secondary forest (1)	74	48	42	56.76	87.50		0.83
Secondary forest (2)	50	50	40	80.00	80.00		0.76
Plantation forest–*Pinus patula* (7)	13	43	12	92.31	27.91		0.25
Plantation forest–*Bischoffia javanica* (8)	30	41	30	100.00	73.17		0.70
Forest	**167**	**182**	**159**	**94.64**	**87.36**		**0.72**
Bushland/shrubs (3)	47	37	30	63.83	81.08		0.78
Secondary bushland–*Psidium guajava* (4)	14	22	14	100.00	63.64		0.62
Bushland	**61**	**59**	**47**	**78.33**	**79.66**		**0.75**
Grassland with scattered trees (5)	18	10	5	27.78	50.00		0.47
Grassland (6)	6	11	4	66.67	36.36		0.35
Grassland	**24**	**21**	**10**	**41.67**	**47.62**		**0.43**
Tea plantation (9)	**21**	**23**	**20**	**95.24**	**86.96**		**0.86**
Agricultural land (10)	**17**	**7**	**6**	**35.29**	**85.71**		**0.85**
Water (11)	7	6	4	57.14	66.67		0.66
Others (12)	5	4	0	0.00	0.00		0.00
Others	**12**	**10**	**4**	**33.33**	**40.00**		**0.38**
Sum	302	302	207			68.54	0.64
Sum	**302**	**302**	**246**			**81.46**	**0.70**

Shown are producer's accuracies, user's accuracies, overall classification accuracies as well as Kappa indices for the original land cover classes and aggregated land cover classes (reclassification A, see Table 2.1).

using 12 land cover classes, 86.5% when using reclassification A, and 92% for reclassification B. Here, the aggregation of four forest formation classes generates a user's accuracy of 89.5% while an aggregation of six classes leads to 96%.

Fragmentation index time series images

Figure 2.2 shows the spatially distributed fragmentation index and its change over time due to land cover change as derived from the multispectral classification of Landsat time series data for two sample areas (note the different scales and spatial resolutions, for locating these areas see Figure 2.1). A fragmentation index of 0 (i.e. no forest fragmentation) is shown in white, while an index of 1 (i.e. total fragmentation with no adjacent forest pixels) is shown in black. A fragmentation index of 0.5 means that of the forest pixels in the 3 x 3 pixel window, half the number their of edges are adjacent to forest and half are adjacent to nonforest. These are depicted with a 50% black tint due to the assignment of a linear grey shade ramp. The area not covered by forest (i.e. pixels without forest adjacent) is moved to the background via a fine hatching. The two areas have been selected to demonstrate two distinct patterns of forest disturbances. For both areas all time steps of the time series show a similar increase in fragmentation towards forest edges. The time series of the Yala/Ikuywa corridor highlights an alarming splitting into two separate forest fragments. In the case of Kakamega Fuel Area, which stretches towards Kakamega town, a severe but gradual forest decline over the last 30 years is

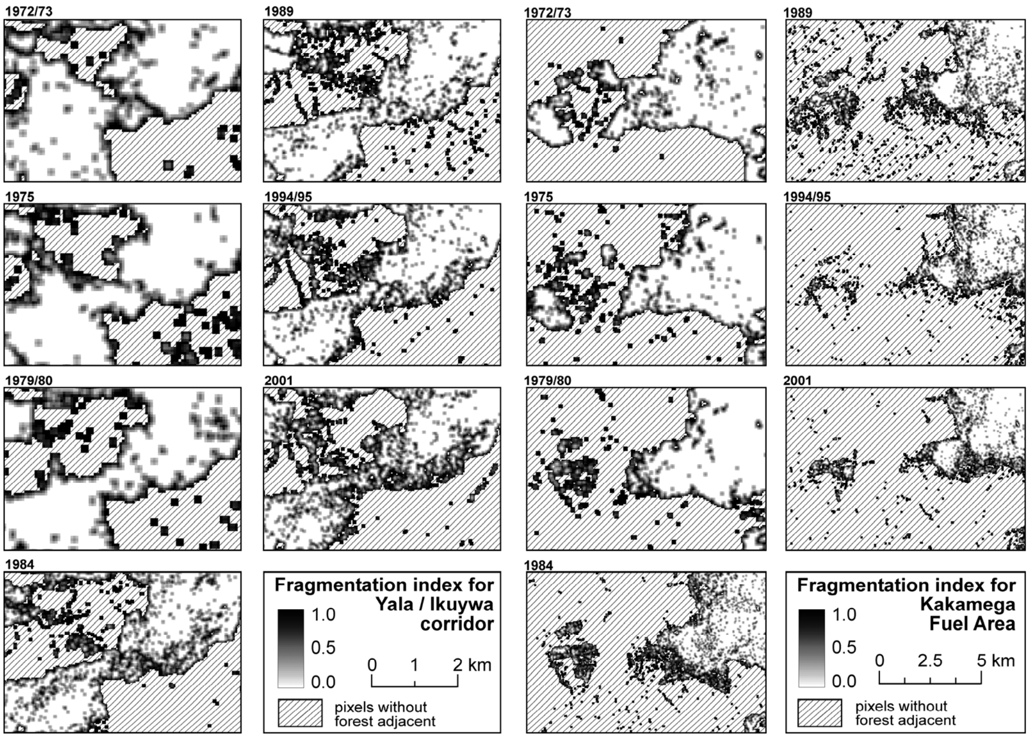


Figure 2.2: Time series, 1972 –2001, of a spatially distributed forest fragmentation index for the Yala/Ikuywa Corridor and Kakamega Fuel Area (note the different scale, for locating these areas see Figure 2.1).

obvious. Mean fragmentation indices as calculated for the ten BDOs (see Figure 2.1) for the most recent time step available (2001) are highest for Kaimosi (0.481), Malava (0.397) and Ikuywa (0.378) whereas lowest mean indices are determined for Salazar (0.077), Kisere (0.091), Isecheno II (0.183), Colobus (0.188) and Yala (0.198). The indices for the remaining BDOs Buyangu (0.288) and Isecheno I (0.258) reveal a moderate degree of fragmentation.

Map of land cover development types

The 100 clusters derived via an unsupervised classification have been summarized to 13 distinct land cover development types (see Table 2.3). Five of the obtained types indicate real changes in land cover between 1972 and 2001. More precisely, three of these types (2, 3 and 5) include forest loss, whereas two types (6 and 10) are characterized by forms of regeneration or succession. Types 1, 4, 7, 8, 9 and 12 describe areas more or less unchanged over time regarding vegetation cover and land use, while type 11 represents a change between agricultural use and grassland. Approximately 4% of the pixels could not be described by a meaningful tendency in land cover development, and together form type 13.

The visualisation of the 13 land cover development types on a map allows instant observation of differing land cover histories for different parts of the forest. In this publication only a subset of the map can be presented (see Figure 2.3; for the complete

Table 2.3: Description of the 13 land cover development types for the area of Kakamega Forest and associated forest areas, 1972–2001, resulting from a cluster analysis based on classified Landsat time series data (see Figure 2.3).

Type	Description of temporal land cover development types
1	**Mainly 'Near natural + old secondary forest'**: areas represented as near-natural forest in ≥6 time steps (represented as 'Secondary forest' in ≤2 time steps – probably misclassifications).
2	**Loss of 'Near natural + old secondary forest' with subsequently regeneration of secondary forest**: mostly 'Near natural + old secondary forest' till around 1975, than total forest loss in favour of grassland and, in parts, also of agricultural land by the late 1970s or the 1980s. Followed from ca. 1995 by growth of bushland and secondary forest (mainly for 2001). In many of these areas stands of *Psidium guajava* are found in 1994/95 and 2001.
3	**Total loss of 'Near natural + old secondary forest' (no regeneration)**: mainly near natural forest till 1980, but in parts also till 1984 or even 1989. Followed by bushland till 2001 or in parts further clear felling and thus agricultural land in 1994/95 and 2001. Typical for forest edges of the North and South Nandi Forests and for parts of the south and northwest of Kakamega Forest.
4	**Mainly secondary forest**: areas represented as secondary forest in ≥4 time steps and mostly 1 to 2, sometimes even 3 time steps with 'Near natural + old secondary forest'. Clear distinction to type 1 very difficult, therefore several areas more likely type 1.
5	**Loss of secondary forest**: at first secondary forest (till around 1980, in parts till 1994/95), afterwards bushland that also disappears in parts and is replaced by agricultural land from ca. 1994/95. Typical for the forest edges, Kakamega Fuel Area and South Nandi Forest.
6	**Succession of (natural) forest formations**: grassland in the 1970s, in parts mixed with scattered trees or small areas of agricultural land, since ca. the mid 1980s marked by growth of bushland and, in parts, secondary forest till 2001. Typical occurrence in the north-central and north-eastern forest margin of Kakamega Forest. Also included: vegetation-free or grass-covered areas in the 1970s that have become plantation forest afterwards; to be distinguished by occurrence in larger patches as compared to the stripes along the forest edges and glades.
7	**Mainly bushland/grassland with scattered trees**: for almost all time steps either bushland or grassland with scattered trees and bushes. Hardly any occurrence in large patches.
8	**Mainly forest plantations**: areas with no. of time steps with forest plantations ≥5, mainly *Pinus patula*. Comment: assignment of areas of *Bischoffia javanica* not satisfactory in this cluster analysis. Also included: small areas with a change in grassland with scattered trees, and agricultural land but without signs of significant development.
9	**Mainly grassland and grassland with scattered trees**: for almost all time steps grassland or grassland with scattered trees and bushes. Typical occurrence on the glades of Kakamega Forest. Also included: areas with *Pinus patula* plantations which disappeared between 1984 and 1989 and were replaced by agricultural land, but which changed to bushland already again since ca. 1994/95.
10	**At first agricultural land, then grassland with scattered trees in parts**: mostly agricultural land till 1980, afterwards grassland, in 1994/95 and 2001 in large parts grassland with scattered trees. Occurrence of areas mainly within the forest, therefore perhaps areas which have been used for the shamba system, now overgrown.
11	**Change in agricultural land and grassland**: agricultural land or grassland, each ca. 3-4 time steps, without signs of a significant development. Comment: due to the spectral similarity of cultivated crops and grassland possibly mainly agricultural land. Also included: areas which were grassland and agricultural land in the 1970s and became plantations of bischoffia in the 1980s. Water areas are in parts also included here.
12	**Mainly agricultural land**: no. of time steps with agricultural land ≥4. Occurrence largely outside the forest areas. Also included: vegetation-free areas in the long-term, e.g. quarries, roads, settlements as well as water.
13	**Meaningful aggregation not possible**: no meaningful tendencies in the development of the land cover revealed, e.g. within one cluster pixels/areas change between agricultural land, forest plantations and near-natural forest (possible misclassifications) or change between grassland and bushland. Adds up to ca. 4% of the investigated buffered forest areas.

map see Lung, 2004) and we simply describe the most striking features revealed by this map. Losses in 'Near natural + old secondary forest' and 'Secondary forest' (types 2, 3 and 5) can be noticed along most of the forest edges, especially along the edges of North and South Nandi Forests and the southern part of Kakamega Forest. Large areas which have been completely deforested (type 3) are found in the north-western (see Figure 2.3) and the southern part of Kakamega Forest as well as in the western part of South Nandi Forest and in the northern part of North Nandi Forest. A reverse trend in the development of land cover can be noticed for the north-eastern and the north-central part of Kakamega Forest (see Figure 2.3). Here, succession of forest (type 6) is shown to take place along the edges of the forest glades. A considerable difference can be discerned when comparing the northern and southern parts of Kakamega Forest: while in the northern part forest loss is almost limited to the area stretching towards Kakamega town in the west, the southern part is characterised by an heterogeneous pattern with areas having experienced various interferences: there completely deforested areas are found (type 3), forest areas being used for plantations over the last 30 years (type 8) or areas not typifyable due to rapid changes or misclassifications (type 13). Characteristic for the area around Lirhanda Hill is the occurrence of areas which were once agricultural but have recovered to grassland with scattered trees since 1994/95. This area separates the northern main forest block from Yala and Ikuywa forest areas in the south. In the case of South Nandi Forest many scattered pixels representing forest loss (types 3 and 5) can be observed throughout the forest, a phenomenon not found in Kakamega Forest and North Nandi Forest in this severity. Considering the outlying forest fragments, Malava is described by an alternating pattern of forest loss, forest plantations, areas of grassland, agriculture as well as stable forest areas. By comparison, Kisere fragment appears to have has experienced very little forest disturbance. In the case of Ururu, Maragoli and Bunyala forest formations have been almost completely lost in favour of agricultural land and we can no longer refer to them as forest fragments. The forest fragments Kaimosi and Kapteroi show severe forest losses too, but tiny patches of stable forest (types 1 and 4) can still be made out. For Taresia Forest most of the pixels have been assigned to type 13 (i.e. not typifyable). The areas around the forests are dominantly assigned to type 12, meaning that they have been used for agriculture throughout.

2.5 Discussion

Classification accuracy

Lung (2004) conducted a visual assessment evaluating the qualities of the classification results for every single time step. In this paper we finally present the required numerical accuracy assessment (see e.g. Lillesand and Kiefer, 2000). Unfortunately recent aerial photography that would have satisfied the demand for reference data of higher spatial resolution (Congalton and Green, 1998), was not at hand. Lacking such data we have had to make use of the Landsat imagery itself, but have included more detailed information via amateur photographs taken during a flight over the forest in the same year. The accuracy assessment of the year 2001 classification is comparable to that of other land cover classifications based on Landsat TM/ETM+ data. Similar to our results of 68.54% and 81.46% overall classification accuracies, (see Table 2.2), are the results of Schöpfer and Lang (2004) who report on a land cover classification along the former iron curtain between Austria and Hungary with an overall accuracy of 70.83% when considering all their original land cover classes and of 87.40% when combining the classes 'Dense pasture' and 'Sparse pasture'. The higher number of correctly classified pixels and, consequently, the higher user's accuracy for aggregated classes is due to the fact that misclassifications between the later grouped original land cover classes are thus merged. In other published classifications the practice of distinguishing between more than one or two forest classes is not even attempted. For example, Read et al. (2001) simply distinguish between 'Forest' and 'Scrub' in a classification of Landsat data for a predominantly forested area in Costa Rica. Here, our user's accuracies of 87.36% and 93.78% for the aggregated classes 'Forest' applying reclassifications A and B, respectively, are comparable to their achieved user's accuracy for 'Forest' of 88% for 1986 and 93% for 1996. However, the original interpretation of land cover classes in the reference data, especially transitional forest classes in heterogeneous and fragmented landscapes like the Kakamega area, might be challenging, as is shown by Powell et al. (2004). For their study site of Rondônia in the Southwest Brazilian Amazon a distinction was made between 'Primary Forest', 'Second-growth forest' and 'Pasture' (meaning 'shrubs'). Five interpreters independently evaluated the reference data with the result of low average agreements especially regarding forest classes. After reassembling and producing a common final reference set the five interpreters obtained an overall accuracy of 75.4%, but highly varying user's accuracies for the forest classes (i.e. 93.4% for 'Primary forest', 28.2% for 'Second-growth forest' and 71.9% for 'Pasture'), a fact which Foody (2002) highlights to still be a prevalent challenge of accuracy assessments.

In our study, the considerable variation in the user's accuracies of the individual land cover classes (see Table 2.2) is highly influenced by the sampling scheme applied for selecting randomly distributed pixels as reference samples. Since almost all of the randomly selected pixels for the six forest classes are found in the forest areas, pixels for the other classes seem to have been preferably selected in areas outside the forest in order to achieve an equally distributed pattern. However, these areas outside the forest are considered to be less accurately classified because during the supervised classification process we focused on an accurate assignment of land cover classes in the forested areas at the expense of an accurate classification of the surrounding farmland. For example, the sampling method strongly effects the result for the land cover class 'Grassland', as no pixels of the presumably correctly classified grassy glades inside the forest have been chosen, but instead pixels outside the forests which had probably been misclassified as grassland were selected. These misclassifications are caused by high spatial and spectral heterogeneity of agricultural land together with its spectral similarity to grassland (compare Kuemmerle et al., 2005). This effect appears to be particularly prevalent in such an intensively cultivated area as Kakamega, especially since sugar cane (belonging to the same life form as grass) is one of the major crops. The difficulty of separating the classes 'Near natural + old secondary forest' and 'Plantation forest–*Pinus patula*' is already described in Lung and Schaab (2004). Here, the low user's accuracy for 'Plantation forest–*Pinus patula*' and the low producer's accuracy for 'Near natural + old secondary forest' are again due to the sampling method selecting evenly distributed random pixels. The misclassified 'Plantation forest–*Pinus patula*' pixels scattered throughout the 'Near natural + old secondary forest' class pixels seem to have been favoured as reference pixels. Furthermore, and especially for the second and third spatial level where only forest areas are considered, low accuracies for non-forest classes should not be overemphasized because these classes are represented by very few pixels (e.g. seven of a total of 50 pixels represent the class 'Agricultural land' in all the buffered forest areas). Congalton and Green (1998) suggest a number of 50 pixels per land cover class in order to determine classification accuracies and we have followed this suggestion for assessing the accuracy of the complete area. As the visual comparison of 600 pixels with reference information is a very time-consuming task and having the drawbacks of the random-pixel-selection in mind, we considered subsets of reference pixels as sufficient when interpreting the resulting accuracies with care instead of again assessing 600 pixels for each of the 2nd and 3rd spatial levels.

It is our opinion, classification accuracies should not only be assessed using statistical methods but also visually, i.e. in a spatial, and if possible, temporal context as performed for our time series in Lung (2004). Visual interpretations however are affected by human subjectivity, but can hold true if the observer is very experienced. These visual assessments should be also considered in, for example, biological analyses when making use of our classification results. Classification of single pixels should not necessarily be taken as reflecting reality but the surrounding landscape composition or the general pattern of land cover change for the different forest areas should also be taken into account.

Fragmentation index imagery

Kakamega Forest and its associated forests show patchy deforestation, a pattern in general described by Geist and Lambin (2001) as being almost exclusively driven by demographic and economic factors. Numerical information is needed for describing landscape composition or forest fragmentation and in order to combine our land cover classification results with biological field findings via statistical assessments. In this context many landscape ecologist researchers make use of landscape metrics (see e.g. McGarigal, 2001) in their studies (e.g. Lung, 2004; Read et al., 2001; Roy and Tomar, 2000). Some indices allow for statements on landscape diversity or for a comparison of neighbouring forest patches in an aggregated manner but do not derive a spatially explicit output, i.e. an image of a spatially distributed index. Read et al. (2001) derived standard indices like edge density, mean patch size, area at least 100 m from an edge, or Shannon's diversity index from a case study on LUCC derived from aerial photography and Landsat data for a tropical rainforest area in Costa Rica. They infer a general increase in habitat fragmentation and landscape diversity and a decrease in mean patch size. However, 'hotspots' of fragmentation or, relatively undisturbed areas cannot be located by such indices since the output is limited to numerical values. To avoid this drawback we have applied a fragmentation index using a means of a moving window as suggested by Wade et al. (2003). However, we consider our application of the index to be a useful reflection of fragmentation rather than a measure of anthropogenic versus natural fragmentation as interpreted by Wade et al. (2003) for their work. Thus, the process of fragmentation can be revealed in space and time by comparing fragmentation index images for the seven time steps. Here, spatial patterns of fragmentation as well as trends can be discerned, such as the alarming on-going splitting of Yala and Ikuywa forests into two separate forest fragments, or the gradual forest decline in the Kakamega Fuel Area. Although this scale-independent index can be applied to raster data of any resolution, it is nevertheless limited to the resolution of the input data. With a resolution of only 60 m for the first

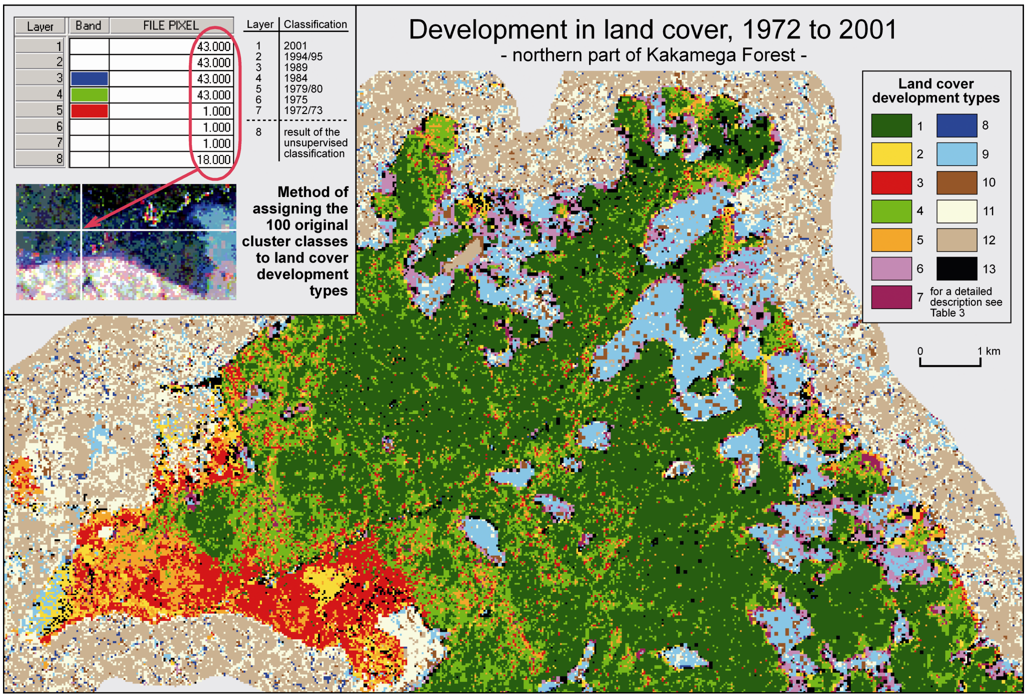


Figure 2.3: Map of land cover development types, 1972–2001, for the northern part of Kakamega Forest together with information on the method of assigning the original 100 cluster classes to thirteen meaningful land cover development types (for a detailed explanation see Section 2.3, for detailed legend see Table 2.3).

three time steps far fewer gaps are detected than those visible in the later time steps with a 30 m spatial resolution. Effects of human encroachments like footpaths or cattle paths cannot be detected as long as the canopy stays closed or gaps and perforations are smaller than the image resolution. Nevertheless, reports of forest disturbances due to human exploitation and misuse over much of Kakamega Forest (Fashing et al., 2004; KIFCON, 1994; Kokwaro, 1988; Muthangh et al., 1992; Wass, 1995) are supported by the results of the spatially distributed fragmentation index. It indicates (i) a degree of, if not severe, fragmentation in most parts of the forest, and (ii) a considerable increase in fragmentation over time, especially in the southern part and along the forest edges.

In order to evaluate our fragmentation index as an indicator of the situation on the ground and thus to argue for its usefulness in correlations with field findings, mean fragmentation indices for the BDOs in 2001 have been calculated. BIOTA-East field surveys regarding the threat status of Kakamega Forest showed a strong effect of management, either by Kenya Wildlife Service (KWS) or FD, on the disturbance status of the forest (Bleher et al., 2006). In general, mean fragmentation indices are lower for BDOs located in areas under management of the stricter KWS (e.g. Salazar, Kisere, and Colobus) as compared to those placed in areas under FD-management (e.g. Malava, Ikuywa, Isecheno I). The Kaimosi BDO, placed in a Quaker settlement isolated within the surrounding farmland, reveals the highest fragmentation index with only tiny forest patches remaining. Bleher et al. (2006) recorded seven disturbance parameters along 20 m wide transects of at least 1000 m length, some passing through the BDOs. A first evaluation of data from these transects shows that the 'number of trees logged/ha' (>20 years, <20 years, and total no.) are best suited for a correlation with our fragmentation index. This might be expected since the felling of individual trees creates gaps in the canopy and should thus influence the multispectral image as sensed by Landsat ETM+. The lowest values for total no. of trees logged/ha might be expected for KWS-managed areas and indeed the results bear this out: Salazar (2.0) and Colobus (5.4) as compared to e.g. Ikuywa (37.0) or Isecheno I (12.5), both FD-managed sites. However, Bleher et al. (2006) also encountered a low value for Yala (2.8) which is likely to be linked to its protection status as a nature reserve. Here, a visual overlay of the BDO geodataset with the road network, population density per sublocation of 1999, as well as forest reserves indicates a correlation with population distribution and accessibility by roads and by lack of accessibility due to the protection status of reserves. High mean fragmentation index values are revealed for the Malava, Ikuywa and also Isecheno I BDOs, all located close to roads and none are within national or nature reserves. Isecheno II with a relatively low fragmentation index of 0.183 for a FD site is not only placed in a nature reserve but is also far from any roads. The unexpectedly high mean indices for the Buyangu and Yala BDOs, both placed in high protection reserves, can be traced to some pixels classified as 'Bushland/shrubs' whereas this vegetation class is considered to be non-forest in our fragmentation index calculations (see Table 2.1).

An in-depth statistical analysis of the correlation between disturbances as observed on the ground and our fragmentation index is still missing. Nevertheless this preliminary assessment of the fragmentation index demonstrates a potential avenue for interdisciplinary research. The presented images of a spatially distributed forest fragmentation index seem to form an appropriate quantitative parameter for more than simply assessing relationships between fragmentation and forest biodiversity, the latter being regularly correlated with ground disturbances (e.g. Farwig et al., 2006). It also allows extrapolation of field findings in space and time, thus hopefully contributing to statements regarding forest conservation measures at the landscape level.

Map of land cover development types

The cluster analysis resulted in a map on land cover development for the area of Kakamega Forest and associated forest areas between 1972 and 2001. With this map only a single image has to be examined to discover typical trends in land cover change. We consider it as excellent for distinguishing forest areas of distinct development, which are less obvious in a visual comparison of the time steps of a time series. Methods similar to the cluster analysis, based on principles of factor analysis, are used in cartography by visually overlaying different thematic layers for the identification of contiguous core areas that are alike regarding their structure (Witt, 1979). Map visualisations originally based on a synopsis of multiple single factors but summarised to types are referred to as 'synthesized maps' in cartography (Arnberger, 1987). To our knowledge the method of cluster analysis has not previously been applied in ecological research for determining characteristic land cover development types. An example of a cluster analysis for geographically classifying South Tyrol in natural landscapes is given by Schirpke and Ruffini (2005). The idea of applying a cluster analysis to our classified satellite time series data arose from a map described by Laux (2001) who conducted a cluster analysis on population data in the National Atlas of Germany. In the resulting map typical population development trends are visualised accompanied by comprehensive explanations for the types.

When comparing multiple thematic maps for detecting changes, inaccuracies in the compared maps, (in our case the seven land cover classifications), influence the level of measurable change and the reliability of the change detection output (Fuller et al., 2003). In our cluster analysis misclassifications in the single time steps had to be accepted. This causes inaccuracies in the output of the pixel assignment to clusters due to error propagation, e.g. plantations of *Maesopsis eminii* could not be separated from 'Secondary forest' and 'Bushland/shrubs' in the classification process (see Lung and Schaab, 2004). These pixels are therefore often assigned to clusters with no meaningful tendency in land cover development (type 13). For clusters aggregated to meaningful land cover development types the assignment of pixels not matching this trend had to be accepted in some case (see comments for types 6, 8 and 9 in Table 2.3). Another limitation was encountered due to the applied method itself. Those pixels assigned to a land cover class in only one single time step (e.g. pixels classified as forest in 1972 but assigned to agricultural land from 1975 to 2001) could not be detected using the cluster analysis.

Nevertheless, the cluster analysis is judged to be a valuable mean for generating one map from seven time steps highlighting typical land cover development trends, which cannot as easily be identified by simply looking at the original time series. The resulting pattern is intriguingly simple to grasp, although the accompanying textual explanations should be carefully noted.

2.6 Conclusions

It can be concluded that each of the presented methods based on remotely sensed data and applied to assess land cover, forest fragmentation or disturbance for the area of Kakamega Forest and its associated forest areas have emerged as suitable means for gaining information on the current state of the forests as well as their disturbance history. The accuracy assessment contributes to a stronger confidence in the reliability of our classified land cover time series data for further use. But area numbers per se resulting from land cover classifications are not always sufficient for statements on the process of fragmentation or the status of disturbance because the spatially resolved information is lost. Here, our fragmentation index based on a moving window offers not only numerical information but also spatial distributions of this index. It can therefore be applied in further assessments combined with field findings and using statistical analyses allowing for extrapolations in space and time. However, the state of the forest is shown per time step and thus makes statements regarding change rather cumbersome. The map resulting from the cluster analysis, as presented here, is excellent for visually assessing the pattern of types of land cover development at a single glance but being a final interpretation presented graphically, it is difficult to relate this outcome to field observations. The results of this study are diverse but each of them can contribute to the interdisciplinary BIOTA work on spatio-temporal biodiversity patterns and the ecological functioning of East African rainforests, thus hopefully serving a sustainable management of Kakamega Forest and its associated forest areas.

3. A comparative assessment of land cover dynamics of three protected forest areas in tropical eastern Africa

(ex EVIRON MONIT ASSESS, 161(1), 531–548)

3.1 Abstract

Processes of deforestation, known to threaten tropical forest biodiversity, have not yet been studied sufficiently in East Africa. To shed light on the patterns and causes of human influences on protected forest ecosystems, comparisons of different study areas regarding land cover dynamics and potential drivers are needed. We analyze the development of land cover since the early 1970s for three protected East African rainforests and their surrounding farmlands and assess the relationship between the observed changes in the context of the protection status of the forests. Processing of Landsat satellite imagery of eight or seven time steps in regular intervals results in 12 land cover classes for the Kakamega–Nandi forests (Kenya) and Budongo Forest (Uganda) whereas ten are distinguished for Mabira Forest (Uganda). The overall classification accuracy assessed for the year 2001 or 2003 is similarly high for all three study areas (81% to 85%). The time series reveal that, despite their protection status, Kakamega–Nandi forests and Mabira Forest experienced major forest decrease, the first a continuous forest loss of 31% between 1972/1973 and 2001, the latter an abrupt loss of 24% in the late 1970s/early 1980s. For both forests, the temporally dense time series show short-term fluctuations in forest classes (e.g., areas of forest regrowth since the 1980s or exotic secondary bushland species from the 1990s onwards). Although selectively logged, Budongo Forest shows a much more stable forest cover extent. A visual overlay with population distribution for all three regions clearly indicates a relationship between forest loss and areas of high population density, suggesting population pressure as a main driver of deforestation. The revealed forest losses due to local and commercial exploitation further demonstrate that weak management impedes effective forest protection in East Africa.

3.2 Introduction

In tropical forest ecosystems, processes of deforestation with their linkages to underlying causal synergies are considered to be one of the largest environmental threats of our time as they are main drivers for biodiversity loss (Hansen et al., 2001; Xu and Wilkes 2004). More subtle changes not totally replacing but modifying the character of land cover type is a highly recognized phenomenon especially in protected forest areas, such as, e.g., changes in forest structure due to selective logging (Plumptre, 1996). In order to assess the influence of land cover modification or change on species distributions as well as ecosystem function, frequent temporal as well as spatially detailed information is needed (Turner et al., 2003). In this context, analyses based on remote sensing data have become essential for ecological and conservation biological applications aiming at quantitative statements over extensive areas not to be captured by field-based methods alone (Kerr and Ostrovsky, 2003). Using remote sensing, many regional case studies have been conducted in tropical forest environments focusing on change detection analyses related to forest biodiversity issues (e.g., Espírito-Santo et al., 2005; Flamenco-Sandoval et al., 2007; Guild et al., 2004; Velázquez et al., 2003), thus contributing to a better understanding of change processes. The need of such studies especially for Africa is pointed out by Geist and Lambin (2001), stating in their global comparison of 152 case studies on tropical deforestation, that few studies have been conducted within Africa. However, the scientific steering committee of the Land-Use/Cover Change (LUCC)–Project of the International Geosphere–Biosphere Programme (IGBP) concludes in their review on local processes and global impacts (see Lambin and Geist, 2006) that comparative analyses of the original data from different case studies are needed, not just metaanalyses of the case studies' results. Moreover, it is suggested there that integrating remote sensing data with ancillary data (e.g., census data) will allow further insights into the causes and effects of land cover change dynamics.

In the past decades, East Africa has experienced tremendous land cover changes with an increase of cropland by 200% between 1900 and 1990 (Klein Goldewijk, 2001). This, in particular, affects tropical forest areas showing a deforestation rate for 1990 to 2000 four times higher than the world average (FAO, 2005). Main drivers of forest loss in East Africa are rapid population growth and low per capita income growth. Together, these restrain people from moving away from subsistence-based livelihood, thus causing an ever-increasing demand for agricultural land (FAO, 2003). For Kenya, in 1995, an estimated population of 2.9 million people lived within a 5-km distance to protected forests. These people depend on forest products for satisfying their daily needs (UNEP, 2004). Population projections from UN-DESA (2007) reveal that population growth rates up to 2025 for Kenya (between 2.02% and 2.65%) and Uganda (between 2.86% and 3.24%) are among the world's highest. Thus, according to scenarios for East Africa from UNEP (2004), the expansion of cropland, grazing land, and forest plantations will continue. Most at risk is natural forest which is predicted to reduce by further 38% of its 1995 areal extent till 2032 (ibid).

The interdisciplinary research framework Biodiversity Monitoring Transect Analysis

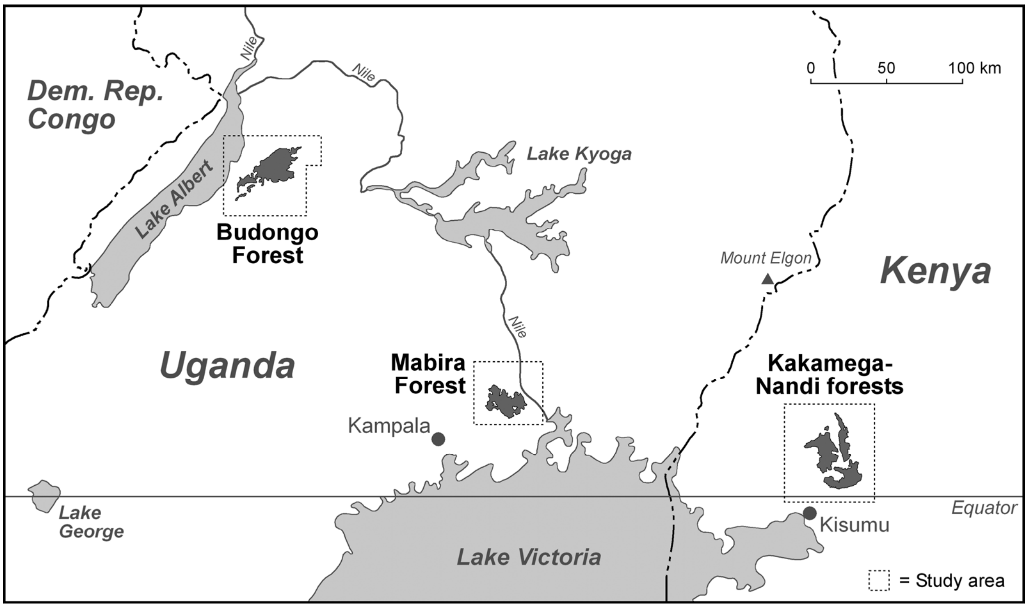


Figure 3.1: The forest areas investigated within the BIOTA East Africa research project.

(BIOTA) East Africa is investigating the anthropogenic influence on the biodiversity of protected rainforest areas and aims at making recommendations for a sustainable forest use (Köhler, 2004; or http://www.biota-africa.de). Three East African forest areas are studied: Kakamega–Nandi forests in western Kenya, Mabira Forest in south eastern Uganda, and Budongo Forest in western Uganda. In this study, Landsat satellite time series data are analyzed as a contribution to investigations into human influence patterns on protected forest ecosystems. The time series will allow the extrapolation of biological field findings in space and time (Schaab et al., 2004) finally enabling conclusions in regard to changes in forest biodiversity and ecosystem function.

The main goal of this paper is to provide for the first time truly comparative information on the development of land cover for the three protected East African forest areas and to assess the relationship between the observed changes in the context of the protection status of the forests. Therefore, three Landsat time series with comparable, temporally dense time steps have been acquired and processed with the aim of capturing both long-term trends and short-term fluctuations in forest composition and cover over time. Differences resulting from dissimilar anthropogenic forest use are discussed focusing on forest management and population pressure as main drivers of deforestation.

3.3 Materials and methods

Study areas and geo-data used

All three study areas in Kenya and Uganda (see Figure 3.1) are medium-sized forest islands surrounded by a substantial amount of farmland. It is dominated by smallholder agriculture for subsistence purposes but also partly under large-scale tea or sugarcane cultivation. The forests hold a high biodiversity but are endangered for various reasons. For a comparative summary highlighting distinct differences, see Table 3.1.

For all three areas, Landsat satellite data has been acquired aiming at intervals of approximately 5 years to reach back to the early 1970s (see Table 3.2). Only totally or at least in most parts cloud-free imagery has been considered resulting in a data gap from the mid-1970s to the mid-1980s for the Ugandan areas. If available, two images per time step, one from the wet and dry season respectively, have been chosen to take seasonal variations in vegetation pattern into account and thus to increase classification accuracy. Table 3.3 provides an overview on various data used as ground truth for the Landsat image classification. Vegetation information has been gathered on the ground during field trips in 2003, 2005, and 2006. Moreover, photographs of the vegetation cover were taken during airplane flights over the three study areas in 2001 and 2006 and included areas difficult to access on the ground. In addition, vegetation information either from printed maps or in a geographic information system (GIS) format has been used.

Landsat imagery pre-processing

Image processing has already been fully conducted and described for the Kakamega–Nandi study area for the period 1972/1973 to 2001 (Lung, 2004; Lung and Schaab, 2004). Following the steps shown in Figure 3.2, preprocessing involved georeferencing in subpixel positional accuracy, the replacement of cloud information, atmospheric as well as terrain corrections by means of ATCOR 3 (Richter, 1998), and in case of TM imagery, the generation of an additional artificial band (ratio 7/2) for improving the separation of vegetation from nonvegetation as well as of water.

Table 3.1: Geographic characteristics for Kakamega-Nandi forests (Kenya), Mabira Forest and Budongo Forest (Uganda).

	Kakamega-Nandi forests	**Mabira Forest**	**Budongo Forest**
Study area size	60 x 65 km	46 x 42 km	65 x 54 km, excluding 10 x 34 km at south eastern corner
Geographical location	34°37'5" to 35°9'25" E and 0°2'52" S to 0°32'24" N	32°46'34" to 33°11'22" E and 0°20'28" to 0°43'16" N	31°15'23" to 31°50'27" E and 1°29'56" to 1°59'14" N
Gazetted area (of main forest blocks)	Kakamega Forest, North Nandi Forest and South Nandi Forest: total of 54,605 ha (Mitchell et al., 2006)	Mabira CFR: 29,974 ha (Karani et al., 1997b)	Budongo CFR: 82,530 ha (Karani et al., 1997a)
Elevation (of main forest blocks)	Kakamega Forest: 1,460 to 1,765 m a.s.l.; Nandi forests: 1,695 to 2,145 m a.s.l.	1,030 to 1,355 m a.s.l.	900 to 1,440 m a.s.l.
Annual rainfall	2,007 mm at Isecheno Forest Station; rainy seasons: March to June and July to September (Farwig et al., 2006)	1,250 to 1,400 mm; rainy seasons: April to May and October to November (Howard, 1991)	1,200 to 1,800 mm; rainy seasons: March to May and September to November (Sheil, 1997)
Biodiversity	botanically unique, some endemic species (Mutangah et al., 1992); large species diversity (KIFCON, 1994)	relatively diverse compared to other Ugandan forests, (Davenport et al., 1996)	highly diverse, some endemic species (Forest Department, 1996; Plumptre, 2002), third in importance for Uganda (Howard et al., 2000)
Population density of surrounding area	Kakamega Forest: 643 inh./km²; Nandi forests: 371 inh./km² (calculated from Central Bureau of Statistics 1999 census data)	302 inh./km² (calculated from Uganda Bureau of Statistics 2002 census data)	158 inh./km² (calculated from Uganda Bureau of Statistics 2002 census data)
Forest threats	pressure from growing population (local forest use); commercial exploitation since the 1930s (Mitchell, 2004)	mainly charcoal burning, timber cutting and agricultural encroachments (Baranga, 2007; Howard et al., 2000)	selective logging over the last 60 years (Plumptre, 1996; Howard, 1991)

Table 3.2: Landsat satellite data at hand for Kakamega-Nandi forests, Mabira Forest and Budongo Forest.

Landsat satellite[a]	MSS		MSS		MSS	TM		TM		TM		ETM+		ETM+	
Time step	1		2		3	4		5		6		7		8	
Year	1972/73	1973/74	1975	1976	1979/80	1984	1986	1989	1990	1994/95	1995	2000	2001	2002/03	2003
Kaka-Nandi forests	✓		✓		✓	(✓)		(✓)		✓			✓		✓
Mabira Forest		✓		(✓)			✓	(✓)			✓		✓	✓	
Budongo Forest	✓		(✓)				✓		(✓)		✓	✓		(✓)	

[a] spatial resolution of Landsat imagery: MSS = 60 x 60 m, TM = 30 x 30 m, ETM+ = 30 x 30 m
✓ 2 images available from both wet and dry season, (✓) 1 image available only (dry season)

For the Mabira and Budongo study areas, this procedure has been followed as closely as possible in order to achieve truly comparable classification results, yet some additional preprocessing steps or modifications had to be included: The known banding problem of MSS data (Lillesand and Kiefer, 2000) occurring to a much stronger degree for the

Ugandan imagery (especially in band 2 for the Mabira and in band 1 for the Budongo Landsat MSS scenes) made it necessary to employ a smoothing low pass filter (3 x 3 pixels) for destriping the imagery. Areas of large-scale sugarcane plantations as well as wetland, both having very high spectral variability, have been manually masked out to avoid misclassifications due to poor separability from other land cover classes. The extents of sugarcane and wetland have been adjusted for every time step based on topographic maps, vegetation maps (see Table 3.3), as well as by a visual interpretation of their extents in the satellite image data. Due to major differences in reflectance, dry and wet season images for some Mabira time steps and all Budongo time steps had to be treated separately in image classification. Additionally, for Budongo, an image split into an agricultural and a nonagricultural part has been performed in order to improve classification accuracy of cropland versus grassland.

Image classification and post-processing

Image classification has focused to achieve two main aims: (a) the greatest possible number of forest classes and (b) the same classes for all three study areas. A supervised multispectral classification making use of the maximum likelihood classifier widely used in remote sensing (Wu and Shao, 2002) has been applied. Assuming normality for the training data statistics, the pixels are assigned to the class with the highest probability value (Jensen, 2005). Training areas have been selected making use of the ground truth data listed in Table 3.3. The desired classes have been evaluated regarding their spectral separability in the feature spaces and, if not normally distributed, they have been temporarily split into subclasses. After classification, for Mabira and Budongo, the manually delineated sugarcane plantations have been joined to agricultural land in order to ensure comparability (i.e., avoiding another additional class). For Budongo, the classifications of the nonagricultural part have been merged with those of the agricultural part. Due to a better distinction of the forest classes, the wet season classification results, if available, were given priority.

Table 3.3: Ground truth information available for Kakamega-Nandi forests, Mabira Forest and Budongo Forest.

	Kakamega-Nandi forests	**Mabira Forest**	**Budongo Forest**
Field trips	May 2003, Mar-Apr 2005	Apr-May 2005, Feb-Mar 2006	Apr-May 2005, Feb-Mar 2006
Amateur photographs	Flight over the forest, Jun 2001	Flight over the forest, Sep 2006	Flight over the forest, Sep 2006
Topographic maps	Series Y731, D.O.S. 423 from 1970, 1:50'000	Series Y732, D.O.S. 426 from 1955/58/60, 1:50'000	Series Y732, D.O.S. 426, from 1966, 1:50'000
Other printed maps or GIS data layers	KIFCON 1:25'000 land use classification from 1991	NFA land use map 1:50'000 from the early 1990s	NFA land use map 1:50'000 from the early 1990s
	Kenya vegetation map 1:250'000 from 1966/69	Uganda vegetation map 1:500'000 from 1964	Uganda vegetation map 1:500'000 from 1964
	Forest Department map 1:10'000 from 1972		
Maps from publications		Forest types (Howard, 1991)	Forest types (Howard, 1991)
			Forest types and forest logging (Plumptre and Reynolds, 1994)

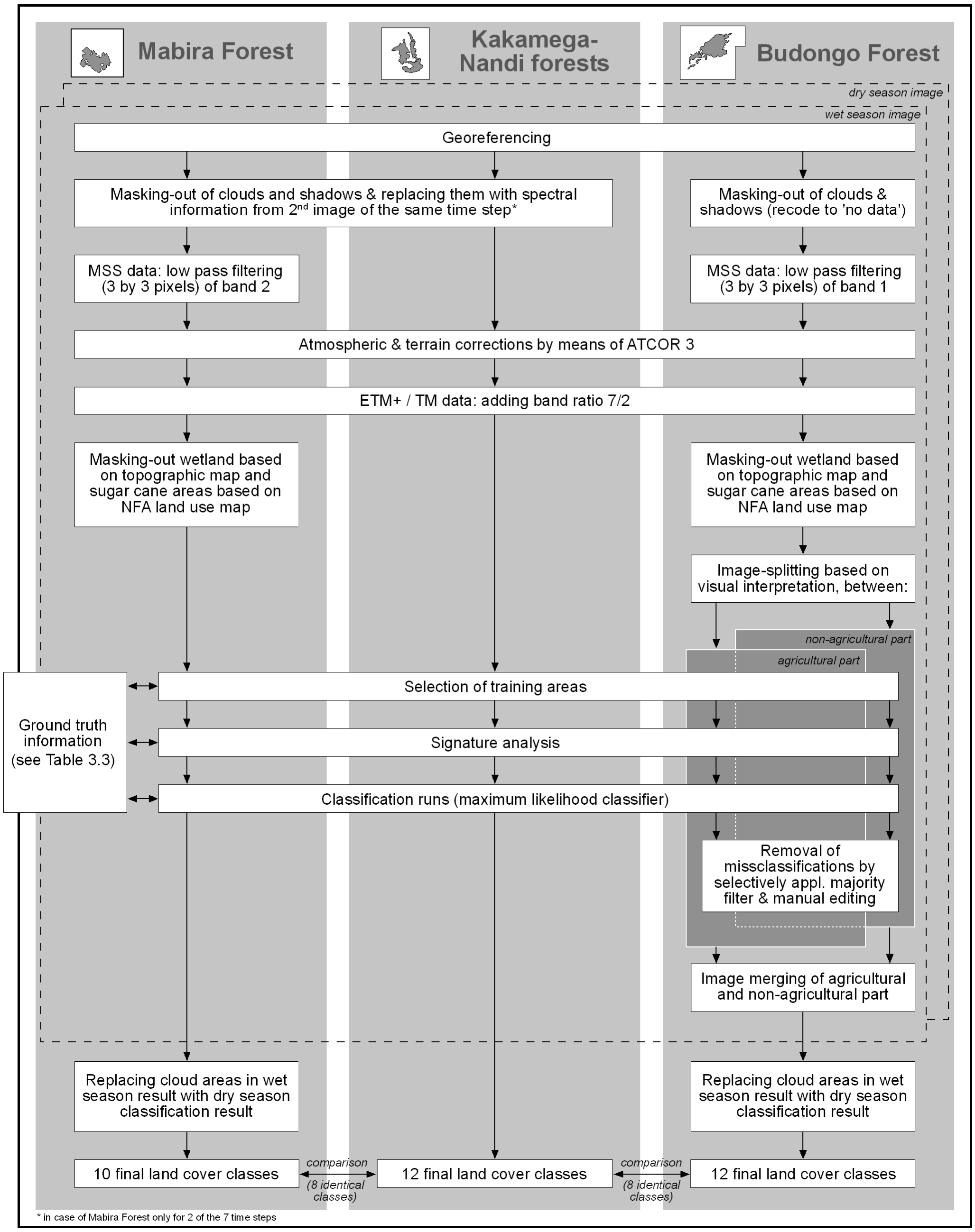


Figure 3.2: Processing methodology for Landsat satellite time series data of Kakamega-Nandi, Mabira, and Budongo study areas for gaining truly comparative land cover classification results.

Accuracy assessment

For the Kakamega–Nandi study area, an accuracy assessment via an error matrix has already been performed for the land cover classification of the year 2001 as described in Lung and Schaab (2006). For the Mabira study area, the newest time step was considered for accuracy assessment as it is closest to the most valuable ground reference information (i.e., 2005/2006 field trips and 2006 amateur photographs). For Budongo Forest, the time step of 2000 was chosen instead of the newest time step since the latter does not distinguish *Cynometra*-dominated mature natural forest as a separate class. Like for Kakamega–Nandi, 50 randomly distributed pixels per land cover class, as suggested by Congalton and Green (1998), have been generated for each of the Ugandan forest areas. These pixels have been individually compared with the original Landsat imagery and the above-mentioned ground reference data. From the resulting error matrix, four measures of accuracy have been calculated: the overall classification accuracy, the user's accuracy, the producer's accuracy, as well as the Kappa index. Additionally, a visual assessment of classification accuracy has been conducted for all the other Mabira and Budongo time steps.

Land cover change analyses

Comparative land use cover change analyses have been conducted on three spatial levels focusing on forest areas. The first level, which is limited to the officially gazetted area of the main forest blocks, i.e., Kakamega forest, North and South Nandi forests, as well as Mabira Forest (Mabira Central Forest Reserve, CFR) and Budongo Forest (Budongo Central Forest Reserve, CFR), is used for determining the area covered by the different land cover classes per time step.

The second level comprises all forests within the study areas, buffered by a distance in order to include the forested areas outside the officially gazetted areas. The buffer size has been set to 1,000 m for Kakamega–Nandi, to 850 m for Mabira, and to 1,500 m for Budongo, i.e., proportionally to the total forest size. On this level, the spatial distribution of forest cover change is revealed applying a postclassification comparison.

The third spatial level considers the entire study areas and is used to visually compare (i.e., not via a statistical analysis) ancillary data on population distribution with forest cover change over time. GIS datasets with census information have been acquired at sublocation level for the Kakamega–Nandi study area for 1999 from the International Livestock Research Institute (Nairobi) and at parish level for Mabira and Budongo study areas for 2002 from the Uganda Bureau of Statistics. Both GIS datasets have been thoroughly cross-checked with the numbers in the original printed population records and corrected if necessary. In order to ensure data comparability regarding average size of area and total number of people per administrative unit, the Kenyan geo-dataset has been aggregated to location level.

3.4 Results

Land cover classes

Based on the available Landsat imagery and ground truth information for the Kakamega–Nandi study area, 12 land cover classes were distinguished (see Lung, 2004; Lung and Schaab, 2004) of which four ('Secondary bushland–*Psidium guajava*,' 'Grassland with scattered trees,' 'Plantation forest–*Pinus patula*,' and 'Plantation forest–*Bischoffia javanica*') are absent in the Mabira study area (see Table 3.4). Instead, a different type of secondary bushland, namely, 'Secondary bushland–*Broussonetia papyrifera*' as well as the manually derived 'Wetland' class are added, resulting in a total number of ten land cover classes. Likewise, in the Budongo study area (see also Table 3.4), four of the 12 classes

Table 3.4: Land cover classes distinguished for Kakamega-Nandi forests, Mabira Forest and Budongo Forest, based on Landsat satellite imagery.

Land cover class	**Description**	**Kaka-Nandi**	**Mabira**	**Budongo**
0 Mature natural forest incl. *Cynometra*	Mature forest, *Cynometra* often dominating			x
1 Near natural & old secondary forest	Forest of low disturbance level, dense canopy, as well as old secondary forest (older than 30 years)	x	x	x
2 Secondary forest	Mid-aged secondary forest of 20-30 years as well as aged *Maesopsis eminii* (originally from Uganda) plantations mixed with indigenous species	x	x	x
3 Bushland/shrubs	Bushed areas interspersed with grasses and herbs plus young (10-20 years) and very young (initial state, younger than 10 years) secondary forest, also early mixed *Maesopsis eminii* plantations	x	x	x
4 Secondary bushland–*Psidium guajava*	Colonization of guava trees (animal-dispersed, e.g. by monkeys)	x		
4 Secondary bushland–*Broussonetia papyrifera*	Paper mulberry, monoculture introduced by spraying		x	
4 Mesic forest/deciduous trees (woodland)	Dry trees and shrubs, average height > 4 m, dominated by few species (e.g. *Terminalia*)			x
5 Grassland with scattered trees	Grassland with single bushes or trees	x		
6 Grassland	Grassland, partially of natural origin, partially due to clearings, partly used as meadows, grass used for roof hatching	x	x	x
7 Plantation forest–*Pinus patula*	Plantation of pine trees (originally from Mexico, monocultures), maybe of cypress	x		x
8 Plantation forest–*Bischoffia javanica*	Plantation of Bischoffia trees (originally from Uganda, monocultures)	x		
9 Tea plantation	Tea plantation	x	x	
10 Agricultural land	Cultivated land of diverse characteristics, highly divided land with trees and bushes along plot boundaries, mainly subsistence agriculture, high percentage of bare ground	x	x	x
11 Water	Rivers, lakes	x	x	x
12 Others	Roads (tarmac or dirt track), rocks, settlements	x	x	x
13 Wetland	Swampy areas with or without papyrus or reeds		x	x
14 Burnt area	Burnt grassland, dry woodland or fallow agricultural land			x
Total no. of classes		12	10	12

obtained for Kakamega–Nandi are not existent ('Secondary bushland–*Psidium guajava*', 'Grassland with scattered trees', 'Plantation forest–*Bischoffia javanica*', and 'Tea plantation'), but four additional classes ('Mature natural forest including *Cynometra*', 'Mesic forest/ deciduous trees (woodland)', 'Wetland', and 'Burnt area') could be distinguished, adding up to a total number of 12 land cover classes. Each study area contains specific bushland/woodland vegetation not found in the other forests. For Kakamega–Nandi and Mabira, these are types of secondary bushland first revealed in the 1995 time step classifications (Kakamega–Nandi: *Psidium guajava*, Mabira: *Broussonetia papyrifera*; see Figure 3.3), whereas in Budongo, woodland areas of dry trees and shrubs interspersed with grass can be found throughout the entire time series. Focusing on the classes of forest formations, six classes could be distinguished for Kakamega–Nandi and Budongo, while in Mabira, only four forest formations are classified due to the absence of the two forest plantation types.

Classification accuracy

The overall classification accuracy for both Ugandan study areas is high with 80.80% (Kappa of 0.79) for Mabira and 85.33% (Kappa of 0.84) for Budongo (see Table 3.5). High user's accuracies have been achieved for the first three forest classes (Mabira: 'Near natural and old secondary forest' 86%, 'Secondary forest' 78%; Budongo: 'Mature forest including *Cynometra*' 92%, 'Near natural and old secondary forest' 82%, 'Secondary forest' 78%), a trend consistent with the Kakamega–Nandi classification results (cp. Lung and Schaab, 2006). Similar or even higher user's accuracies are found in the classes 'Agricultural land', 'Tea plantation' (Mabira only), 'Water', and 'Wetland', the latter being manually delineated and thus having a user's accuracy of 100% for both Ugandan areas. Most misclassifications occurred in the class 'Grassland' (user's accuracy of 56% for Mabira and 70% for Budongo) caused by omission errors in favor of agriculture. Furthermore, difficulties arose regarding the distinction between bushland and secondary bushland or woodland (revealed by the change matrix, not shown here). For the Mabira study area, omission errors in favor of 'Bushland/shrubs' resulted in a relatively low user's accuracy of 60% for 'Secondary bushland–*Broussonetia papyrifera*', whereas for the Budongo area, commission errors to 'Mesic forest/deciduous trees (woodland)' caused a user's accuracy of only 68% for 'Bushland/shrubs'.

Land cover change analyses

Quantities of land cover over time for the three study areas were calculated for the first spatial level. For display (see Figure 3.3), the classes 'Tea plantation', 'Others', 'Water', and 'Wetland' are not considered and the two plantation classes are grouped. Examining the area values of land cover, distinctive trends are revealed for each study area. Whereas the forest cover of Budongo Forest (considering here the classes 'Mature natural forest including *Cynometra*', 'Near natural and old secondary forest', and 'Secondary forest') has experienced little changes over the past 30 years (similar values for all time steps, lowest value of 44,934 ha in 1972/1973 and highest of 46,244 ha in 1995), for both Mabira Forest and Kakamega–Nandi forests, serious alterations are revealed. Kakamega–Nandi forests have experienced a continuous decrease in forest cover by 31% from 1972/1973 to 2001 (39,468 to 27,354 ha). For Mabira Forest, an abrupt, tremendous forest loss of about 24% is revealed between 1976 and 1986 (27,421 to 20,977 ha). However, a slight increase in forest cover in the subsequent years to 22,338 ha in 2002/2003 indicates some forest regeneration, a trend also found for Kakamega–Nandi forests in very recent times (2001 to 2003). Similarities between Kakamega– Nandi forests and Mabira Forest are also obvious when looking at the forest classes separately. But, while in the Kakamega–Nandi area, the forest was lost mainly in favor of 'Bushland/shrubs' (increase from 4,564 ha in 1972/1973 to 11,541 ha in 2001), in Mabira Forest, many of the deforested portions were turned to smallholder agriculture (sharp increase of agriculture in 1986 and 1989 compared to the 1970s).

The spatial distribution of changes in forest cover for the three study areas is shown for the buffered forest areas (second spatial level of analyses, see Figure 3.4), focusing on three time steps only (i.e., first, middle, and last) in order to preserve map legibility. For Kakamega–Nandi forests, total losses of forest cover without subsequent regeneration

Table 3.5: Accuracies of the supervised multi-spectral classification results for Mabira Forest (time step 2002/03) as well as for Budongo Forest (time step 2000), derived from a visual comparison of 50 randomly selected pixels (per land cover class) with the original satellite image as well as photographs and maps.

	Mabira Forest			**Budongo Forest**		
Land cover class	Producer's accuracy [%]	User's accuracy [%]	Kappa index	Producer's accuracy [%]	User's accuracy [%]	Kappa index
Mature natural forest incl. *Cynometra* (0)	-----	-----	-----	88.46	92.00	0.91
Near natural & old secondary forest (1)	89.58	86.00	0.85	78.85	82.00	0.80
Secondary forest (2)	78.00	78.00	0.76	95.12	78.00	0.76
Bushland/shrubs (3)	60.61	80.00	0.77	79.07	68.00	0.66
Secondary bushland–*B. papyrifera* (4)	78.95	60.00	0.57	-----	-----	-----
Mesic forest/deciduous trees (woodland) (4)	-----	-----	-----	69.35	86.00	0.84
Grassland (6)	100.00	56.00	0.53	67.31	70.00	0.67
Plantation forest–*Pinus patula* (7)	-----	-----	-----	100.00	98.00	0.98
Tea plantation (9)	100.00	90.00	0.89	-----	-----	-----
Agricultural land (10)	55.41	82.00	0.79	73.33	88.00	0.87
Water (11)	100.00	98.00	0.98	100.00	100.00	1.00
Others (12)	76.47	78.00	0.76	89.19	66.00	0.64
Wetland (13)	98.04	100.00	1.00	92.59	100.00	1.00
Burnt areas (14)	-----	-----	-----	100.00	96.00	0.96
Overall	**80.80**		**0.79**	**85.33**		**0.84**

occurred after the early 1970s (dark red in Figure 3.4) or after the late 1980s (light red), this for extensive areas in the northern part of North Nandi Forest, in the north-western part of South Nandi Forest as well as in the southern part and the western arm of Kakamega Forest. Furthermore, substantial forest loss is also found at the northern forest edge of South Nandi Forest, at most edges of North Nandi Forest, in the central part of Kakamega Forest, and at Bunyala, Malava, Ururu, and Kapteroi forest fragments. In contrast, some forest regeneration (dark and light green in Figure 3.4) has occurred in the northeastern and north-central part of Kakamega Forest, while the regrowth shown in the southern part and in the western arm is rather due to misclassifications (secondary forest instead of plantation forest, see Lung (2004) for a detailed description). In the Mabira Forest study area, tremendous forest losses are revealed in the eastern and north-eastern part of Mabira CFR (mainly north of a power line cut through the forest) as well as in the gazetted forest patches north-east of it where hardly any forest has remained. While these gazetted patches stay agricultural land up to 2002/2003, the eastern and north-eastern part of Mabira CFR have turned from agriculture to 'Secondary bushland–*Broussonetia papyrifera*' from 1995 onwards (not to be seen in Figure 3.4). In the southern part of Mabira CFR, some areas of recent (yellow in Figure 3.4) as well as older forest regeneration (dark green in Figure 3.4), also found at the western edge of the forest, are revealed. Contrary to Kakamega–Nandi and Mabira study areas, forest loss in the Budongo area mainly occurred outside the officially gazetted forest areas. Minor areas of forest regrowth are found in the northern areas of Budongo CFR where the forest is surrounded by woodland and grassland vegetation. Most of the small gazetted areas south of Budongo CFR contained no forest or only forest remnants already in the early 1970s.

On the third spatial level, a visual overlay of population density with the distribution of areas affected by forest loss or gain (see also Figure 3.4) shows a relationship for most parts of the three studied forest areas. High population densities of mostly >600 inhabitants/km^2 in the Kakamega–Nandi area are revealed for those locations adjacent to forest areas having experienced severe losses (western and southern part of Kakamega Forest, western and northern part of South Nandi Forest). This pattern is also found in the eastern part of Mabira CFR and the other gazetted forest areas east of it which are surrounded by parishes of higher population densities compared to the western part of Mabira CFR having experienced some forest regrowth along the forest edges. In line with this trend, Budongo study area reveals lowest population densities (<200 inhabitants/km^2 for most parishes) as well as low forest loss. However, for some areas, like the northern part of North Nandi Forest, opposed trends are seen, i.e., large areas of deforestation in close proximity to less densely populated areas.

3.5 Discussion

Land cover classes and classification accuracy

The derived land cover classes have been initially defined for the Kakamega–Nandi study area aiming at a best distinction of forest classes based on the available Landsat satellite imagery (Lung, 2004). Extending image processing to the two Ugandan study areas shows that full inference from one regional land cover change study to another in terms of classification methodology and scheme is hardly possible. Instead, slight modifications, as described in the “Landsat imagery preprocessing” and “Image classification and postprocessing” sections, had to be incorporated in order to meet differences in satellite data quality as well as in vegetation composition and phenology for the Ugandan areas, thus ensuring direct comparability of the classification results. For all the three study areas, the supervised classification approach has been favored over the approach of the Land Cover Classification System (LCCS, as applied by FAO; Di Gregorio and Jansen, 2000). LCCS defines land cover classes via a hierarchical expert system based on visual interpretation, a methodology not feasible for our change detecting analyses considering seven or eight time steps. A comparison of our achieved forest classes with other land cover change studies based on medium to high-resolution satellite data (e.g., Landsat or SPOT) reveals that distinguishing between more than one or two forest classes and performing more than a bitemporal analysis is often not attempted. This applies both to our research areas (cp. ICRAF, 1996 for Kakamega Forest; Westman et al., 1989 for Mabira Forest; Plumptre, 2002 for Budongo Forest) as well as to other tropical forest environments (e.g., Guild et al., 2004; Huang et al., 2007). In contrast, our multiseasonal, temporally dense change detection distinguishing up to six different forest formations allows for capturing ecologically important short-term fluctuations (e.g., regrowth of secondary forest in some areas of Kakamega–Nandi in very recent times).

Due to detailed ground truth information (Table 3.3) for the three study areas, high classification accuracy could be achieved. This applies not only to the time steps for which accuracy statistics have been presented (Table 3.5; Lung and Schaab, 2006), but also for the earlier time steps which have been visually assessed, thus ensuring reliability in trend, quantity, and pattern of change as presented in Figures 3.3 and 3.4. Classification

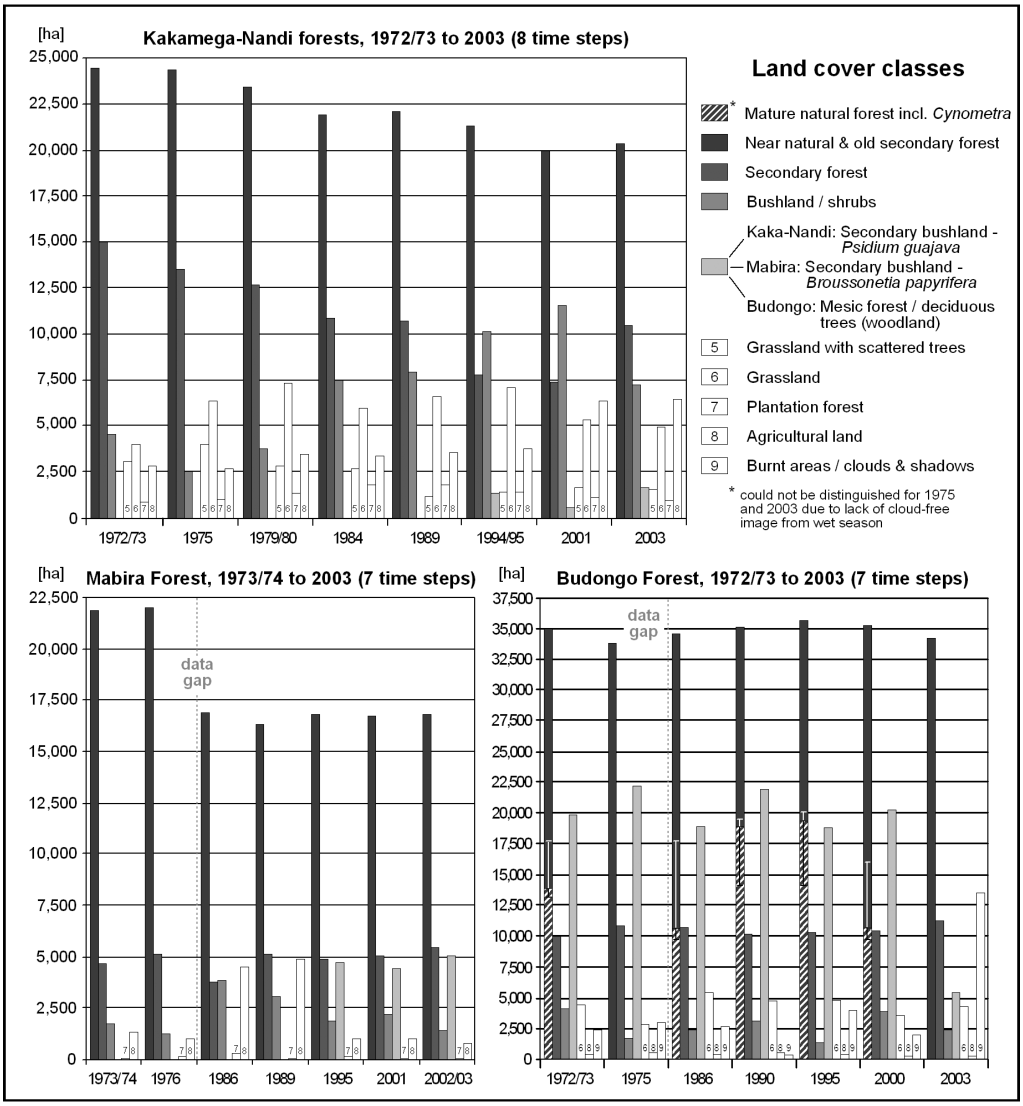


Figure 3.3: Land cover change from 1972 to 2003 for Kakamega-Nandi forests, Mabira Forest and Budongo Forest: area covered per land cover class [in ha] within the main forest blocks as delineated by their official forest boundaries (first spatial level of analysis); note the uncertainties indicated for class 0 (and thus also for class 1) of the Budongo Forest results.

accuracy generally increases for those time steps with cloud-free images from both wet and dry seasons, allowing vegetation differences to be differentiated (cp. Giri et al., 2003), in particular regarding grassland versus agricultural land used for crop production. For Kakamega–Nandi and Mabira, seasonal within-forest differences in spectral reflectance are relatively small. In contrast, a distinctive difference in the NIR (Landsat near infrared band 4) for *Cynometra*-dominated mature natural forest compared to *Celtis*-dominated near natural or secondary forest is revealed in the Budongo wet season images. This allows 'Mature natural forest including *Cynometra*' to be separated as an additional forest class. The difference in reflectance is perhaps due to leaf flush of *Cynometra* trees in the rainy

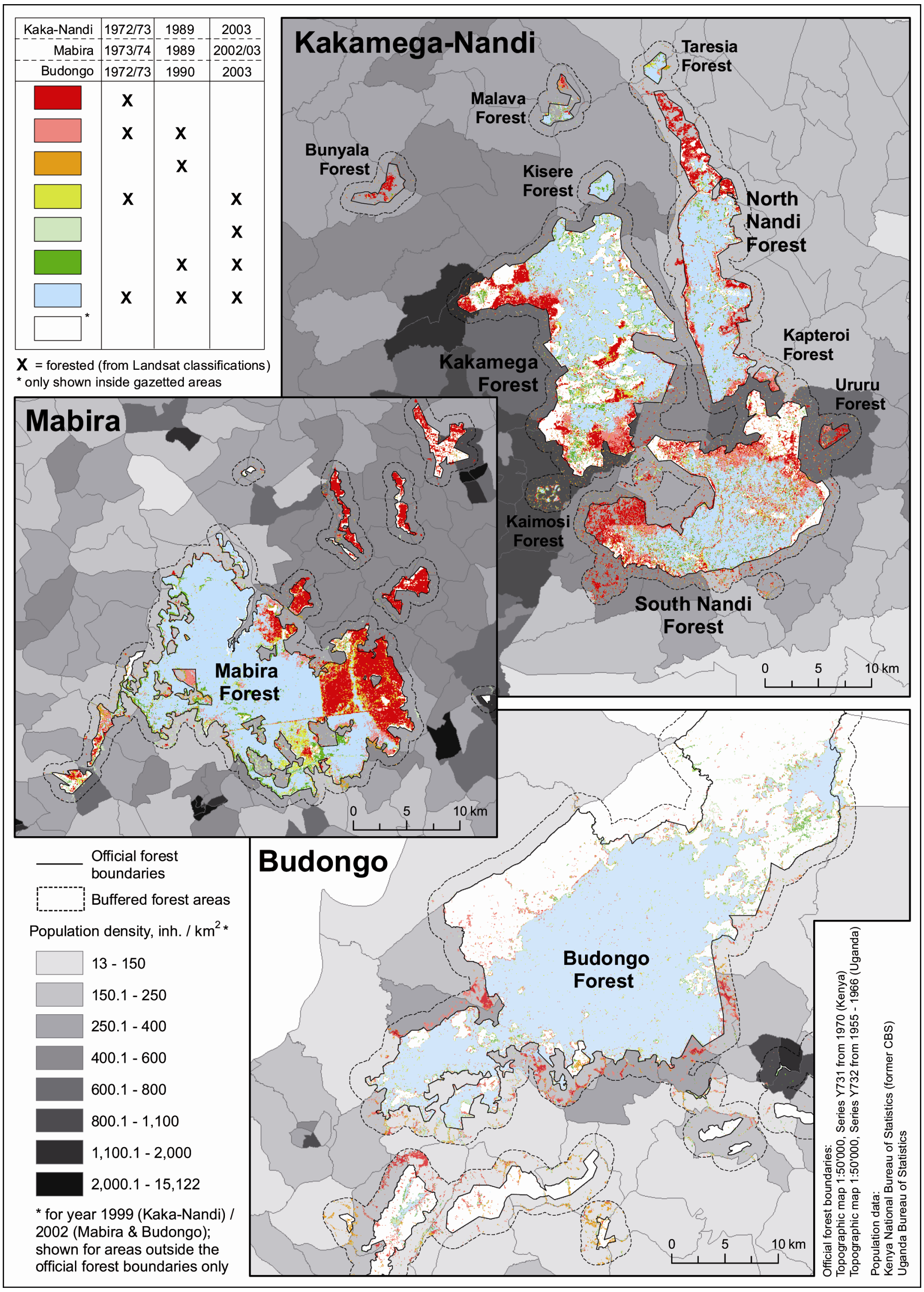


Figure 3.4: Visual representation of changes in forested areas (considering classes 0, 1 and 2) for the buffered areas of Kakamega-Nandi forests, Mabira Forest and Budongo Forest (second spatial level) from 1972 to 1989 or 90 and 2003; displayed together with population density of 1999 (Kakamega-Nandi, per location) or 2002 (Mabira and Budongo, per parish) for the complete study areas (third spatial level).

season, putting forth a huge amount of young, reddish colored shoots in contrast to the green colored leaves of most other trees (personal communication with E. Fischer). Unfortunately, the distinction could not be made for the time steps 1975 and 2003, both without a wet season image available, as well as for the areas covered by clouds in the other time steps (see uncertainties of up to 40% for *Cynometra*-dominated forest as indicated in Figure 3.3).

Land cover change and forest protection

In order to derive results suitable for extrapolating field findings on forest biodiversity, our study aimed at detecting detailed "from year to year" changes showing the nature of change instead of a binary change/no-change detection resulting for example from image rationing (e.g., Prakash and Gupta, 1998) or principal component analysis (e.g., Muchoney and Haack, 1994). Change detection techniques based on the original spectral values of the input images like trajectory-based change detection (Kennedy et al., 2007) or change vector analysis (e.g., Allen and Kupfer, 2000; Groß, 2003) are not applicable to our multiseasonal approach deliberately using images with major intra-annual phenological differences. Thus, postclassification comparison is an adequate choice for our study as it provides a change matrix revealing the nature of change and as it minimizes the impact of differing atmospheric and phenological conditions, the latter of outstanding importance when comparing not only different years but different areas. Furthermore, Maas (1999) showed that high classification accuracies (around 80%) successfully diminish postclassification comparison's often objected drawback of dependency on the accuracy of the initial classifications (as pointed out by, e.g., Coppin et al., 2004).

When examining underlying causes of deforestation processes, change detection results are also suited for integration with ancillary, e.g., demographic data (Geist and Lambin, 2001). Population growth is considered to play a major role in understanding the causes and effects of changes in forest cover. For example, Biggs and Scholes (2002) found a high correlation between the expansion of cropland and population density in South Africa particularly if the food demand cannot be met by merely increasing the yields through fertilizer use. Positive correlations between population pressure and forest clearings have also been proven in tropical areas like Thailand (Cropper et al., 2001), Guatemala (Carr, 2005), and the Congo Basin (Zhang et al., 2006). For the study area surrounding Kakamega Forest, a dramatic population increase is noticed (from 401 inhabitants/km^2 in 1979 to 643 inhabitants/km^2 in 1999, calculated from the Central Bureau of Statistics census data). This can be linked to high total fertility rates (7.1 in 1979, CBS, 1979; and 6.4 in 1989, CBS, 1996) and to in-migration from nearby overpopulated areas (Mitchell, 2004). Both factors are recognized as typical phenomena for frontier deforestation in current research (Carr, 2004). For the Budongo Forest study area, having experienced the least forest clearings and showing the lowest population density of the three study areas, a similar trend is predicted for the near future: increased pressure from local communities due to migration movements from more densely populated Ugandan areas (Langoya and Long, 1997).

However, the Mabira Forest study area demonstrates that a simplistic reduction of deforestation to population pressure would ignore other complex forces like institutional influences playing a key role especially for protected areas. This is manifested in Mabira

Forest as largescale forest conversion to agricultural land (cp. Figures 3.3 and 3.4) due to mechanized commercial timber harvesting and subsequent settlement by subsistence farmers that took place with government approval (Howard, 1991). Similar patterns of government-sanctioned clear felling are found in the Kakamega–Nandi area (e.g., forest excisions and settlement in the western part of South Nandi and the northern part of North Nandi Forest, personal communication with N. Mitchell, cp. Figure 3.4). Budongo Forest has experienced selective timber logging only, but this also with government approval (Plumptre, 1996). It is significant to note that Mabira and Budongo Forests, even though governed under the same authority (NFA, National Forest Authority of Uganda, former Forest Department), reveal strongly differing forest change dynamics.

Thus, our comparative study shows that officially protected forests in East Africa are not exempted from depletion as long as policies are not enforced on the ground. Instead, the results from Ervin (2003) are supported, that protected areas often lack effective and adequate management. Therefore, realistic forest management regulations should be developed in cooperation with the local population (i.e., in a participatory manner) and then strictly enforced by the local forest authorities. Indeed, an assessment of forest disturbance in differently managed areas of Kakamega Forest by Bleher et al. (2006) revealed that effective forest management as implemented in its northern part, reduces human disturbance (e.g., logging activities) and thus enables forest regrowth (Figure 3.4; Lung and Schaab, 2006).

3.6 Conclusions and outlook

The presented study demonstrates the value of change detection analyses based on medium- to high-resolution satellite imagery for deriving land cover time series back to the early 1970s for different protected rainforest areas in East Africa. For the first time, highly comparable and detailed land cover classifications based on a homogeneous data source (Landsat) for three forest areas, namely, Kakamega–Nandi forests in Kenya as well as Mabira Forest and Budongo Forest in Uganda, are achieved in a dense temporal sequence. It is shown that distinctions of different forest classes can be achieved with high accuracy by means of a supervised multispectral classification. The comparative assessment of the land cover dynamics in the protected forest areas reveals substantial forest losses for two (Kakamega–Nandi forests and Mabira Forest) of the three study areas, suggesting that formal protection status alone does not prevent tropical forest decline in East Africa. The different forest use histories due to local and commercial exploitation tolerated by the protection authorities underline the need for an effective forest management enforcing policies on the ground in order to prevent further forest depletion and to facilitate forest regrowth. Visual comparisons of the spatial pattern of forest change with population distribution in each area clearly reveal a relationship and show the potential of the time series for further investigations on human–forest interactions.

An in-depth statistical correlation analysis of the land cover time series results with population data from several time steps in a spatially explicit model should facilitate the running of predictions on land cover change inside and around the three protected forest areas. This model will need to consider the different forest management regimes found in the three areas, the accessibility potential by, e.g., roads, or its restriction due to a certain protection status. The extrapolation of field findings on biodiversity (as collected in the

BIOTA project) in space and their subsequent integration into the model will enable for running scenarios on forest biodiversity change. Thus, insights into the consequences of dissimilar anthropogenic influences on tropical forest biodiversity will finally lead to recommendations toward a sustainable forest management and use in order to effectively protect the forests and their diversity.

4. Combining long-term land cover time series and field observations for spatially explicit predictions on changes in tropical forest biodiversity

(ex INT J REMOTE SENS, accepted)

4.1 Abstract

Combining spatially explicit land cover data from remote sensing and faunal data from field observations is increasingly applied for landscape-scale habitat and biodiversity assessments, but without modelling changes quantitatively over time. In a novel approach we used a long-term time series including historical map data to predict the influence of one century of tropical forest change on keystone species or indicator groups in the Kakamega-Nandi forests, western Kenya. Four time steps of land cover data between 1912/13 and 2003 derived from Landsat satellite imagery, aerial photography and old topographic maps formed the basis for extrapolating species abundance data on the army ant *Dorylus wilverthi*, the guild of ant-following birds and three habitat guilds of birds differing in forest dependency. To predict the species' spatio-temporal distribution, we combined spatially explicit GIS-based modelling with statistical modelling, i.e. ordinary least square (OLS) regression models for *D. wilverthi* and simultaneous autoregressive (SAR) models for ant-following birds. Bird habitat guilds were directly related to five forest classes as distinguished in the land cover time series. Extrapolation results over time predict dramatic losses in abundance for *D. wilverthi* (56%), ant-following birds (58%) and forest bird individuals in general (47%) due to a forest loss of 31% and small-scale fragmentation within the past century. Extrapolations based on a scenario of further deforestation revealed the negative consequences of clearing and splitting-up continuous forest into isolated patches, whereas a reforestation scenario suggests the positive impact of natural forest re-growth and indigenous tree plantings. This study demonstrates the high potential of integrating remote sensing and field-based faunal data for landscape-scale quantitative assessments over time. In addition it shows the suitability of extrapolation studies for evaluating measures of forest conservation.

4.2 Introduction

Due to human activities, tropical rainforest ecosystems are currently undergoing unprecedented changes causing a severe loss in global biodiversity (Sala et al., 2000). About 50% of the potential tropical forest area has already been removed and the land turned to other uses, mainly agriculture (Wright, 2005). For the coming decades, most scenarios anticipate continued growth of agricultural land at the expense of tropical forests, especially in Africa (Kemp-Benedict et al., 2002). Rates of tropical forest loss have been estimated by numerous remote sensing-based land cover change studies published at global (e.g. Achard et al., 2002; DeFries et al., 2002) and regional scales (e.g. Etter et al., 2006; Hayes et al., 2002; Lung and Schaab, 2008; Mwavu and Witkowski, 2008; Svan Hansen, 2005). The vast majority of them do not extend further back than the early 1970s when remote sensing satellites emerged (Ramankutty et al., 2006). Some efforts to extend satellite-derived time series for the tropics with land cover information from aerial photography and/or old topographic maps have been made both regionally (e.g. Imbernon, 1999; Mitchell et al., 2006; Petit and Lambin, 2001; Reid et al., 2000) and globally (Klein Goldewijk and Ramankutty, 2004). Regardless of the temporal scope, common to these remote sensing-based change studies is the lack of an explicit focus on assessing biodiversity changes although tropical deforestation is recognised as an important factor.

Beyond this role of documenting forest changes, other studies have shown that remote sensing can be a valuable means for applications aiming at biological assessments for extensive areas that cannot be surveyed by field methods alone (Kerr and Ostrovsky, 2003). In particular, combining remotely-sensed land cover data with field-based species information is ascribed great potential as habitat changes can be converted into estimates of changes in biodiversity (Fuller et al., 1998; Turner et al., 2003). Indeed, from a review of studies in the field of avian research, Gottschalk et al. (2005) conclude that bringing together biological survey data and geo-spatial land cover data has increased the ability to assess causal effects in species–environment relationships and provides an efficient means to estimate bird population sizes for large areas. While the majority of these studies use presence/absence data to model potential bird species distributions based on landscape-scale, remotely-sensed data (e.g. Saveraid et al., 2001, using land cover data as derived from SPOT imagery or Fuller et al., 2005, employing the UK Land Cover Map 2000), only a limited number makes use of species abundance data (e.g. Acevedo and Restrepo, 2008; Fearer et al., 2007), thus allowing for quantitative assessments. Similarly, remote sensing data have been applied for modelling the distribution of insects, e.g. locusts (Sivanpillai et al., 2006), butterflies (Debinski et al., 1999; Luoto et al., 2002) or beetles (Eyre et al., 2003). However, virtually all studies aiming to establish links between remote sensing and biodiversity field data have limited their research to one point in time. An exception is the recent work of Buchanan et al. (2008) who utilized deforestation estimates from two dates (1989 and 2000) as derived from Landsat scenes for the tropical island of New Britain to assess their effect on the endemic avifauna, but without presenting spatially explicit species distributions.

Although the potential of remote sensing for providing information on changes/loss of biodiversity in tropical forests has been clearly pointed out (e.g. by Foody, 2003), little research has been conducted so far on the development of models linking remote sensing time series data to species abundance data in order to allow for quantitative spatio-temporal assessments. Approaches applying remote sensing to bird or insect data as shown above have improved our understanding of species-habitat relationships, but they mostly lack a temporal component and partly also a spatially explicit output. In contrast, change studies focussing on remote sensing techniques typically provide a discussion on the effects for tropical biodiversity (e.g. Muñoz-Villers and López-Banco, 2008; Hansen et al., 2008), but they are rather limited in their ability to predict quantitative changes in animal abundances and distributions. A conventionally applied approach in this regard usually involves two steps. Firstly, research on change detection from satellite imagery to derive improved land cover/forest cover change assessments is conducted. Subsequently, the potential consequences for faunal biodiversity are inferred in a general, non-measurable manner from the changes in native (forest) vegetation. Consequently, information on landscape-level species abundance distributions and their temporal dynamics are still very limited, with a particular scarcity of data from the tropics (Rodríguez et al., 2007). Therefore, applications of remote sensing time series data to biological field data are needed to derive quantitative estimates, i.e. hindcasts of changes in faunal biodiversity, and thus to provide information aiding decisions towards sustainable tropical forest management (cf. Foody, 2003). This is the research gap we are addressing with this study.

The first objective of this study is to combine a long-term land cover time series derived from remotely sensed imagery and historical map data with keystone species or indicator group abundance data from the field. Based on the spatially explicit extrapolation results, the second objective is to determine quantitative estimates of the influence of forest change on the tropical fauna for several time steps over the course of one century. In addition, as the third objective, this research aims to demonstrate the suitability of integrative remote sensing – biodiversity change studies for evaluating measures for forest conservation. The first research objective is achieved by spatially explicit modelling within a geographical information system (GIS) aided by statistical modelling. As input, a land cover time series covering 90 years generated from Landsat satellite imagery, aerial photography and old topographic map sheets for the area of the Kakamega-Nandi forest complex in western Kenya (Mitchell et al., 2006; Lung and Schaab, 2010) is employed. Comprised of four time steps between 1912/13 and 2003, it forms the basis for extrapolating sets of field data on the abundance of (a) the swarm-raiding army ant *Dorylus wilverthi*, (b) the feeding guild of ant-following birds, and (c) three habitat guilds of birds differing in forest dependency. A numerical analysis of the extrapolation results addresses the second research aim while additional forecasts (i.e. extrapolations on scenarios of deforestation and reforestation) allow for conclusions on the third objective, the usefulness of the approach for conservationists and others engaged in forest management.

4.3 Materials and methods

Study area

The study area is located in western Kenya and comprises an area of 60 km by 65 km between 34°37'05" and 35°09'26" E and 0°02'53" S and 0°32'24" N around the Kakamega-Nandi forest complex (Figure 4.1), the easternmost relict of the Guineo-Congolian rainforest belt (Wagner et al., 2008). The area encompasses three major forests, Kakamega Forest, North Nandi Forest and South Nandi Forest, and seven smaller forest fragments. The Nandi Escarpment forms a strong contrast in altitude between North Nandi Forest, with its highest point at 2 140 m, and Kakamega Forest with its lowest point at 1 460 m. Two major rivers are found in the area, the Isiukhu River passing through the northern part of Kakamega Forest and the Yala River passing South Nandi Forest and the southern part of Kakamega Forest. Thus, the forests are an important water catchment area for the Lake Victoria basin (Kamugisha et al., 1997). With around 2 000 mm Kakamega Forest receives one of the highest amounts of mean annual precipitation in Kenya with peaks in April/May and October (Farwig et al., 2006), while the Nandi Forests are believed to receive slightly less annual rainfall (Mitchell and Schaab, 2008). Kakamega Forest comprises a botanically unique mix of Guineo-Congolian and Afro-montane species (Althof, 2005) and is also known for its faunal diversity (KIFCON, 1994; Mitchell et al., 2009). Both Kakamega Forest and the Nandi Forests have the status of Important Bird Areas, with Kakamega Forest holding in total 410 bird species (Shanni and de Bruijn, 2006) of which 46 species are probably not found

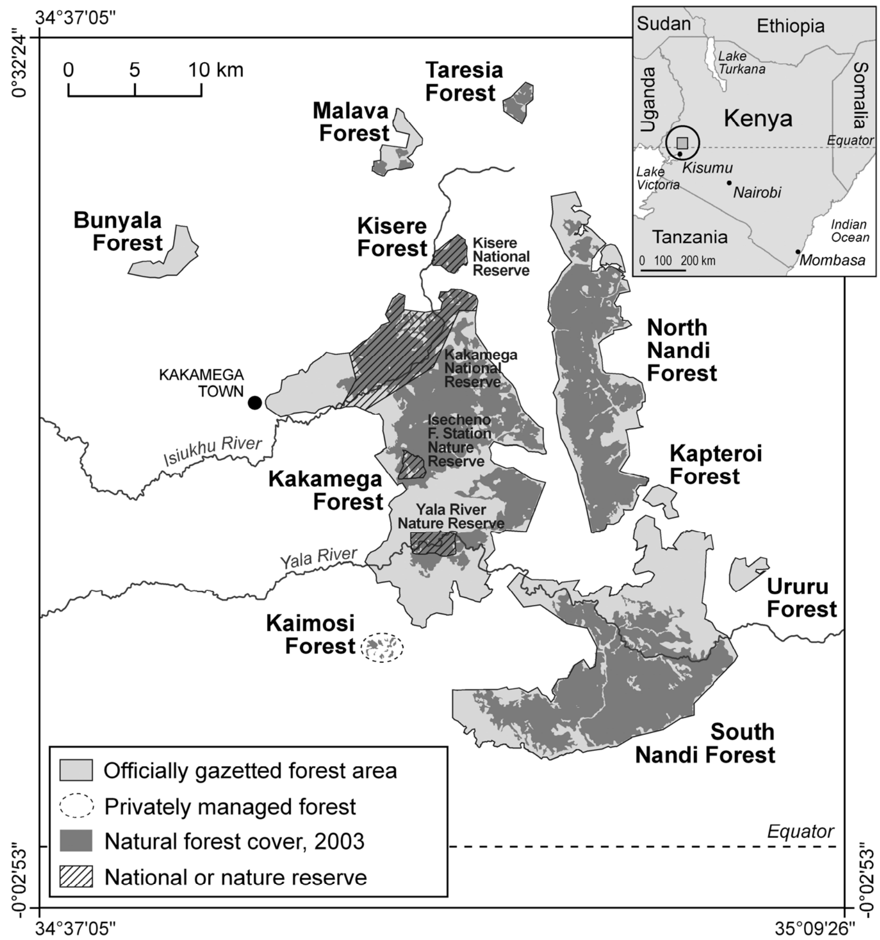


Figure 4.1: Map of the Kakamega-Nandi forest complex area in western Kenya; official forest boundaries displayed together with national/nature reserves and the natural forest cover of 2003 as derived from a visual interpretation of Landsat imagery.

elsewhere in Kenya (Bennun and Njoroge, 1999). For at least one species of army ants (*Dorylus wilverthi*) Kakamega Forest represent the easternmost part of its Central African distribution (Peters et al., 2008).

Whereas in 1999 the area surrounding the Nandi Forests had a density of 371 people km^{-2}, Kakamega Forest is placed in one of Kenya's most densely populated rural areas with 643 people km^{-2} (Lung and Schaab, 2010). These areas are intensively used for subsistence agriculture dominated by cultivation of maize, beans, tea and sugar cane (KIFCON, 1994). The growing population at the borders depends on the forest to support their livelihood, with charcoal burning, cattle grazing and pit-sawing as the major threats to the forest (Mitchell, 2004). Additionally, various legal commercial logging activities as well as different management types (*ibid*) have caused Kakamega Forest to develop into what it is today, a mosaic of various forest types, bushland and open areas.

In particular, five different forest types can be distinguished: near natural forest, secondary forest, mixed indigenous plantations, indigenous monocultures and exotic monocultures, thus making Kakamega Forest an ideal study system for ecological research (Farwig et al., 2008).

Long-term land cover time series

A spatially explicit time series on land cover, covering a 90 year period was derived from three different data types focussing on distinguishing forest formations. Whereas Landsat imagery was acquired for eight dates between 2003 and 1972, the time series was extended further back in time by using aerial photography from 1965/67 and 1948/(52) as well as by two old topographic map sheets from 1912/13 (see Table 4.1, for a complete list of satellite imagery see Lung and Schaab, 2010). In order to reach back in time as far as possible and to cover approximately similar intervals, we chose 1912/13, 1948/(52), 1965/67 and two of the eight Landsat-derived datasets, 1984 and 2003, for extrapolation of biological field data (see Figure 4.2).

Pre-processing of satellite imagery involved georeferencing at sub-pixel accuracy and atmospheric and terrain corrections using ATCOR 3 (Richter, 1998), version for Imagine 8.7. For atmospheric corrections, the true "radiance at sensor" was approximated by adjusting the standard sensor calibration coefficients c1 and c0 for each band in an iterative process comparing them with reference library spectra and checking areas invariant throughout the time series, while terrain effects were corrected applying an empirical BRDF correction function (Richter, 1998). Using a maximum likelihood classifier (MLC), a supervised multi-spectral classification including an additional artificial band (ratio 7/2) was created (for details see Lung, 2004; Lung and Schaab, 2004). In total, 12 land cover classes could be distinguished of which six are forest formations (four forest classes and two bushland classes, see Table 4.2 and Lung and Schaab (2004) for a detailed description of all land cover classes). An accuracy assessment for the classification of 2001 revealed an overall classification accuracy of 81.46% and a user's accuracy of 87.36% for the four forest classes (Lung and Schaab, 2006). However, two of the forest plantation types found in Kakamega Forest, mixed indigenous plantations and indigenous monocultures, could not be distinguished as separate classes by means of the multi-spectral classification and had to be included in the class 'Secondary forest' (Lung and Schaab, 2004). Therefore, we manually delineated them by visually interpreting the original, contrast-enhanced Landsat images of 2003 and 1984 considering the following reference data: very high resolution QuickBird imagery dating from 21/02/2005 and 06/03/2005, ground reference information and a 1:10 000 Forest Department forest map from 1972 with thematic information dating back to the 1940s but also including updates regarding forest plantations up to 2000.

Mosaics of aerial photography from 1965/67 and 1948/(52) were visually interpreted to delineate the same land cover classes as defined for the satellite imagery in order to ensure data homogeneity and comparability (for details see Mitchell et al., 2006). As with the satellite imagery of 2003 and 1984, we separated mixed indigenous plantations and indigenous monocultures. As far as possible, the same or compatible reference data sources, in particular the Forest Department forest map, were used to ensure consistency of the additional two classes maintaining plausible progressions across all four time steps. The forest fill of old topographic map sheets from 1912/13 served for extending the time series back to the early 20th century. It represents areas of near natural forest and was on-screen digitized from the map sheets (Mitchell et al., 2006). The datasets derived from the aerial photography and the old topographic map sheets were converted to 30m x 30m raster data corresponding to the spatial resolution of the Landsat TM/ETM+ data.

Table 4.1: Overview on data sources and processing methods for deriving a long-term land cover time series (1912/13 to 2003) for the area of the Kakamega-Nandi forest complex in western Kenya.

	1912/13	**1948/(52)***	**1965/67**	**1984**	**2003**
Data type	Topographic map	Aerial photography & topographic map	Aerial photography	Satellite imagery	Satellite imagery
Data source	East Africa map series, sheets North A-36 W Mumias & North A-36 X Uasin Gishu, Ordnance Survey	Royal Air Force, UK (courtesy to T. Brooks & Rhodes House, Oxford, UK); East Africa 1:50 000 (Kenya), Series SKII, sheets 102/II & 102/IV	Hunting Survey & Consultants Ltd., UK (courtesy to T. Brooks & Ordnance Survey, UK)	Landsat TM (USGS)	Landsat ETM+ (USGS)
Scale / resolution	1: 250 000	1:30 000 (photos) 1:50 000 (map)	1:55 000 (1965) / 1:35 000 (1967)	30 m x 30 m	30 m x 30 m
Processing method	Digitising of forest fill	Visual interpretation & digitising of forest fill	Visual interpretation	Supervised multi-spectral image classification	Supervised multi-spectral image classification

* 22.8% of area not covered by aerial photography but supplemented with forest fill from topographic map (which is based on aerial photography from 1948)

Table 4.2: Forest formations, as derived by means of a supervised, multi-spectral classification of Landsat imagery (2003, 1984) and a visual interpretation of aerial photography (1965/67, 1948/(52)), each with a description in accordance with Althof (2005).

Class	**Vegetation description**
(1) Near natural forest*	Near primary forest, lowest disturbance level, dense canopy, older than 50 years; also included: old secondary forest (< 40 years)
(2) Secondary forest	Young and mid-aged secondary forest of 10-30 years
(3) Bushland/shrubs	Bushed areas interspersed with grasses; also included: very young secondary forest (initial state, younger than 10 years)
(4) Secondary bushland	Areas of colonising *Psidium guajava* trees (animal-dispersed, e.g. by monkeys)
(5) Plantation–exotic monoculture**	Plantations of either *Pinus patula* (originally from Mexico) or *Bischoffia javanica* (originally from Asia)
(6) Plantation–indigenous monoculture***	Plantations of *Maesopsis eminii*
(7) Plantation–mixed indigenous***	Mixed plantings of e.g. *Cordia africana*, *Markhamia lutea*, *Prunus africana*, *Olea capensis*

* originally called 'Near natural and old secondary forest' in Lung and Schaab (2010)

** grouped from the originally distinguished classes 'Plantation forest–*Pinus patula*' and 'Plantation forest–*Bischoffia javanica*'

*** derived by an additional visual interpretation of the Landsat imagery and the aerial photography using secondary map information and very high resolution QuickBird imagery as reference data

Scenarios of deforestation and reforestation

In order to evaluate consequences of different forest management and conservation practices on the future development of forest biodiversity, for Kakamega Forest two additional scenarios were created based on the land cover classification of 2003 (Figure 4.2). In the first, a deforestation scenario, we assumed that forest remains only in the national and nature reserves for which protection policies are the most strict (Bleher et al., 2006; Mitchell, 2004). Therefore, for the areas outside the spatially isolated patches of the national and nature reserves, all forest and bushland classes were reclassified to non-forest. The second scenario is a normative landscape scenario, portraying a plausible and desirable future of the forest (Nassauer and Corry, 2004). This reforestation scenario has a time frame of around 40 years into the future (for forest classes cp. Althof, 2005 and Table 4.2) and was generated taking the following assumptions: (1) secondary forest will turn to near natural forest and bushland to secondary forest, (2) historic glades remain open and (3) existing plantations remain unchanged, (4) open areas within the officially gazetted forest boundaries are re-planted with either of the three plantation types, each covering one third of these areas. The spatial allocation of the three plantation types in the open areas was done arbitrarily, but constrained exotic monocultures to areas of easy access and placing mixed indigenous plantations in areas far away from roads and in areas of high conservation value. The use of the two scenarios for extrapolation of biological field data is explained further in section "Extrapolations in space and time".

Field data collection on army ants and birds

Three sets of field observations on tropical fauna were used for this study: species abundance data on army ants, ant-following birds and bird habitat guilds. All three are considered either keystone species or indicator groups of tropical forest ecosystems with well studied habitat preferences. Raids of *D. wilverthi* sustain the diversity of leaf-litter arthropods, but are highly susceptible to forest decline and fragmentation (Peters et al., 2009). Many invertebrates and vertebrates, such as ant-following birds, are associated with them (Peters et al., 2008; Peters and Okalo, 2009). Birds perform several important ecosystem services (Sekercioglu, 2006) and are ideal indicators for complex forest environments (Farwig et al., 2008; Gardner et al., 2008). For all three datasets, the positions of the transects and point count stations were recorded using a GPS (Global Positioning System) device. The swarm-raiding army ant *Dorylus wilverthi* was monitored along 51 transects of 500 m length between 2002 and 2008. 30 transects were located in Kakamega Forest, nine in the surrounding forest fragments and 12 in farmland habitats. The transects were placed in forested areas at least 100 m away from each other and were re-visited successively between 12 and 57 times (for details on sampling see Peters et al., 2009).

Ant-following birds were monitored from April 2004 to August 2005 at 33 of the 51 transects installed for ant monitoring (Peters and Okalo, 2009). Six count stations per transect (four in one case) with a distance of 100 m to each other were re-visited six times and all birds seen or heard within a radius of 25 m were recorded with standardized point count methodology. Specialized ant-followers were identified by comparing species attendance at army ant swarm-raids with species abundances independent of the raids (for details see Peters et al., 2008). The three species identified as most specialized ant-followers were included in this study: the White-tailed Ant Thrush (*Neocossyphus poensis*), the Brown-chested Alethe (*Alethe poliocephala*) and the Red-tailed Bristlebill (*Bleda syndactyla*). For our analyses, the abundances of the three species were summed.

Further point counts of birds were conducted between March 2005 and March 2006 in the five different forest types found in Kakamega Forest: near natural forest, secondary forest, mixed indigenous plantations, indigenous monocultures and exotic monocultures. For each type, three 1-ha plots with nine point count stations each were established for a monitoring period of 13 months. Point counts were carried out recording all birds seen or heard within a radius of 20 m in the early morning for a period of 10 min. The present study is based on Farwig et al. (2009). From the census pool, 115 bird species were classified into habitat guilds according to their forest dependency as either forest specialists, forest generalists or forest visitors (for details on bird classification see Farwig et al., 2008). Like for the ant-following birds, the abundances of the species classified as forests specialists, generalists and visitors were summed, respectively.

Extrapolations in space and time

In order to extrapolate the three sets of field observation data in space and time we combined spatially explicit GIS modelling with statistical modelling, applying three different approaches (see Figure 4.2). For two of the species abundance data sets (ants and ant-following birds) regression models were performed to test for correlations with the spatial information on land cover from 2003 and/or small-scale forest fragmentation in the vicinity of the observation points. Small-scale forest fragmentation, defined as a measure of the proportion of forest edge within the forest landscape, was derived from the land cover data. Extrapolations for ants and ant-following birds were conducted for all forests within the study area of 60 km by 65 km. In contrast, abundance data on bird habitat guilds were directly related to the land cover time series data and the extrapolations were limited to an area enclosing the official boundary of Kakamega Forest. We used R 2.6.1 and the R package spdep, version 0.4-13 (Bivand et al., 2007) for statistical analyses, while the spatial extrapolation modelling was performed with the GIS software ArcGIS 9.2.

For army ants we first generated 40 buffers around each of the 51 transects covering distances between 100 m and 4 000 m (incrementing by 100 m). For each buffer we calculated the proportions of all land cover classes. While a publication about the details of statistical modelling of army ant abundances in relationship to forest cover is in preparation, here we focus on the approach of integrating the formulae as derived from the statistics into the workflow of GIS modelling functionalities for establishing a spatial extrapolation procedure. Therefore, the parameters for spatially explicit modelling are reported in detail while the description of the statistics is limited to the most important measures. Ordinary least square (OLS) regression models using log-transformed ant abundance data (LN (ant abundance + 0.1)) were run to determine within which buffer size (hereafter referred to as the 'spatial level') which of the land cover classes (treated individually or possibly combined) are most significantly correlated with the field observations. In this process we also accounted for the number of explanatory variables (land cover classes), applying the Akaike Information Criterion (AIC) (Akaike, 1974). Highest significance was revealed at a spatial level of 1 400 m and when grouping natural forest cover (classes 'Near natural forest' and 'Secondary forest') together with the two bushland-classes ('Bushland/shrubs' and 'Secondary bushland–*Psidium guajava*') into

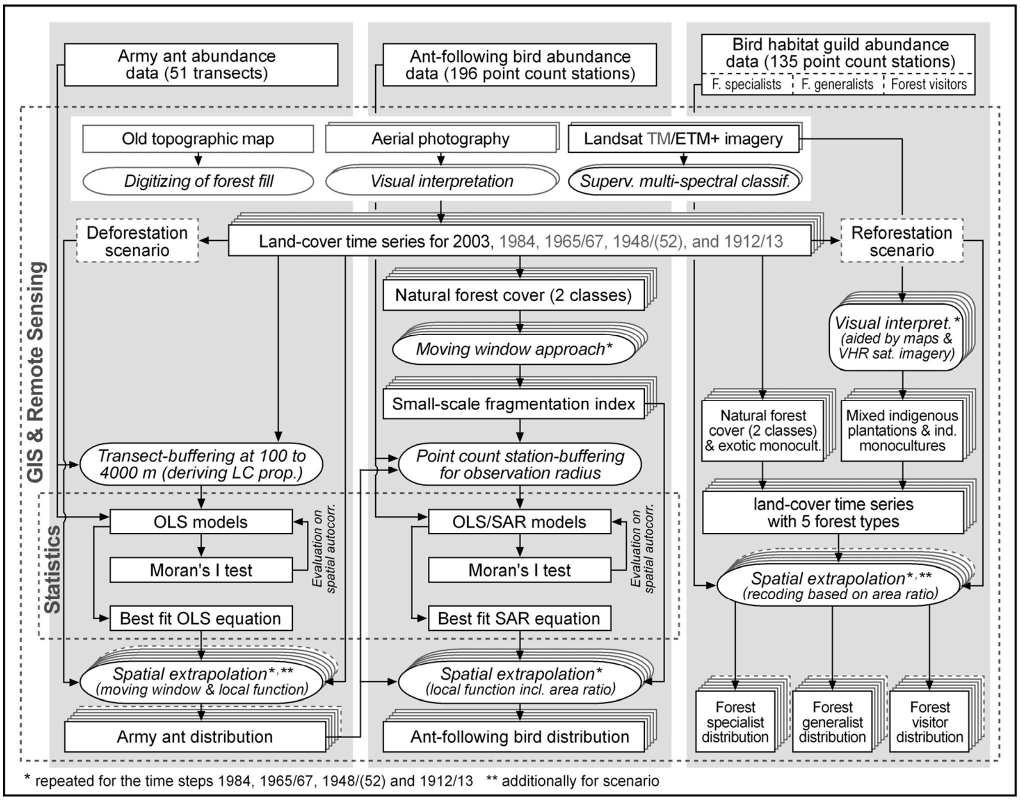


Figure 4.2: Flow-chart of processing methodologies for extrapolating field data on the army ant *D. wilverthi*, on the guild of ant-following birds, and on bird habitat guilds of forest specialists, generalists and visitors, in space and time; based on a remote sensing-derived land-cover time series for the Kakamega-Nandi forest complex from 1912/13 to 2003.

one single class 'Forest cover' and all other land cover classes to 'Non-forest'. Based on a Moran's I test on spatial autocorrelation (Cliff and Ord, 1981), which showed no significance (for distance classes up to 10 km $|\text{Moran's I}| < 0.14$, $P > 0.10$), the best fit OLS regression (1) was used for spatial extrapolation. For this step, the ModelBuilder within ArcGIS was employed to extrapolate mean ant abundance per transect kilometre (MAA_{trkm}), to the entire 60 km x 65 km area under investigation.

$$MAA_{trkm} \sim e^{(-2.54\,+\,2.14\,(\text{PFC at 1 400 m}))} - 0.1 \qquad (1)$$

$$(F_{1,\,49} = 67.72,\ P < 0.001;\ R2 = 58\%)$$

The spatial level of highest significance as determined from the best fit OLS model (1 400 m) was used to define the size of a moving window. This algorithm, called a 'focal neighbourhood function' in map algebra terminology (Tomlin, 1990), calculates the proportion of forest cover (PFC) within a radius of 1 400 m and assigns the result to the centre pixel, moves on to the next pixel and repeats the calculation until every pixel of the study area has received a proportion-value. Next, for every pixel, the calculated proportions are passed to a local function (cf. Tomlin, 1990) containing the parameter estimates of the best fit OLS model equation. This local function then calculates the abundance of army ants per transect kilometre for every single pixel. The functions were applied within the ModelBuilder for all dates of the time series and for the scenario of deforestation outside the national/nature reserves. The resulting spatial distributions were visualized using a bi-polar hue progression (Robinson et al., 1995) ranging from red (low values) to green (high values). Subsequently, we conducted a quantitative numerical analysis of the extrapolation results for a subset of our study area. The subset box includes all forests where army ant field observations were conducted (i.e. Kakamega Forest, Kisere Forest, Malava Forest and Kaimosi Forest; see 'Analysis area' in Figure 4.3). For the area of the subset box we summed up the abundances of all pixels in order to generate a measure of total ant abundance for each date of the time series.

For ant-following birds, the MAA_{trkm}-distribution was used as an explanatory variable (Figure 4.2) since Peters and Okalo (2009) proved a direct dependence on *D. wilverthi* colonies for the three bird species considered in this study. As the MAA_{trkm}-distribution indirectly includes the proportion of forest cover in the vicinity (see equation 1), forest cover was not used as model input in order to avoid collinearity. Instead, taking into account that ant-following birds are highly susceptible to forest fragmentation and degradation (Peters et al., 2008), a test on the significance of a spatially explicit small-scale forest fragmentation index (F_{frag}) was conducted by computing its mean value for each bird observation area. F_{frag} is calculated in a 3 by 3 pixel-sized moving window as a ratio of the number of 'Forest' to 'Non-forest' edges (FN_{edge}) vs. the number of 'Forest' to any edges (FA_{edge}) (Equation 2).

$$F_{frag} = FN_{edge} / FA_{edge} \qquad (2)$$

'Forest' was defined as land cover classes 'Near natural forest' and 'Secondary forest', 'Non-forest' as all other land cover classes, and 'edge' as the imaginary line that separates any adjacent pixels. The index gives a spatial pattern of the degree of forest fragmentation while for areas without natural forest cover it returns 'No data'. Whereas $F_{frag} = 0$ indicates no forest fragmentation (i.e. all edges are 'Forest' to 'Forest'), the level of fragmentation increases up to $F_{frag} = 1$ indicating total fragmentation (i.e. no edges 'Forest' to 'Forest' are found) (for details on the index see Lung and Schaab, 2006). Instead of an OLS model, showing strong correlations for point count data from adjacent stations (Morans' I = 0.22, P < 0.01 for a distance class of 1 km), a simultaneous autoregressive model (SAR) which controls for spatial autocorrelation (cf. Kissling and Carl, 2008) was used. The SAR model showed the lowest AIC-value when including both MAA_{trkm} and F_{frag} as opposed to merely using either MAA_{trkm} or F_{frag}. Therefore, the regression equation of this best fit model (Equation 3) for modelled ant-following bird abundance (MABA) was included to a local function within the ModelBuilder of ArcGIS.

$$MABA \sim (0.36 + 0.84\ MAA_{trkm} - 0.22\ F_{frag})\ (900\ /\ 1\ 963) \qquad (3)$$

(R^2 = 34%; MAA_{trkm}: z = 3.74, P < 0.001; F_{frag}: z = -2.24, P = 0.025)

The function receives F_{frag} and MAA_{trkm} as input and calculates ant-following bird abundance for every pixel of the study area considering the area ratio 900 m^2 / 1 963 m^2 (i.e. the area of one 30 m by 30 m pixel in the land cover data divided by the area of one bird observation point with r = 25 m). As for army ants, the extrapolation procedure was repeated for all dates of the time series and the results were visualized with the above described colour scheme. A numerical analysis was performed on the same subset area as for the army ants.

Farwig et al., (2009) found significant differences in the total number of bird individuals for forest specialists, generalists and visitors among the five forest types distinguished in our land cover time series, while no forest edge distance effects could be measured. Therefore, we directly related the mean number of bird individuals per observation plot and forest type as recorded in the field to the five forest types as distinguished in the spatio-temporal time series (Figure 4.2). First, we calculated an area ratio from the bird observation area per plot (11 310 m^2, derived from nine point count stations each with an observation radius of 20 m) vs. the area covered by a 30 m by 30 m pixel in the land cover data (900 m^2). For all three habitat guilds, the ratio was then applied to the mean number of individuals per forest type as recorded in the field (I_{field}) in order to derive the mean number of individuals per pixel (I_{pix}) (see Equation 4).

$$I_{pix} = I_{field} \, (900 \, / \, 11\,310) \tag{4}$$

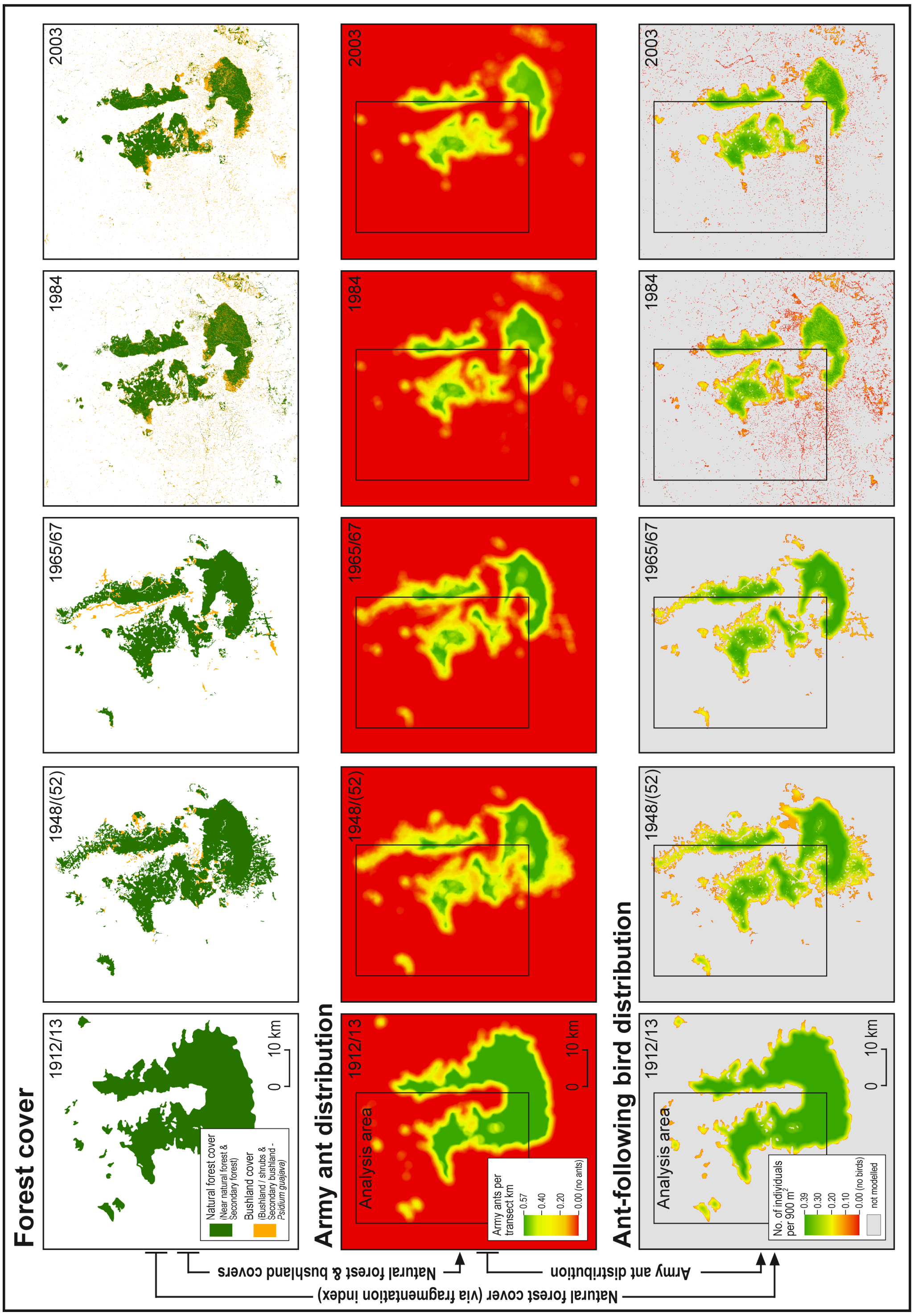
Thus, the five forest classes were recoded to I_{pix} whereas all other land cover classes (e.g. 'Agricultural land', 'Grassland' etc.) were recoded to 'No data', repeating the process for all three habitat guilds, all dates of the time series and the reforestation scenario. The resulting spatial distributions were visualized based on a uni-polar colour ramp ranging from reddish hues for the lowest values, via blue, brown and yellow, to green hues for the highest values, combined with an increase in saturation.

4.4 Results on time series of landscape level species distributions

Ants and ant-following birds

The map series on forest cover shows a break-up of the single, U-shaped forest block into three isolated forests (Kakamega Forest, South Nandi Forest and North Nandi Forest (see Figure 4.3). Over time, these forests were further reduced in size and became increasingly fragmented. An exception is Kakamega Forest for which an improvement regarding fragmentation is seen from 1984 to 2003. The extrapolated ant abundances reveal a spatial distribution pattern according to the development of forest cover. Highest ant abundances per transect kilometre are predicted in the forest core areas whereas abundances are decreasing towards the edges of the forests. Low abundances are also predicted in highly fragmented forest areas and the small forest fragments around the three main forests. Ant abundance is estimated to reach zero (bright red in Figure 4.3) at a proportion of forest cover of less then 11% within a spatial level of 1 400 m. The quantitative analysis for the subset area (Figure 4.4) reveals a decrease in forest cover of 31% between 1912/13 and 1984 and an even stronger loss of ant colonies by 56%. From 1984 to 2003 the amount of forest cover stayed approximately constant, while for *D. wilverthi* a 4% increase is predicted. For the deforestation scenario extrapolation results (not shown here) estimate the total ant colony abundance of *D. wilverthi* to drop to only 10% of the 1912/13 value. Moreover, it is suggested that army ants in Isecheno Forest Station Nature Reserve

Figure 4.3: Map series depicting modelled abundance distributions of army ants (*D. wilverthi*) and ant-following birds (*N. poensis*, *A. poliocephala*, *B. syndactyla*) resulting from spatial extrapolations based on land-cover time series data from 1912/13, 1948/(52), 1965/67, 1984 and 2003; each date is displayed together with the forest cover at that time for the area of the Kakamega-Nandi forest complex.


Forest cover
1912/13
1948/(52)
1965/67
1984
2003
Natural forest cover (Near natural forest & Secondary forest)
Bushland cover (Bushland / shrubs & Secondary bushland - Psidium guajava)
0 10 km
Army ant distribution
Analysis area
Army ants per transect km
0.57
0.40
0.20
0.00 (no ants)
Ant-following bird distribution
No. of individuals per 900 m²
0.39
0.30
0.20
0.10
0.00 (no birds)
not modelled
Natural forest & bushland covers
Army ant distribution
Natural forest cover (via fragmentation index)

and in Yala River Nature Reserve form isolated populations of small size. In contrast, the modelling results suggest that Kakamega National Reserve and Kisere National Reserve form a single continuous population. The two reserves are close to each other and therefore army ant colonies may easily migrate between them.

As with army ants, the spatial distribution of extrapolated ant-following bird abundance over time is predicted to reach highest values in the forest core areas and lowest numbers of ant-following bird individuals at forest edges. A comparison between the modelled distributions of ant-following birds and army ants reveals significant differences. The modelled ant-following bird distributions show a less homogenous pattern inside the forests with small areas of low abundances or even 'No data' (grey colour in Figure 4.3) which mostly represent either forest glades or forest openings created by logging. This applies in particular to 1984 and 2003, reflecting the distribution of forest cover as derived from the multi-spectral classification of Landsat imagery. Likewise, differences in the decline patterns towards the edges of the forests are revealed. Modelled army ant distributions show a steady decrease reaching less than 60% of their maximum abundance (0.57) already at a distance of around 650 m inside the forest, but do not decrease to zero before a distance of around 850 m into the farmland. In contrast, ant-following bird abundance is predicted to stay above the 60% threshold of its maximum (0.39) until around 150 m to the forest edge, but drops to zero already at around 30 m out in the farmland. When summing the ant-following bird abundances for our analysis area around Kakamega Forest, a similar trend as compared to the army ants is predicted: a strong continuous decrease of 58% between 1912/13 and 1984, and subsequently a slight increase by 4% for the year 2003 (Figure 4.4).

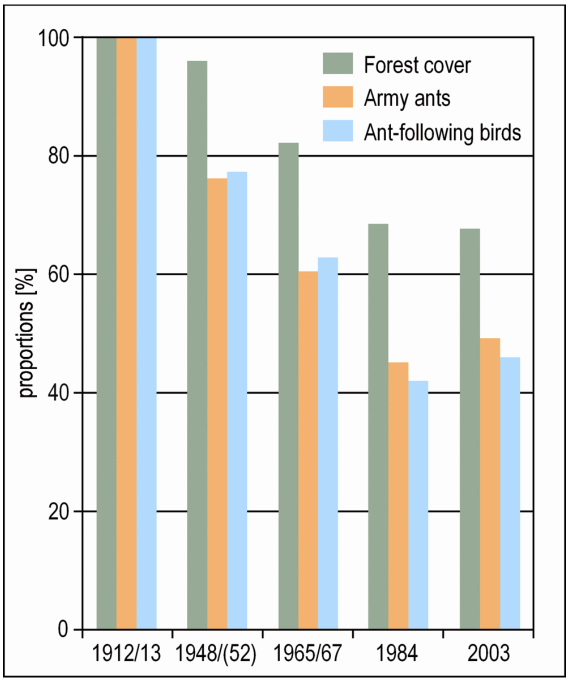


Figure 4.4: Development [in %] of forest cover, army ants and ant-following birds, 1912/13 to 2003, for an analysis area enclosing Kakamega Forest, Kisere Forest, Malava Forest, Bunyala Forest and Kaimosi Forest (cf. Figure 4.3).

Bird habitat guilds

The spatial distributions of the extrapolated bird habitat guilds from 1912/13 to 2003 (Figure 4.5, 1948/(52) and 1984 not shown in order to preserve map legibility) show generally highest abundances for forest specialists, followed by forest generalists and forest visitors (cf. Farwig et al., 2009). For forest specialists highest numbers of individuals are seen in near natural forest, mixed indigenous plantations and indigenous monocultures. Least preferred by forest specialists and also by forest generalists are exotic monocultures and secondary forest, both hosting the highest numbers of forest visitors. For Kakamega Forest, our extrapolation results of bird habitat guilds in the area covered by the five forest types predicts a decline of 47% in the total number of individuals dropping from about 1 660 000 in 1912/13 to about 880 000 in 2003 (Figure 4.6a). With regard to the different habitat guilds, our results model losses of 54% and 47% for forest specialists and forest generalists, respectively, but no major changes in the occurrence of the much smaller number of forest visitors. For the reforestation scenario, the total number of bird individuals is predicted to rise back to a level of around 1948/(52), with the strongest increase for forest generalists and specialists (54% and 53%, respectively, compared to 2003). Examining the implications of the proportions of the five forest types on the proportions of the three habitat guilds over time reveals considerable effects (Figure 4.6b). Whereas the loss in the proportion of near natural forest (100% in 1912/13 to 58% in 2003) is predicted to cause a decrease in the proportion of forest specialists from 54% to 47%, the proportional increase of secondary forest (from 0% to 27%) and exotic monocultures (0% to 6%) is assumed to lead to a proportional increase of forest visitors from 8% to 15%. No major effect was predicted for forest generalists. A comparison of the reforestation scenario with the 2003 figures regarding the proportions of the five forest types (Figure 4.6b) reveals a distinct decrease in the proportion of secondary forest (27% to 17%) and an increase in the proportions of all three plantation types (from in total 14% to 27%). The 1948/(52) data, with similar numbers of modelled individuals as in the reforestation scenario (Figure 4.6a), reveal also a similar proportion of secondary forest (18%), but only 2% of plantation forest and a much larger proportion of near natural forest (80% compared to only 57% in the reforestation scenario). Despite these differences in the proportions of the forest types, the proportions of the three bird habitat guilds are predicted to be fairly similar for 1948/(52) and the reforestation scenario.

4.5 Discussion and conclusions

Use of remote sensing land cover time series data

Since remotely-sensed long-term land cover time series are usually derived from disparate sources (e.g. satellite imagery and aerial photography), a consistent scheme of land cover classes is indispensable in order to ensure data homogeneity. In this context, the definition of classes distinguishable in all data sources as well as intensive ground-truthing for the newest date(s) has been pointed out as important factors (Reid et al., 2000). These were met with the Landsat imagery, the aerial photography and the topographic map information used for generating the land cover time series for this study. All classes distinguished in the satellite imagery could also be distinguished in the aerial photography, if not generally absent at that time (see Mitchell et al., 2006). Although being a very different product usually derived by ground survey, several studies have shown the value of historical map data for deriving spatially explicit information on historic forest management practices (Weir, 1997) and for extending time series further back in time (e.g. Hamandawana et al., 2005). However, two aspects should be carefully considered, the positional and the thematic fit of such data to the other data sources of a time series (Petit and Lambin, 2001). Regarding the former, the historical map sheets at a scale of 1:250,000 used here have a lower level of detail compared to the land cover information

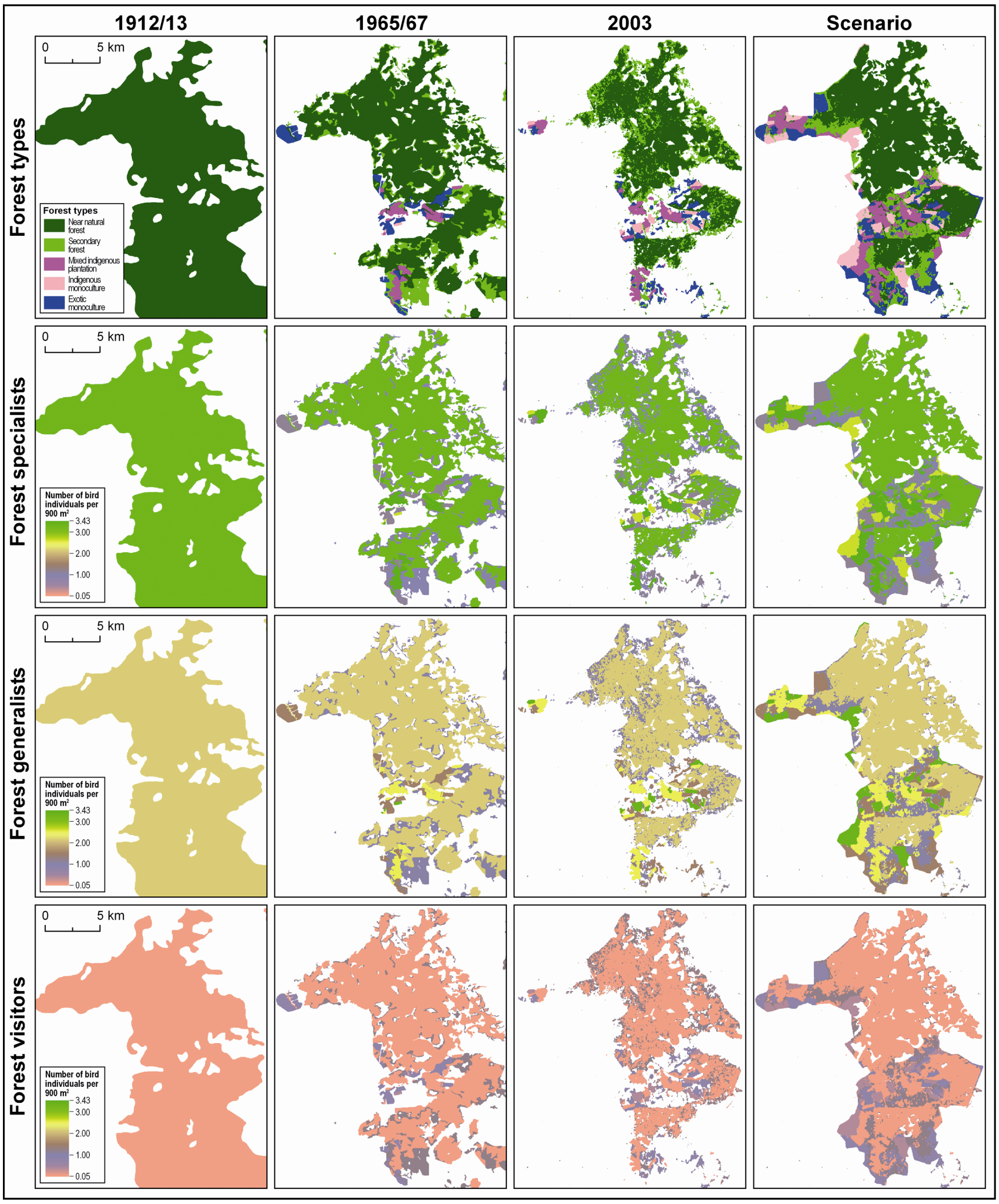


Figure 4.5: Spatial distribution of extrapolated bird habitat guild abundances of forest specialists, generalists and visitors, presented as a matrix of maps together with forest type for 1912/13, 1965/67, 2003 and a reforestation scenario, each for an area enclosing the official forest boundaries of Kakamega Forest.

as derived from the aerial photography and Landsat imagery (see Table 4.1). However, this drawback was accepted in the light of the enormous value provided by these historical data: the possibility to reach back to the early 20th century. In terms of thematic fit, our detailed knowledge of the forest history makes us confident in claiming that

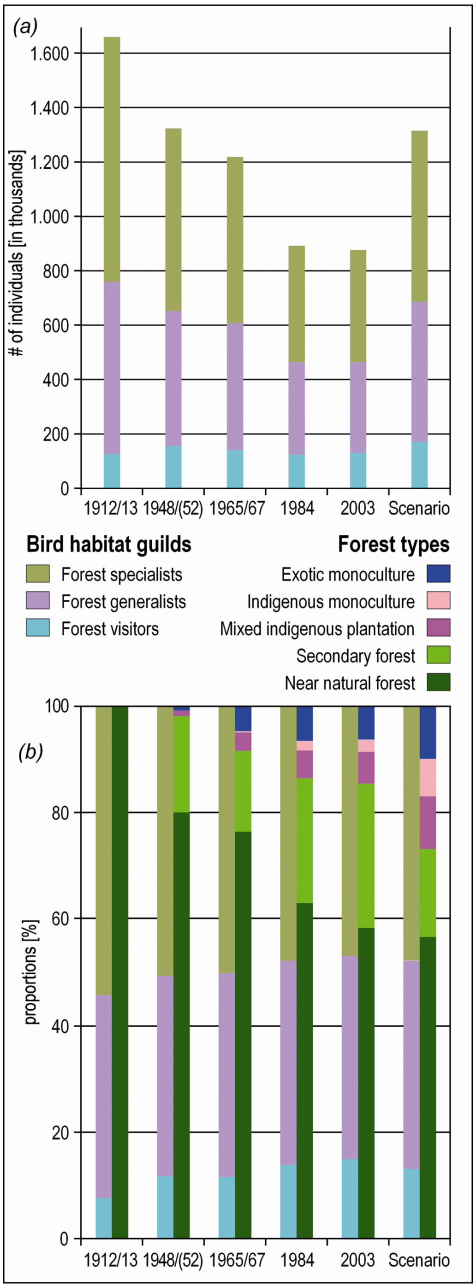


Figure 4.6: (a) Number of bird individuals, (b) proportions of bird habitat guilds of forest specialists, generalists and visitors, 1912/13 to 2003 and for a reforestation scenario, for an area enclosing the official forest boundaries of Kakamega Forest; in (b) for each date and the scenario the proportions of the five forest types are also shown.

the forest fill is fully comparable to the class "Near natural forest" as also distinguished from the imagery of the other dates. At that time, the forest was only marginally disturbed by local people and commercial utilisation had not started (Mitchell, 2004). Additionally, Mitchell et al., (2006) conclude from an analysis based e.g. on oral histories that bushland is definitely not included in what was surveyed and drawn as 'forest' in the topographic map of 1912/13.

Considering four time steps (in similar intervals) enabled us to capture the temporal patterns of change more precisely as compared to studies based on two years, often applied when investigating changes over time with remotely-sensed imagery (e.g. Velázquez et al., 2003). Regarding the degree of differentiation in terms of land cover classes our study has demonstrated that the requirements strongly depend on the nature of the biological field data to be extrapolated. The extrapolation of army ants revealed highest significance when using binary forest/non-forest layers, but the different forest classes were initially required in order to derive the best possible definition of 'Forest cover', i.e. to test which classes constitute 'Forest cover'. Likewise, our data on bird habitat guilds necessitated a high within-forest distinction. Other extrapolation studies have shown that an insufficient distinction of land cover classes compromises the modelling results (e.g. Prins et al., 2005), whereas a high differentiation of classes as shown here provides greater flexibility for extrapolations of multiple field observations. On the other hand, the accuracy of a classification often decreases as the number of classes increases (Rees, 2001). Furthermore, the use of satellite imagery with a spatial resolution not fine enough to discriminate critical habitats has been identified as another potential source of error (e.g. Gottschalk et al., 2005; Saveraid et al., 2001). A good example is riparian areas that typically require very high resolution imagery (e.g. Johansen et al., 2007). To serve as an appropriate input for ecological modelling, the spatial resolution of remote sensing data should match the field observations to be extrapolated (Seto et al., 2004). Therefore, a careful evaluation of the required level of detail according to species habitat preference versus the capabilities of the satellite data in terms of spectral and spatial resolution is essential. In this context, Landsat imagery with a 30 m spatial resolution is highly compatible with small-grain field measurements on birds and ants, similar to other findings for birds (Gottschalk, 2002) or birds and butterflies (Seto et al., 2004).

Extrapolation methods applied

The extrapolation modelling procedure, applying remotely sensed data in order to derive spatio-temporally explicit quantitative faunal biodiversity assessments, for the first time integrates long-term land cover time series data with three sets of biological field findings. This allows for unique landscape-level hindcasts on tropical faunal biodiversity back to 1912/13. However, from a comprehensive review of studies using remote sensing to assess terrestrial faunal species/groups, Leyequien et al. (2007) identified one factor particularly crucial when combining field measurements with discrete habitat types: the assumption that empirical conditions at the field survey points can be extrapolated over a larger area. Here, our approach might raise questions as we not only extrapolated species field observations, collected between 2002 and 2008, in space (i.e. to our entire study area) but we also used those observations to extrapolate back in time (i.e. to the early 20th century). Certainly, our spatially explicit, GIS and remote sensing-based approach involves a number of assumptions and simplifications. One assumption is that the investigated forests have been stable over time. Wagner et al. (2008) demonstrated very high biogeographic similarities between the Kakamega-Nandi forest complex and central African forests (Guineo-Congolian) although they have been separated for many centuries. In addition, there is evidence from long-term records back to 1923 that climatic conditions in terms of rainfall have stayed the same (Tsingalia, 1988). Therefore, despite severe losses and fragmentation, the forest system as a whole is very likely to have stayed relatively stable over our study period, i.e. the last century. Regarding our study species we assumed a constant species pool, equilibrium of species with habitat without major time lags, and a linear relationship between abundances and habitat area (i.e. no thresholds for an abrupt system change). Moreover, we are also aware that our extrapolations in space and in time do not consider other complex forces that might have impacted the forest ecosystem and thus the species we studied over the last century (e.g. competition with other species, changes in predators, diseases, etc).

Forest configuration at a spatial level of 1 400 m as derived from the best-fitting OLS model is considered very reasonable for *D. wilverthi*. The abundance of this highly mobile (nomadic) species is not determined by the local habitat but by the landscape configuration at larger spatial levels. Army ant colonies frequently move from one place to another (nomadism), crossing distances of on average 223 m per emigration (Raignier and van Boven, 1955). Therefore, habitats at distant areas may influence the local influx of colonies. While the ant model was based on a high coefficient of determination (R^2), for the ant-following bird model a lower R^2 was inevitable due to high variance in the field observation data. However, the inclusion of the forest fragmentation index improved the AIC-value and thus also the overall accuracy of the modelled species distribution. Some authors focussing on modelling species richness have advocated landscape diversity indices for this task (e.g. Prins et al., 2005; Saveraid et al., 2001). An approach similar to ours, making use of a spatially explicit moving window-based fragmentation index, however, is not known to us. A drawback of using the fragmentation index is that it causes less accurate extrapolation results for some small areas outside the forests for 1984 and 2003. These areas are made up of groupings of more than one pixel classified as either 'Near natural forest' or 'Secondary forest' (representing gallery forests, very small sacred forests or woodlots and partly also some misclassifications) and have a much stronger effect on the small-scale 3 by 3 pixel-sized moving window of the fragmentation index compared to the 1 400 m radius of the moving window as used to extrapolate the ants. Thus, for these small areas outside the forest, modelled abundances of ant-following birds which are forest specialists rise above zero (see Figure 4.3) although no species are expected there (Laube et al., 2008). A smoothing filter (e.g. a majority filter) applied to the land cover classifications of 1984 and 2003 would have reduced this effect, but at the same time it would have compromised the results of the fragmentation index for the edges and fragmented areas of the forest patches.

Value of the extrapolation results

Although tropical rainforests are given much conservation attention since they contain half of the world's species (Olsen and Dinerstein, 2002), relatively few studies that include data on the spatial distribution of wildlife species have been conducted in the tropics (Gottschalk et al., 2005). In particular, very little is known about bird communities of more than 20 species (*ibid)*. No studies are known to the authors that attempt to hindcast spatially explicit species distributions back to the beginning of the 20th century while considering five time slots to take temporal fluctuations into account. In this context, our extrapolation results for the swarm-raiding army ant *D. wilverthi*, for ant-following birds and for bird habitat guilds provide unique insights.

The spatially explicit modelling results revealed details of interest particularly in the context of forest conservation. Here, noteworthy is the indication of a diverging development of *D. wilverthi* and ant-following birds compared to forest cover from 1984 to 2003 (Figure 4.4) showing hardly any change in the amount of forest cover but increases in species abundances. Examining the spatial configuration of the forest cover classification of 2003 compared to 1984 reveals forest losses in some areas, but also re-growth of secondary forest in areas formerly logged or disturbed (Lung and Schaab, 2010), resulting in a less fragmented overall forest area for 2003. The spatial extrapolations of the statistically derived relationship between forest cover and field data demonstrate that species abundances are not only determined by the proportion of forest cover in their vicinity, but also by the spatial distribution of forest cover. In other words, the stronger the degree of fragmentation of a forest landscape, the more forest area is necessary to host the same number of ants and ant-following birds (assuming everything else being equal). This calls for effective measures of forest protection and management (as also pointed out by Bleher et al., 2006) enabling the re-growth of natural forest vegetation in logged or disturbed areas of Kakamega Forest.

The impact of different measures of forest management and conservation on the fauna is highlighted even more strongly when comparing the extrapolations based on the scenarios of deforestation (applied to army ants) and reforestation (applied to bird habitat guilds). On the one hand, the scenario of complete deforestation outside the boundaries of the four spatially isolated national/nature reserves of Kakamega Forest (cf. Section 4.3, 'Scenarios of deforestation and reforestation') demonstrates the harmful consequences of management decisions that provoke the break-up of continuous forest areas. Besides the estimated decrease of 90% in ant colony abundance compared to 1912/13, populations in two of the four reserves are projected to become isolated. For ants not capable of dispersing through agricultural land, such as *D. wilverthi*, it is therefore questionable as to whether these isolated populations would be large enough to be viable in the long term (see Partridge et al., 1996; Peters et al., 2009). On the other hand, a comparison of the 2003 forest status with the reforestation scenario as described in Section 4.3 and shown in Figure 4.5, suggests a strong positive influence on the absolute number of individuals for all bird habitat guilds (Figure 4.6a), but only a marginal influence on their proportions (Figure 4.6b). While the absolute number of forest specialists is predicted to increase the most, their proportion stays similar. This is caused by the fact that the total proportion of the three forest types least preferred by forest specialists also stays at a similar level: the proportional decrease of secondary forest is compensated by a proportional increase of exotic monocultures and indigenous monocultures. Another compensation effect is noticeable when comparing the forest type proportions of 1948/(52) and of the reforestation scenario in Figure 4.6b with the number of birds for these years in Figure 4.6a. Although forest proportions are different with a 23% lower proportion of near natural forest in the reforestation scenario, it is mainly the portion of mixed indigenous plantations (~ 10%) that compensates for the loss of near natural forest. This results in the predicted number of forest specialists in the reforestation scenario reaching 94% of their 1948/(52) level. These findings show the potential of mixed indigenous plantations as measure for biodiversity conservation and support other studies emphasising the importance of forest types with structural heterogeneity for sustaining high bird species richness (e.g. Peh et al., 2005). Overall, the results demonstrate how integrative studies combining remotely-sensed time series and biological field data can contribute to the landscape-scale evaluation of potential consequences of future forest management and conservation decisions on the forest fauna.

In conclusion, our study has demonstrated that remotely-sensed long-term land cover time series provide a highly suitable means for extrapolating sample-based field observations in space and time in order to derive quantitative predictions at the landscape level. Nevertheless, regarding both the spatial and the temporal aspect we suggest that some methodological and data-related factors should be considered. Regarding space these are the employment of remote sensing data detailed enough to match the species data both in terms of differentiation of land cover classes and spatial resolution, the use of field data for species with well-known habitat preferences, and the cross-checking of extrapolation methods against spatial autocorrelation. Time-specific issues include the need of homogeneous remote sensing time series data, the application of multiple time steps to capture fluctuations in time and the careful evaluation of the empirical model assumptions. Our study further showed that spatially explicit landscape metrics deduced from remote sensing data can be effectively used to model species abundance distributions for tropical forests. With this remote sensing-based approach, detailed landscape level species distributions and assessments on the quantity of change for D. wilverthi, ant-following birds and bird habitat guilds are available for four time steps back to the year 1912/13. This provides a unique opportunity to hindcast the change of these important species of tropical forest ecosystems almost throughout one century. On the one hand our results for all three species/groups under investigation highlight the dramatic biological consequences of tropical deforestation and forest fragmentation, with faunal losses considerably exceeding those in forest cover. On the other hand the results point out the value of reforestations with a mix of indigenous tree species for biodiversity conservation. Therefore, the study demonstrates the potential of linking remote sensing time series data with biological field data for landscape-scale evaluations on the effects of forest management decisions on the fauna of tropical forests. Particularly, it is shown how such applications can contribute to the demanded recommendations regarding forest conservation (cf. Foody, 2003). For the future, an extension of the current work towards a more complete assessment of the forests' faunal biodiversity including more species/groups and also ecosystem functions would be desirable. Here, the development of a tool for building empirical extrapolation models coupled with a land cover change model would also enable to run likely future scenarios in an automated manner

5. Synthesis – land cover time series for assessing changes in tropical forest ecosystems

5.1 Processing and analysis of satellite imagery

Due to the structure of this thesis with three stand-alone manuscripts, major aspects of satellite data processing and analysis have been discussed in Chapters 2 and 3 already. Therefore, Table 5.1 provides an overview of the different topics and where to find the relevant discussions. This section attempts to synthesise and conclude on the lessons learned by completing the main points from Chapters 2 and 3 with important issues not or only briefly discussed before.

The results of Chapters 2 and 3 clearly demonstrate the suitability and value of medium- to high-resolution Landsat satellite imagery for deriving comparable time series of detailed land cover classifications for regional case studies of tropical rainforest change. However, when utilising multi-date imagery for change studies, a given target is likely to have different radiometric responses over time due to several factors such as e.g. variations in atmospheric conditions, differences in relative radiometric response between sensors, topography, or effects caused by viewing and illumination geometry (described by the bi-directional reflectance function BRDF). Therefore, radiometric corrections to compensate for these effects except for the actual changes on the ground have become indispensable for change detection studies (Coppin et al., 2004). For Landsat imagery, Paolini et al. (2006) showed that post-classification comparisons based on uncorrected images can lead to unrealistic or biased change results especially when comparing images from different sensors (e.g. TM and ETM+). The multitude of approaches and algorithms that have been developed over the last decades can be grouped into two major types: absolute atmospheric corrections and relative atmospheric corrections (Jensen, 2005). For the three satellite time series presented in this work, the ATCOR 3 module, an absolute correction approach employing the MODTRAN 4 radiative transfer code (Richter, 1998) yielded satisfying results. The approximation to a correct "radiance at sensor", adapting the standard gradient of calibration (sensor gain, c1 value) and offset (bias, c0 value) for each band in an iterative process by comparing them with reference library spectra and checking areas invariant throughout the time series for similar values

Table 5.1: Overview of topics related to processing and analysis of satellite imagery that have been discussed in Chapters 2 and 3.

Topic	**Where to find**
Data processing	
Satellite image pre-processing	Section 2.5(KN), Section 3.5 (MF & BF)
Satellite image classification approach	Section 3.5
Classes distinguished & classification accuracy	Section 2.5 (KN), Section 3.5 (MF & BF)
Change detection method chosen	Section 3.5
Moving window-based landscape metrics	Section 2.5
Cluster analysis	Section 2.5
Analysis on land cover change and forest fragmentation	
Land cover changes: comparison of KN, MF and BF	Section 3.5
Forest fragmentation	Section 2.5 (KN)

in each image, ensured data homogeneity. The application of empirical BRDF correction functions (for details see GEOSYSTEMS, 2004) to adjust for terrain effects due to anisotropic reflectance behaviour have further improved the quality of the data.

For classifying the radiometrically corrected time series imagery, the widely used pixel-based maximum likelihood classifier was regarded most appropriate for the purpose of this study. Object-based/-oriented image classification approaches, although currently en vogue in the remote sensing community, were considered unfeasible for the medium to high-resolution Landsat time series data, for which the derivation of true objects is especially problematic due to the highly structured nature of the landscape in the study areas. Additionally, Im et al. (2007) found that object-based change detection based on post-classification comparison can cause problems due to the differences in object geometry. In contrast, object-based image analysis seems to be best suited for very high spatial resolution imagery like IKONOS (e.g. Platt and Rapoza, 2008, Eisfelder et al., 2009) or QuickBird (e.g. Im et al., 2007). As outlined in Sections 3.3 and 3.5, data processing for three different geographical areas necessitated some modifications in terms of classification methodology and scheme (cf. Figure 3.2) in order to ensure the differentiation of the greatest possible number of forest classes with high accuracy (cf. Section 3.4 and Tables 3.4 and 3.5). These modifications can be considered as moving away from an approach purely based on a supervised multi-spectral classification towards a hybrid procedure. Hildebrandt (1996) defines a hybrid classification as a combination of a supervised maximum likelihood classification and the manual delineation of single land cover classes not or poorly distinguishable by the maximum likelihood approach, as applied for sugar cane and wetland for the Ugandan imagery. Lillesand and Kiefer (2000) emphasise the importance of hybrid approaches for land cover classes with complex variability in the spectral response and suggest the employment of guided clustering based on a set of subclasses, which are finally aggregated back to the original land cover class. This procedure was successfully applied especially for 'Grassland', 'Agricultural land' and 'Others', but also for the forest classes 'Secondary forest' and 'Bushland/shrubs'.

Regarding the accuracy of the achieved land cover classes, generally higher accuracy was found for the years for which two cloud-free images could be used, one from the wet season and one from the dry season. This study further found that the season of image capture (i.e. wet or dry season) can but not necessarily must influence the number of distinguishable forest classes and their classification accuracy. While for the Kakamega-Nandi forests no difference between wet season and dry season imagery could be found in terms of spectral separability of forest formations, for Budongo Forest the wet season imagery yielded considerably better results than the dry season imagery (see Section 3.5). A comparison with other regional change studies in tropical forest areas based on medium to high resolution remote sensing imagery showed that distinguishing more than one or two forest classes as well as considering a series of multiple time steps back to the early 1970s is rarely attempted. Most often, a bi-temporal analysis considering only one class 'Forest cover' is conducted (e.g. Etter et al., 2006; Mwavu and Witkowski, 2008). In some cases, temporally dense change series with more time steps have been generated, but they are usually also limited to one or two forest classes (e.g. Songer et al., 2009). In turn, some studies have put emphasis on distinguishing a large number of different tropical forest vegetation classes, but without considering more than two dates (e.g. Sesnie et al., 2008). In contrast, this study distinguishing up to six different forest formations in a temporally dense sequence enables the capture of ecologically important short-term fluctuations over 30 years and additionally provides the unique opportunity to truly compare three different case study areas to each other. The classification results (except 2003) for the Kakamega-Nandi forests are shown in Lung (2004), whereas those for Mabira Forest and Budongo Forest are found in Lung and Schaab (2008). For the comparative analysis of the derived changes, postclassification comparison was considered the adequate choice. Despite its dependency on the classification accuracy of the initial classifications (cf. Sulieman and Buchroithner, 2007), its major advantages for this study are that it (a) allows the use of a time series with intra-annual phenological differences (see Section 3.5) and that it (b) yields results suitable for extrapolating biological field findings (see Section 5.2).

To conclude, the processing of the Landsat time series imagery in approximately five-year intervals back to the early 1970s for three East African rainforest areas showed that a careful application of approved remote sensing methods are a suitable means for deriving comparable, homogeneous land cover change time series suitable to be used as a basis for modelling of linkages with biological field findings. The pre-processing involving atmospheric and terrain corrections and the masking-out of cloud areas followed by a hybrid procedure of building subclasses as part of a supervised multi-spectral image classification resulted in land cover time series data with high accuracy. The subsequent postclassification comparison revealing from–to change class information, for the first time allowed for a detailed comparative analysis of changes in three case study areas of tropical rainforest capturing both short-term fluctuations and long-term trends.

5.2 Extrapolation modelling of biological field findings in space and time

As for processing and analysis of satellite imagery, the major points discussed in Section 4.5 will be amended and rounded off with additional aspects in order to derive a conclusive picture of the strengths and weaknesses of the three different indirect remote sensing-based biodiversity modelling approaches developed in this study.

In regards to the use of remote sensing data, it has been concluded that the classified Landsat imagery used in this study does meet the requirements of the field data on birds and ants in terms of both spatial resolution and degree of land cover class differentiation (see Section 4.5). Conversely, one might ask what kind of biological data is best suited when modelling species–environment relationships. Here, Cushman and McGarigal (2004) found that species abundance data is generally preferable as compared to presence/absence data since it gives better ecological information. Similarly, Fuller et al. (2005) admit an uncertainty in their extrapolation model due to having been forced to limit bird sampling to presence/absence scores, an issue also identified as one of the obstacles in the field of species distribution modelling (Dormann, 2007). Furthermore, from a comprehensive review of 109 ecological studies using remote sensing data, Gottschalk et al. (2005) identified too short field census periods as a frequent source of bias. For this study, both issues could be avoided by making use of sound species abundance data collected over long time periods of 13 months to six years (Farwig et al., 2009; Peters et al., 2009).

Another concern often raised relates to the predictive power of the modelled relationships between land cover and species field data, with habitat-specificity of the modelled species as the crucial factor. The higher the degree of habitat-specificity and the better the habitat-specific knowledge of the modelled species, the higher is the predictive value of the modelled relationships between land cover and species data (Leyequien et al., 2007). Consequently, species using more than one single habitat type such as forest generalists are less accurately represented by a single distinct habitat type (Jones et al., 2000). The army ant *D. wilverthi* as well as the ant-following birds as modelled in this study are known to be highly dependent on forest (i.e. they have a high forest-specificity) and are not found in other forest-surrounding habitats (Peters et al., 2008). Therefore, these species are considered well suited for habitat modelling based on land cover data distinguishing forest cover. Similarly, among the three bird habitat guilds included in this study, forest specialists are known for a high habitat-specificity as they are not expected in other areas than in closed forest (Laube et al., 2008), i.e. they only occur in the five forest types distinguished. In contrast, forest generalists and especially forest visitors are also found in other habitats like e.g. grassland or agricultural land for which field abundance data has been absent. Nevertheless, this does not necessarily mean the disqualification of forest generalists and visitors for extrapolations based on the discrete land cover data. It only means that all numerical extrapolation results which include these two guilds have to be interpreted as numbers of individuals within the forested area of the respective year. In other words, the quantitative analysis for ants and ant-following birds (cf. Figures 4.3 and 4.4) shows the predicted number of all individuals expected to be found in the analysis area, whereas the according quantitative analysis for bird habitat guilds (cf. Figures 4.5 and 4.6) refers to the forested areas only, i.e. the absolute total number of birds in the area is expected to be higher than the number that has been modelled.

Landscape metrics have become a highly appreciated tool in landscape ecology (Turner, 2005) and were also used here as part of the extrapolation modelling approach for ant-following birds. Nevertheless, their use often causes misleading results not contributing to a better ecological understanding of the landscape pattern under analysis. Li and Wu (2004) identified three major critical issues when employing landscape metrics deduced from land cover classifications: conceptual flaws, inherent limitations of landscape metrics and improper use. Conceptual flaws refer to problems like ecological irrelevance of the metrics applied or to confusion between the scale of field observation and the scale of (remote sensing) data analysis. Both issues have been accounted for in this study. For ant-following birds, Peters et al. (2008) proved a high susceptibility to forest fragmentation and degradation, thus ensuring the ecological relevance of the forest fragmentation index used. As discussed in Section 4.5, the resolution of the classified Landsat TM/ETM+ data (30 m by 30 m) from which the index has been deduced does fit well to the scale of bird field monitoring. In order to extrapolate back in time as far as possible, additional land cover data from pre-satellite sources like aerial photography and old topographic map sheets had to be employed. Due to different data processing methods (i.e. on-screen digitising based on visual interpretation or delineation of forest fill from the map sheets), the resulting land cover data are considered slightly less suited for applying the forest fragmentation index. However, for the aerial photography on-screen digitising aimed to generate land cover data at a reproduction scale of 1:30,000, reflecting a level of detail comparable to that of Landsat imagery (i.e. assuming a drafting accuracy of 0.1 mm, a map scale of 1:30,000 corresponds to a pixel size of 30m, cf. Jacobsen, 2002). The second critical issue mentioned by Li and Wu (2004), inherent limitations of landscape metrics, refers e.g. to the sensitivity of (most) landscape metrics to different levels of detail and to difficulties in interpreting indices that result from complex computations. This is closely linked to the third issue, improper use, which applies to quantifications of spatial patterns without considering processes or to caveats of correlation analysis with landscape indices. To address the second and third issue of concern Li and Wu (2004) conclude that, on the one hand, quantifications of landscape patterns should not be considered an end in itself but carefully linked with ecological data, and on the other hand, correlation analysis with landscape indices should be limited to simple metrics like e.g. edge metrics. Therefore, the use of the relatively simple forest fragmentation index for establishing a linkage to ant-following bird field data is considered a step into the right direction.

According to the taxonomy of models used in environmental science and GIS proposed by Skidmore (2002), the spatially explicit GIS and remote sensing-based modelling approaches to extrapolate biological field findings in space and time are characterised as inductive-empirical. Inductive because they are built upon biological data collected in the field and empirical because they employ data-driven statistical methods (i.e. regressions) to model the species response to the independent variables 'Forest cover' (in case of ants) or 'Modelled mean ant abundance' and 'Forest fragmentation' (in case of ant following birds). Similarly, the direct extrapolations of bird habitat guilds are to be categorised as empirical since they have a fixed output (number of individuals) for a specific input (forest type) derived empirically from field plot measurements within the five forest types. One of the key characteristics of empirical models is that they are usually site-specific because the data they are built upon have been collected 'locally' (Skidmore, 2002). Consequently, the modelling approaches developed for the Kakamega-Nandi area should not be directly transferred to other tropical forest areas with a different natural environment, possibly also not to the Ugandan study areas of Mabira Forest and Budongo Forest for which truly comparable remote sensing-derived time series have been processed. However, at least for Budongo Forest strong similarities with the Kakamega-Nandi forest complex regarding its biogeography have been proven (Wagner et al., 2008). Therefore, if biological field data were recorded or made available (e.g. Owiunji and Plumptre (1998) observed distinctive differences in bird abundance for several guilds in selectively logged and unlogged, *Cynometra*-dominated parts of the forest), a test of the modelling approaches in Budongo Forest would seem worthwhile, but should be followed by a careful verification of the modelled distributions with independent field reference data.

In conclusion, the three approaches combining land cover data from Landsat imagery with field data on species abundance of ants and guilds of birds proved to be suitable for deriving landscape-level abundance distributions of these species/groups. It was further shown that relatively simple, biodiversity-relevant and spatially explicit landscape metrics can be a suitable means to increase the predictive power of such approaches. In contrast to most species distribution models commonly deriving maps of species distribution probabilities or habitat suitability only, the use of species abundance data and their application to time series data allowed for quantitative hindcasts of the changes in species distribution back to the early 20th century. Despite some simplifications in the model assumptions, the extrapolation results enable for a quantitative assessment of the impact of land cover changes on different keystone species of tropical forest ecosystems throughout the last 100 years. Moreover, extrapolations based on a scenario of further deforestation and a scenario of reforestation allowed for an assessment of the consequences of possible future forest developments on the investigated keystone species/groups. Although not generally transferable to other study areas, a test of the model variables and procedures seems to be worthwhile at least for biogeographically similar rainforest areas. In case of positive test results, such extrapolations would even allow quantitative comparison studies of different regions.

5.3 Visualisation of analysis and modelling results

As pointed out by Dykes et al. (2005), one of the main challenges in GI science is the focus on human-centred visualisations instead of general "build and they will come" (p. 8) approaches (see also Section 1.4). Therefore, three different user groups have been identified for which the various outcomes of this thesis should be of relevance: the scientific audience, decision makers from Kenya and Uganda, and the local people living in vicinity of the forest areas (see Figure 5.1). Each of the groups has specific needs and requirements driven by the purposes for which they would use the spatially explicit analysis and modelling results (research, decision making etc.) and by dissimilar levels of knowledge (in general and on geo-spatial data). Detailed questioning on the demands of the different groups was not conducted as such surveys would reach beyond the scope and focus of this thesis. However, results of initial tests in Kenya independently of this work (Schaab et al., 2009) were considered. These tests on e.g. mental maps, familiarity with map reading or the effectiveness of animated/interactive forms of communication revealed that spatial depictions are out of the ordinary not only for local people but also for decision makers and even for most scientists (*ibid*).

Due to the length of the land cover time series for the three study areas (i.e. seven or eight dates in approximately five-year intervals), the diverse patterns of land cover change are rather cumbersome to reveal from juxtapositions of single land cover maps. One way of addressing this problem would be a visualisation approach combining elements of clustering and dimensionality reduction such as SOM (cf. Section 1.4). However, SOM is best suited when aiming to detect relationships between disparate geospatial datasets (cf.

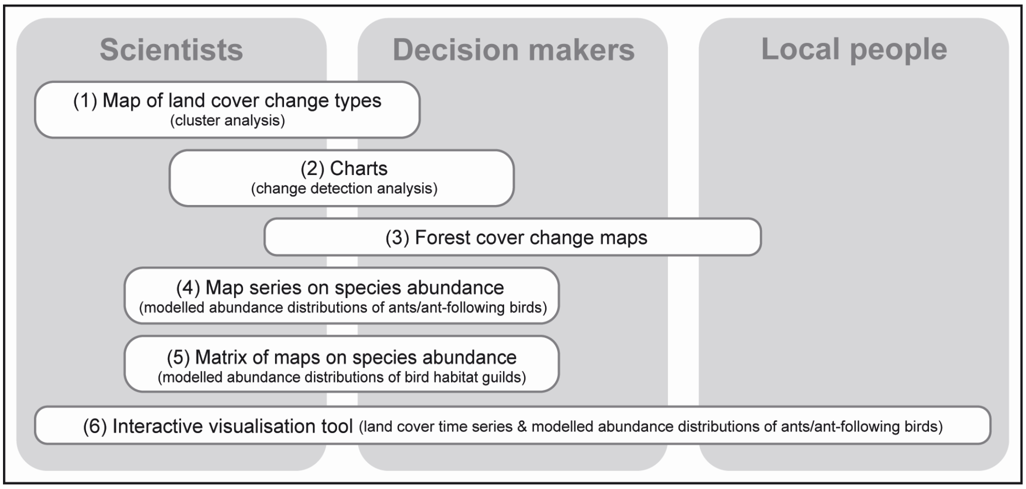


Figure 5.1: The suitability of six different approaches visualising the spatio-temporal research results for three user groups: scientists, decision makers and local people.

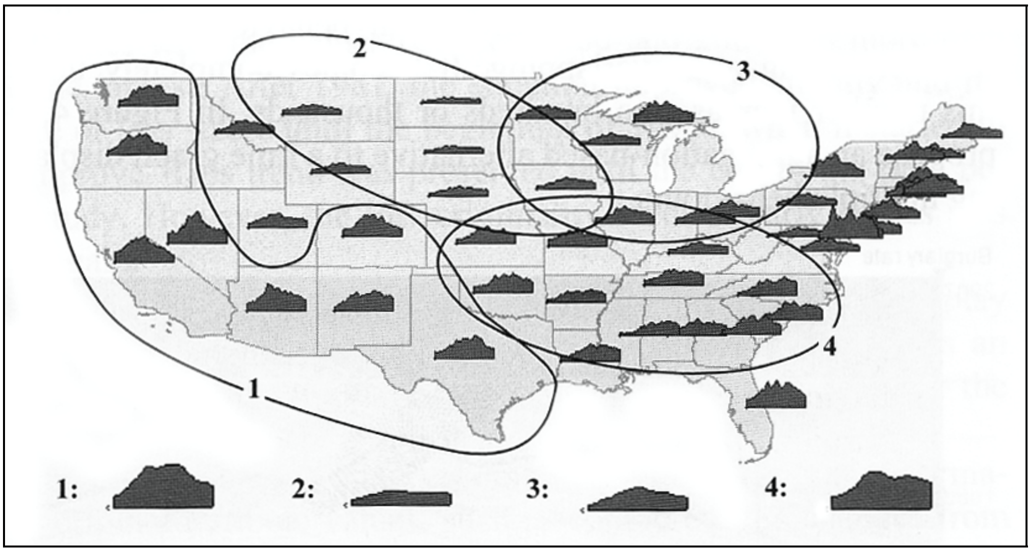


Figure 5.2: Spatial clusters of states with similar temporal behaviour (from Andrienko and Andrienko, 2007, Figure 3).

Skupin and Agarwal, 2008) but seems less applicable for deriving trajectories of changing land cover over time. Therefore, as an alternative approach the isodata clustering algorithm (e.g. Schowengerdt, 2007) was utilised, grouping pixels with similar or identical temporal development into one cluster. Applying the isodata-algorithm to the seven- or eight-dimensional stacks of land cover classifications followed by manual aggregations resulted in a two-dimensional map per study area showing types of characteristic land cover developments (for details on methodology and results for the Kenyan focus area see Sections 2.2 and 2.3; for map subsets of the two Ugandan areas see Appendix B). This allows for the assessment of typical change patterns from one single map per study area. In a way, the cluster analysis technique as applied in this thesis is considered comparable to the concept of analytical visualisation of local behaviours introduced by Andrienko and Andrienko (2007), which focus on the visualisation of changes of thematic properties over time. For studying the temporal behaviour of any possible location (e.g. a pixel or an administrative unit), they employed interactive time graphs. Based on an overview map displaying the temporal behaviour patterns for all locations, they identified four spatial clusters of similar behaviours by "visual inspection of the map" (see Figure 5.2). In relation to the cluster analysis employed here, their manually derived, typical clusters correspond to the land cover change types of this study. Their approach allows users to interactively view each single time graph, but requires the manual delineation of the typical spatial patterns. Compared to the cluster analysis approach, this corresponds to the phase of manually aggregating the clusters generated by the isodata-algorithm to types of land cover change. This highlights the difference between the two approaches: whereas Andrienko and Andrienko (2007) provide a tool emphasising the possibilities for user interaction in the data exploration phase, the cluster analysis map focuses on the communication of the revealed changes to the user. It therefore presents the final change types as a map, accompanied with textual explanations. These change types were symbolised with different hues reflecting the qualitative difference of the clusters.

Since the cluster analysis accounts for temporal changes in all land cover classes and additionally requires a careful consideration of the textual explanations accompanying the map, it might not meet the needs of local stakeholders. Instead, simplified visualisations in the form of change maps (cf. Section 1.4) only showing the changes in forest cover have been regarded more suitable (see Figure 5.1). For a time series with eight dates like the one for the Kakamega-Nandi area, 255 (i.e. 2^8-1 where -1 represents areas not forested in all dates) different change trajectories are possible. Studies have shown that the number of colours discriminable by the human eye drops rapidly as their number in a map increases. In a test, nearly 100% of the probands were able to discern 10 colours while the proportion of correct discriminations dropped to around 70% when using 17 colours (MacEachren, 1995). Therefore, the maps were limited to three dates, i.e. the first, the middle and the last, resulting in seven different change combinations. Displayed as a matrix legend, the changes were visualised using associative colours (i.e. red and green) for forest losses/gains and a light blue as a neutral colour for stability over time (cf. Figure 3.4). Although not spatially explicit, supplementary charts showing the changes in all major land cover classes from 1972 to 2003 (i.e. areas covered within the official forest boundaries, cf. Figure 3.3) allow decision makers a rapid general assessment of the main trends and short-term fluctuations.

In contrast to the land cover time series, the spatially explicit modelling results for ants and ant-following birds in the Kakamega-Nandi study area only comprise five dates in intervals of around 20 years (35 years for one time step). Therefore, changes from one date to another are more pronounced and hence, the visualisation as a map series (i.e. the juxtaposition of the five dates) seemed more feasible (see Figure 5.1). Similar to the forest cover change maps, associative hue progressions were used, i.e. from red (low values) to green (high values) (cf. Figure 4.3). The characteristic differences of the extrapolated abundance distributions of bird habitat guilds are easiest to grasp if the results for the three guilds (forest specialists, generalists and visitors) are directly comparable. Each guild shows a distinctive level of abundance (as recorded in the field) for each of the five forest types distinguished. As the field data were directly related to the land cover data, the spatial distribution and extent of the extrapolated bird habitat guild data and of the land cover data are identical, for each date respectively. Therefore, a matrix of 16 small maps with the dates of 1912/13, 1965/67, 2003 and the reforestation scenario as the x-axis and the forest cover (consisting of the five forest types) and the extrapolated abundance distributions of forest specialists, generalists and visitors on the y-axis was considered the best compromise between enabling direct comparisons and preserving map legibility (cf. Figure 4.5). Similar to the map series of extrapolated distributions of army ants and ant-following birds and the charts resulting from the land cover change analysis, this matrix of maps is judged relevant for both scientists and decision makers (see Figure 5.1).

Despite the tailoring of the described visualisations to the needs of the users, it is still questionable as to whether they will be viewed as ‘interesting pictures’ rather than understood in its complexity by local decision makers and people. In particular, these ‘static’ maps do not fully account for the basic paradigm shift in cartography away from passively communicating ideas of the designer of the map towards encouraging and facilitating the active exploration of information for the discovery of knowledge (Edsall

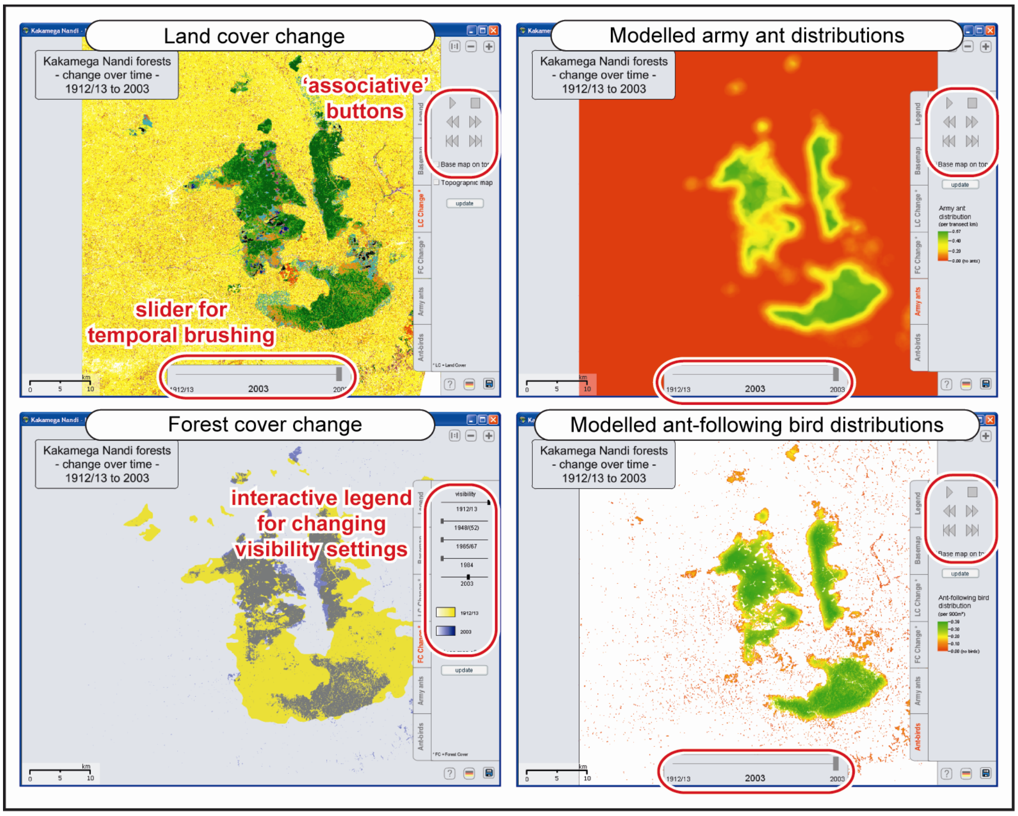


Figure 5.3: Selected functionalities and topics included in an interactive visualisation tool on land cover change and its ecological consequences for the area of the Kakamega-Nandi forests (western Kenya) (modified and extended from Asser, 2008).

and Sidney, 2005). Therefore, for the focus area in Kenya, a Flash-based visualisation tool for the land cover time series data with an interactive, dynamic display was developed (for details see Asser, 2008). It covers not only the eight dates between 2003 and 1972 as derived from Landsat imagery, but also includes the three earlier dates back to 1912/13 used for the extrapolation modelling of biological field findings. By creating an interface with intuitive buttons (i.e. with a commonly recognised shape) offering several facilities like e.g. 'pause', 'forward', 'backward)', the user is provided with functionalities to 'play around' with the data. Interaction is further stimulated by incorporating a slider allowing for temporal brushing (cf. Kraak and Ormeling, 2003), i.e. to manually move from one date to another (see Figure 5.3, a CD-ROM with a trail version is attached to the back cover of the thesis). Although most functionalities should be self-explaining, a help system was integrated to assist the user.

However, many local people in the Kakamega-Nandi area have only limited access to computers at all or at least to those with up-to-date performance and/or the minimum specifications needed for the tool. To overcome this drawback, a screenshot-export function was included which saves each date, creating a sequence of JPG-images as a simple animation that can be viewed on low-performance computers or even be printed out. In combination with the zoom the function can be used for exporting the land cover change information e.g. for a subset area of specific interest. Additionally to the land cover time series, the two time series of modelled abundance distributions of army ants and ant-following birds were added to the tool in order to enable the users to explore the effects of forest loss and fragmentation on the abundance of the investigated keystone species of the forest ecosystem. From a didactic point of view, the tool primarily aims to address three functions, (i) demonstration, (ii) setting in context, and (iii) motivation (Dransch, 2007): 'demonstration' of the land cover changes in the area to help the user to get a realistic picture of the past, 'setting in context' the land cover changes with ecological consequences (i.e. the changes in species distribution), and 'motivation' to stimulate a rethinking in the way the forests are perceived.

Drawing back the attention to the initially introduced general framework of cartographic visualisation (MacEachren, 1994; cf. Section 1.4) now raises the question of how the six visualisation approaches of this work are to be positioned. Regarding the first axis, private vs. public, all outcomes of this thesis have to be placed somewhere at the upper part of the cube as they are communicated to the public (see Figure 5.4). However, although the spatio-temporal patterns on land cover and species distribution are of relevance for the general public, there are geovisualisations of greater public interest, e.g. weather maps in a newspaper. Therefore, the results were not positioned at the uppermost edge of the cube. In relation to the second dimension of the cube, presenting knowns vs. revealing unknowns, the results mainly represent unknowns for all three user groups (scientists, decision makers and local people) and were therefore placed in the front part of the cube. The third axis of the cube addresses the degree of human–map interaction. The maps of land cover change types, the charts, the forest cover change maps, the map series on species abundance and the matrix of maps on species abundance all represent 'static' visualisations with interaction confined to cognitive processes (e.g. visually scanning the map). Consequently, they are more on the cartographic communication side. In contrast,

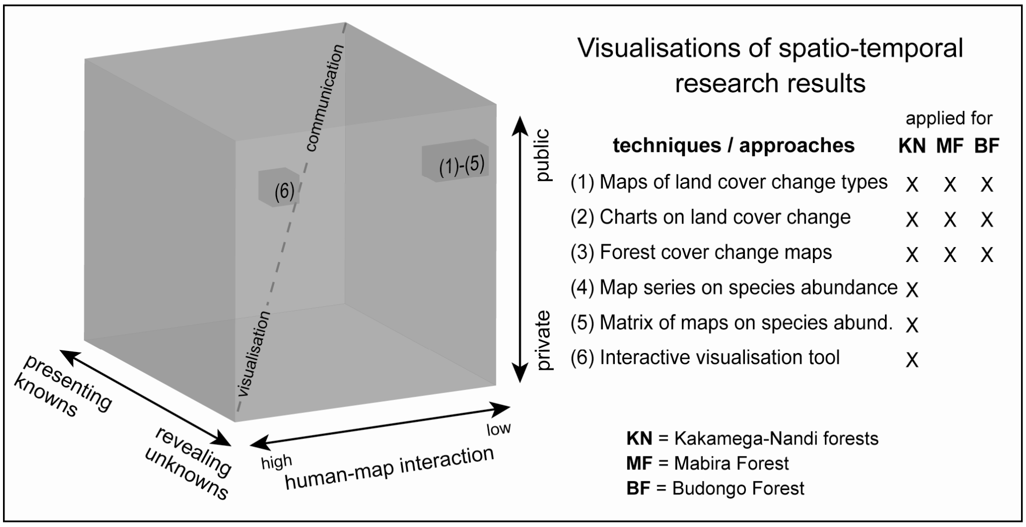


Figure 5.4: The positioning of the visualisations of the spatio-temporal research results as derived from this study within the cartography-cubed representation of map use (modified and extended from MacEachren, 1994).

the interactive visualisation tool provides a high level of user interaction and is therefore stronger related to the dimension of visualisation facilitating visual data exploration.

To conclude, the combination of different concepts and techniques has resulted in a comprehensive set of visualisations of the spatio-temporal patterns and processes investigated in this study. Each of the visualisations was conceptualised keeping in mind the needs of the three user groups addressed, and attempting to account for and contribute to the progress in geovisualisation. Therefore, the resulting static map visualisations in conjunction with the interactive exploration tool will hopefully aid a broad audience concerned with the studied forest areas.

5.4 Implications for conservation and forest management planning

Although the major objectives of this study as outlined in Section 1.1 have been posed from a more technical/methodological perspective, they also aim at contributing to the ultimate goal of the BIOTA East-project, the provision of recommendations and the implementation of instruments for a sustainable use and conservation of the forests' biodiversity (Köhler, 2004). Therefore, the presentation of analysis/modelling results is always followed by a discussion also addressing the issue of forest conservation and management (see Sections 2.5, 3.5 and 4.5). However, in order to derive a more complete and conclusive picture on the implications of the results of this study for forest conservation and management, at this point it is necessary to bring together the results and discussion of the different steps of analysis and modelling in the light of forest management planning.

For the focus area in Kenya, the change detection analysis of a temporally dense sequence of Landsat imagery from 1972 to 2003 revealed a continuous decrease of natural forest classes up to 2001 as well as short-term fluctuations such as the occurrence of *Psidium guajava*, an exotic species, within the last ten years. Although formally under protection, large areas of complete deforestation as well as losses especially along the forest edges of all three major forests (Kakamega Forest, North Nandi Forest and South Nandi Forest) are depicted by the map as derived from the cluster analysis (cf. Section 2.3) and the forest cover change map (cf. Figure 3.4). In particular South Nandi Forest, having received less research and conservation attention than Kakamega Forest, has suffered enormous losses in forest cover (figures on changes in natural forest cover from 1972 to 2003 for all three study areas are found in Appendix A). Especially the losses along the edges of all the forests can be interpreted as an indicator of encroachments by the local residents due to forest protection policies poorly enforced on the ground. On the other hand, the maps also reveal limited forest re-growth particularly in areas under the management of the KWS, which is known to be stricter compared to that of Kenya Forest Service (KFS, former Forest Department, FD) (see e.g. Bleher et al., 2006). A correlation of forest loss and fragmentation with forest management is also indicated by the spatially explicit small-scale forest fragmentation index calculated from the land cover data: lowest mean values were found for BDOs placed inside the strictly protected national and nature reserves while those placed outside these reserves revealed much higher values (see Section 2.5). Extending the remote sensing-based analysis to the two Ugandan reference areas revealed a similar, if not a worse development for Mabira Forest: tremendous, large-scale losses and the subsequent growth of exotic secondary bushland species. Although under the same management authority (the NFA), Budongo

Forest shows a more stable forest extend over time with forest losses almost exclusively occurring outside the protected area, thus underlining that simplistic reductions of the observed deforestation patterns to weak institutional forest management measures would ignore other complex forces (see Appendix B for maps depicting types of land cover development for the two Ugandan study sites, accompanied with a detailed textual explanation on their generation by means of the cluster analysis technique). In this context, an assessment of the relationship with population distribution and accessibility by roads indicated a strong influence of both factors in all three study areas (see Section 3.5). For Kakamega Forest, the influence of the latter has been confirmed by the forest fragmentation index with lower mean values for BDOs further away from roads. To conclude, the comparative analysis on land cover change and forest fragmentation demonstrated that weakly enforced forest management policies have not played the only but a major role in the (mostly negative) development of the three protected forest areas in Eastern Africa.

For the Kakamega-Nandi forests, the time series was extended by another three dates of land cover data (derived by N. Mitchell, Mitchell et al., 2006) to reach back as far as 1912/13. The spatially explicit, GIS and remote-sensing-based extrapolation modelling for the first time integrated long-term land cover time series data with field abundance data of three keystone species/groups (for methodologies of modelling approaches see Section 4.3). This allowed for quantitative predictions on the ecological influence of the derived land cover changes and of forest fragmentation. For all three species/groups, decreases in the total number of individuals considerably stronger than that of forest cover (i.e. decreases of 58%, 56% and 47% vs. 31%) were modelled over time. Moreover, modelling for the ants and ant-following birds suggested that the species abundances are not only determined by the available amount of forest cover, but also by its degree of fragmentation (see Sections 4.4 and 4.5). With these modelling results, forest management is provided with spatially explicit, quantitative assessments at the landscape scale regarding the alarming consequences of deforestation and forest fragmentation over the last 90 years for some keystone species/groups of the Kakamega-Nandi forests.

However, informing about the past should be accompanied with constructing alternative futures or contrasting trends allowing decision makers to anticipate consequences beyond the immediate future and to make choices (Peterson et al., 2003). In this regard, scenario approaches are a means to forecast anthropogenic effects on e.g. climate change or biodiversity loss (e.g. Sala et al., 2000) and could help to bridge the gap between science and policy. Two types of scenarios can be distinguished, projective and prospective scenarios (Nassauer and Corry, 2004). Whereas the first type usually involves a simulation of the future as a function of current land use/cover patterns and their driving forces within a confidence level of uncertainty (e.g. Pontius Jr. et al., 2008), the latter type describes how the future could be, what might be reachable. Prospective scenarios are more useful than projective scenarios if uncertainty is great and somehow uncontrollable (Peterson et al., 2003). Due to the complicated network of different forest-influencing forces coupled with political instability and a weak forest management as outlined above, uncertainty in the Kakamega-Nandi area is considered high. In particular, forest management decisions and the enforcement of protection policies on the ground do have a major impact on the development of the forests, as all remaining forest areas in the study area are located within legally protected areas. However, the predictability of a real-world system that exhibits such path-dependent behaviour is necessarily limited (Brown et al., 2005) and consequently, setting up and calibrating a land cover simulation model based on different macro-scale driving forces (e.g. distance to roads, distance to previously deforested areas etc.) would be subject to substantial uncertainty. Therefore, instead of applying a land cover simulation tool, priority was given to developing a set of prospective scenarios based on forest management assumptions. A special type of prospective scenarios are normative landscape scenarios which portray plausible and desirable futures that should be, but that are not necessarily assuredly achievable. Normative scenarios are ascribed particular potential for inspiring policy by providing spatially explicit images of landscapes that could meet societal goals (Nassauer and Corry, 2004) and they are easier to comprehend for local stakeholders and decision makers than future scenarios as derived from land cover simulations. Thus, for Kakamega Forest a set of normative 'should-be future scenarios' of reforestation/natural forest re-growth were constructed and contrasted with scenarios of deforestation, taking into account the protection status of the different forest areas. Two of the scenarios, one scenario of deforestation and one normative scenario of reforestation, were used for spatial extrapolation of the biological field findings (for details see Section 4.2, the other scenarios are described in Farwig et al. (submitted) and shown in Appendix C). On the one hand, the results showed the detrimental influence that potential future logging activities splitting-up continuous forest areas into small and isolated forest patches could have. According to the model, two of today's strictly protected national and nature reserves would probably not be large enough to sustain viable populations of D. *wilverthi* and as a consequence possibly also ant-following birds, if they would remain as isolated forest islands. On the other hand, the extrapolations based on the normative reforestation scenario demonstrated the high potential of reforestation measures relying on indigenous plant species for the recovery of bird populations.

In conclusion, what are the lessons learned from the results of this study and what does this imply for the future management and conservation of the three East African forest areas, in particular the focus area in Kenya? Firstly, the applied methodology based on remote sensing data processing and analysis followed by spatially explicit GIS modelling of biological field findings proved to be suitable for evaluating measures of forest conservation at the landscape scale. Secondly, the results showed that weakly enforced forest management policies have played a major, but not the only role in the development of the three formerly protected forest areas in Eastern Africa. Despite their official status as protected forest areas, two of them (the Kakamega-Nandi forests and Mabira Forest) have suffered from tremendous losses of their natural forest cover which in large areas has been replaced by bushland (Kakamega Forest, South Nandi Forest), agricultural land (Mabira Forest and the Nandi Forests), exotic secondary bushland species (Mabira Forest and Kakamega Forest) or exotic forest plantations (Kakamega Forest). For the focus area in Kenya the study further demonstrated that these deforestation and fragmentation processes have had dramatic consequences for the forests' biodiversity as they have caused decline rates of their fauna stronger than the forest loss itself. On the other hand, normative scenarios of desirable forest futures showed the potential for the recovery of the forest ecosystem with its keystone species. The findings of this study therefore underpin the urgency for an improved, sustainable forest management which should ensure a continued strict protection of the existing national and nature reserves. Moreover, the results showed that measures need to be established to effectively conserve the officially protected areas outside the national and nature reserves to ensure contiguous, large-scale areas of natural forest vegetation. In this context, protection efforts should be expanded to highly threatened areas that have received less attention so far (e.g. South Nandi Forest). Furthermore, forest management strategies should also focus on antagonising illegal activities of any kind in order to prevent further small-scale forest fragmentation and on triggering the reforestation of encroached and clear-felled forest areas with mixed indigenous species.

6. Outlook – towards simulation and automation

This study has demonstrated the value and suitability of detailed land cover time series as derived from remote sensing for gaining a better understanding of changes in tropical forest ecosystems and their biodiversity. However, for the future, an extension of the current work towards a more complete assessment of the forests' faunal diversity including more species/groups and also ecosystem functions/services would be desirable. First statistical analyses in this direction have already been conducted (Schleuning et al., 2008). However, such an assessment should consider spatially explicit, landscape-scale GIS models with the ability to reveal relationships between landscape-scale patterns of biodiversity and ecosystem services, and should also incorporate possible future scenarios. Here, several interesting issues have evolved during the course of this work. In particular, two fields of desirable future research building upon the achievements of this thesis have been identified, (a) the generation of projective scenarios of land cover change and (b) the development of a framework for building empirical extrapolation models capable to run landscape-scale biodiversity assessments in an automated manner. The two are closely related to each other and should therefore, if possible, be addressed together. The following sections describe potential frameworks for land cover change modelling and for empirical extrapolation modelling and finally elucidate how the two could eventually be combined into one integrated tool to be used for participatory land use planning.

A framework for simulations of land cover change scenarios

For extending the time series into the future, the current work employed prospective scenarios on how the future could be, making use of GIS-based land cover allocation procedures (cf. Nassauer and Corry, 2004). More precisely, normative scenarios of deforestation and reforestation have been created from assumptions related to aspects of forest management and protection. In contrast, projective scenarios might lack credibility due to the uncertainties and the strong influence of forest management in the Kakamega-Nandi area as discussed in Section 5.4. However, the credibility of a scenario is not necessarily always related to its likelihood to come true but can also be associated with the internal logic, consistency and coherence of a land cover change model (Almaco et al., 2006). A clear documentation and communication of a scenario's basic assumptions and its underlying input data could help to improve the transparency. For the Kakamega-Nandi area, this should in particular take into account the role of forest management regimes and decisions. Following this path, spatially explicit simulations of future scenarios based on a trend analysis of the land cover changes as derived from the existing time series could serve as a feasible supplement to the normative scenarios generated in the course of this study. For example, the future development of forest cover could be simulated based on the mostly negative development of forest destruction between 1972 and 2001, assuming that formal protection would continue to be weakly enforced on the ground. This could be contrasted by e.g. a simulation of forest recovery, defining more rigid area restriction parameters (e.g. for the nature and national reserves or for all forest reserves) based on the general assumption that an improved forest protection enables forest re-growth. Such projective scenarios would be based on a model that derives, statistically or stochastically, functional relationships between a set of explanatory variables used to predict locations of change in the landscape.

Building upon an already existing modelling framework could potentially save time and effort. A wide range of spatially explicit models capable of simulating future land cover patterns as well as incorporating both socio-economic and biophysical driving factors has been developed in the last decade (Verburg et al., 2006). An important criterion to distinguish the enormous variety of approaches and concepts underlying the models is the level of analysis, i.e. whether a model is based on the micro-level perspective or on the macro-level perspective (Verburg et al., 2004). The challenge with micro-level agent-based models is to link agent behaviour to actual land areas (Rindfuss et al., 2004). As typical agents (e.g. large scale farming households at the Amazon frontier, Deadman et al., 2004) are absent in the Kakamega-Nandi area, this approach seems not promising. The second group, regional scale, macro-level models are based on the spatial patterns of land cover and often utilise GIS and remote sensing data in order to derive relations between macro-scale variables. Here, an often used approach is the cellular automata-technique implementing neighbourhood interactions (e.g. Entwisle et al., 2008) which recently has been applied successfully for modelling forest change processes (e.g. GEOMOD, Echeverria et al., 2008; or DINAMICA, Soares-Filho et al., 2002). Other macro-level modelling concepts of potential interest for the Kakamega-Nandi forests would be artificial neural networks (e.g. LTM, Pijanowski et al., 2002) or empirical-statistical analyses employing regression-techniques (e.g. CLUE-S, Castella et al., 2007).

More important for the choice of a modelling framework than its underlying technique are its capabilities in terms of possible input data, modelling procedure and output. In this regard, several issues related to the specific characteristics of the Kakamega-Nandi area, to data availability and to the desired use of the model have evolved during the course of this work (see Table 6.1). Some of the criteria are considered compulsory for deriving simulations of future land cover patterns suited for extrapolations of biological field findings in the Kakamega-Nandi area: (i) the model must be able to deal with multiple land cover classes, (ii) it must allow processing multiple predictor variables, (iii) it must allow the definition of area restriction parameters, and (iv) bi-directional modelling must be possible. Of particular importance for a potential land cover change model is that multiple land cover classes can be modelled, especially the different forest classes. Although much progress has been made in the development of land cover change modelling approaches within the last decades, a major weakness of most existing landscape scenarios is their limitation to one single class 'Forest cover' (Almaco et al., 2006). A potential land cover change model for the Kakamega-Nandi area, capable to model gains and losses of five forest classes and two bushland classes could significantly contribute to an improvement in this regard. Other capabilities are regarded desirable but not mandatory (e.g. possibilities for defining land conversion elasticities or the calculation of land demand and land allocation, see Table 6.1)

A second area that requires improvement is the inability of most of today's modelling approaches to adequately deal with scaling issues. Macro-level approaches do usually not take into account micro-level conditions and decision making which in turn influence the land cover patterns at the macro scale. To overcome this obstacle, implementations of multi-scale procedures linking macro-level models with micro-level dynamics are needed (Verburg et al., 2006). A simulation model for the Kakamega-Nandi area should address this issue by creating a model interface where management decisions or intentions of individual stakeholders or organisations (i.e. micro-level issues) can be incorporated into

Table 6.1: Desired capabilities of a potential land cover change modelling framework for the area of the Kakamega-Nandi forests related to input data, modelling and output/others.

	Criteria / capability
Input	Use of multiple land cover classes (not only binary forest – non-forest) *
	Use of multiple predictor/explanatory variables *
	Sketch-based user interface (for adding freehand drawings)
	Continuous predictor variables
	Dynamic predictor variables (i.e. recalculation before each model iteration)
	Area restriction parameters (e.g. protection areas/regimes) *
Modelling	Modelling both losses and gains (bi-directional modelling) *
	Possibility of defining conversion elasticities (related to reversibility of change)
	Calculation of transition rates (land demand)
	Calculation of change probabilities (land allocation)
	Flexible number to time steps
	Soft predictions (maps of vulnerability to change)
Output / others	Tight model coupling[1] with GIS/extrapolation modelling framework
	Coupling with visualisation component
	User customisability / open source code

* considered compulsory

[1] adopted from Maguire (2005), distinguishing three coupling levels: a) loose (employs a common data exchange format, GIS mainly used for pre- and post-processing), b) medium (uses remote procedure calls, automated interfaces for data exchange, c) tight (full integration of model in GIS, direct function calls)

the land cover simulation at the macro-level in an interactive manner, e.g. by delineating an area of a planned forest plantation. One approach in this regard could be to adopt some principles of the concept of sketch-based interfaces of modeling (SBIM) (Olsen et al., 2009) which allows sketches – hasty freehand drawings – to be used in the modelling process. This would enable a scenario development with a strong involvement of local stakeholders (Verburg et al., 2006), who could directly incorporate their ideas as sketches to the model. Such a participatory land use planning approach would also enhance the legitimacy of the created simulations and thus hopefully lead to an increased acceptance and credibility. Other studies have shown that active local involvement is not only a valuable means for assessing landscape changes (Sulieman and Buchroithner, 2008) but that participatory management approaches may indeed contribute to an improved forest conservation (e.g. Blomley et al., 2008).

A framework for building empirical extrapolation models

In order to achieve a more complete landscape-scale assessment of changes in the biodiversity of the Kakamega-Nandi forests, biological field data from more species/groups and also ecosystem functions and services should be employed. A large variety of field data have been collected in the study area by the BIOTA East Africa project over the last nine years (e.g. Mitchell et al., 2009). These as well as data from other biologists and ecologists working in the Kakamega-Nandi forest area could be used. For each of the potential datasets, empirical extrapolation models have to be developed, linking the field data to the land cover time series data and/or to measures deduced from it such as e.g. the forest fragmentation index used in this study or 'distance to forest edge'. If the field data cannot be directly related to remotely-sensed imagery (as for ants and ant-following birds), this involves the establishment of modelling procedures which combine spatially explicit GIS functionalities with statistical modelling. In the case of ants and ant-following birds used for this study, a processing sequence of GIS functionalities has been 'manually' built in the Model Builder within ArcGIS in order to implement the results as derived from the statistical analysis.

However, in order to enable an active decision making process allowing local stakeholders (which mostly are GIS novices) to be actively engaged in the model development (cf. Daily et al., 2009), a customized framework limited and tailored to functionalities for building such extrapolation models would be needed. Although the requirements in terms of GIS functions might vary depending on the characteristics of the field data used, typical generic functionalities needed for almost every extrapolation model should be included. Buffering operators to calculate the proportions of different land cover classes within certain distances around a field point count station or transect is an example of such a typical function. Furthermore, a set of focal neighbourhood functions (i.e. a moving window algorithm) and local functions (see Tomlin, 1990) should also be available. All identified functions should be embedded into an intuitive, self-explaining graphical user interface (GUI) following the example of Ojha et al. (in prep.). For some modelling parameters the user might be prompted to select among pre-defined values (e.g. the size of a moving window). Each function would be accompanied with a comprehensive, self-explaining help system. The framework should also provide an interface for running zonal statistics on the modelling results (i.e. on the derived landscape-level distributions of single species/groups or ecosystem functions/services) for one or multiple user-defined areas. Again, the SBIM-concept (Olsen et al., 2009) could be applied to enable local stakeholders to easily delineate areas of interest. For these areas the spatially explicit modelling results are to be automatically totalled for each single time step and/or scenario the user wants to consider. An additional option should allow visualising the derived zonal statistics as bar chart(s).

An integrated forest ecosystem assessment tool

As mentioned before, empirical extrapolation modelling of biological field data is closely interlinked with the desired land cover change modelling. Therefore, the implementation of a tight coupling (Maguire, 2005) of both frameworks, enabling the user to directly use a projected scenario derived from the land cover change modelling framework as basis for spatial extrapolation modelling of biological field findings would be desirable. Ideally, the two frameworks are combined into an integrated forest ecosystem assessment tool (see Figure 6.1). It would be advantageous if the land cover change framework would not only allow for land cover change simulations (cf. Section 6.1), but if it would also enable decision makers to create additional prospective scenarios, using of the SBIM-concept for adding their ideas to geospatial datasets. As such, the land cover modelling part would provide the basis not only for defining and generating land cover scenarios used as input for empirical extrapolation modelling. It would also allow stakeholders to 'play around' with the different parameters (e.g. area restrictions) of a land cover simulation in order to anticipate the effects on a projected landscape scenario. In contrast, the empirical extrapolation modelling framework would enable decision makers to learn about the

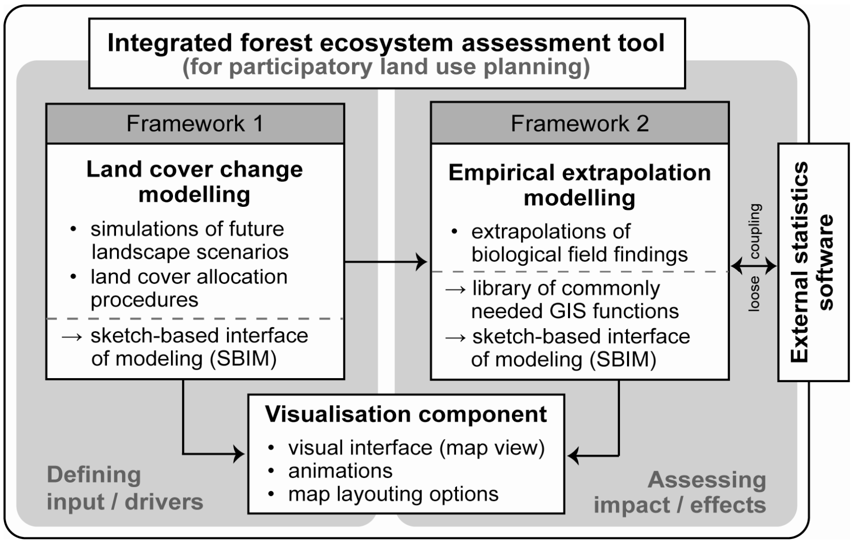


Figure 6.1: The general framework of an integrated forest ecosystem assessment tool combining land cover change modelling, empirical extrapolation modelling and the visualisation of modelling results.

impact of the generated landscape scenarios on the distribution of single species/groups or ecosystem functions/services. Such a tool would also include a common visualisation component for GIS non-professionals that should provide (i) a visual interface for data exploration, (ii) functions for creating animations from the modelling results, and (iii) basic functionalities for map layout (e.g. pre-defined colour ramps, functions for adding and modifying a legend). In order to ensure the use of the tool in Kenya in the long term, financial obstacles in terms of GIS-licence costs should be reduced. In this regard, building upon e.g. ArcEngine technology could be a feasible alternative to the more costly ArcGIS package. In case the tool would be implemented, the only external software still needed would a package to calculate the statistical part of the extrapolation modelling, e.g. the open-source software 'R'.

The application of such an integrated forest ecosystem assessment tool, combining land cover change modelling and empirical extrapolation modelling of biological field findings to the landscape scale, would not only allow users to hindcast spatially explicit distributions of species and ecosystem functions back to the early 20th century. It would also enable the anticipation of possible effects of land cover scenarios developed in a participatory manner on landscape-scale forest biodiversity patterns. Designed to the specific needs of local decision makers and others engaged in forest management, it could therefore serve as Spatial Decision Support System (SDSS) (Keenan, 2003). As the tool would display generic functionalities it would be re-usable across studies, thus allowing a more holistic, participatory assessment of the forest resources and its driving forces not only for the Kakamega-Nandi forests but also for other tropical forest areas.

Summary

This work describes the processing and analysis of remote sensing time series data for a comparative assessment of changes in different tropical rainforest ecosystems in East Africa. Based on the derived changes in land cover and forest fragmentation, the study makes use of spatially explicit modelling approaches within a geographical information system (GIS) to extrapolate sets of biological field findings in space and time for assessing the effects on biodiversity change patterns. The spatio-temporal analysis and modelling results are visualised attempting to consider requirements of different user groups and their dissimilar levels of knowledge (on geo-spatial data).

Tropical forest ecosystems are known to support more than half of the described species but are vanishing at an alarming rate. In sub-Saharan Africa, a combination of causal synergies between factors such as rapid population growth, low per capita income growth and institutional weakness have resulted in deforestation rates three to five times higher than the world average. In order to evaluate measures of forest conservation and to derive recommendations for an effective management of the remaining forest resources, landscape-scale assessments on the quantity and extent of land cover changes and their influence on tropical forest biodiversity patterns are needed. In this context, remote sensing has become essential for capturing spatially detailed and temporally frequent information on long-term changes over extensive areas and for deducing landscape metrics/indices on forest fragmentation. Several studies have shown that spatially explicit remote sensing data can also be a suitable means for modelling linkages with biological field-based species information aiming at landscape-scale species distributions.

However, very few change studies based on remote sensing data have accounted for all of the following factors at the same time: (i) a dense temporal sequence of land cover change/forest fragmentation information, (ii) the coverage of several decades and (iii) the distinction between multiple forest formations. Therefore, most studies have been limited in one or another aspect, e.g. regarding their ability to capture short-term fluctuations. Moreover, few studies have focussed on detailed, direct comparisons of different regional case study areas, especially in Africa. Calculating measures of landscape configuration from land cover data has become commonplace, but instead of linking one or few simple and relevant measures to ecological data, applications of landscape metrics often struggle with redundancies and conceptual flaws. In regards to linkages of remote sensing with biological field data, almost all efforts so far have been limited to one point in time while no attempts are known that make use of time series data for quantitative statements of landscape-scale biodiversity changes over prolonged periods of time. In this context, this work aims to address the mentioned deficiencies and/or research gaps to contribute with advancement within the field of applied land change science.

The work is conducted within the interdisciplinary research framework BIOTA East Africa and studies three areas in Eastern Africa: the Kakamega-Nandi forests (KN) in western Kenya serving as focus area, and Mabira Forest (MF) in south-eastern Uganda and Budongo Forest (BF) in western Uganda, both used for comparison purposes. All these areas have the status as officially protected forest areas. Considering only totally or at least in most parts cloud-free imagery, Landsat data has been acquired at approximately five-year time steps to reach back to the early 1970s. If available, one image from the wet season and one from the dry season was considered to take seasonal vegetation variations

into account. In total, imagery for eight dates from 1972/73 to 2003 for the Kenyan area and for seven dates from 1972/73 to 2003 for the Ugandan areas was used. Aiming at detailed 'from year to year' land cover change matrices for each time step, image classifications followed by a postclassification comparison is considered the appropriate image processing approach for the three long-term time series. In order to derive truly comparable results, a procedure developed for the Kenyan study area prior to this work (cf. Lung, 2004) was followed as closely as possible for the Ugandan areas: georeferencing in sub-pixel accuracy, atmospheric and terrain corrections by means of ATCOR 3, masking-out of clouds/shadows and replacing them with the spectral information of the second image, and finally a supervised multispectral image classification, including an additional artificial band (ratio 7/2), using the maximum likelihood classifier. Yet, the study showed that transferring an image processing procedure from one regional case study area of tropical forest to another requires slight modifications. Due to differences in satellite data quality and vegetation differences, some additional steps towards a more hybrid approach had to be included, such as the manual delineation of certain areas with very high spectral variability (wetlands, sugarcane).

In total, 12 land cover classes of which six are forest formations were distinguished for the Kakamega-Nandi forests. Four of these classes are absent in the two Ugandan study areas. Instead, another two classes not existent in the Kakamega-Nandi area could be distinguished in the Mabira study area, resulting in a total number of ten classes (four forest formations). In the Budongo study area, four additional classes could be realized adding up to a total number of 12 classes of which six are forest formations. An accuracy assessment via error matrices for one date of each land cover time series (2001 for KN, 2002/03 for MF and 2000 for BF) revealed overall classification accuracies between 81% and 85% with user accuracies for the natural forest vegetation classes reaching from 78% to 92%. Additional visual assessments judged all other image classifications to be of similar accuracies, especially those dates with cloud-free imagery from both dry and wet season. The change detection analysis of the time series revealed a tremendous loss in natural forest cover for the Kakamega-Nandi forests and Mabira Forest whereas Budongo Forest shows a relatively stable forest cover extent within the last three decades. While the Kakamega-Nandi forests are characterised by a continuous decrease between 1972/73 and 2001 of 31%, Mabira Forest experienced an abrupt loss of 24% in the late 1970s/early 1980s. Both areas show ecologically important short-term fluctuations such as the occurrence of exotic secondary bushland species from the 1980s onwards and the indication of a slight overall forest recovery in recent time (i.e. from 2001 to 2002/03). Therefore, this work has demonstrated that officially protected forest areas in Eastern Africa are not exempted from forest depletion and destruction processes as long as policies are not enforced on the ground. Moreover, an assessment of the spatial patterns of forest losses revealed congruence with areas of high population density, thus indicating population pressure as an important driver of deforestation.

Aiming at an additional measure of landscape configuration/fragmentation also of relevance for linkages with biological field data, a spatially explicit forest fragmentation index derived from the land cover data was implemented. In accordance with Wade et al. (2003), it calculates the proportion of forest edge within the forest landscape based on a 3 x 3 pixel sized kernel providing values normalised between 0 (no fragmentation) to 1 (total fragmentation). A visual assessment of its mean values for the 1 x 1 km sized

BIOTA Biodiversity Observatories (BDOs) in the Kakamega-Nandi forests indicates a strong correlation of forest fragmentation with forest management regime and accessibility by roads with lower values for areas further away from roads and for areas more strictly protected.

For the Kenyan focus area, the Landsat-derived land cover time series (2003 to 1972/73) was extended with another three land cover data sets derived from visual interpretation of aerial photography (1965/67, 1948/(52), cf. Mitchell et al., 2006) and the forest fill as delineated from old topographic map sheets from 1912/13 (cf. Mitchell et al., 2006), thus forming a long-term land cover time series covering almost one century in regular intervals. Three sets of biological field data on keystone species/groups were used for a quantitative assessment of the influence of long-term changes in tropical forests on landscape-scale biodiversity patterns. (i) Abundance data on the army ant *Dorylus wilverthi* (Peters et al., 2009) was extrapolated in space and time based on the land cover data by combining GIS operators (focal and local functions) and statistical tests (ordinary least square regression models, by M. Peters) into a spatial modelling procedure. (ii) For ant-following birds (Peters and Okalo, 2009), which are highly susceptible to fragmentation processes, the forest fragmentation index was used as additional explanatory variable again applying a GIS-modelling procedure but using simultaneous autoregressive (SAR) models for statistical analysis (by M. Peters). (iii) Abundance data on three guilds of birds differing in forest dependency (Farwig et al., 2009) were directly extrapolated to five forest cover classes as distinguished in the time series. The results predict declines in species abundances of 56% for *D. wilverthi*, 58% for ant-following birds and an overall loss of 47% for the bird habitat guilds, which in all three cases greatly exceed the rate of forest loss (31%). For *D. wilverthi* and ant-following birds the results indicate that species abundances are not only determined by the proportion of forest cover in their vicinity but also by the spatial configuration and distribution of forest cover. Additional extrapolations on scenarios of further deforestation and reforestation confirmed the negative ecological consequences of splitting-up contiguous forest areas while on the other hand showing the potential of mixed indigenous forest plantings. Combining remotely sensed land cover time series data with biological field findings proved to be a highly suitable means for spatially explicit hindcasts on species abundance distributions and for evaluating effects of measures of forest management on biodiversity patterns at the landscape-scale.

The spatially explicit results of this study were visualised aiming to account for the needs of three user groups: scientists, decision makers and local people. This has resulted in a mixture of different outcomes. While the extrapolation modelling results were visualised as map series or as a matrix of maps aiming to address scientists and decision makers, the results of the land cover change analysis were synthesised in a map of land cover development types for each study area, respectively. These maps are designed mainly for scientists and are based on a cluster analysis procedure: as a first step, the isodata algorithm is applied to the pre-weighted and -normalised classification results of all dates of imagery. Subsequently, the derived clusters of similar change trajectories are manually aggregated to types of land cover development. The resulting map presentations allow for a rapid visual assessment of the distinct patterns of land cover change over time but require extensive accompanying textual explanations. Therefore, additional maps of change, limited to a single, aggregated class of forest cover and to three dates of the time series were generated to ensure an easy-to-grasp communication of the major forest changes to decision makers. Additionally, a self-explaining, easy-to-handle visualisation tool to be used by all three groups was developed. Adopting major principles proposed in geovisual analytics (e.g. interactive visual interfaces for space-related decision making), it provides a means for effective information communication.

For the future, a more complete assessment of the ecological consequences of forest degradation and fragmentation in the Kakamega-Nandi area including more species/groups and also ecosystem functions and services would be desirable. The existing land cover time series should be used as basis for GIS-based spatio-temporal extrapolations of the plethora of field data collected within the last nine years by the BIOTA East Africa project and by other scientists. Additionally, extrapolations on future landscape scenarios should be used in order to anticipate possible effects of future land cover changes on landscape-scale biodiversity patterns. In this regard, this study made use of normative, prospective land cover scenarios of deforestation and reforestation in order to account for the high level of uncertainty in the Kakamega-Nandi area. However, provided a careful selection of input parameters and transparent and clearly communicated model assumptions, an automated simulation of future land cover scenarios based on a trend analysis of the time series data could be a suitable supplement to the normative scenarios. A potential framework for land cover change modelling should include a sketch-based user interface to input spatially explicit forest management decisions (e.g. in regards to excisions or the spatial allocation of forest plantations), thus allowing for a participatory land use planning. Furthermore, the land cover simulation framework should be tightly coupled with a framework for running empirical extrapolation models as developed in this study, but in an automated manner. Linking both frameworks could ideally result in a GIS-based, integrated forest ecosystem assessment tool. Consisting of generic functionalities and tailored to the needs of local decision makers, it could serve as spatial decision support system towards a sustainable long-term management and use of the Kakamega-Nandi forests and potentially also other tropical forest ecosystems.

Zusammenfassung

Diese Arbeit beschreibt die Prozessierung und Analyse von Fernerkundungs-Zeitreihendaten für eine vergleichende Abschätzung von Veränderungen verschiedener tropischer Waldökosysteme Ostafrikas. Basierend auf den abgeleiteten Veränderungen bzgl. Landbedeckung und Waldfragmentierung werden verschiedene räumlich explizite Modellierungssätze innerhalb eines geographischen Informationssystems (GIS) zur räumlichen und zeitlichen Extrapolation biologischer Felderhebungsdaten benutzt, um Effekte auf Veränderungsmuster in der Biodiversität abzuschätzen. Die Analyse- und Modellierungsergebnisse werden unter Berücksichtigung der spezifischen Anforderungen von verschiedenen Nutzergruppen mit ihren unterschiedlichen Bildungs- und Kenntnisniveaus (bezogen auf georäumliche Daten) visualisiert.

Tropische Waldökosysteme sind dafür bekannt mehr als die Hälfte der beschriebenen Arten zu enthalten, verzeichnen aber alarmierende Rückgangsraten. Im subsaharischen Afrika hat eine Kombination von kausalen Synergien zwischen Faktoren wie z.B. starkem Bevölkerungswachstum, niedrigem Pro-Kopf-Einkommenswachstum und institutionellen Schwächen zu dreimal höheren Abholzungsraten als im Weltdurchschnitt geführt. Um Waldschutzmaßnahmen zu evaluieren und Empfehlungen für ein effektives Management der verbleibenden Waldressourcen abzuleiten, sind Abschätzungen der Quantität und des Ausmaßes von Landbedeckungsveränderungen, sowie ihres Einflusses auf tropische Waldbiodiversitätsmuster nötig. In diesem Zusammenhang ist der Fernerkundung eine essentielle Rolle zur Erfassung von räumlich detaillierten und zeitlich dichten Informationen bzgl. Langzeitveränderungen großflächiger Gebiete, sowie zur Ableitung von Landschaftsstrukurmaßen bzgl. Waldfragmentierung zuteil geworden. Mehrere Studien haben gezeigt, dass räumlich explizite Fernerkundungsdaten außerdem ein geeignetes Mittel für Modellierungen von Verknüpfungen mit biologischen Felddaten sein können, bei denen Artenverteilungen auf Landschaftsebene angestrebt werden.

Bislang haben jedoch wenige fernerkundungsbasierte Studien alle der folgenden Faktoren berücksichtigt: (i) Informationen zu Veränderungen von Landbedeckung und Waldfragmentierung für eine Sequenz von zeitlich dicht beieinander liegenden Aufnahmezeitpunkten, (ii) die Abdeckung von mehreren Jahrzehnten und (iii) die Unterscheidung zwischen mehreren Waldformationen. Aus diesem Grund weisen die meisten Studien in der einen oder anderen Hinsicht Limitierungen auf, so z.B. im Bezug auf das Vermögen kurzzeitige Fluktuationen erfassen zu können. Darüber hinaus waren bislang nicht viele Studien auf direkte Vergleiche von unterschiedlichen regionalen Fallstudien ausgerichtet; besonders für Afrika war dies nicht der Fall. Die Berechnung von Landschaftsstrukturmaßen aus Landbedeckungsdaten ist Standard geworden, jedoch haben Anwendungen von Landschaftsstrukturmaßen oft mit Redundanzen und konzeptionellen Mängeln zu kämpfen, anstatt ein oder wenige einfache und relevante Maße tatsächlich mit ökologischen Daten zu verknüpfen. Im Bezug auf Verknüpfungen von Fernerkundung und biologischen Felddaten sind bisher fast alle Bemühungen auf Fernerkundungsdaten eines Aufnahmezeitpunktes beschränkt geblieben. Versuche, Zeitreihendaten für quantitative Aussagen zur Veränderung von Biodiversitätsveränderungen auf Landschaftsebene über ausgedehnte Zeiträume zu verwenden sind nicht bekannt. In diesem Kontext möchte diese Arbeit die angeführten Forschungslücken adressieren und zu einem Fortschritt in der Landnutzungsänderungsforschung („land change science“) beitragen.

Die Arbeit wird im Rahmen des interdisziplinären Projektverbundes „BIOTA-Ostafrika" durchgeführt und untersucht drei Gebiete: die Kakamega-Nandi forests (KN) in Westkenia als Hauptuntersuchungsgebiet sowie Mabira Forest (MF) in Südost-Uganda und Budongo Forest (BF) in West-Uganda, die beide Vergleichszwecken dienen. Alle drei Gebiete sind offiziell unter Schutz gestellt. Es wurden Landsat-Daten in Abständen von ungefähr fünf Jahren zurückreichend bis in die frühen 1970er Jahre erworben, wobei nur vollständig oder mindestens zum Großteil wolkenfreie Bilder berücksichtigt werden konnten. Um jahreszeitlich bedingte Vegetationsunterschiede zu berücksichtigen, wurden, falls verfügbar, je eine Szene aus der Regenzeit und der Trockenzeit ausgewählt. Insgesamt wurden für das kenianische Gebiet Szenen für acht Zeitpunkte zwischen 1972/73 und 2003 und für die ugandischen Gebiete Szenen für jeweils sieben Zeitpunkte zwischen 1972 und 2003 verwendet. Die Satellitenbild-Zeitreihen sollten mit dem Ziel, detaillierte „von-Jahr-zu-Jahr" Veränderungsmatrizen der Landbedeckung zu erhalten, ausgewertet werden. Deshalb wurde die Vorgehensweise, zunächst die einzelnen Szenen zu klassifizieren und diese anschließend mittels einer „postclassification comparison" zu vergleichen, als probat erachtet. Um wirklich vergleichbare Ergebnisse zu erzielen, wurde eine für das kenianische Untersuchungsgebiet im Vorwege dieser Dissertation erarbeitete Methodik (vgl. Lung, 2004) auch auf die Ugandischen Gebiete angewandt: subpixel-genaue Georeferenzierung, Atmosphären- und Geländekorrektur mittels ATCOR 3, Ausmaskierung von Wolken/-schatten und Ersetzen dieser Bereiche mit der Spektralinformation des zweiten Bildes, und schließlich eine überwachte, multispektrale Klassifizierung, die ein zusätzliches Ratiobild (7/2) berücksichtigt und den Maximum-Likelihood-Klassifikator verwendet. Es zeigte sich jedoch, dass die Übertragung der Auswertungsmethodik von einer regionalen Fallstudie tropischer Regenwälder auf eine andere nicht eins-zu-eins möglich ist, sondern geringfügige Anpassungen nötig sind. Aufgrund von Unterschieden in der Güte der Satellitenbilddaten, sowie von Vegetationsunterschieden mussten einige zusätzliche Arbeitsschritte hin zu einer stärker hybriden Auswertung ergänzt werden, so zum Beispiel die manuelle Abgrenzung von einigen Flächen mit sehr hoher spektraler Variabilität (Sümpfe, Zuckerrohr).

Für die Kakamega-Nandi forests wurden insgesamt 12 Landbedeckungsklassen unterschieden, darunter sechs Waldformationen. Vier der 12 Klassen sind in den ugandischen Untersuchungsgebieten nicht vorhanden. Im Mabira-Untersuchungsgebiet konnten stattdessen zwei andere Klassen unterschieden werden, wodurch sich eine Gesamtzahl von zehn Klassen ergibt (davon vier Waldformationen). Im Budongo-Untersuchungsgebiet konnten vier zusätzliche Klassen realisiert werden, was insgesamt 12 Klassen ergibt, unter denen ebenfalls sechs Waldformationen sind. Eine Genauigkeitsprüfung mit Hilfe von Fehlermatrizen für jeweils eine Klassifikation der drei Landbedeckungszeitreihen (2001 für KN, 2002/03 für MF und 2000 für BF) ergab Gesamtklassifizierungsgenauigkeiten („overall classification accuracies") zwischen 81% und 85% sowie Nutzer-Genauigkeiten („user accuracies") für die natürlichen Waldvegetationsklassen zwischen 78% and 92%. Alle anderen Klassifikationen der Zeitreihen wurden hinsichtlich ihrer Klassifizierungsgüte visuell bewertet und als von ähnlicher Güte eingeschätzt, insbesondere jene Klassifikationen, für welche wolkenfreies Bildmaterial sowohl aus der Regen- als auch der Trockenzeit vorhanden war. Die Veränderungsanalyse („change detection") der Zeitserien zeigte einen enormen Verlust von natürlicher Waldvegetation für die Kakamega-Nandi forests und für Mabira Forest, jedoch eine relativ stabile Waldbedeckung innerhalb der letzten drei Jahrzehnte für Budongo Forest.

Während die Kakamega-Nandi forests durch eine kontinuierliche Waldabnahme von 31% zwischen 1972/73 und 2001 gekennzeichnet sind, ist Mabira Forest durch einen abrupten Waldverlust von 24% in den späten 1970ern / frühen 1980ern geprägt. Beide Gebiete zeigen ökologisch bedeutsame kurzzeitige Fluktuationen wie zum Beispiel das Auftreten von exotischen Sekundärbuschland-Arten ab den 1980ern oder geringfügige Anzeichen von Waldregeneration in jüngster Zeit (d.h. von 2001 auf 2002/03). Diese Arbeit hat somit gezeigt, dass offiziell geschützte Waldgebiete in Ostafrika nicht von Raubbau und Zerstörungsprozessen ausgenommen sind, solange entsprechende Schutzbestimmungen nicht vor Ort umgesetzt werden. Zudem hat eine Abschätzung der räumlichen Muster von Waldverlusten eine hohe Deckungsgleichheit mit Gebieten hoher Bevölkerungsdichte ergeben, was auf Bevölkerungsdruck als wesentlichen Einflussfaktor für Entwaldung hindeutet.

Mit dem Ziel, ein zusätzliches Maß bzgl. Landschaftskonfiguration/-fragmentierung zu erzeugen, das gleichzeitig auch für die Kopplung mit biologischen Felddaten relevant ist, wurde ein räumlich expliziter Waldfragmentierungsindex implementiert, der aus den Landbedeckungsdaten abgeleitet wurde. In Übereinstimmung mit Wade et al. (2003) berechnet der Index den Anteil von Waldrand innerhalb von Waldlandschaft basierend auf einem 3x3-Pixel großen Fenster, wobei zwischen 0 (keine Fragmentierung) und 1 (maximale Fragmentierung) normalisierte Werte ausgegeben werden. Eine visuelle Abschätzung seiner Mittelwerte für die 1x1 km großen BIOTA Biodiversity Observatories (BDOs) in den Kakamega-Nandi forests deutet auf eine starke Korrelation zwischen Waldfragmentierung und Waldmanagement-Praktiken sowie Waldfragmentierung und Erreichbarkeit von Wald über Straßen hin, da sich generell niedrigere Werte für weiter von Straßen entfernte Gebiete und für strenger geschützte Gebiete ergaben.

Für das kenianische Hauptuntersuchungsgebiet wurde die aus Landsat-Daten abgeleitete Landbedeckungszeitreihe um drei weitere Datensätze ergänzt, die mittels visueller Interpretation von Luftbildern (1965/67, 1948/(52), vgl. Mitchell et al., 2006) sowie durch Abgrenzung des Walddeckers von alten topographischen Kartenblättern von 1912/13 (vgl. Mitchell et al., 2006) gewonnen wurden. Folglich ergibt sich dadurch eine Langzeit-Landbedeckungszeitreihe, welche fast ein Jahrhundert in regelmäßigen Abständen abdeckt. Um den Einfluss von Langzeitveränderungen in tropischen Regenwäldern auf Biodiversitätsmuster auf Landschaftsebene quantitativ abzuschätzen, wurden drei Datensätze mit biologischen Felderhebungen von Schlüsselarten/-gruppen verwendet. (i) Abundanzdaten der Treiberameise *Dorylus wilverthi* (Peters et al., 2009) wurden basierend auf den Landbedeckungsdaten räumlich und zeitlich extrapoliert, indem GIS-Operatoren (fokale und lokale Funktionen) und statistische Tests („ordinary least square“-Regressionsmodelle, von M. Peters) in einem räumlichen Modellierungsablauf kombiniert wurden. (ii) Für Ameisen-folgende Vögel (Peters und Okalo, 2009), die stark anfällig für Fragmentierungsprozesse sind, wurde der Waldfragmentierungsindex als zusätzliche erklärende Variable verwendet und erneut GIS-Operatoren zu einem Modellierungsablauf verkettet, jedoch wurden für die statistische Analyse „simultaneous autoregressive models“ (SAR) eingesetzt (von M. Peters). (iii) Abundanzdaten von drei sich hinsichtlich ihrer Abhängigkeit von Wald unterscheidenden Vogelgilden (Farwig et al., 2009) wurden direkt auf fünf Waldbedeckungsklassen hochgerechnet, die in der Zeitreihe unterschieden werden konnten. Die Ergebnisse prognostizieren Abundanzabnahmen von 56% für *D. wilverthi*, von 58% für Ameisen-folgende Vögel und einen Gesamtverlust von 47% für die Vogelgilden, was in allen drei Fällen eine deutliche Überschreitung der Waldverlustrate von 31% darstellt. Für *D. wilverthi* und für die Ameisen-folgenden Vögel deuten die Ergebnisse darauf hin, dass die Abundanzen nicht nur durch den Anteil von Waldbedeckung in ihrer Umgebung beeinflusst werden, sondern auch von der räumlichen Konfiguration und Verteilung der Waldbedeckung. Zusätzliche Extrapolationen basierend auf Szenarien weiterer Waldverluste bestätigten die negativen ökologischen Konsequenzen der Zerteilung zusammenhängender Waldflächen, während Extrapolationen basierend auf Aufforstungsszenarien das Potential von Anpflanzungen einer Mischung aus einheimischen Arten aufzeigten. Die Kopplung von fernerkundungsbasierten Landbedeckungszeitreihen mit biologischen Felderhebungen erwies sich als ein höchst geeignetes Verfahren, um räumlich explizite Rückberechnungen von Abundanzverteilungen durchzuführen und um Auswirkungen von Waldmanagement-Maßnahmen auf Biodiversitätsmuster auf Landschaftsebene zu evaluieren.

Die räumlich expliziten Ergebnisse dieser Arbeit wurden mit dem Ziel visualisiert, die Bedürfnisse der folgenden drei Nutzergruppen zu berücksichtigen: Wissenschaftler, Entscheidungsträger und die lokale Bevölkerung. Die Ergebnisse der Extrapolations-Modellierung wurden als eine Reihe von nebeneinander positionierten Einzelkarten oder als Matrix von Einzelkarten visualisiert, mit denen Wissenschaftler und Entscheidungsträger angesprochen werden sollen. Aus den Ergebnissen der Landbedeckungsanalyse für die drei Untersuchungsgebiete wurden jeweils Landbedeckungsveränderungstypen generiert und in einer synthetischen Karte dargestellt. Diese Karten sind hauptsächlich für Wissenschaftler gedacht und basieren auf einem Cluster-Analyse-Ansatz. Dieser umfasst in einem ersten Schritt die Anwendung des isodata-Algorithmus auf die zuvor gewichteten und normalisierten Klassifikationen aller Zeitschritte. Nachfolgend werden die erzeugten Cluster gleicher Veränderungstrajektorien manuell zu Landbedeckungsveränderungstypen aggregiert. Die daraus resultierenden Karten ermöglichen eine rasche visuelle Abschätzung der unterschiedlichen Muster der Landbedeckungsveränderung, wobei allerdings ausführliche, begleitende textliche Erklärungen notwendig sind. Um die wesentlichen Waldveränderungen auch auf einfache Weise den Entscheidungsträgern gegenüber kommunizieren zu können, wurden deshalb zusätzliche Karten erstellt, die nur eine einzige aggregierte Klasse „Waldbedeckung" zeigen und auf drei Zeitschritte der Zeitreihe begrenzt sind. Zusätzlich wurde ein leicht zu bedienendes, selbsterklärendes Visualisierungstool entwickelt, das für alle drei Benutzergruppen gedacht ist. Es berücksichtigt wesentliche, im Forschungsgebiet „geovisual analytics" vorgeschlagene Prinzipien (z.B. interaktive visuelle Schnittstellen für raumbezogene Entscheidungsfindung) und stellt somit ein wirksames Mittel der Informationskommunikation dar.

Für die Zukunft wäre eine umfassendere Abschätzung der ökologischen Konsequenzen von Waldzerstörung and Fragmentierung im Kakamega-Nandi-Gebiet wünschenswert, die zusätzliche Arten/-gruppen sowie auch Ökosystemfunktionen und -dienstleistungen berücksichtigt. Die existierende Zeitserie sollte hierbei als Grundlage für weitere GIS-basierte, raum-zeitliche Extrapolationen der Vielzahl von Felddaten dienen, die in den letzten neun Jahren im BIOTA-Ostafrika-Projekt und auch von anderen Wissenschaftlern erhoben wurden. Um mögliche Effekte von zukünftigen Landbedeckungsänderungen auf Biodiversitätsmuster auf Landschaftsebene abschätzen zu können, sollten zusätzliche Extrapolationen auf Landschaftsszenarien durchgeführt werden. Im Rahmen dieser Arbeit wurden diesbezüglich normative Szenarien von Abholzung bzw. Aufforstung verwendet, um dem hohen Maße an Unsicherheiten im Kakamega-Nandi-Gebiet Rechnung zu tragen. Im Falle einer sorgfältigen Auswahl der Eingangsparameter sowie transparenten und eindeutig kommunizierten Modellannahmen könnten jedoch automatisierte Simulationen zukünftiger Landbedeckungsszenarien basierend auf einer Trendfortschreibung der Zeitreihendaten eine gute Ergänzung zu den normativen Szenarien darstellen. Eine potentielle Applikation zur Landbedeckungsmodellierung sollte eine skizzenbasierte Benutzerschnittstelle beinhalten, um räumlich explizite Entscheidungen zum Waldmanagement eingeben zu können und demzufolge eine partizipatorische Landnutzungsplanung zu ermöglichen. Die Applikation zur Landbedeckungsmodellierung sollte außerdem eng mit einer Applikation zur Ausführung von empirischen Extrapolationsmodellen gekoppelt sein, die jedoch in stärkerem Maße automatisiert auszuführen sein sollten, als dies in dieser Arbeit der Fall war. Die Verknüpfung beider Applikationen könnte im Idealfall in ein GIS-basiertes Tool zur integrativen Bewertung von Waldökosystemen münden. Da ein derartiges Tool allgemein gebräuchliche Funktionen bereitstellen würde und auf die Bedürfnisse von lokalen Entscheidungsträgern zugeschnitten wäre, könnte es als räumliches Entscheidungsunterstützungssystem einen Beitrag zu einem langfristig nachhaltigen Management und einer nachhaltigen Nutzung der Kakamega-Nandi forests und potentiell auch anderer tropischer Waldökosysteme leisten.

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Appendices

A) Forest area figures for the three study areas

Table A1: Natural forest cover [in ha] 1972/73 to 2003 within the official forest boundaries of Kakamega Forest, North Nandi Forest, South Nandi Forest, Mabira Forest and Budongo Forest, as derived from a multispectral classification of Landsat imagery (classes 'Near natural & old secondary forest' and 'Secondary forest').

	Kakamega-Nandi forests				
Year	**Kakamega Forest*[1]**	**North Nandi Forest[1]**	**South Nandi Forest[1]**	**Mabira Forest[2]**	**Budongo Forest[2]**
1972/73	15,827	9,325	14,316	26,532 (1973/74)	44,934
1975	15,137	8,777	13,980	27,421 (1976)	44,962
1979/80	14,611	8,075	13,316		
1984	13,136	7,419	12,271	20,976 (1986)	45,581 (1986)
1989	13,691	7,643	11,503	21,847	45,134 (1990)
1995	13,226 (1994/95)	7,349 (1994/95)	8,489 (1994/95)	21,991	46,244
2001	13,067	6,780	7,504	22,052	45,864 (2000)
2003	13,925	7,072	9,840	22,338 (2002/03)	45,512

* including Kisere Forest

[1] values have been used for creating Figure 3.3 [published in Lung and Schaab (2010)]; they do not match exactly with the values as published in Lung (2004) since by that time the Landsat satellite classifications had not yet been corrected for misclassifications of pine pixels scattered throughout the forested areas.

[2] values as published in Lung and Schaab (2008)

Note: during the course of this study, the current official forest boundaries for the Kakamega-Nandi forests have been provided to the BIOTA project by UNEP, Nairobi (cf. Figures 1.4 and 4.1). However, as these boundaries exclude areas (e.g. in the northern part of North Nandi Forest and in the western part of South Nandi Forest) that had still been forested at the beginning of the satellite time series, the figures given in Table A1 refer to the boundaries as digitised from the topographic map sheets 1:50'000 (Series Y731 (D.O.S. 423), Edition 6, 1970) (cf. Figures 2.1, 3.1 and 3.4) which include these areas.

B) Cluster analysis for Mabira Forest and Budongo Forest time series data

(ex Chapter 5 from KGS D9, 2008)

Additionally to an analysis per time step, characteristic changes in land cover for each forest area have been summarised to land cover development types, thus allowing the visualisation of the most striking developments in one single map instead of a time series presentation. Again, the methodology as applied for the Kakamega-Nandi forests (for a detailed description of the method see Lung and Schaab (2006) [or Section 2.3]) has been adopted as closely as possible to allow for a comparison. This means that the cluster analysis has not been carried out for the entire study areas but for the gazetted forest areas buffered proportionally to their area by 850 m and 1500 m, respectively. The first step of the cluster analysis applies a weighted normalisation that stretches the values of the original land cover classes but limiting the range to a maximum value of 256 (see Table B1), followed by combining the classification results of all seven time steps in one image stack and running the isodata-algorithm. Subsequently, the high number of automatically generated clusters is aggregated to meaningful types of land cover development by manually reviewing each cluster regarding the assigned land cover classes over the seven time steps for randomly chosen pixels. The resulting land cover development types are visualised in a colour-coded map (for a subset see Figures A1 and A2) supported by a descriptive textual legend (see Tables B2 and B3).

Generation and assessment of land cover development types

For Mabira and Budongo forests, some modifications to the methodology as applied for the Kakamega-Nandi forests had to be made. First, the number of clusters had to be reduced to 50 for Mabira Forest and to 70 for Budongo Forest as compared to the 100 clusters for the Kakamega-Nandi forests, in order to ensure a minimum number of around 2000 pixels to be automatically assigned to each cluster. Clusters with fewer pixels do usually not show a spatial grouping but their pixels are rather randomly distributed as 'salt and pepper' throughout the analysis area. Such a distribution impedes a meaningful assignment to a distinct type of land cover development. Second, the values defining the 'distances' (i.e. reflecting similarities between the land cover classes) have been slightly modified to: 4 for very close, 8 for close, 16 for average, 32 for far and 64 for very far. For the Ugandan forests this scheme of 'distances' yielded a better assignment of the characteristic land cover developments to distinct clusters as compared to the scheme used for the Kakamega-Nandi forests. Table B1 reveals the spreading of the class values after the weighted normalisations (for Budongo Forest see 'Reclass 1' values). Furthermore, when ordering the land cover classes, 'Water' has been placed after 'Wetland' (i.e. away from 'Others') as it is considered to be 'more similar' to 'Wetland' than to 'Others'. For Budongo Forest the class 'Burnt area' has been placed near the three classes 'Bushland/shrubs', 'Mesic forest/deciduous trees (woodland)' and 'Grassland' since most of the burnt areas are likely to belong to one of those classes. Whereas for Mabira Forest the 'distance' between 'Near natural & old secondary forest' and 'Secondary forest' has been set to 'close' (i.e. to a distance value of 8), for Budongo Forest it has been defined as 'average' (i.e. a distance value of 16). With this setting which places 'Secondary forest' further away also from the additional class 'Mature natural forest incl. *Cynometra*', a better assignment of the distinct types of forest to different clusters could be achieved.

Table B1: Reclassification schemes by a weighted normalisation for a subsequent cluster analysis, as applied to the land cover classes distinguished for Budongo Forest and Mabira Forest.

Value	Land cover classes for Mabira	Reclass	Value	Land cover classes for Budongo	Reclass 1	Reclass 2
1	Near natural & old secondary forest	1	0	Mature natural forest incl. *Cynometra*	1	1
2	Secondary forest	9	1	Near natural & old secondary forest	5	5
3	Bushland/shrubs	25	2	Secondary forest	21	21
4	Secondary bushland–*B. papyrifera*	33	3	Bushland/shrubs	37	37
6	Grassland	65	4	Mesic forest/deciduous trees (woodland)	45	45
9	Tea plantation	97	6	Grassland	61	61
10	Agricultural land	113	14	Burnt area	77	77
12	Others	145	7	Plantation forest–*Pinus patula*	141	157
13	Wetland	177	10	Agricultural land	173	109
11	Water	185	12	Others	205	125
			13	Wetland	237	221
			11	Water	245	229

Unfortunately, for Budongo Forest the aggregation to meaningful land cover development types based on the results of the cluster analysis performed on the 'Reclass 1' values did neither show a satisfactory assignment to distinct clusters for areas having experienced forest loss, nor did the assignment allow the distinction between areas of stable woodland versus stable grassland over time. Therefore, a second run of the isodata-algorithm based on a modified weighting has been conducted, reducing the distance from 'Agricultural land' to 'Others' and placing 'Plantation forest–*Pinus patula*' after those two classes (see values of 'Reclass 2' in Table B1). This second run performed better assigning the mentioned trends to six of the 70 clusters defined for Budongo Forest (i.e. three clusters depicting forest loss and three clusters revealing stable grassland over time). However, the remaining 64 clusters from the second run showed a less accurate assignment to distinct types as compared to those from the first run. Therefore, the final result for Budongo Forest study area has been derived by merging the six clusters from the second run with the otherwise preferable clusters from the first run.

For Mabira Forest, thirteen distinct land cover development types could be realised (see Table B2). Five of the obtained development types represent changes regarding forest. Four of them (2a, 2b, 3 and 5) are forms of forest loss whereas type 6 shows succession of forest formations. Two types describe changes between agricultural land and bushland either with (type 14) or without (type 11a) a clear trend. Types 1, 4, 7a, 12 and 15 represent areas of stability over time. Only one cluster (containing around 2.5% of the total number of pixels) did not show a meaningful tendency in land cover and has therefore been named 'Not typifyable' (type 13).

For Budongo Forest, eleven distinct land cover development types could be revealed (see Table B3). Only development type 3a, depicting forest loss of either near natural or secondary forest, shows a change regarding forest. Most other types reflect stable land cover over time or, as type 11b grouping changes of agricultural land to woodland, bushland or grassland, or vice versa, no clear trend. Clusters which could not be aggregated to a distinct type of land cover development (i.e. type 13) account for 4.5% of the total number of pixels.

Comparing the land cover development types obtained for Mabira Forest and for Budongo Forest with those realised for the Kakamega-Nandi forests (see Table 3 in Lung and Schaab (2006) [or Table 2.3]) demonstrates that deriving exactly the same or very similar types for three different study areas is hardly possible. Only three types representing no change but stable conditions over time for near natural forest, secondary forest, and agricultural land (types 1, 4 and 12) are present in all three study areas. Another four types represent similar, but not identical land cover developments. For these four types (2, 3, 7 and 11) 'subtypes' have been created: Whereas type 2 (present for the Kakamega-Nandi forests) combines both regeneration to secondary forest and secondary bushland, in Mabira Forest re-growth to secondary forest (type 2a) is distinct from re-growth to secondary bushland (type 2b). Type 3, present in the Kakamega-Nandi forests and Mabira Forest shows loss of near natural and old secondary forest. For Budongo Forest type 3 also includes loss of secondary forest, thus it has been given type

Table B2: Description of the 13 land cover development types for Mabira Forest, 1973/74 to 2002/03, as resulting from a cluster analysis based on classified Landsat data (numbering of types follows those of the Kakamega-Nandi forests, see Lung & Schaab 2006).

Type	Description of land cover development types revealed for Mabira Forest
1	**Mainly near natural & old secondary forest**: no. of time steps with 'Near natural & old secondary forest' ≥ 5; partly 1-2 time steps with 'Secondary forest'.
2a *	**Loss of near natural & old secondary forest or secondary forest, subsequently regeneration to secondary forest**: till around 1976 mostly 'Near natural & old secondary forest' or 'Secondary forest'; forest loss to 'Agricultural land' before 1986 followed by re-growth of 'Bushland /shrubs' in 1989 or 1995 and to 'Secondary forest' in 2001 or 2002/03.
2b *	**Loss of near natural & old secondary forest, subsequently growth of paper mulberry trees**: till around 1976 mostly 'Near natural & old secondary forest'; forest loss to 'Agricultural land' before 1986 followed by growth of 'Secondary bushland–*Broussonetia papyrifera*' or in parts 'Bushland/shrubs' from 1995 onwards.
3 *	**Total forest loss of near natural & old secondary forest (no regeneration)**: till 1976 mainly 'Near natural & old secondary forest' followed by 'Bushland/shrubs' or 'Agricultural land' from 1986 onwards (within Mabira CFR mainly from 1995 onwards).
4	**Mainly secondary forest**: no. of time steps with 'Secondary forest' ≥ 5 and often 1-2 time steps with 'Near natural & old secondary forest'.
5 *	**Loss of secondary forest (no regeneration)**: till 1976 mainly 'Secondary forest'; forest loss to 'Agricultural land' before 1986, without any forest re-growth. Typical occurrence in the forest fragments north-east of Mabira CFR.
6 *	**Succession of (natural) forest formations**: 'Agricultural land' in the 1970s; then 'Bushland/shrubs' in the 1980s, 'Secondary forest' from 1995 or 2001 onwards.
7a	**Mainly bushland/shrubs**: no. of time steps with 'Bushland/shrubs' ≥ 5. Hardly any occurrence as larger patches.
14	**Temporarily growth of bushland**: 'Agricultural land' in the 1970s, 'Bushland/shrubs' in the 1980s; 'Agricultural land' again from the 1990s onwards.
11a	**Change in agricultural land and bushland**: 'Agricultural land' or 'Bushland/shrubs' (or 'Grassland' for some small areas), each for ca. 3-4 time steps; without signs of a typical development.
12	**Mainly agricultural land**: no. of time steps with 'Agricultural land' ≥ 5.
15	**Mainly water or wetland**: no. of time steps with 'Water' or 'Wetland' ≥ 6.
13	**Not typifyable**: meaningful tendencies in the development of land cover not to be revealed, e.g. due to pixels representing opposed trends within the same cluster.

* changes regarding forest

Table B3: Description of the 11 land cover development types for Budongo Forest, 1972/73 to 2003 as resulting from a cluster analysis based on classified Landsat data (numbering of types follows those of the Kakamega-Nandi forests, see Lung & Schaab 2006).

Type	Description of land cover development types revealed for Budongo Forest
0	**Mainly mature natural forest incl. *Cynometra***: no. of time steps with 'Mature natural forest incl. Cynometra' ≥ 5; partly 1-2 time steps with 'Near natural & old secondary forest'.
1	**Mainly near natural & old secondary forest**: no. of time steps with 'Near natural & old secondary forest' ≥ 5; partly 1-2 time steps with 'Secondary forest'.
4	**Mainly secondary forest**: no. of time steps with 'Secondary forest' ≥ 5 and often 1-2 time steps with 'Near natural & old secondary forest'.
3a *	**Total forest loss of near natural & old secondary forest or secondary forest (no regeneration)**: till around 1990 mostly 'Near natural & old secondary forest' or 'Secondary forest'; subsequently forest loss to 'Bushland/shrubs' or 'Agricultural land'. Occurrence almost exclusively outside Budongo CFR.
16	**Mainly woodland**: no. of time steps with 'Mesic forest/deciduous trees (woodland)' ≥ 5 and mostly 1-2 time steps with 'Grassland'.
7a	**Mainly bushland/shrubs**: no. of time steps with 'Bushland/shrubs' ≥ 5.
9	**Mainly grassland**: no. of time steps with 'Grassland' ≥ 5.
11b	**Change between agricultural land and bushland or grassland**: either 'Agricultural land' or 'Bushland/shrubs', 'Mesic forest/deciduous trees (woodland)' or 'Grassland', each for ca. 3-4 time steps; without signs of a typical development.
12	**Mainly agricultural land**: no. of time steps with 'Agricultural land' ≥ 5.
15	**Mainly water or wetland**: no. of time steps with 'Water' or 'Wetland' ≥ 6.
13	**Not typifyable**: meaningful tendencies in the development of land cover not to be revealed, e.g. due to pixels representing opposed trends within the same cluster.

* change regarding forest

number 3a. For the Kakamega-Nandi forests type 7 represents mainly bushland and grassland with scattered trees, for the two Ugandan forest areas it only includes bushland as no land cover class of 'Grassland with scattered trees' was distinguished, naming it type 7a. Type 11 represents a change between agricultural land and grassland for the Kakamega-Nandi forests, for Mabira Forest it reflects the change between agricultural land and bushland with only very few grassland areas (type 11a), whereas for Budongo Forest it shows the change between agricultural land and either bushland or grassland (type 11b). Finally, four types (5, 6, 9 and 15) are present only in two of the three studied areas, while five types are unique to one of the three study areas (types 8 and 10 to Kakamega-Nandi, type 14 to Mabira and types 0 and 16 to Budongo).

The main reason for the slightly differing land cover development types is the varying natural conditions of the three study areas, i.e. the land cover classes occurring in the three areas (only seven classes are identical for all three areas, cf. Lung and Schaab (2010) [or Section 3.4]) together with the differing development in land cover. Furthermore, short term fluctuations in land cover are almost impossible to get assigned to separate clusters by the isodata-algorithm, i.e. classifications to a certain land cover class occurring in only one of the seven time steps do mostly not result in the assignment to a different cluster. For example, pixels classified as 'Agricultural land' in all seven time steps and pixels classified as 'Near natural & old secondary forest' in the first time step but as 'Agricultural land' in all subsequent time steps are normally grouped into the same

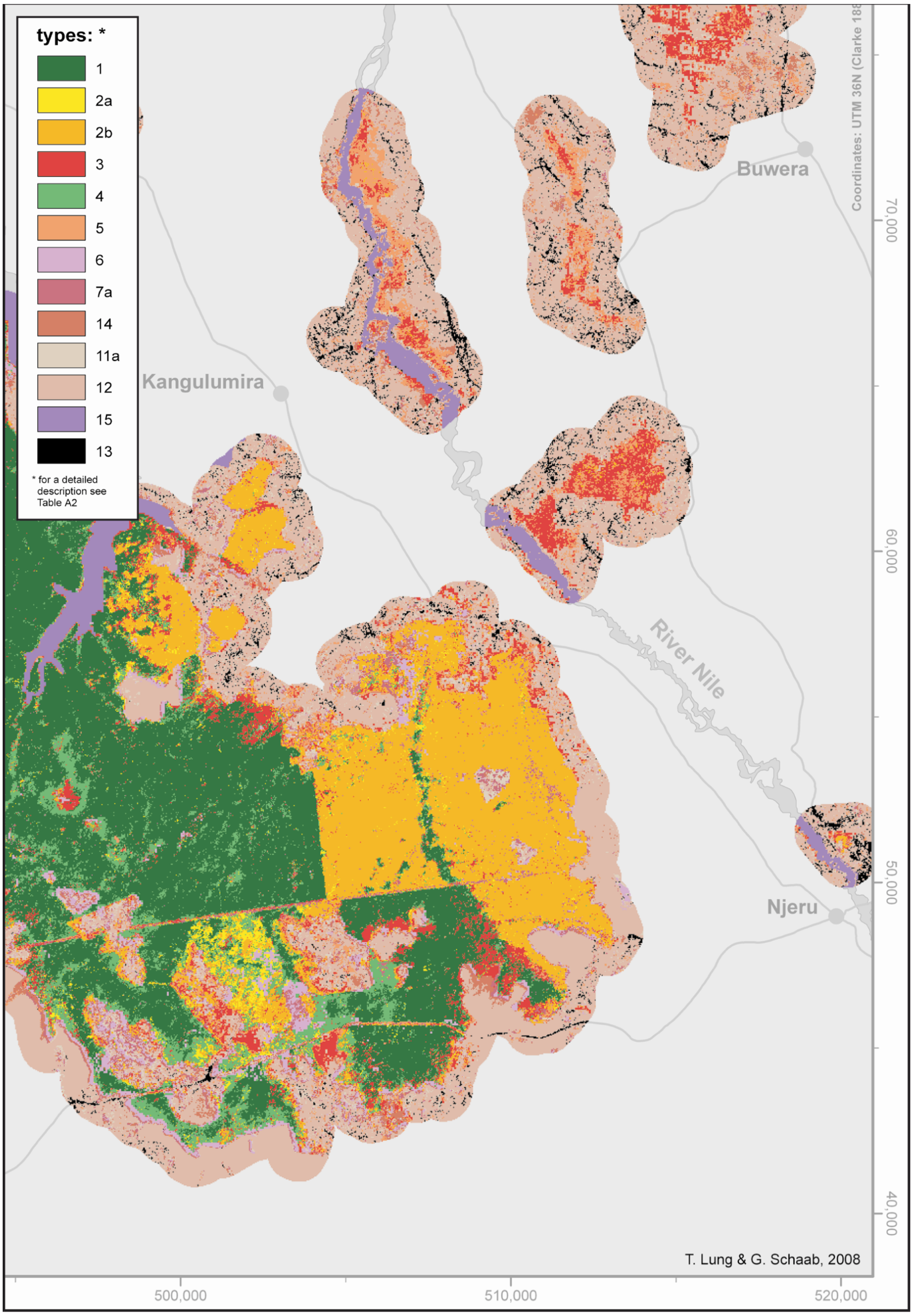

Figure B1: Subset of map presentation consisting of 13 types describing characteristic land cover developments for Mabira forest, 1973/74 to 2002/03 (from Lung and Schaab, 2008).

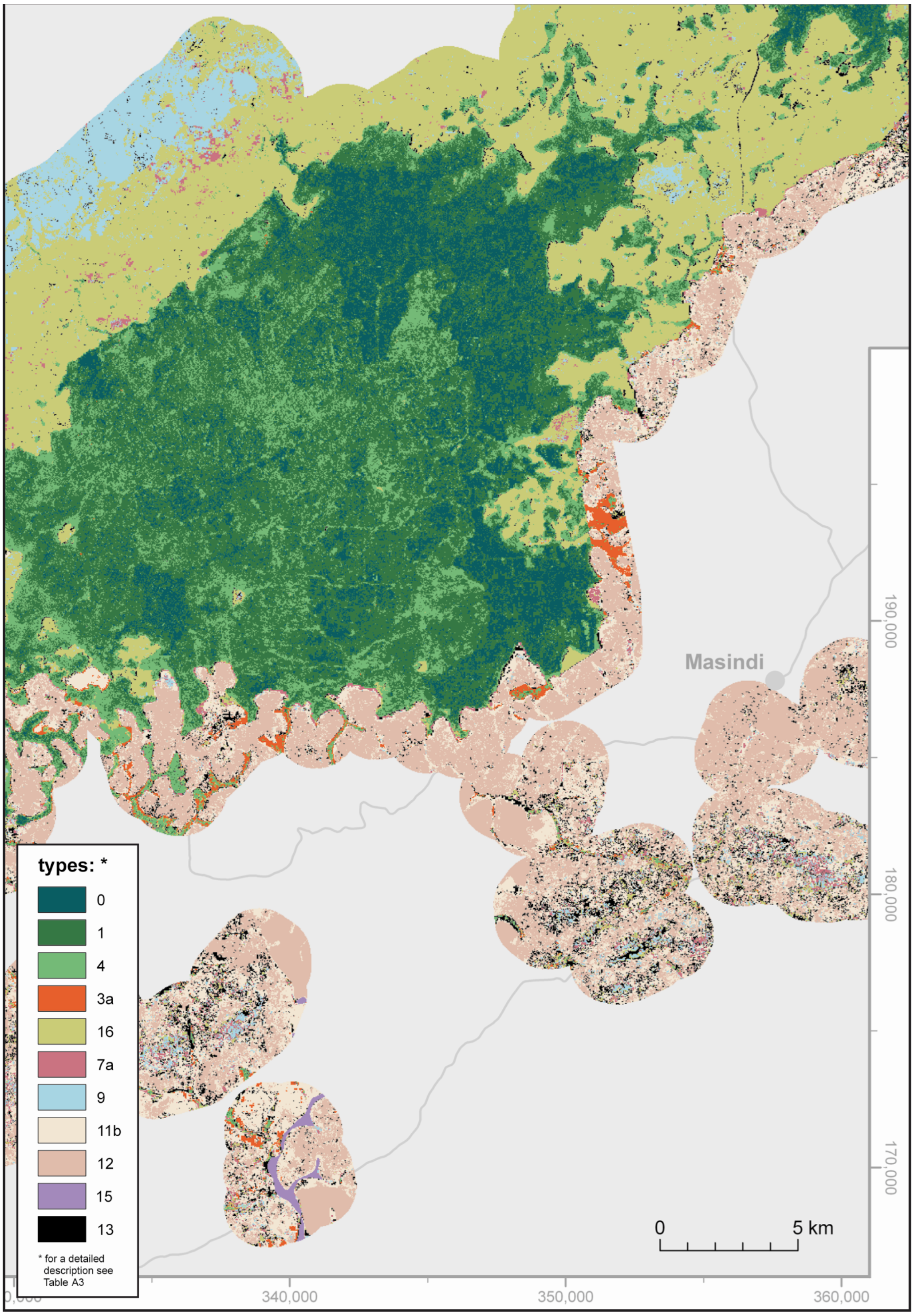

Figure B2: Subset of map presentation consisting of 11 types describing characteristic land cover developments for Budongo forest, 1972/73 to 2003 (from Lung and Schaab, 2008).

cluster, although they reflect different developments in land cover (see type 12 'Mainly agricultural land' as opposed to type 3 'Total forest loss of near natural & old secondary forest (no regeneration)'). Similarly, trends only occurring for a relatively small number of pixels (mostly less then 2000) are often not assigned to separate clusters by the isodata-algorithm. Here, an example is 'Total forest loss of near natural forest & old secondary forest (no regeneration)' (type 3) versus 'Loss of secondary forest' (type 5). Whereas this distinction could be made for the Kakamega-Nandi forests and Mabira Forest, it could not be made for Budongo Forest (type 3a), where loss of secondary forest occurs much more localised.

Despite these minor limitations, the cluster analysis is judged to be a valuable means for generating one map from seven single land cover classifications covering 30 years back in time. The resulting maps for Budongo Forest and Mabira Forest enable to grasp typical land cover development trends (e.g. areas of stability or areas of change) at a glance, which cannot be as easily identified when looking at the classification results of the time series one by one.

C) Prospective forest management scenarios for Kakamega Forest

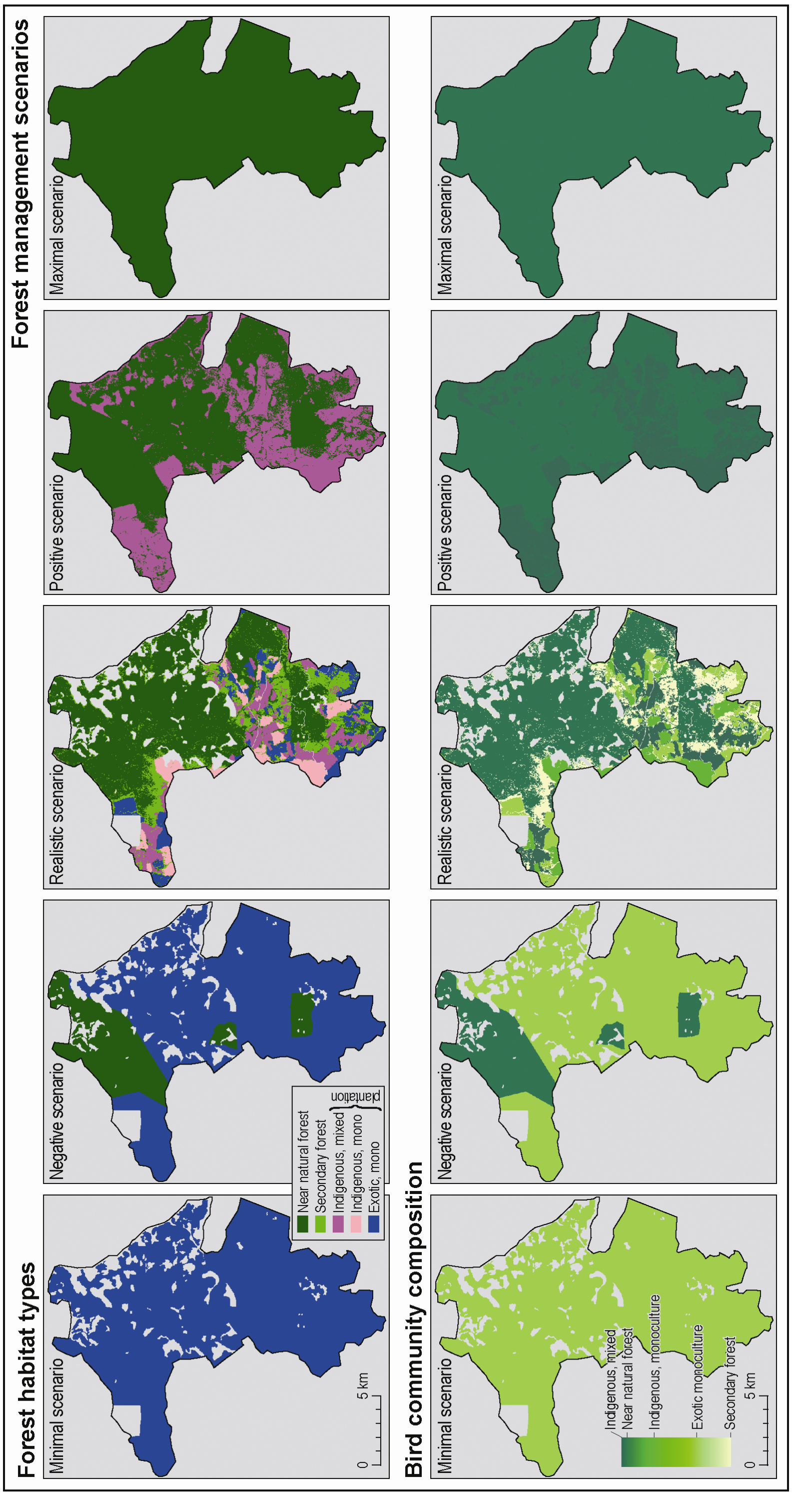

Figure C1: Spatial distribution of five different forest types and corresponding bird community composition for five forest management scenarios, within the officially gazetted area of Kakamega Forest (from Farwig et al., submitted)