Long-term Changes in Land Cover and Carbon Storage in Tanzania, East Africa

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Submitted in accordance with the requirements for the degree of
Doctor of Philosophy

The University of Leeds
School of Geography

August 2012

The candidate confirms that the work submitted is his own, except where work which has formed part of jointly-authored publications has been included. The contribution of the candidate and the other authors to this work has been explicitly indicated below. The candidate confirms that appropriate credit has been given within the thesis where reference has been made to the work of others.

Chapters 3, 4 and 5 are the result of collaborations. These jointly-authored manuscripts were led by Simon Willcock. The data used in these manuscripts includes those from a collaborative database of unpublished plot data. Contributions to the collaborative dataset came from PP, AA, ND, KD, EF, JG, JH, KH, ARM, BM, PKTM, NO, EJTJ and RDS (see author list below).

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Acknowledgements

I thank my supervisors, Dr Simon Lewis, Prof Oliver Phillips, Prof Pantaleon Munishi and Prof Jon Lovett for introducing me to the study of tropical forest ecology; for the opportunity to work with both the AFRITRON and RAINFOR consortiums; and for their advice, help and encouragement. I acknowledge financial support from the Leverhulme Trust and the Stokenchurch Charity.

This project would have been impossible without the friendship and assistance of all the members of the Valuing the Arc project. In particular, I am very grateful to Prof Andrew Balmford, Prof Neil Burgess, Dr Philip Platts, Dr Ruth Swetnam, Dr Antje Ahrends, Dr Andrew Marshall, Dr Rob Marchant, Dr Marion Pfeifer, Dr Brendan Fisher, Dr Marije Schaafsma, and Dr Julian Bayliss.

In Tanzania, I thank the Tanzania Commission for Science and Technology (COSTECH), the Tanzania Wildlife Research Institute (TAWIRI), the Sokoine University of Agriculture (SUA), and WWF-Tanzania for permission and support given whilst the research was undertaken. In addition, I thank the many foresters, biologists and volunteers who assisted with the collection of the unpublished data utilised in this study; including Nike Doggart, Kathryn Doody, Eibleis Fanning, Alex Lowassary, Boniface Mbilinyi, Nisha Owen, Deo Shirima, and Elmer Topp-Jorgensen. Asante sana.

Many people have offered assistance and advice during my PhD; my thanks go to Nikée Groot, Carol White, Stephanie Organ, Kate Staines, Sophie Fauset, Keith Bloomfield, Michelle Johnson, Pengfei Li, Gemma Dooling, Dr Ian Lawson, Dr Tim Baker, Prof Emanuel Gloor, and the Ecology and Global Change cluster. I would also like to thank the support staff within the School of Geography; in particular, Calum Carson, Dominic Emery, Samantha Bowman and Jacqui Manton.

I would like to thank my parents, my brother, my sister, and Jessica Weyell for their never-ending support and understanding throughout the PhD process.

I dedicate this thesis to the memory of Amani Mahundu (a superb field assistant and a better friend), Laura Harpin, Patrick Rolfe, and Freya Willcock. You will all remain in my thoughts.

Abstract

The carbon stored in vegetation varies spatially and temporally due to a complex mix of anthropogenic, climatic and edaphic variables. Thus, the success of climate change policy developments such as REDD+ (Reducing Emissions from Deforestation and Forest Degradation) relies heavily on measuring and understanding this variation in the past, present and future. Here, I first analyse the change in forest cover within a 33.9 million hectare tropical study area in eastern Tanzania. I develop both linear and non-linear baselines of deforestation, providing evidence that Tanzanian forest policy has resulted in forest transition. I then present an Intergovernmental Panel on Climate Change (IPCC) ‘Tier 2’ reporting-compliant look-up method to estimate regional carbon storage, and associated 95% confidence intervals (CI). Applying this method to my study area indicates that 1.58 (95% CI: 1.56-1.60) Pg of aboveground live carbon (ALC) was stored across the landscape in the year 2000. Combining these Tier 2-type values with the historical land use/cover data I derived, I estimate that my study area had a total committed carbon release of 0.94 (0.37-1.50) Pg C between 1908 and 2000. However, look-up methods are overly simplistic for heterogeneous landscapes. Using regression equations, including the effects of disturbance, my IPCC ‘Tier 3’ compliant estimate for the same region in the year 2000 is 1.32 (0.89-3.16) Pg ALC. The most influential variables of carbon storage in the region are human, the strongest impact variables being the nature of the local governance regime (land under national control contained only 40-65% of the ALC stored in areas under local control) and historical logging (areas that had previously experienced logging held 51-77% of the ALC of never-logged areas). Throughout, I provide spatially explicit estimates to aid decision-makers who, due to the influence of anthropogenic variables, could significantly affect landscape carbon storage across this important area.

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Glossary of Terms and Acronyms

Acronym	Term	Definition
AGB	Aboveground live biomass	All biomass contained in living vegetation, both woody and herbaceous, above the soil including stems, stumps, branches, bark, seeds, and foliage.
	Afforestation	The conversion of land that has not been forested (for at least 50 years) into forested land. This may occur via human-induced planting, seeding and/or promotion of natural seed sources.
AIC	Akaike information criteria	A measure of the relative goodness of fit of a statistical model.
ALC	Aboveground live carbon	All carbon contained in living vegetation, both woody and herbaceous, above the soil including stems, stumps, branches, bark, seeds, and foliage.
AWG	Ad Hoc Working Groups	Ad Hoc Working Groups were established to advice the UNFCCC on REDD+ strategies.
	Baseline scenarios	A business-as-usual emissions scenario, i.e. without any mitigation measures.
	Belowground carbon	All carbon contained in live roots. Fine roots of less than (suggested) 2mm diameter are often excluded because these often cannot be distinguished empirically from soil organic matter or litter.
	Bushland	Vegetation typically between 1m and 3m tall, rarely exceeding 5m. Bushland is predominantly comprised of plants that are multi-stemmed from a single root base.
C	Carbon	A chemical element common in natural systems.
	Carbon flux	The transfer of carbon between a terrestrial carbon pool and the atmosphere.
	Carbon stock	The absolute mass of carbon held within a pool per unit area at a specified time.
CBERS	China-Brazil Earth Resource Satellite	The CBERS programme consists of two satellites, the earliest of which was launched in 1999. They carry a high resolution (20m) sensor capable of detecting visible and near infrared spectra, as well as those of lower resolution (80m and 260m) capable of using shortwave and thermal infrared spectra.
CDM	Clean Development Mechanisms	Emission reduction projects ensuring the protection and enhancement of sinks and reservoirs of greenhouse gases, promotion of sustainable forest management practices, afforestation and reforestation.

CEEST	Centre for Energy and Environment, Science and Technology	An independent research institution in Tanzania whose objectives are to undertake research and studies in areas related to energy, environment, science and technology.
CI	Confidence interval	A statistical parameter used to indicate the reliability of an estimate.
	Committed carbon source	The total expected carbon emission from the terrestrial pool to the atmosphere following a LCC event.
COP	Conference of Parties	A global organisation consisting of representatives of all nations.
	Cropland	Areas converted to agriculture, including maize, wheat, vegetables, sugar cane, and tea.
CV	Cross validation	A technique for estimating how the results of a statistical analysis will generalise to an independent dataset.
CWD	Coarse woody debris	All non-living woody material not contained in the litter, either standing, lying on the ground, or in the soil. Dead wood includes wood lying on the surface, dead roots, and stumps, larger than or equal to 10 cm in diameter (or the diameter specified by the country).
DBH	Diameter at breast height	The stem diameter at the point of measurement (typically 1.3m above the ground).
	Deforestation	The conversion of forest and/or woodland into an alternative land cover (i.e. bushland, grassland or cropland).
	Degradation	The temporary or permanent deterioration in the density or structure of vegetation cover or its species composition.
EAM	Eastern Arc Mountains	Ancient crystalline mountains within Tanzania and Kenya, under the climatic influence of the Indian Ocean.
eCEC	Effective cation exchange capacity	The bio-available quantity of cations held within the soil.
	Ecosystem services	The benefits, or goods, people obtain from natural systems.
EKC	Environmental Kuznets curve	An inverted U-shaped relationship between national deforestation and income.
FAO	Food and Agriculture Organisation	A specialised agency of the United Nations that leads international efforts to ensure global food security.
FBD	Forestry and Beekeeping Division	FBD is one of five divisions within the MNRT and has overall responsibility for the management of the forestry and beekeeping sectors on mainland Tanzania.
FCPF	Forest Carbon Partnership Facility	A global facility funded by the World Bank, aiming to help LEDC build capacity for REDD+.
	Forest Transition	A theory describing to change in a nations forest cover over time, predicting that patterns shift from deforestation trends to those of

		forest establishment.
FRA	Global Forest Resources Assessment	Regular global assessments performed by the FAO, aiming to describe the world's forests and how they are changing.
	Forest	A continuous stand of trees some of which attain a height of 50m. Forests have three general strata; a regenerative sub canopy layer, a main canopy, and occasional emergent trees extending above the main canopy. Forests are further characterised by the frequent occurrence of lianas and epiphytes, and by the rare occurrence of fire.
	Forest establishment	The combined effects of afforestation, reforestation and/or regeneration.
GHG	Greenhouse gas	An atmospheric gas that absorbs and emits thermal infrared radiation.
GIS	Geographic information systems	Systems designed to spatially analyse geographic data.
	Grassland	A community dominated by herbaceous plants, where exposure and/or edaphic conditions do not allow much development of woody plant types
HRBM	High Resolution Biosphere Model	A process based ecosystem model.
HYDE	History Database of the Global Environment	A model predicting historical LCC between 1700 and 2000.
IBIS	Integrated Biosphere Simulator	A process based ecosystem model.
IPCC	Intergovernmental Panel on Climate Change	The leading international body for the assessment of climate change.
IRSS	Indian Remote Sensing Satellite	The IRSS detects a range of spatial resolutions (5.8m to 56m) with visible and near infrared spectra detected at high resolutions and short wave spectra being added to lower resolution data.
IUCN	International Union for Conservation of Nature	A leading authority on the environment and sustainable development.
KITE	York Institute for Tropical Ecosystems	A Marie-Curie Excellence Centre, whose research focuses on East Africa.
	Land cover	The observed physical and biological cover of the Earth's land as vegetation or man-made features.
	Land use	The total of arrangements, activities and inputs undertaken in a certain land cover type (set human actions).
LCC	Land use/cover change	Shifts from one land use/cover to another

	Leakage	The spatial or temporal shifting of deforestation or forest and woodland degradation processes.
LEDC	Less economically developed countries	A country with low levels of economic development.
	Litter carbon	All non-living organic carbon with a size greater than the limit for soil organic matter (suggested 2 mm) and less than the minimum diameter chosen for dead wood (e.g. 10 cm), in various states of decomposition above or within the mineral or organic soil. Live fine roots above the mineral or organic soil (of less than the minimum diameter limit chosen for below-ground biomass) are included in litter where they cannot be distinguished.
LPJ	Lund-Potsdam-Jena Dynamic Global Vegetation Model	A process based ecosystem model.
MAT	Mean annual temperature	The mean temperature experienced by a region over a set time period.
MSS	Multispectral Scanner System	A scanner on the Landsat satellite capable of delivering data from four spectral bands (two in visible light and two in near infrared) at a spatial resolution of 80m.
MNRT	Ministry of Natural Resources and Tourism	A ministry within the Tanzanian government focused on formulating policies and strategies that would lead to sustainable conservation, whilst also contributing to national income.
NAFORMA	National Forestry Resources Monitoring and Assessment	A multi-stakeholder project aimed at performing the first ever comprehensive national forest inventory in Tanzania.
NDVI	Normalised Difference Vegetation Index	A graphical system that indicates vegetation levels.
NFI	National Forest Inventory	The systematic collection of forest information throughout a nation.
NGO	Non-governmental organisation	An organisation that operates independently from any form of government.
NKMCAP	The Noel Kempff Mercado Climate Action Project	The first REDD+ style project, developed as a result of a joint partnership between the Bolivian government, Fundación Amigos de la Naturaleza (Friends of Nature Foundation), the Nature Conservancy, American Electric Power, British Petroleum Amoco and PacificCorp.
NTFP	Non-timber forest products	Any commodity obtained from forests and woodlands that does not involve the destructive harvesting of trees.
PC	Principal components	The variables that can be used to explain a greater set of linearly uncorrelated variables.

PES	Payments for ecosystem services	The practice of offering incentives in exchange for the maintenance or enhancement of ecosystem services.
	Population pressure	The pressure on forest and woodland resources, resulting in degradation, when all persons in the landscape (not just those living locally) have been accounted for.
	Protected area	An area of land and/or sea especially dedicated to the protection and maintenance of biological diversity, and of natural and associated cultural resources, and managed through legal or other effect means.
REDD+	Reducing Emissions from Deforestation and Forest degradation	Reducing Emissions from Deforestation and Forest Degradation' (REDD) whilst safeguarding biodiversity, protecting vulnerable social groups and providing compensation for opportunity costs in a just and transparent manner.
	Reference levels	Modified baselines, reflecting emission responsibilities, benefits and costs, and can be altered over time as countries' circumstances change such that they are able to bear greater responsibility for climate mitigation.
	Reforestation	The conversion of non-forested land into forested land (through planting, seeding and/or the human-induced promotion of natural seed sources) on land that was previously forests within the last 50 years.
	Regeneration	The natural regeneration of forest on land that was previously non-forest. This process is not human induced, often occurring via succession.
RPIN	Readiness Plan Idea Note	A plan required for submission before a nation can gain assistance from FCPF
SAGE	Centre for Sustainability and Global Environment	A model predicting historical LCC between 1700 and 2000.
SAR	Synthetic aperture radar	An active sensor, transmitting pulses of polarised microwaves to the ground, and receiving the reflected radiation
	Soil carbon	Includes organic carbon in mineral soils to a specified depth chosen by the country. Live and dead fine roots and dead organic matter within the soil, that are less than the minimum diameter limit specified (suggested 2 mm), are included with soil organic matter where they cannot be distinguished.
	Soil fertility	The eCEC of the soil, once the presence of aluminium ions has been controlled for.
TAFORI	Tanzanian Forestry Research Institute	The national institution within Tanzania that is tasked with forestry research

TEM	Terrestrial Ecosystem Model	A process based ecosystem model.
	Tier 1	In Tier 1 methods, the carbon flux resulting from LCC is calculated using the difference between the carbon stock of the two land covers (as estimated using global default values).
	Tier 2	A Tier 2 approach is similar to that of Tier 1 but involves country- or region-specific carbon stock estimates and/or stock change factors.
	Tier 3	Tier 3 approaches are the highest order methods, and require the use of models and inventories tailored specifically to national circumstances and repeated over time.
TM	Thematic Mapper	A scanner on the Landsat satellite designed to investigate vegetation type, soil moisture and other key landscape features.
UNDP	United Nations Development Program	The United Nations global development network that provides expert advice and support to LEDC.
UNEP	United Nations Environment Programme	An international institution that coordinates the environmental activities of the United Nations, particularly assisting LEDC in implementing environmental policies.
UNFCCC	United Nations Framework Convention on Climate Change	The United Nations secretariat charged with supporting decisions taken at the COP.
VtA	Valuing the Arc	An international collaborative research programme focused on valuing the ecosystem services provided by the forests of the EAM.
	World Bank	An international financial institution that provides loans for LEDC.
	Woodland	An assemblage of trees with canopy covers ranging from 20% to 80%, although, on rare occasions, canopy closure may be attained. Stature is generally in the range of 5m to 20m, but contains only two main strata; a herbaceous ground layer, and the main canopy. Many woodland areas burn on an annual or biennial basis.
WSG	Wood specific gravity	The density of wood relative to the density of water.

Chapter 1
Introduction

1.1 Rationale

Human-induced climatic changes caused by the release of greenhouse gases, such as carbon dioxide, are predicted to cause significant environmental damage at a high economic cost (Stern and Treasury, 2007) and threatens to reduce human wellbeing including via food security (Godfray et al., 2010). Thus, such emissions are currently an area of concern for decision-makers – ranging from governments to individuals (Balmford et al., 2002). Whilst sources of greenhouse gas (GHG) emissions are varied, ranging from land cover change to fossil fuel burning, anthropogenic destruction of tropical forests (responsible for between 10% and 28% of global carbon dioxide emissions (Achard et al., 2004, IPCC, 2007, Gullison et al., 2007, van der Werf et al., 2009, Pan et al., 2011, Harris et al., 2012)) have received particular attention. For example, the Kyoto Protocol set targets for the reduction of GHG emissions from more economically developed countries and includes the “Clean Development Mechanism”, by which these countries can implement emission reduction projects (e.g. limiting forestry activities or increasing forest area, in order to reduce carbon dioxide pollution against a ‘no action’ baseline) in developing countries in return for certified emission reduction credits (UN, 1998).

Recently, broad agreements within the United Nations Framework Convention on Climate Change (UNFCCC) were reached to implement a scheme titled ‘Reducing Emissions from Deforestation and Forest Degradation’ (REDD) as a means to encourage the reduction of these emissions. REDD was later expanded the to include the sustainable management of forests and the conservation and enhancement of forest carbon stocks, termed REDD+ (Burgess et al., 2010). Since tropical regions emitted 0.69-1.52 Pg C yr^{-1} between 1990 and 1999 (Achard et al., 2002, DeFries et al., 2002, Houghton, 2008) and 0.68-1.47 Pg C yr^{-1} between 2000 and 2005 (Houghton, 2008, van der Werf et al., 2009, Hansen et al., 2008b), REDD+ schemes have the potential to make a substantial contribution to reducing the impacts of climate change.

The REDD+ programme is aimed at contributing to reductions in carbon dioxide emissions whilst providing economic incentives for better management and protection of forests. This policy has been widely acclaimed as it is suspected that the financial incentive will be enough to have a dramatic effect. For example, at carbon prices of US\$10 t^{-1} C it is estimated that carbon rental values for standing forest would be US\$85-US\$252 ha^{-1} yr^{-1} (Kindermann et al., 2008) and that over US\$43 billion could be made available to developing countries through REDD+ (Roe et al., 2007). The effect of this could be dramatic. According to some models, annual payments of only US\$20 billion may be able to reduce global emissions from deforestation by 90% (equivalent to 3.2-6.4 Pg C), four to eight times the annual target of the Kyoto Protocol (Strassburg et al., 2009).

The potential for REDD+ to reduce GHG emissions is clearly evident. However, there are several specific issues to overcome before successfully implementing such a programme. These are establishing long-term funding sources, developing robust monitoring systems, preventing leakage and estimating accurate historical baselines, all the while ensuring an increase in social wellbeing. This thesis seeks to address two scientific issues related to REDD+ and its implementation: estimating long-term historical carbon emissions, and robust mapping of contemporary carbon storage.

The development of baseline scenarios is necessary in order to monitor reduced emissions from activities such as REDD+. To show an emissions reduction, it must be demonstrated that carbon expected to be emitted to the atmosphere was retained. Hence, emission reduction schemes require the development of future projections of emission pathways without any mitigation measures, termed baseline scenarios (GOFC-GOLD, 2010). It is likely that, under REDD+, realised emissions will be compared to these baseline scenarios to evaluate country performance and allocate payments. In the tropics, analysis is normally limited to a period of a few decades, as determined by the availability of remotely sensed data (Lambin, 1997). Remotely sensed data are often used to create linear baselines describing business-as-usual land use/cover changes. However, linear approaches are over simplified and resulting in high uncertainties, both over- and under-estimating expected emissions (Umemiya et al., 2010). I use historical maps to estimate land use/cover changes across the watershed of the Tanzanian Eastern Arc Mountains (EAM; a 34 million hectare area of East Africa) beyond the satellite era, substantially increasing the available data. As a result of increased data availability and an expanded time-span, non-linear baselines, based on the forest transition model (Mather, 1992), can be created, which show significantly lower uncertainties (Umemiya et al., 2010). Non-linear deforestation baselines have not previously been estimated for Tanzania, and thus their development represents a substantial advancement in land change science for the region.

Whilst the development of land use/cover change baselines is a substantial step towards being able to monitor historical GHG emissions, methods of applying carbon values to land use/cover types are also required. Typically, most developing country governments rely on contemporary global default values to estimate the carbon stored within land use/cover types, commonly via IPCC Tier 1 carbon estimates. However, Tier 1 estimates are highly uncertain and thus can be substantially improved, and uncertainty reduced, through the development of country-specific (Tier 2) carbon estimates, particularly those developed using regression equations to describe spatial variation within land use/cover types (Tier 3) (GOFC-GOLD, 2010). However, many developing countries lack the data required for Tier 2 and Tier 3 methods and so are unable to benefit from the reduced uncertainty associated with such approached. To support such nations, I develop a seven-stage method by which Tier 2-type carbon estimates can be produced in data-deficient regions. Using this seven-stage method could substantially improve the REDD+ reporting of those nations currently using a Tier 1 approach. I then follow this seven-stage method for the EAM, producing the first Tier 2-type carbon estimate for the EAM watershed. I further improve this seven-stage method by investigating the spatial patterns of both carbon storage and carbon sequestration in EAM for the present day. I focus on identifying the influential variables that correlate with carbon storage, including anthropogenic (e.g. distance from markets), climatic (e.g. mean annual air temperature) and edaphic (e.g. soil fertility) factors. To ensure the above methods fit the requirements for governmental needs, the maps I produce are of sufficient resolution to be useful for decision-makers and can be combined with scenarios to estimate future service provision and the effect of various policies. In addition, I critically compare the carbon estimates resulting from the methods developed here with previous estimates to evaluate the added benefit derived from such advancements in REDD+ reporting. Finally, due to a lack of historical carbon values, I apply these contemporary carbon estimates to the land use/cover change estimates developed above, indicating the carbon emissions that resulted from land cover change in the twentieth century. The combination of historical land use/cover change patterns with country-relevant carbon estimates could substantially reduce the uncertainty in the REDD+ reports of many developing nations.

In summary, this thesis investigates the past and current provision of carbon storage in the EAM, providing methods, techniques and results useful for REDD+ reporting. I provide detailed data on historical conditions, furthering scientific knowledge of how tropical land covers have changed over long-term time scales. I develop a method by which data-deficient countries globally may use to improve their carbon estimates. Finally, I identify influential variables of carbon storage, providing indications into which mechanisms influence the spatial distribution of this ecosystem service in the present day. By providing practical outcomes, I hope that this thesis can assist country governments in improving REDD+ monitoring and reporting in time for consideration during the REDD+ negotiation process.

1.2 Tropical Forests and Woodlands

This thesis concerns ecosystems over 34 million ha of Tanzania (see Section 1.6), therefore I will briefly review these systems, placing them in a pan-tropical context to emphasise the similarities and differences between my study site and other developing nations.

1.2.1 Definitions

Tropical tree-dominated ecosystems are globally significant; containing ~45% of all carbon in terrestrial vegetation (IPCC, 2000), as well as high biodiversity (Myers et al., 2000). They also provide ecosystem services (such as timber provision, non-timber forest product provision (Timko et al., 2010), and mitigate climate change (Lewis et al., 2009b, Phillips et al., 1998)). Despite their recognised importance, a globally agreed definition of forests is lacking (Putz and Redford, 2010). A commonly used definition is that of the Food and Agriculture Organisation (FAO), which states that forest is land, over 0.5ha, with a tree crown cover of over 10 percent and trees that (when mature) reach over 5m in height (FAO, 2000a) (Figure 1.1). A forest is considered to be tropical if it lies between the tropics of Cancer and Capricorn ($23^{o}26'16''$N and $23^{o}26'16''$S respectively). Using this definition, tropical forests cover a substantial portion of the globe, accounting for ~50% of global forest area (Malhi and Grace, 2000, Pan et al., 2011).

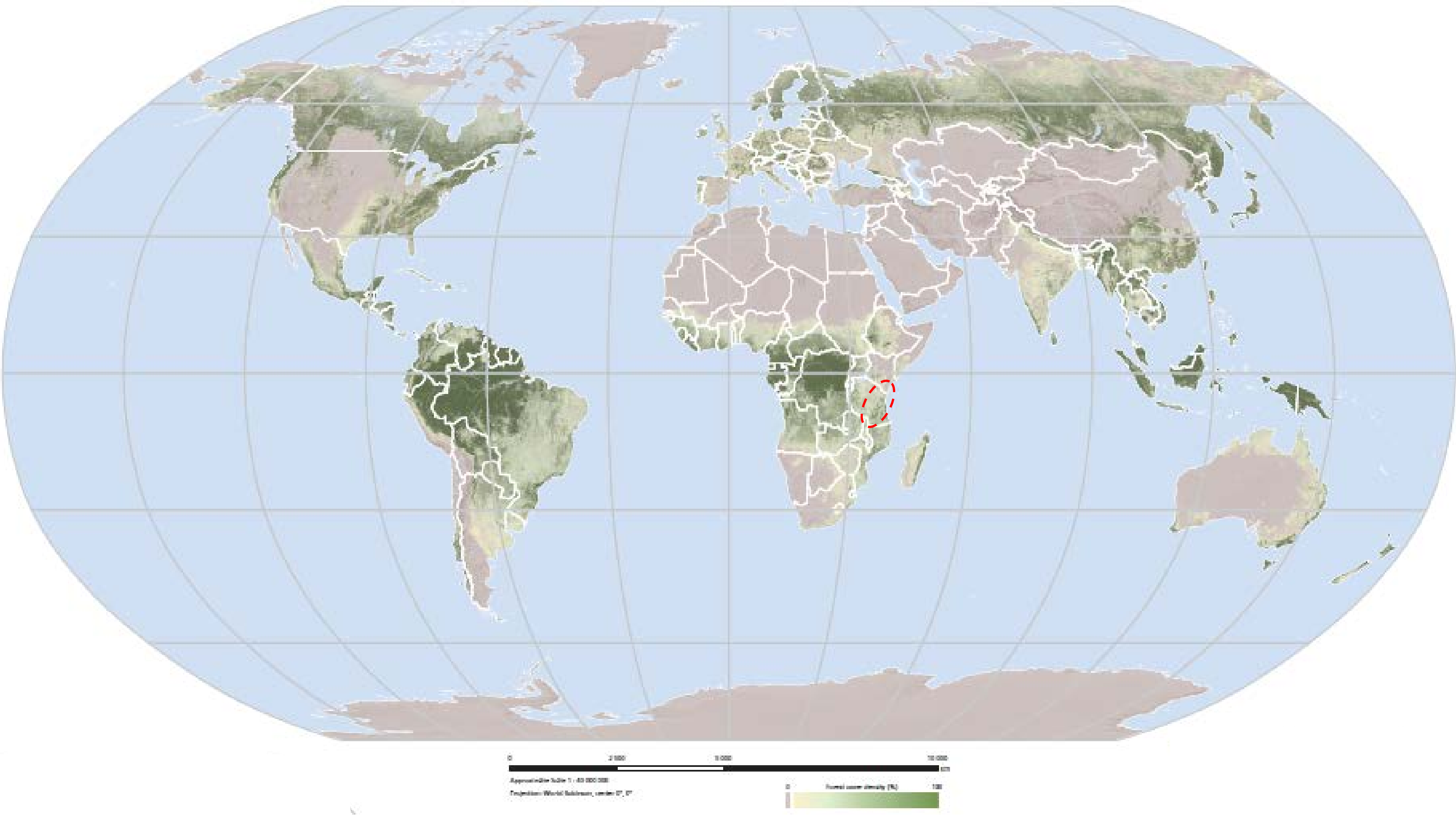


Figure 1.1 The distribution and canopy cover of the worlds' forests (FAO, 2010e). The dashed red oval indicates the study area.

Table 1.1 Definitions of land cover categories used throughout this thesis, derived from (HTSL, 1997).

Land cover category	Definition	Sub-category
Forest	A continuous stand of trees some of which attain a height of 50m. Species composition is quite different to that of woodland, being more similar to the extensive Guineo-Congolian forests (Lovett, 1993b). Canopy covers are almost entirely closed. Forest is typically found at altitude and so is subdivided by elevation. See Table 1.3 and Table 1.4	• Lowland forest (<1000m) • Submontane forest (1000-1500m) • Montane forest (1500-2000m) • Upper montane forest (>2000m) • Forest mosaic (<40% canopy cover)
Woodland (savanna)	An assemblage of trees with canopy cover ranging from 20% to 80% but, on rare occasions, canopy may be entirely closed. Woodland is subdivided into closed woodland and open woodland at a threshold of 40% canopy cover. Generally trees are between 5 and 20m in height, beneath which grasses are often abundant.	• Closed woodland (>40% canopy cover) • Open woodland (<40% canopy cover)
Bushland	Bushland is typically between 1m and 3m tall, rarely exceeding 5m. Bushland is predominantly comprised of plants that are multi-stemmed from a single root base.	N/A
Grassland	A community dominated by herbaceous plants, where exposure and/or edaphic conditions do not allow much development of woody plant types.	N/A
Cropland	Areas converted to agriculture, including maize, wheat, vegetables, sugar cane, and tea.	N/A

Whilst the quantitative FAO definition provided above is widely used, it is exceedingly inclusive, including both closed canopy forests, and savannah-type systems composed of trees and grasses. Hence, numerous different vegetation system classifications have been proposed (Köppen, 1923, Holdridge, 1947). In this thesis, I adopt a biome-type approach to vegetation classification (Whittaker, 1975). Thus, ecological communities are defined via convergent similarities in structure, function and physiognomy (Whittaker, 1975, Haxeltine and Prentice, 1996, Woodward et al., 2004, Lomolino, 2010). This broadly has the effect of subdividing tropical forest (as defined by the FAO (FAO, 2000a)) into two distinct categories; forest and woodland (Table 1.1). Specifically, to be consistent with other studies in East Africa (HTSL, 1997), I adopted the definitions used by Greenway (1973). Thus, forest is defined as a continuous stand of trees some of which attain a height of 50m (Greenway, 1973). Forests can be considered to have three general strata; a regenerative sub canopy layer, a main canopy, and occasional emergent trees extending above the main canopy. Forests are further characterised by the frequent occurrence of lianas and epiphytes, and by the rare occurrence of fire. Woodland is defined as an assemblage of trees with canopy cover ranging from 20% to 80%, although, on rare occasions, canopy closure may be attained (HTSL, 1997). Stature is generally in the range of 5m to 20m, but contains only two main strata; a herbaceous ground layer, and the main canopy. Many woodland areas burn on an annual or biennial basis. Species composition in forest and woodland is quite difference, except perhaps in forest areas of high disturbance (Gentry, 1992, Prance, 1994).

Altitude is known to be important in determining forest structure and physiognomy. Many ecophysical conditions are correlated with elevation (for example; temperature, precipitation and soil depth), and so as elevation increases there may be a direction change in the constraints experienced by plant communities (Girardin et al., 2010, Whitmore, 1998, Lovett, 1993a). Thus, I further subdivide forest by elevation into four categories; lowland forest (<1000m), sub-montane forest (1000-1500m), montane forest (1500-2000m), upper montane forest (>2000m). In areas of high disturbance, again ecophysical constraints significantly vary (Laurance, 2004). If the canopy cover of a forest falls below 40% I term it forest mosaic. A parallel division occurs in woodland, being divided into open and closed woodland at a 40% canopy cover threshold. I adopted these definitions to be consistent with the land cover map (dated 1995) considered to be the best current representation of Tanzanian land use by Tanzanian stakeholders (HTSL, 1997).

1.2.2 Biogeographic Characteristics

Whilst both tropical forests and woodlands across the globe show substantial convergence in structure, function and physiognomy, tectonic shifts, coupled with limited plant dispersal, have resulted in regionally distinct evolutionary pathways. Angiosperm vegetation is thought to have become the dominant terrestrial vegetation, much like in the present day tropics, between 90 and 100 million years before present, coinciding with the separation of Gondwana (Davis et al., 2005, Burnham and Johnson, 2004). Thus, the three main regions supporting present day tropical forests and woodlands (Amazonia, Africa and Asia) have been largely reproductively isolated for a substantial period of geological time, allowing for the independent evolution of distinct lineages (Corlett and Primack, 2006, Corlett, 2007, Donoghue, 2008), although some long-distance genetic exchange is apparent, e.g. *Ceiba pentandra* shows low levels of genetic exchange between the Neotropics and West Africa (Dick et al., 2007).

Despite up to 100 million years of separation, modern tropical vegetation show striking similarities (Ricklefs and Renner, 2012). The familial composition of global tropical forest and woodland assemblages shows remarkable consistency, with Annonaceae, Euphorbiaceae, Fabaceae, Lauraceae, Meliaceae, Moraceae, Mysristicaceae, Rubiaceae and Sapotaceae all commonly found in the three main tropical regions (Gentry, 1988). Families found in woodland tend to be the same as those found in forest, though species are usually different (Prance, 1994). As well as shared phylogenies, tropical forests show remarkably similar structural traits. Stems typically show large buttress, with particularly thin bark (usually smooth, but sometimes with spines to deter herbivores) and large drip-tipped leaves (Table 1.2). By contrast, across the tropics, woodland typically holds ~50% of the plant biodiversity of forests (Gentry, 1988). However, there is high uncertainty in this estimation. For example, the woodlands found in subtropical Mexico are species rich when compared to woodlands of the inner tropics, and have a comparable level of diversity to forests in Brazil, Panama, Cameroon and Australia (Gentry, 1988). Additionally, tropical woodlands are, in general, made up of shorter trees, lacking buttresses but with thicker bark, a possible adaptation to fire (Midgley et al., 2010).

Table 1.2 Key physiognomic features of tropical forest types (Thomas and Baltzer, 2001).

Forest type	Canopy height	Emergent trees	Typical leaf size	Tree buttresses	Lianas	Vascular epiphytes	Non-vascular epiphytes
Lowland evergreen rain forest	25–45 m	Common	45–180 cm^2	Common	Common	Common	Occasional
Semi-evergreen rain forest	20–30 m	Common	45–180 cm^2	Common	Abundant	Occasional to common	Occasional
Dry deciduous forest	3–25 m*	Absent	2–180 cm^2	Occasional	Common to abundant	Absent to occasional	Absent to occasional
Lower montane forest	15–33 m	Occasional	45–180 cm^2	Occasional	Rare	Common	Occasional to common
Upper montane forest	3–18 m	Absent	2–20 cm^2	Absent	Absent	Common	Abundant
Heath forest	3–30 m*	Absent	20–45 cm^2	Occasional	Rare	Common	Occasional
Mangrove (mangal)	3–30 m*	Absent	45–180 cm^2	Prop roots and pneumatophores common	Rare	Occasional	Occasional
Freshwater swamp Forest	3–35 m*	Absent - comon	2–180 cm^2	Prop roots common	Common to abundant	Occasional to abundant	Common
Peat swamp forest	12–55 m*	Absent - common	2–180 cm^2	Prop roots common	Rare to abundant	Rare to abundant	Occasional to common

* Indicates forest formations generally characterized by gradients in canopy height and other physiognomic features.

Despite broad similarities in phylogeny and structure across continents, there are also notable differences. These are discussed below, with particular relevance given to differences in carbon storage, and potential variables causing this spatial variation (discussed in Section 2.3). In general, less information on the global comparison of woodland is available (Pennington et al., 2009).

Woodland biomes are much more varied than those of forests, showing wider variations in canopy cover, tree height, species composition and biomass (Pennington et al., 2009). As such, there are many regional differences between woodlands (see Section 2.3.1) but few cross-continental patterns (Hirota et al., 2011, Staver et al., 2011). Additionally, woodlands are generally heavily exploited by people but, with respect to flora, have been less intensively inventoried than forests. This, in combination with the numerous names applied to woodland, makes continental comparisons difficult (Pennington et al., 2009).

Despite the broad similarities discussed above, differences between each region have evolved in their 90-100 million year separation (Davis et al., 2005, Burnham and Johnson, 2004). Thus, each region is generally considered a unique biological entity. Here, I will discuss some of the unique characteristics of each region.

1.2.2.1 Amazonia

The single largest contiguous area of tropical forest in the world, stretching from the mouth of the Amazon River to the Andes Mountains, is the Amazon basin forests and those contiguous with it. In addition to the pan-tropical flora families, Bignoniaceae, Chrysoblananaceae, Lecythidaceae and Vochysiaceae are relatively common (Turner, 2001). There is an abundance of flowering shrubs in the forest understory, providing a plentiful source of nutrients for fauna (Gentry, 1982). Structurally, Amazonian forest trees are shorter than their other tropical counter parts, both overall and for a given diameter (Feldpausch et al., 2011, Banin et al., 2012).

The periphery of the Amazon region supports the majority of the world's woodland (Miles et al., 2006), which is particularly associated with nutrient poor soils (Richards, 1996). South American woodlands are extremely varied, found in both seasonal and ever-wet conditions. However, aseasonal woodland may be a relic from earlier climate periods, maintained by anthropogenic disturbance and fire (Eden, 1974, Sarmiento and Monasterio, 1975). The Fabaceae family is the most species rich family in nearly all areas of Amazonian woodland, with the exception of some northerly regions where Myrtaceae dominate (Holzman, 2008). Although there are woodland species endemic to this region, there are no endemic families and very few endemic genera (Holzman, 2008).

Recent estimates suggest that, overall, the Amazonian region stores 90-110 Pg C (Baccini et al., 2012), equivalent to between 104-137 Mg C ha^{-1} (Baccini et al., 2012, Friedlingstein et al., 2010, Le Quere et al., 2009), though this can be separated between forests (40-160 Mg C ha^{-1}) and woodland (33-104 Mg C ha^{-1}) (Brown and Lugo, 1984, Ruesch and Gibbs, 2008). Between 2000-2007, the area was a net sink of carbon, absorbing 0.42 Pg C yr^{-1}, despite 1.37 Pg C yr^{-1} being emitted due to deforestation (Pan et al., 2011).

1.2.2.2 Asia

Asian forests and woodlands occur across Borneo, Sumatra, Java and the Malay Peninsula. Despite the large expanses of sea between islands, the forests are relatively uniform. Asian forests are unique due to the majority of large stems and biomass being accounted for by just one family, the Dipterocarpaceae (Corlett, 2007). The understory is dominated by non-flowering juveniles of canopy trees, in stark contrast to Amazonian forest (Corlett, 2007, Corlett and Primack, 2006). Dipterocarp forests often have canopy heights exceeding 50m, higher than other areas of tropical forest (de Gouvenain and Silander, 2003, Banin et al., 2012), perhaps as result of lower wind speeds (Thomas, . 2004). As a result of the dominance of large Dipterocarps, Asian forests show higher basal areas, and therefore biomass, when compared with Amazonian forests (Brown, 1997, Paoli et al., 2008, Slik et al., 2010).

Rather uniquely, Dipterocarp forests undergo mass flowering events every 2-7years, thought to be triggered by low night-time temperatures (Yasuda et al., 1999, Numata et al., 2003), in which almost every large stem reproduces (van Schaik et al., 1993, Sakai et al., 1999, Sakai, 2002). The stochastic nature of the resultant mass fruiting events is thought to prevent the build-up of frugivorous fauna (Janzen, 1974, Kelly, 1994).

The woodlands of Asia predominantly support an understory of *Imperata cylindrica* (Richards, 1996). Unlike Amazonia, aseasonal woodland is absent, with most areas experiencing annual dry seasons, and often burning as a result (Streets et al., 2003). However, much like South America, the current distribution of woodland has been attributed to past climatic conditions, as their occurrence does not correlate well with modern environmental factors (Eden, 1974). Asian woodlands are relatively poor in climbing species, with the exception of palms and dipterocarps (Holzman, 2008). Dipterocarps, although present in Asian woodland as well as forest, are not dominant (Holzman, 2008). Typically, Euphorbiaceae, Sapindaceae, and Gesneriaceae are most abundant (Holzman, 2008).

The most recent estimates suggest that the entire Asian region stores between 40 and 50 Pg C (Baccini et al., 2012), equivalent to 66-160 Mg C ha^{-1} (Baccini et al., 2012, Friedlingstein et al., 2010, Le Quere et al., 2009). On average, forests hold 60-200 Mg C ha^{-1} and woodland 20-140 Mg C ha^{-1} (Brown and Lugo, 1984, Ruesch and Gibbs, 2008). Between 2000-2007, the area was a net sink of carbon, absorbing 0.12 Pg C yr^{-1}, despite 0.85 Pg C yr^{-1} being emitted due to deforestation (Pan et al., 2011).

1.2.2.3 Africa

The world's second largest block of tropical forest is centred on the Congo River basin. Tropical forest is found in east and West Africa, although these are not connected to the main forest block of the Congo (Martin, 1991, Lovett and Wasser, 2008, Bakarr et al., 1999). For example, the fragments of forest remaining in east Africa, mostly centred on mountains, are considered an Eastern outlier of the extensive Guineo-Congolian forests, but are thought to have been isolated for millions of years (Lovett, 1993b).

African tropical forests are species poor relative to Amazonian and Asian forests (Parmentier et al., 2007). This is thought to be due to African forests being drier than elsewhere (Parmentier et al., 2007), hence in inter-glacial periods when tropical regions were drier, most of the forest extent was lost, leading to high species extinction (Maley, 2001). Similar to Asian forests, large areas of African forests are dominated by a single tree species, particularly from the Fabaceae family (Hart, 1990, Newbery et al., 2000). Whilst this may reduce the diversity of insects present, larger herbivores, such as forest elephants, are known to play a vital role, both as a seed dispersal agent and a source of disturbance (White et al., 1993, Yumoto, 1999). In general, African forests tend to have lower tree densities than those of Asia and Amazonia, however forests tend to have a larger basal area (Gentry, 1988).

Africa contains the second largest total area of woodland of the three major tropical regions (Miles et al., 2006). African woodland is extremely heterogeneous, ranging from fully deciduous to evergreen stands. Overall, diversity is higher than that found in Amazonian woodland (Holzman, 2008). Common genera include *Acacia, Bachystegia, Adanosnia, Triplochiton, Milicia, Combretum and Isoberlinia* (Primack and Corlett, 2005). Within Africa, the forest and woodland maybe be separated by a particularly narrow boundary (<50m in places) of transitional woodland, including a mixture of fire-tender and fire-tolerant species in which *Anogeissus leiocarpus* is often particularly abundant (Hopkins, 1974).

The most recent estimates suggest that the African region stores 45-60 Pg C (Baccini et al., 2012), equivalent to between 66-92 Mg C ha^{-1} (Baccini et al., 2012, Friedlingstein et al., 2010, Le Quere et al., 2009). Forests and woodland, on average, store 50-240 Mg C ha^{-1} and 20-130 Mg C ha^{-1} respectively (Brown and Lugo, 1984, Ruesch and Gibbs, 2008). Between 2000-2007, the area was a net sink of carbon, absorbing 0.48 Pg C yr^{-1}, despite 0.59 Pg C yr^{-1} being emitted due to deforestation (Pan et al., 2011).

1.3 Deforestation and Degradation of Tropical Forests and Woodlands

Due to the numerous benefits acquired from tropical forests and woodlands, they have played a large role in human development. Thus, an interaction between people and forests goes back millennia, across the globe. Once people began to develop agriculture, cattle herding and metal production, the negative effects on forests and woodland were profound (Bechmann, 1990). For example, slash and burn agriculture dates back to over 3000 years BC (Williams, 2003). Slash and burn is an example of deforestation, which I define here as the conversion of forest and/or woodland into an alternative land cover (i.e. bushland, grassland or cropland). Deforestation may occur via natural processes (e.g. tree mortality and forest loss following an extreme drought) or by anthropogenic processes (e.g. slash and burn). Forests and woodlands may be further negatively affected without changes in land use/cover type, termed degradation. Both deforestation and forest degradation contribute substantially to GHG emissions and understanding the drivers of this process may important is REDD+ schemes are to succeed (Achard et al., 2004, IPCC, 2007, Gullison et al., 2007, van der Werf et al., 2009, Pan et al., 2011, Harris et al., 2012). Here, I critically evaluate the variables effecting both deforestation and forest degradation.

1.3.1 Deforestation

Due to the numerous benefits acquired from tropical forests and woodlands, they have played a large role in human development. Thus, an interaction between people and forests goes back millennia. Once people began to develop agriculture, cattle herding and metal production, the negative effects on forests and woodland were profound (Bechmann, 1990). For example, slash and burn agriculture dates back to over 3000 years BC (Williams, 2003). Slash and burn is an example of deforestation, which I define here as the conversion of forest and/or woodland into an alternative land cover (i.e. bushland, grassland or cropland). Deforestation may occur via natural processes (e.g. tree mortality and forest loss following an extreme drought) or by anthropogenic processes (e.g. slash and burn).

Historically, deforestation is considered a result of a local shift from nomadic hunter-gatherer lifestyles to sedentary agriculture (often resulting in an increasing population and so increasing demand for food and fuel). However, within tropical regions, the majority of land use/cover change (LCC) is considered to be relatively recent, having occurred within the last 100 years (Gower, 2003, Rudel et al., 2009, Fearnside, 2005). Tropical deforestation is estimated at ~13million ha year^{-1} between 2000 and 2010, a decrease on deforestation rates in the 1990s (Achard et al., 2002, FAO, 2010d, Asner et al., 2009b), although these estimates are highly uncertain, with century-long trends from data unclear (Grainger, 2008b, Watson et al., 2000) and scale-dependent (Pan et al., 2010, Gibson et al., 2000, Marceau, 1999, Hall et al., 1995). Thus, considering the uncertainty surrounding tropical deforestation rates, is it possible to determine what drives modern tropical deforestation?

Today, more distant anthropogenic and socioeconomic drivers, including population growth and global demand for tropical commodities, are becoming increasing important with regards to deforestation (Veldkamp and Lambin, 2001, Lambin et al., 2001, Mather and Needle, 2000, DeFries et al., 2010). Hence present day deforestation is driven by both proximate and underlying factors. Whilst, studies have attempted to identify the drivers of deforestation for several decades, the debate is yet to be resolved. Several studies focus on a single causal factor such as shifting cultivation (Myers, 1993, Ranjan and Upadhyay., 1999) and population growth (Ehrhardt-Martinez, 1998, Mather and Needle, 2000). However, when considering multiple causes, no consistent set of proximate and underlying drivers is observed (Mather et al., 1998, Angelsen and Kaimowitz, 1999).

Recent studies identify agricultural expansion as, by far, the leading cause of deforestation, contributing in 96% of cases of 142 sub-national case studies (Geist and Lambin, 2002). For example, in the 1980s and 1990s, tropical forest and woodland was the primary source of new agricultural land (Gibbs et al., 2010). However, this process can be broken down into several actions that need not necessarily share motivations. For example, forest can be converted for permanent cropping, cattle ranching, shifting cultivation, and/or colonisation agriculture (Geist and Lambin, 2002), each with a distinct combination of proximate and underlying drivers.

Deforestation has also been shown to occur closer to major settlements (Southworth and Tucker, 2001) but some have indicated that this relationship is non-linear (Mertens and Lambin, 1999). Within east Africa, population pressure is known to be correlated with deforestation (Lung and Schaab, 2010). Areas with high population density exhibit higher levels of demand on local resources and also possess the availability of labour required to cause substantial deforestation. However, this pattern can be complicated by the interaction of rural and urban populations (Laurance et al., 2002). Other causes of deforestation include infrastructure extension, wood extraction, extreme climatic events and extreme social events (e.g. war) (Geist and Lambin, 2002).

In most cases, proximate causes of deforestation are themselves driven by a combination of underlying factors (Figure 1.2). These include economic factors (such as commercial logging), institutional factors (for example, specific policies aimed to encourage colonisation of forest), technological factors (e.g. agricultural intensification may reduce the need for LCC), and demographic factors (such as migration) (Geist and Lambin, 2002). Thus, policies aimed to reduce deforestation will likely fail unless these underlying causes are addressed (DeFries et al., 2010).

Although the drivers of deforestation are debated, consensus is that anthropogenic LCC results in a substantial carbon emission (van der Werf et al., 2009, DeFries et al., 2002, Pan et al., 2011). Thus, in order to preserve the forests as a valuable biodiversity and timber resource as well as slow climate change, legally protected areas are created to stop/slow LCC. However, in many localities across the world, protected status is mostly administrative, without patrols or guards (often referred to as ‘paper parks’). The creation of ‘paper parks’ often does little to deter local deforestation and nothing to stem the underlying drivers (Wyman and Stein, 2010, Lung and Schaab, 2010, Hayes, 2006). Thus, in some areas, legally protected areas are ineffective in slowing deforestation rates. If REDD+ is to be more successful than current protected areas at slowing deforestation, it is vital to address both the proximate and underlying factors. Thus, success, in part, rests on robust scientific information on the rates of LCC in tropical regions and how they change over time. However, quantitative data on where, when and why LCC occurs are typically incomplete and/or unreliable (Meyer and Turner, 1992, Ramankutty et al., 2007, Grainger, 2008b) and the impacts of spatial scale on analyses add further complications and uncertainty (Pan et al., 2010, Gibson et al., 2000, Marceau, 1999). Fundamentally, consistent monitoring of levels of deforestation has been difficult as the definition of forest is in near constant flux (Putz and Redford, 2010). Additionally, there is a distinct lack of data. Prior to satellite imagery, historical records in the tropics are rare (Lambin, 1997), so past deforestation rates are very uncertain, particularly for low latitude regions of the world. In this thesis, I seek to address this for eastern Tanzania, providing an estimate of deforestation rates over the last century.

1.3.2 Degradation

Deforestation can occur as one sole action, leading to a dramatic change in land cover. However, it could also occur gradually, with forests and woodland being slowly degraded over time until LCC is achieved. Up until the point at which the land cover exceeds the respective definitions of forest and woodland, this change would not be recorded as deforestation (Putz and Redford, 2010), but is instead termed degradation. Specifically, degradation is the ‘temporary or permanent deterioration [of natural or anthropogenic origin] in the density or structure of vegetation cover or its species composition’ (Grainger, 2009). This process is most commonly a result of human actions but covers a range of activities, from selective logging and short rotation shifting cultivation to over-hunting and pollution, but is thought to have already impacted up to one-third of today’s tropical forest (Johns, 1997, Asner et al., 2005). However, forest degradation receives less attention than deforestation, in part, as it is substantially harder to monitor (Lambin, 1999).

A major difficulty when investigating anthropogenic degradation is the inherent variability of tropical biomes. Unless the result of direct experiment, the spatial and temporal effect of environmental variables driving differences in forest and woodland characteristics need to be accounted for before any human impact can be inferred. Despite these difficulties, several key

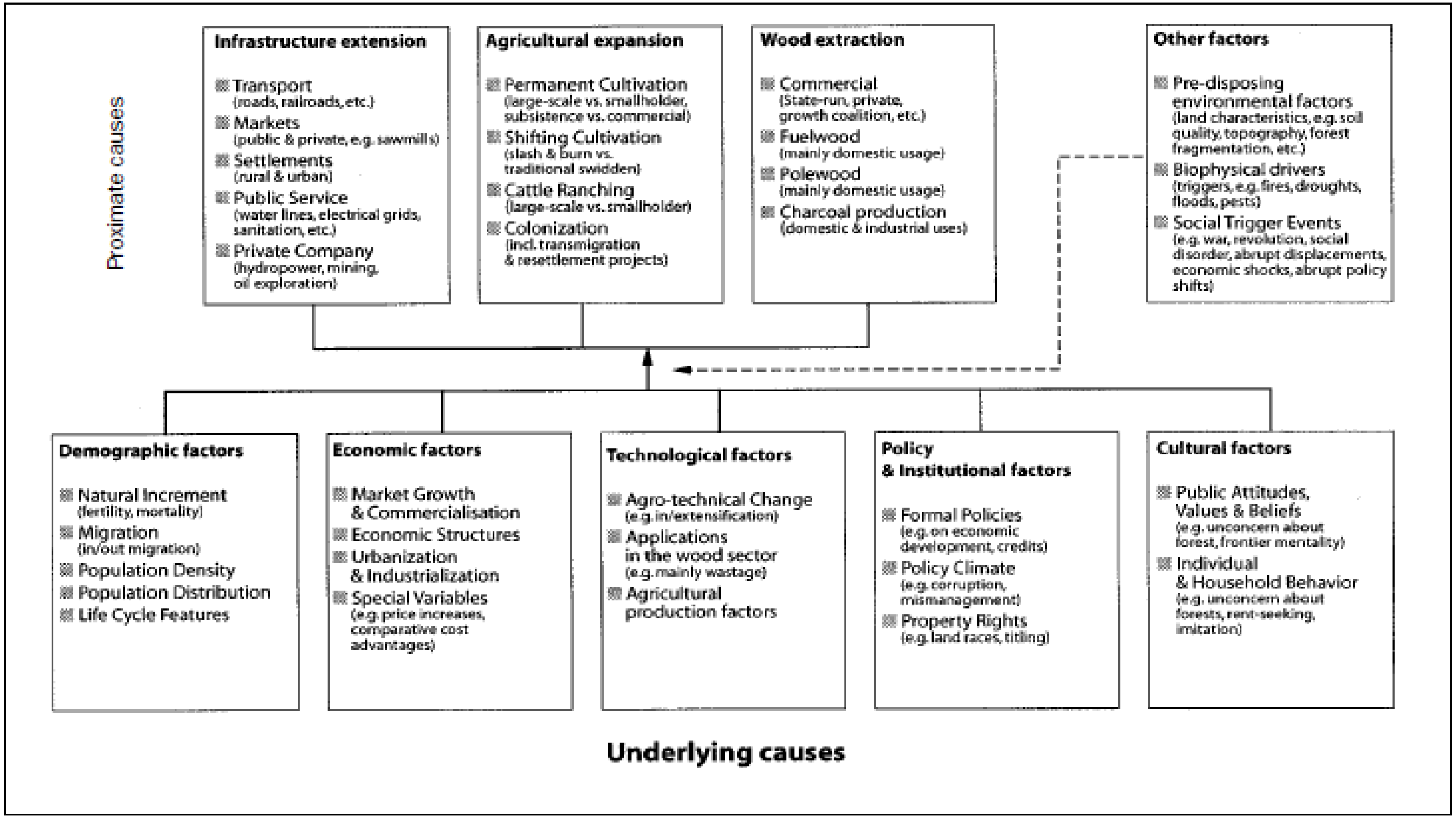


Figure 1.2 The local and underlying causes of deforestation (Geist and Lambin, 2002).

processes resulting in anthropogenic degradation have been identified across the tropics and will be discussed here.

Although natural processes, such as lightning, can ignite tropical woodlands (and, more rarely, forests), the vast majority of fires are of anthropogenic origin (Guyette et al., 2002). Across the globe, many pastoral societies use burning as a means to encourage re-growth in woodland areas, increasing the quantity and quality of grazing available (Hough, 1993). When well-managed, this process can be both highly successful and sustainable but, if burns occur too frequently or surpass a threshold of intensity, lands can be degraded over time (Cochrane, 2001). Once degradation has begun, the system is more vulnerable to burning, resulting in positive feedback loops due to increasing fuel loads, shifting the biome from one stable state (forest/woodland) to another more tolerant of high burn frequencies (e.g. grassland) (Cochrane et al., 1999, Nepstad et al., 1999).

A further process of degradation is that of over-grazing. Much like the previous example, the grazing of animals has the potential to be sustainable if population densities do not exceed the carrying capacity of the land. If the density of animals becomes too great, vegetation growth is unable to keep pace with the rate at which it is consumed, resulting in a direct decrease in vegetation cover (Oba et al., 2000). In addition, soil compaction and the increased proportional abundance of unpalatable species may prevent the area recovering, even if grazing is ceased (Drewry et al., 2008).

In tropical regions, the major source of energy for cooking is derived from tropical forests and woodlands (Heltberg, 2004). This make take the form of charcoal production or fuelwood collection and, though sustainable in small quantities, can result in severe degradation (Leach and Mearns, 2009). Interestingly, the effects of fuelwood collection interact with the impacts of grazing. Once fuelwood begins to become scarce, populations shift from collecting fuelwood and often switch to animal manure as an alternative. This, in turn, implies less manure is available to replenish soil nutrients and so further increases soil degradation (Duraiappah, 1998).

The final degradation process I will discuss is that of selective logging, a protocol conceived in order to enable the valuable timber resource to be extracted whilst retaining the biome as a whole as well as its associated ecosystem services (Putz et al., 2008a, Putz et al., 2008b). In the Amazon, it is estimated that the removal of only 8 Mg C ha^{-1} of roundwood timber is accompanied by a loss of 34-50 Mg C ha^{-1} due to damage during the harvesting process (Asner et al., 2005). Although efforts to ensure selective logging only occurs at sustainable rates are in place, an increase in fuel load often results, potentially providing the opportunity for further degradation to occur if ignited.

In general, degradation can be considered a precursor to deforestation as prolonged periods of degradation may eventually result in LCC and thus a deforestation event. Thus, it has been suggested that the factors driving forest degradation are similar to those driving deforestation (Section 1.3.1) (Ringrose et al., 1990, Lambin et al., 2003, Freitas et al., 2010). Like deforestation, the process can be need-driven, whereby the local populations utilise forests resources to address their immediate needs and this disturbance degrades the forest over time, or profit-driven. If degradation is profit-driven then economic theory can be used to describe the patterns and processes (von Thünen et al., 1966). The most accessible, valuable resources are first extracted. As supplies dwindle, less valuable (but still profitable) resources are extracted from the most accessible site and the search for the most valuable resources may move on elsewhere. This can be seen in ecosystems as waves of degradation from major demand centres (Ahrends et al., 2010).

Although understanding the drivers and extent of degradation is somewhat limited, attempts to quantify its effects have occurred. The latest FAO deforestation estimates, covering the period between 2000 and 2010, do not contain any estimates of rates of degradation. However, estimates of degradation have been made for previous periods. Between 1990 and 1997, 2.3 ± 0.7 million hectares of forest were visibly degraded, with 47% occurring in Asia and 36% and 17% occurring in Amazonia and Africa respectively (Achard et al., 2002). Current estimates suggest that carbon emissions as a result of degradation are about 25-47% of those estimated for deforestation (Asner et al., 2005, Asner et al., 2010). Thus, current carbon emission as a result of degradation are estimated at ~0.5 Pg C yr^{-1} (Putz et al., 2008b), approximately half that absorbed by current tropical regrowth (Pan et al., 2011).

Hence, the impacts resulting from degradation are substantial. However, most on-going REDD+ research and discussions focus on deforestation whilst mostly disregarding the effects of degradation (Gullison et al., 2007, da Fonseca et al., 2007). Since degradation is often a precursor to deforestation, this disregard is shortsighted (Asner et al., 2005, Nepstad et al., 1999). An increased focus on estimating the carbon emissions from degradation and understanding the proximate and underlying drivers of such changes is vital to decrease the uncertainty surrounding REDD+ emission estimates.

1.4 The Reducing Emissions from Deforestation and Degradation Scheme

Recent decades have seen an increase in the concern over the impacts of GHG emissions, partly as a result of deforestation and forest degradation, on human society, ecosystems and their species via climatic changes (Wigley et al., 1980, Lashof and Ahuja, 1990, Meinshausen et al., 2009). However, reducing GHG emissions is politically difficult because these gases are well mixed globally in the atmosphere, thus there is a ‘free rider’ problem. If one country increases its emissions, this could be enough to offset reductions by other countries. Hence, some agreement across all or most countries is likely to be necessary to reduce emissions significantly. Such agreements are even more difficult given the countries with the largest GHG emissions are not necessarily those that are being worst impacted by climate change and so the political will of high emission countries may be lacking. In fact, the developed, high-emission nations are perhaps best prepared to face the problems associated with climate change, whilst developing nations (especially those that are low-lying), who’s emissions are relatively low, may be unable to meet these challenges (Botzen et al., 2008). Here, I describe the history of the global negotiations of REDD+ schemes, focussing on the key issues of limited capacity, baseline scenarios and leakage.

1.4.1 History of UNFCCC Negotiations

Many consider that the seeds of REDD+ were planted in the Kyoto Protocol, December 1997 (Figure 1.3). As previously described, the Kyoto Protocol sets GHG emissions reduction targets for more economically developed countries. Article 2 of the Kyoto Protocol states that each developed country (termed Annex 1) should initiate “Clean Development Mechanisms” (CDM), by which these countries can implement emission reduction projects (ensuring the ‘protection and enhancement of sinks and reservoirs of GHGs, promotion of sustainable forest management practices, afforestation and reforestation’) in developing countries in return for certified emission reduction credits (UN, 1998).

Whilst the Kyoto Protocol was a key development in the pathway to global REDD+ negotiations, some local REDD+ projects precede it. The Noel Kempff Mercado Climate Action Project (NKMCAP) is regarded as the first REDD+ style project. NKMCAP is located in north-east Bolivia, around Noel Kempff Mercado National Park, and developed as a result of a joint partnership between the Bolivian government, Fundación Amigos de la Naturaleza (Friends of Nature Foundation), the Nature Conservancy, American Electric Power, British Petroleum Amoco and PacificCorp. These governmental, non-governmental and private organisations united to protect nearly 4 million ha of in return for carbon credits. Between 1997 and 2005, the project avoided more than 1Tg of CO_2 emissions (Virgilio et al., 2009).

Figure 1.3 A timeline of key negotiations on the route to REDD+.

However, the ratification of the Kyoto Protocol and the early success of CDM did not lead to rapid development of global REDD+ legislation. In August 2001, REDD+ negotiations took a backwards step as the Marrakesh Accords from the Conference of Parties (COP) 7 to the United Nations Framework Convention on Climate Change (UNFCCC) ruled that only afforestation and reforestation activities could generate eligible credits for trading under the CDM (UNFCCC, 2001). Thus, reduced emissions as a result of avoided deforestation or forest degradation were not eligible as carbon offset activities. It has been suggested that the inability to monitor leakage (reducing deforestation and/or degradation in one area only for it to increase in another; see Section 1.4.4) was a major driver of this decision (Pirard, 2008).

REDD+ negotiations continued, and substantial progress was made in 2005. In February, the European Commission published a policy paper entitled ‘Winning the battle against global climate change’ (EU, 2005). This communication provided a strong call for the world’s nations to initiate a scheme by which developing countries could be included in international emission reduction activities through and incentive-based mechanism that would help to halt deforestation. By May, the Coalition for Rainforest Nations, led by Papua New Guinea, had formed (Holloway and Giandomenico, 2009). This coalition aimed to fully couple forest stewardship and economic developing, uniting tropical countries to provide a stronger voice during global negations. As a result of the Bali Action Plan, the Coalition for Rainforest Nations, via the governments of Papua New Guinea and Costa Rica, requested ‘reducing emissions from deforestation in developing countries’ (RED) be included on the agenda for COP11 due to take place in November (UNFCCC, 2005). Citing the Kyoto Protocol, these nations re-emphasised the need to protect existing forests and called upon the UNFCCC to consider deforestation in developing countries (Holloway and Giandomenico, 2009). After deliberations, it was agreed that developing countries should be encouraged to reduce emissions from deforestation and appropriate methodologies and capacity should be developed to support this. The Subsidiary Body for Scientific and Technological Advise (SBSTA) was assigned the task of resolving the methodological issues necessary for successful monitoring of carbon emissions from deforestation (UNFCCC, 2005).

Considerable progress on RED was achieved between 2005 and 2009. At COP 13, RED was expanded to include forest degradation (and so became REDD) (UNFCCC, 2008a). However, there were five main issues that remained contentious: scope; measurement, reporting and verification (MRV); the rights of indigenous people; financing options; and institutional arrangements (Holloway and Giandomenico, 2009). Issues of scope surrounded the definition of REDD: as well as enhancing forest carbon stocks, should it also encompass biodiversity and social benefits? In addition, there were methodological debates as to how avoided emissions could be measured addressing the issues of leakage, permanence and additionality (see Section 1.4.4). Should indigenous people and local communicates be considered as stake holders and given rights to participate and be included in reward mechanisms? Further uncertainty surrounded funding. Several options of REDD funding were proposed, varying from government to government support to market funding systems. Finally, at what institutional level should REDD be managed; local, national, regional? Ad Hoc Working Groups (AWG) were established to address these issues alongside the SBSTA.

In December 2008, REDD evolved once again. The SBSTA published a report in which REDD was linked to the conservation and sustainable management of forests (Holloway and Giandomenico, 2009). Since then, REDD has been referred to as REDD+, the '+' indicating considerations beyond GHG emissions, for example to the welfare of vulnerable social groups and to local biodiversity conservation. However, at the following UNFCCC meetings, the US, Canada, New Zealand and Australia blocked the inclusion of reference to indigenous peoples and their rights (UNFCCC, 2008b). In June 2009, the SBSTA addressed fears that REDD+ would promote the replacement of natural forest with forest plantations by instigating safeguards to prevent this (UNFCCC, 2009). However, yet again, consensus was not reach on indigenous rights, MRV or financing. In another backwards step, the safeguards protecting biodiversity established at this SBSTA meeting were removed at the Bangkok meeting of the AWG in late 2009.

In the Copenhagen Accord, the crucial role of REDD+ in mitigating climate change was officially recognised (UNFCCC, 2010). Whilst no legislation was ratified, negotiations were productive, leading to a statement of intent for REDD+ mechanisms to be developed and implemented in the near future. The following year, in the Cancun Agreement, the REDD+ mechanism was officially launched under the UNFCCC. The mechanism launched contained safeguards to protect biodiversity and indigenous peoples, however, no consensus was achieved on how REDD+ would be funded, with that decision postponed until Durban 2011 (UNFCCC, 2010). The agreements in Durban extended the Kyoto Protocol, creating a second commitment period which began on January 1st 2013. The meetings also saw the launch of the Green Climate Fund, although there were few indications of how this long-term fund will be maintained or mobilised. The Durban negotiations did not yield robust guidelines of MRV nor mechanisms to ensure the safeguarding of social and environmental integrity, although transparency was encouraged (UNFCCC, 2012b). Negotiations continued in Doha in December 2012, and preliminary outcomes suggest that the urgent need for action to mitigate climate change was again re-affirmed, but without specific funded actions being agreed (UNFCCC, 2012a). Once again, consensus was not reach on many issues surrounding REDD+. For example, although developed countries reiterated their commitment to provide long-term climate funds of up to US$100 billion, only Germany, France, Denmark, Sweden, the UK and the European Union Commission committed finances (totalling US$6 billion) between 2012 and 2015.

Hence, although the potential for REDD+ mechanisms to provide incentives for reducing emissions in the developing world is great, several important issues still need to be resolved before these schemes can become fully established. The broad issues (scope; MRV; the rights of indigenous people; financing options; and institutional arrangements) remain contentious and the exact form that a REDD+ agreement will take remains to be decided.

1.4.2 Development of Support for National Implementation

In preparation for the successful conclusion of REDD+ negotiations and to demonstrate the feasibility of such programmes, international organisations implemented REDD+ readiness programmes to enhance the capacity of developing nations to undertake REDD+ activities. The two main mechanisms to promote REDD+ readiness were launched between 2007 and 2008, namely: the World Bank’s Forest Carbon Partnership Facility (FCPF); and UN-REDD (a collaboration between the Food and Agriculture Organisation [FAO], the United Nations Development Program [UNDP] and the United Nations Environment Program [UNEP]). Here, I will describe both programmes.

The FCPF was launched at COP 13 in Bali, but did not become operational until June 2008. The FCPF compliments UNFCC negotiations on REDD+ by building capacity of tropical and sub-tropical developing countries in their efforts to conform to REDD+ requirements whilst simultaneously testing performance in some pilot countries, demonstrating, on a relatively small scale, how REDD+ can be applied at the country level (FCPF, 2012). The FCPF helps countries prepare for future REDD+ systems by developing baseline scenarios (Section 1.4.3), adopting REDD+ strategies, and designing MRV systems. These preparation activities are collectively termed REDD+ readiness.

The World Bank serves as trustee and secretariat to the FCPF, but the decision-making body is composed of the participants committee, the donor committee, and six observers. The participants committee comprises of 14 country members elected by the FCPF REDD+ country participants (of which 14 are in Africa, 15 are in Latin America and the Caribbean, and eight are in Asia), whereas the donor committee consists of an equal number (14) of elected members from the financial contributors to the programme. Finally, the observers represent forest-dependent peoples, international organisations, non-governmental organisation (NGO) and the non-contributing private sector. The decision-making body reaches decisions by consensus and decides upon grant resource allocation, although it must be noted that observers do not have voting rights and can only influence discussions (FCPF, 2012).

Two separate funds have been set up to support the objectives of FCPF: the Readiness Fund; and the Carbon Finance Fund. The Readiness Fund currently consists of about US$230 million (committed or pledged by 15 public donors) and focussing on building capacity and REDD+ readiness, including the proper safeguards for biodiversity and social integrity. To access the Readiness Fund, countries must submit a Readiness Plan Idea Note (RPIN). This may entitle them to receive a US$200,000 grant to prepare a Readiness Preparation Proposal, providing a framework and budget by which the country plans to achieve ‘REDD+ readiness’ (i.e. to meet the fundamental conditions of REDD+ such as: sustainable use of forest resources, forest governance and land tenure; mechanisms to address the causes of deforestation; and the consultation and incorporation of key stakeholders). If successful, the country is then allocated a grant of US$3.4 million (FCPF, 2012) to develop a readiness package that contains: the results of studies, consultations and actions implemented under the preparation proposal; a national REDD+ strategy document; a deforestation baseline; a MRV system; preliminary identification of emission reduction activities; and a draft environmental social management framework, consistent with the World Bank safeguards on environmental policy (Dooley et al., 2011). So far, a total of 26 countries have prepared Readiness Preparation Proposals, although only three countries have received grants to implement these (FCPF, 2012).

However, the FCPF mechanism has received criticism. For example, Davis et al. (2009) review the RPIN and identify numerous deficiencies common over most plans. Illegal logging is identified as a major driver of deforestation and forest degradation in many of the RPIN, but the majority do not demonstrate the causes of this beyond insufficient capacity for strong law enforcement, nor do they present any potential solutions (Davis et al., 2009). REDD+ negotiations have identified unclear land tenure as a major challenge, preventing equitable transfer of compensation payments. Almost all the RPIN recognise the need to improve land tenure, but, again, few provide practical solutions of how to attain this or how to resolve any conflicts that arise (Davis et al., 2009). Furthermore, most plans fail to recognise policy conflicts between the REDD+ policies and those of agricultural and infrastructure sectors (Davis et al., 2009). A successful REDD+ strategy should take a holistic approach to increase policy coherence and decreases the likelihood of conflicts. Finally, few RPIN address the challenges of data management, information sharing, transparency and independent monitoring, all vital for the success of REDD+ activities (Davis et al., 2009).

The World Bank Carbon Finance Fund pre-empts a decision by the UNFCC on the long-term funding of REDD+, providing payments for verified emission reductions from REDD+ programmes in about five pilot countries. Pilot countries have yet to be selected, but will gain access to a US$205 million fund (committed or pledged by ten public and private contributors). Programmes will be results-based and on a large-scale (national; or sub-national but consistent with national REDD+ strategies) but must be consistent with UNFCCC standards, with clear mechanisms and transparent stakeholder consultations (FCPF, 2012).

In September 2008, the UNDP, UNEP and FAO launched the UN-REDD Programme, aimed at enhancing capacity, governance, stakeholder consultation and technical abilities to ensure REDD+ readiness. The UN-REDD Programme and FCPF agreed to coordinate work, with the FCPF leading investigations into the economic analysis of REDD+, whilst UN-REDD focussed on providing technical expertise to improve MRV (UN-REDD, 2009c).

The UN-REDD Programme initially focussed on nine pilot countries (Bolivia, Democratic Republic of Congo, Indonesia, Panama, Papua New Guinea, Paraguay, Tanzania, Vietnam, and Zambia), but now encompasses 44 countries (16 of which are implementing or finalising national UN-REDD

Programmes and 16 which are receiving small funding grants of around US$100,000) (UN-REDD, 2009a). To date, the UN-REDD Programme has approved a total of US$67.3 million for national programmes, with the majority of these funds being supplied by Norway (UN-REDD, 2009a). The programme aims to provide capacity support for technical needs, addressing the issues of MRV, stakeholder engagement and equitable benefits sharing at the national level.

As one of the nine pilot countries, Tanzania provides an example of the work of the UN-REDD Programme. Felician Kilahama, Director of the Forestry and Beekeeping Division (FBD) of Tanzania's Ministry of Natural Resources and Tourism (MNRT), described the action of UN-REDD in Tanzania: Tanzania "*lacked the finance, the technical support, the capacity-building, and this is what the UN is coming in to do, to reduce those gaps. They are not coming up with a new project or a new idea. They are helping us to achieve our own objectives*" (UN-REDD, 2009b). Tanzania has received a large amount of donor funding to establish REDD+ actions in the country, including ~US$80 million from the government of Norway and US$4.28 million from the UN-REDD Programme to support national REDD+ strategy development, sub-national pilot projects, research and capacity building, invest in MRV, and establish and pilot a trust fund (Burgess et al., 2010). The main challenges in Tanzania are: 1) a lack of relevant data to set REDD+ baselines; 2) a lack of capacity to implement REDD+ and carry out MRV; 3) a need for REDD+ mechanisms to be tested; and 4) a widespread lack of understanding of the issues surrounding REDD+ (Burgess et al., 2010). The UN-REDD Programme seeks to address all these issues through a series of interventions. Firstly, UN-REDD aims to assist the Tanzania government in developing a REDD+ strategy, including safeguards protecting vulnerable social groups and biodiversity. Secondly, UN-REDD will train local people and organisations in remote sensing, mapping and forest inventory techniques, establishing a nationwide system of sampling clusters, and enabling current and historic extent of forest resources to be mapped. Thirdly, UN-REDD aim to further decentralise the forest sector in Tanzania, enhancing local capacity for various forms of community-based forest management. Finally, as REDD+ evolves as a result of UNFCC negotiations, UN-REDD+ will establish a system to rapidly inform all stakeholders of the practical outcomes.

More than four years after the development of FCPF and the UN-REDD Programme, both mechanisms are still developing. Procedures, documents and strategies are regularly revised in accordance with discoveries from on-the-ground activities and to incorporate the outcomes of the on-going UNFCCC negotiations. The mechanisms will continue to be developed until REDD+ mechanisms are finalised but, in-the-meantime, FCPF and the UN-REDD Programme are attempting to pre-empt the needs of REDD+, developing methodologies and building capacity to ensure a rapid up-take of REDD+ once the legislation is fully ratified.

1.4.3 Baseline Scenarios/Reference Levels

One of the main scientific challenges remaining before an effective REDD+ mechanism can be established is the methodology via which baseline scenarios (business-as-usual emissions expectations) or reference levels (a threshold over which reduced emissions will be compensated under REDD+ schemes) can be set (introduced here, but described in detail in Chapter 2). In order to demonstrated that REDD+ activities actually resulted in realised emission reductions, countries must demonstrate that carbon expected to be emitted to the atmosphere was retained. Thus, in order to evaluate the impact of REDD+ activities, it is necessary to develop business-as-usual baselines that predict emissions in a scenario without any mitigation measures (GOFC-GOLD, 2010). Baselines can be calculated via short-term or long-term land cover change modelling, and using linear or non-linear trends. The method of baseline derivation may impact the success of any REDD+ project as short-term linear approaches show high uncertainties, both under- and over-estimating expected emissions, but long-term non-linear approaches may not be feasible in data-deficient areas, such as the tropics (see Section 2.6 for a full discussion).

Depending on outcomes of UNFCCC negotiations, REDD+ payments may be awarded to a country if emissions are below that baseline, in which case, it is termed a crediting baseline (Angelsen et al., 2009). However, these baselines ignore the ability of REDD+ countries to share the costs of their own emission reductions in a manner consistent with their respective capabilities and in line with the national benefits (or costs) associated with such reductions (Angelsen et al., 2009). Reference levels can be viewed as modified baselines, reflecting emission responsibilities, benefits and costs, and can be altered over time as countries' circumstances change such that they are able to bear greater responsibility for climate mitigation. The setting of reference levels is a key aspect of REDD+ negotiations that remains unresolved, and could have substantial implications for the success of REDD+ schemes. High reference levels increase the risk of non-realised reductions in emissions as uncertainty may make it hard to distinguish between realised emission reductions and those that would have occurs under the business-as-usual baseline when the reference level and the baseline are close. To reflect this uncertainty incentives may be reduced, perhaps resulting in lower global emission reductions (Angelsen et al., 2009). Conversely, low reference levels may discourage participation. Although the certainty of realised emission reductions increases the further from the business-as-usual baseline the reference level is set, if REDD+ countries have to reduce emissions substantially below the baseline before being credited, then the costs of these activities may be higher than the compensation available (Angelsen et al., 2009).

The derivation of reference levels can only be set after agreement at the UNFCCC negotiations. Negotiations are on-going and the exact criteria for establishing reference levels are not fully established. Future UNFCCC negotiations may result in the production of a table of country-specific reference levels derived from broadly agreed principles supported by country-specific data. Alternatively, reference levels could be allocated to countries by SBSTA as and when countries develop the capacity to participate in REDD+ mechanisms. It is also possible that countries could put forward their own reference levels, or that some combination of the three methods proposed above be utilised. Negotiation of reference levels *en masse* is unlikely to be successful as countries vary greatly in REDD+ readiness and their circumstances will change at different rates, thus allocating and reviewing reference levels on a country-by-country basis may be more successful. Methods for identifying baseline trends for REDD+ reference levels are further described in Section 2.8.

1.4.4 The Problem of Leakage

A concern surrounding REDD+ projects is that any deforestation or forest and woodland degradation observed may simply result from the spatial or temporal shifting of the deforestation outside the area being monitored, termed leakage. Under REDD+, forests will be conserved for their value as a carbon store. However, in many places, maintaining the carbon store is in direct conflict with expected LCC predictions. Historical data, ever-rising population levels, and increased demand for products grown on tropical lands indicate that there is a demand for converting forested land to other land use/cover types. As discussed previously, one of the main drivers of tropical deforestation and forest degradation is agricultural expansion and so this will be used as an example.

As populations and welfare increase there is an increased demand on natural resources. For example, humans require a certain daily calorie intake (~2500Kcal day^{-1}) in order to be sustained (van Wesenbeeck et al., 2009). Thus, in order to feed an increasing population, agricultural output needs to increase at an equal rate. Agricultural output can be increased in two ways; increasing agricultural area and increasing yield. Throughout the tropics, farming typically results in low yields (Paul et al., 2002, FAO, 2012b, Licker et al., 2010) and so there is substantial scope for improvement. However, improving yields often requires a significant increase in agricultural inputs, raising the investment cost required. Since most tropical agriculture takes place in the form of subsistence farming, the participants are unable to afford the increased investment (Licker et al., 2010). As a result, instead of yields increasing over time as farming practices improve, we typically observe a decrease in yield (Singh and Byerlee, 1990). Thus, historical increases in tropical populations have tended to be supported and sustained via increases in agricultural area (Boserup, 2005). Protecting a forest from agricultural expansion, whilst mitigating climate change, does not alter the food requirements of the local population. Hence, conversion of forested land not protected under a REDD+ scheme may take place, thereby negating any deforestation avoided in the REDD+ protected forest. Thus, leakage is anticipated if the demand for increased resources cannot be met on existing land.

Few REDD+ schemes are currently in operation, and so the debate on how best to avoid leakage is still on-going (Atmadja and Verchot, 2012). Broadly, mechanisms to prevent leakage fall under two categories; those that reduce resource demand, and those that increase current yield/efficiency. Returning to the example, the current low yields obtained from agricultural land could be dramatically increased through improvements in management practices and technological advances. Increasing the application of fertilisers has been shown to be a cost-effective means by which agricultural yield can be increased for relatively low investment (Sanchez, 2010). A reduction in the demand for resources may be obtained via technological advancement. For example, the demand for timber can be reduced if products traditionally made from timber are substituted by those made of other materials, such as metal or plastic (although these, of course, likely contribute to carbon emissions and are a differing form of leakage that is rarely considered). However, many populations on the forest-agriculture boundary lack the financial means to be able to afford these non-wood products, which are often more expensive, due to high manufacturing and transport costs, and, as such, are less readily available. The uptake of such practises can be encouraged via REDD+ proceeds, e.g. through the use of compensatory payments for successful emission reduction activities. Preliminary investigations indicate that the investment required to increase the yield of current land may be met by the financial incentives provided under REDD+. In eastern Tanzania, it is estimated that a doubling of crop yields, via the application of fertilisers, and a reduction in charcoal demand, via the provision of fuel efficient stoves, could be met by REDD+ payments if market prices were ~US$12.30 per Mg CO_2, significantly lower than the European Union's Emission Trading Scheme market value for CO_2 (~US$24 per Mg CO_2) (Fisher et al., 2011).

The impact of social change cannot be ignored, but is not the focus of this thesis and so will only be discussed briefly here. Changes in society have the potential to both increase and decrease resource demand. For example, reducing levels of meat consumption across developed countries would reduce the global demand for agricultural land, as, for the same calorie content, animal husbandry requires a greater land area than crop production (Peters et al., 2007). However, alternative sources of the protein, previously obtained through meat consumption, may need to be provided to ensure a balanced diet. Conversely, inequality, corruption and other barriers in society may prevent the appropriate compensation reaching the local population whose opportunity cost sacrifices enabled the reduction of deforestation and degradation (Burgess et al., 2010, Blom et al., 2010).

REDD+ has a distinct social element, requiring an increase in welfare and equitability, and so the impact of REDD+ practices on local livelihoods must also be considered. The implementation of conservation strategies designed to reduce deforestation and degradation have the potential to significantly reduce the welfare of local populations and vulnerable groups. This, in part, can be address via mechanisms designed to prevent leakage via increasing yields on existing farmland, and ensuring adequate payments of any opportunity costs. Actions taken to reduce demand on resources may, simultaneously, be able to increase welfare. For example, the provision of fuel efficient stoves reduces the demand for fuelwood and charcoal, the burning of which is responsible for substantial carbon emissions, by between 20% and 40% (Kammen, 1995, Zein-Elabdin, 1997). Concomitantly, welfare, particularly of women and children (whom are primarily responsible for cooking and fuel wood collection (Cooke et al., 2008)) may increase as journeys to collect fuel would may become less frequent and/or less arduous, with lighter loads.

In summary, for climate change mitigation to successfully occur under REDD+ schemes, leakage must be minimised; and for long-term success local people must agree with broad aims and outcomes of any approved scheme. A keen understanding of drivers of deforestation and forest and woodland degradation is required in order to best direct efforts aimed at reducing demand on resources. Monitoring efforts must occur at landscape scales so that any spatial and temporal shifts in resource demand resulting in a carbon emission are documented and deducted from carbon gains as the result of REDD+ activities. However, care must be taken to ensure that the local population, who bear most of the opportunity cost associated with forest conservation, experience a continual increase in welfare over time.

1.5 Research Aims

In this thesis, I map long-term changes in land cover, investigating the possibility that eastern Tanzania has proceeded through a forest transition, moving from net deforestation trends to those of forest regeneration. For the present day, I perform detailed statistical analyses to estimate the carbon stocks at fine resolution across the landscape, assessing the correlations of those differences with climatic, edaphic and anthropogenic impacts (App. 1.1). I use this information to achieve the following research aims:

1. To increase the current LCC data available from satellites by complementing this dataset with historical maps and, using both datasets, to estimate the historical rate of tree cover change, identifying the possible pathways of any observed forest transition (Chapter 3).

2. To improve on contemporary carbon stock estimates (currently using Tier 1 methods) by producing a Tier 2 carbon storage map for the EAM region that is of a high enough spatial and temporal resolution to be of use to policy-makers (Chapter 4).

3. To determine how carbon stocks have altered over the twentieth century across the Eastern Arc Mountains drainage basin as a result of land cover change, providing a long-term baseline of carbon emissions as a result of LCC (Chapter 4).

4. To discover which anthropogenic, edaphic and climatic variables are correlated with the present day distribution of carbon storage and sequestration in the EAM and to produce Tier 3 carbon stock

estimates for forests and woodlands, identifying the most influential variables (Chapter 5).

1.6 Study Area

The study area is the watershed of the EAM in Tanzania, covering 33.9 million hectares (Figures 1.4-1.9). Historically, East Africa has experienced a hominid presence for over two million years, being home to some of the earliest known human fossils (Isaac and McCown, 1976). The Eastern Arc has been climatically stable for long periods, possibly preceding the end of the Miocene (Lovett, 1993a). Previous research and anecdotal evidence suggests large changes in land use over the past century, but no long-term spatial analysis has been conducted. The EAM are thought to have once been nearly covered by forest but it has been estimated that between 70% and 96% of the original forest cover has been lost (Newmark, 2002, Hall et al., 2009), mainly to agricultural encroachment (Burgess et al., 2001). It is thought that in 1900 there was about three times as much forest cover present compared with today (Madoffe et al., 2006) (Table 1.3; Table 1.4). Lowland forest in particular has been extensively exploited, with vast tracts of this forest type having been cleared for agriculture (Newmark, 2002, Lovett, 1993b). Unlike in many areas of the tropics, this time period is relatively well documented as several older land use maps are available (Gillman, 1949, Baumann, 1891, Engler, 1908-10, Shantz and Marbut, 1923). This is mainly due to Tanzania's colonial past, firstly by Germany in the late 19^{th} century, before being designated as a British Mandate from 1919 until 1961. During this period Tanzania's natural resources were exploited, including timber resources and agricultural land for exports of timber, cloves and sisal. Despite much resource extraction, Tanzania has a long history of establishing protected areas, with the oldest protected area in my study area dating back to 1907 (IUCN and UNEP-WCMC, 2010, NPW, 2010).

The present day watershed is a heterogeneous mix of cropland, woodland and forest (the three major tropical biomes) and contains the administrative and commercial capitals of Dodoma and Dar es Salaam, respectively (see Swetnam *et al.* (2011) (2011) for further details) (Figure 1.5; Table 1.1). The watershed also shows a heterogeneous climate, under influence of the Indian Ocean (Mutai et al., 1998). Altitudinal ranges from sea level to over 2000m provide a wide temperature range (Lovett, 1993b) (Figure 1.6). Rainfall and dry season length are also extremely varied. In the northern part of the study area, there are two peaks in rainfall (from October to December and from March to May). More southerly areas experience a single dry (June to September) and wet (November to May) season (Lovett, 1993b) (Figure 1.7). Further heterogeneity arises as large areas of woodland, savannah and croplands are burnt, often annually (Krawchuk et al., 2009) (Figure 1.9).

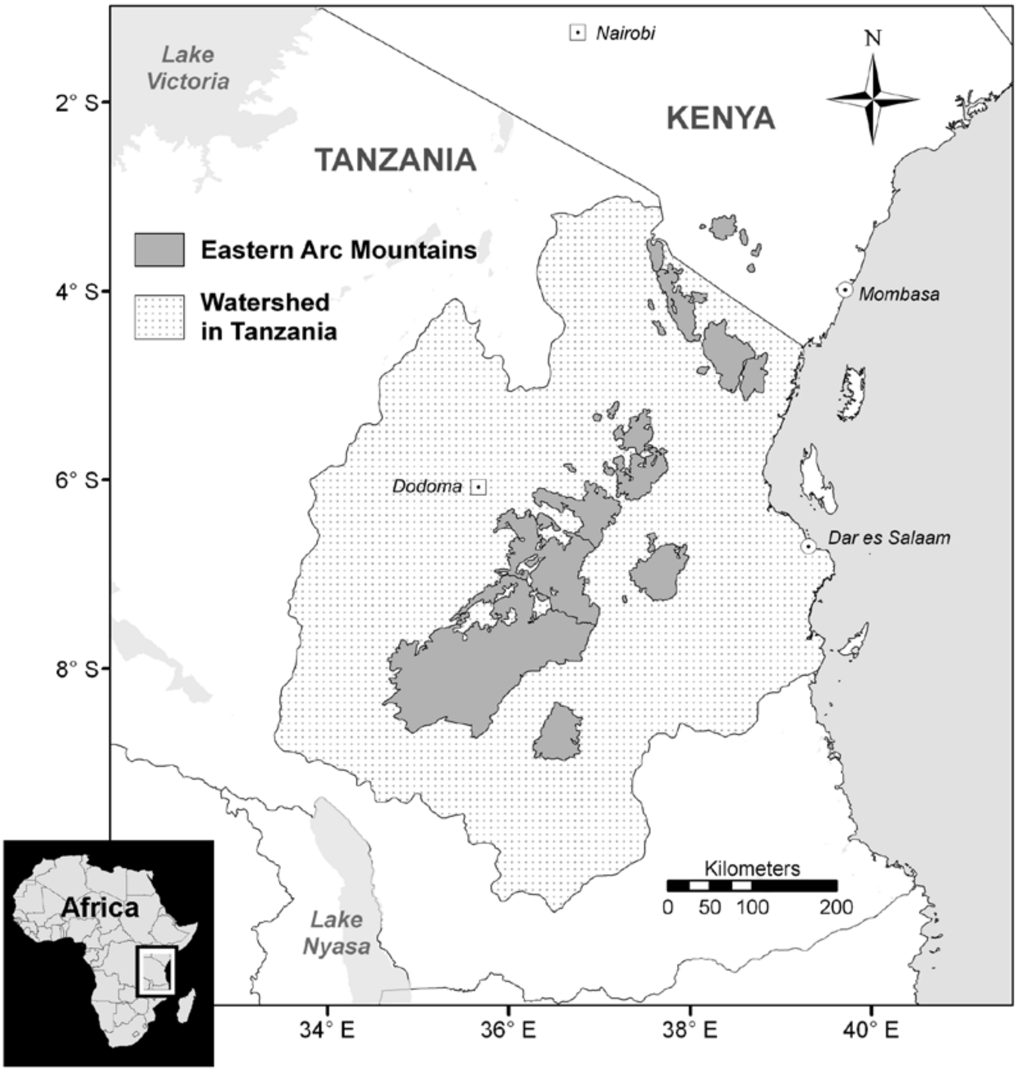


Figure 1.4 The Eastern Arc Mountains of Tanzania and Kenya (Platts et al., 2011). The study area is the Eastern Arc watershed in Tanzania (Swetnam et al., 2011).

Broadly, the region can be subdivided into six distinct zones (the northern, western, central; eastern, southern and south eastern zones [Figure 1.10]) based on climatic, edaphic and anthropogenic criteria (Figures 1.5-1.10), giving rise to a natural, factorial experiment. The northern zone is typically characterised by a high anthropogenic disturbance and large monthly temperature ranges, but low levels of precipitation, soil fertility and fire

(Figure 1.10). The western zone, whilst similar to the northern zone, experiences low anthropogenic disturbance and a high annual probability of fire. The central zone, again similar to the northern zone in that it shows high anthropogenic disturbance and low levels of fire, is an area of high fertility, experiencing both low mean annual temperatures and small monthly temperature ranges but high levels of precipitation. The eastern zone is an area of high anthropogenic disturbance, similar to the northern zone but showing small monthly temperature ranges and high levels of precipitation. The southern zone shows many similarities with the central zone, but shows much lower levels of anthropogenic disturbance. The south eastern zone is relatively unique, being an infertile area with low levels of anthropogenic disturbance and small monthly temperature ranges, but high mean annual temperatures, levels of precipitation and occurrences of fire. Thus, in various combinations, the effects of climatic, edaphic and anthropogenic variables may be statistically isolated. For example, comparing tree inventory plots in the central and southern zones isolates the effect of varying anthropogenic disturbance, whilst keeping other variables relatively constant. Other examples include comparing the central and eastern zones (isolating the effects of mean annual temperature and soil fertility); the central and northern zones (isolating the effects of precipitation and soil fertility); the northern and western zones (isolating the effects of anthropogenic disturbance and fire); and the eastern and northern zones (isolating the effect of month temperature range and precipitation) (Figure 1.10).

The EAM themselves (5.2 million ha, as delimited in Platts et al. (2011)) are nested within the broader study area (Figure 1.11), and are considered a global priority for biodiversity conservation due to the high levels of plant and animal endemism (Lovett, 1990, Myers et al., 2000, Burgess et al., 2007). At the time of the last national census, the population of Tanzania was 34.4 million people (NBS, 2006), of which 2.2 million lived in the EAMs and 12.9 million lived within the wider watershed catchment. Over the last 14 years, the national population growth rate has been 2.9% yr^{-1}, tending to increase pressure on land and resources (NBS, 2006). Pressure on local resources derives from global, as well as local demand. Each year, a large amount of, mostly illegally felled, timber is exported from the study area (Milledge et al., 2007). The true extent of timber removal is highly uncertain, but is estimated to have a significant economic impact, with 58 million US$ in timber royalties lost annually (Milledge et al., 2007). Through a combination of external and internal demand, waves of forest degradation radiate from Dar es Salaam

(Ahrends et al., 2010). This is of concern as the importance of this region to global biodiversity is well recognised (Myers et al., 2000).

Despite broad climate stability since the Miocene (Lovett, 1993a), the region is predicted to experiences alterations in the future. The current population increase is expected to continue, reaching 43.9 million by 2015 (World Bank, 2004). East Africa is one of few tropical regions where future climate projections are in broad agreement (Hulme et al., 2001, Ruosteenoja et al., 2003, Christensen JH et al., 2007, Sitch et al., 2008). Over the next century, most simulations show a robust future warming and general annual-mean rainfall increases, divided into more precipitation during rainy seasons but less or no change during dry seasons (Doherty et al., 2009). However, the simulations provide highly uncertain projections future extreme precipitation anomalies and do not account for any changes in land use or vegetation structure (Doherty et al., 2009). In addition, fires are predicted to become less frequent, although this prediction could also be affected by anthropogenic activities (Krawchuk et al., 2009). Furthermore, plausible storylines estimating the land cover distribution within my study area in the year 2025 have been developed (Swetnam et al., 2011). In combination, modelling these climatic and anthropogenic changes provides the potential to make predictions of the effect of valuable ecosystem services, such as carbon storage. In this thesis, I use the heterogeneous landscape to model and map carbon storage, in both the past and present. In addition, I assess the variables potentially causing the observed spatial distribution. I hope that, as Tanzania is a United Nations REDD+ pilot country, a better understanding of LCC and the current carbon stock in Tanzania will inform policy makers (Burgess et al., 2010), both nationally and internationally.

Table 1.3 Eastern Arc forest type categories and characteristics (Lovett, 1993b).

Forest Type	Altitude (m above sea level)	Rainfall (mm)	Canopy height (m)	Emergent's height (m)	Basal area (m^2/ha)	DBH (cm)	Stem density (>20cm dbh)	Number of species (Lovett, 1999)
Montane	>1500	1000-1200	10-20	Up to 30	20-40	Few > 100 Most < 40	240	42
Upper montane forest	>1800	>1200	10-20	Up to 25	30-70	Few > 100 Most < 40	330	57
Montane	1200-1800	>1200	25-40	Up to 50	30-120	Many > 50 High proportion > 100	250	120
Submontane	800-1400	>1500	25-40	Up to 50	30-70	Many > 50 High proportion > 100	170	114
Lowland	<800	>1500	25-40	Up to 50	-	Many > 50 High proportion > 100	140	91
Dry lowland	<800	1000-1500	15-20	Up to 35	-	-	-	52

Table 1.4 A summary of the Eastern Arc Mountains

Mountain Block	Coordinates (degrees and minutes) (Burgess et al., 2007)	Block Area (km^2) (Burgess et al., 2007)	Forest Cover (km^2) (Mbilinyi and Kashaigili, 2005)	Altitudinal range of forest (m above sea level) (Burgess et al., 2007)	Number of forest patches (Newmark, 1998)	Number of single block endemics (MNRT, 2006)	Forest cover loss 1995-2000 (km^2) (Hall et al., 2009)
North Pare	0335-0346 S, 3733-3740 E	454	27	1300-2113	2	0	27.8
South Pare	0404-0434 S, 3745-3801 E	1578	138	820-2463	5	2	28.7
West Usambara	0420-0507 S, 3806-3841 E	2507	319	1200-2200	17	5	39.9
East Usambara	0445-0520 S, 3826-3848 E	1082	263	130-1506	8	4	38.1
Nguu	0527-0538 S, 3736-3732 E	1591	188	1000-1500	Included within Nguru	0	9.2
Nguru	0527-0613 S, 3726- 3737 E	1673	297	400-2000	8	0	6.3
Ukaguru	0619-0635 S, 3653-3703 E	1259	172	1500-2250	1	1	16.5
Uluguru	0651-0712 S, 3736-3745 E	1478	278	300-2400	5	14	17.5
Rubeho	0648-0772 S, 3634-3658 E	4637	464	520-2050	6	2	26.8
Malundwe	0724 S, 2718 E	1662	13	1200-1275	-	0	0.0
Udzungwa	0722-0843 S, 3507-3658 E	16131	1353	300-2580	26	17	22.4
Mahenge	0837-0838 S, 3642-3644 E	2802	19	460-1040	3	0	31.4

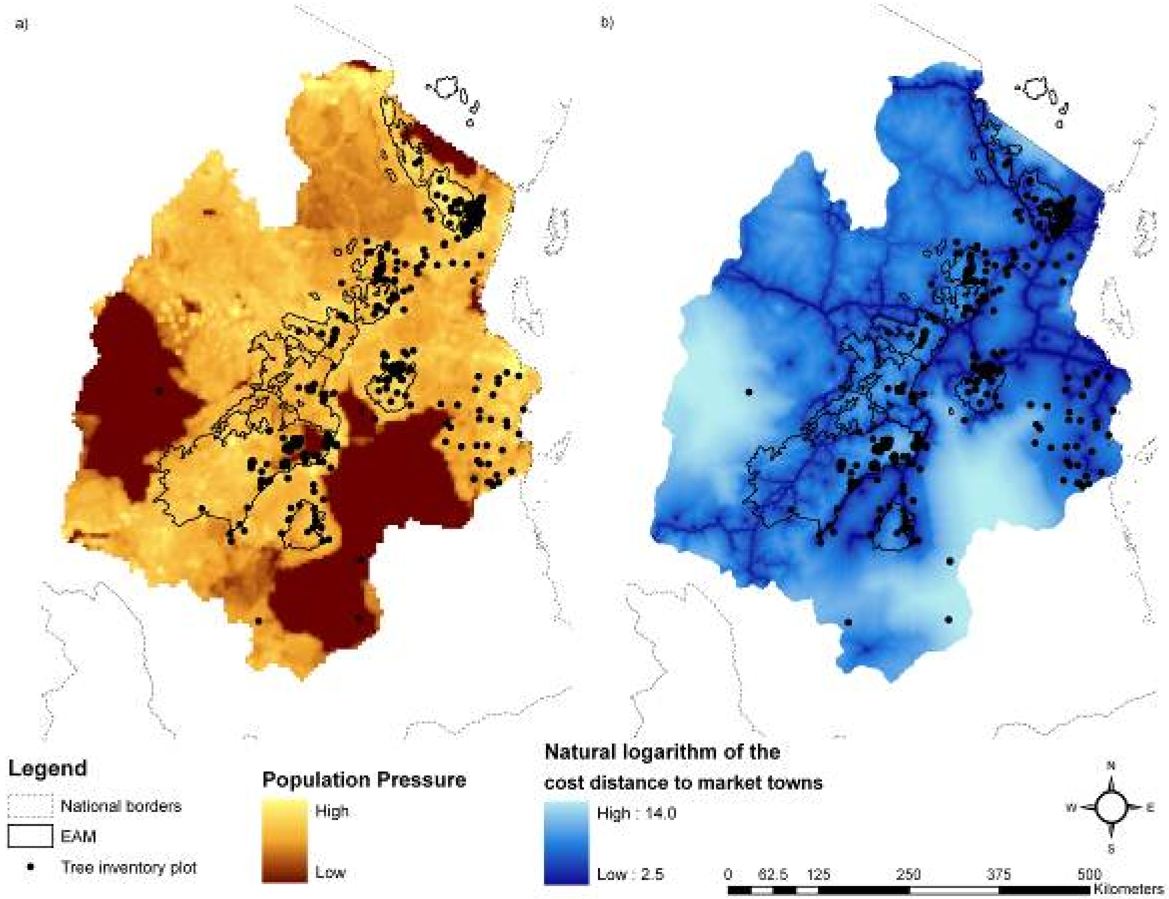


Figure 1.5 Examples of the anthropogenic heterogeneity of the study area, illustrated using (a) the natural logarithm of the population pressure with decay constant of 1.7km and (b) the natural logarithm of the cost distance to market towns (Platts et al., 2011).

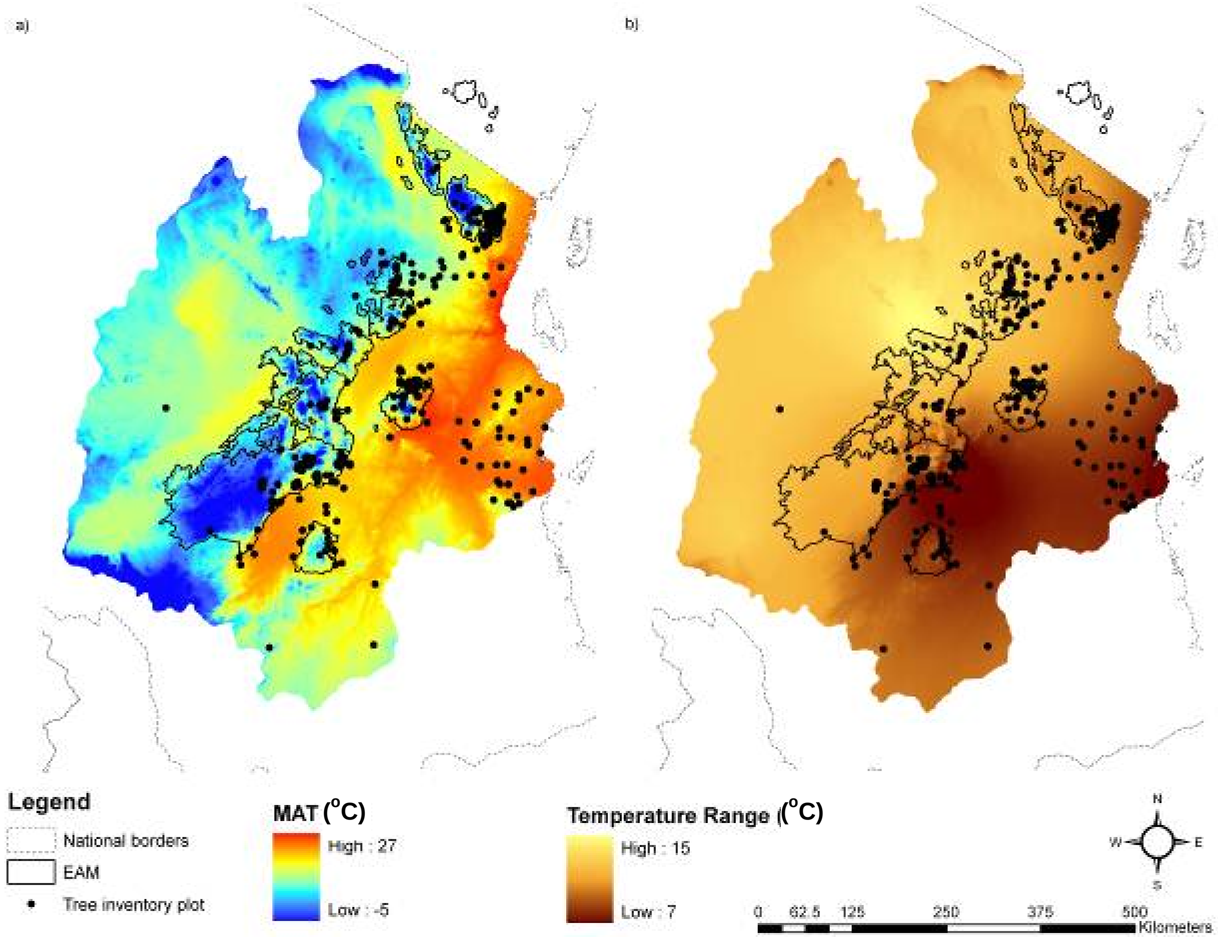


Figure 1.6 Differences in temperature across the study area, illustrated using (a) the mean annual temperature (MAT) and (b) the mean annual monthly temperature range (Hijmans et al., 2005, Jarvis et al., 2008).

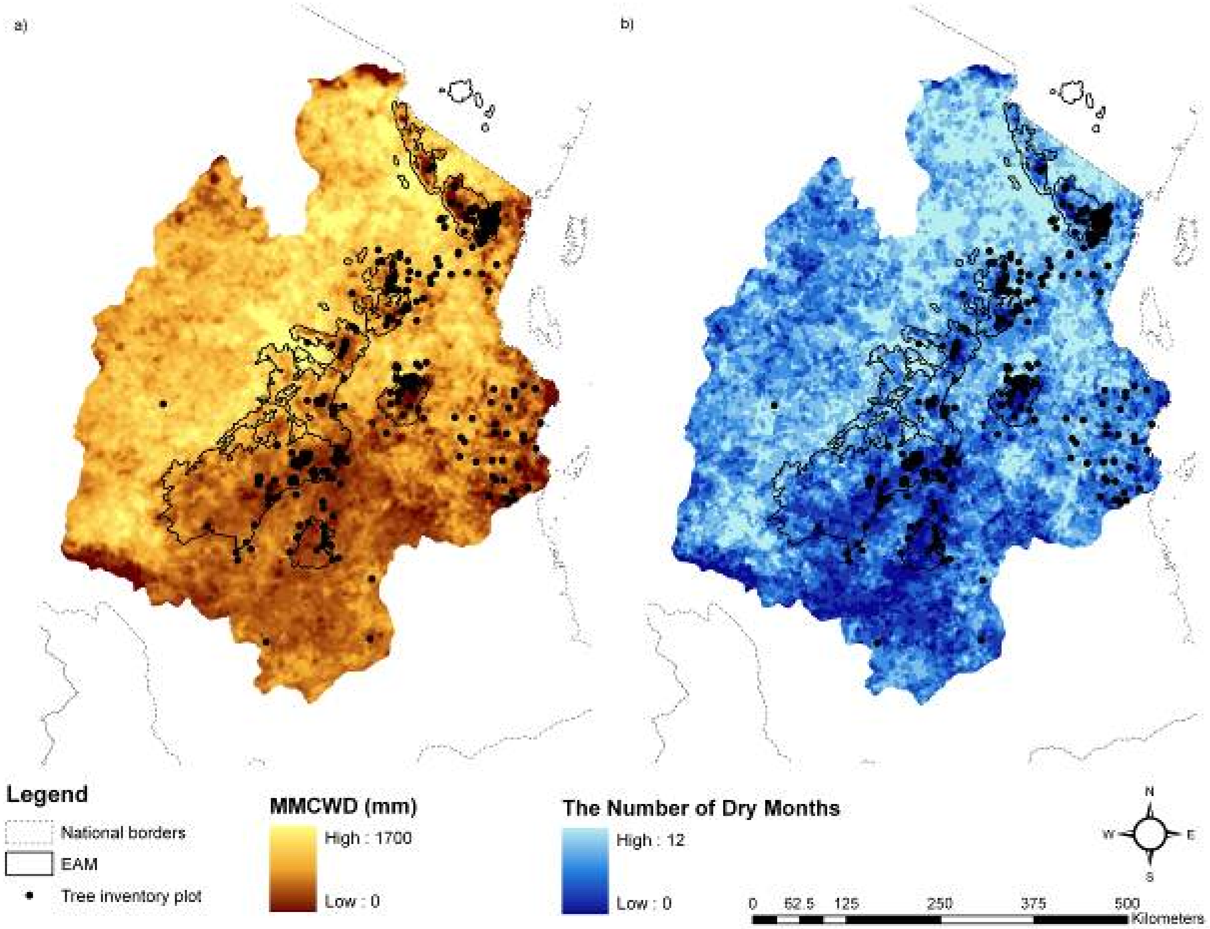


Figure 1.7 Difference in precipitation across the study area, illustrated using (a) the mean maximum cumulative water deficit and (b) the number of dry months annually (Zomer et al., 2008, TRMM, 2010).

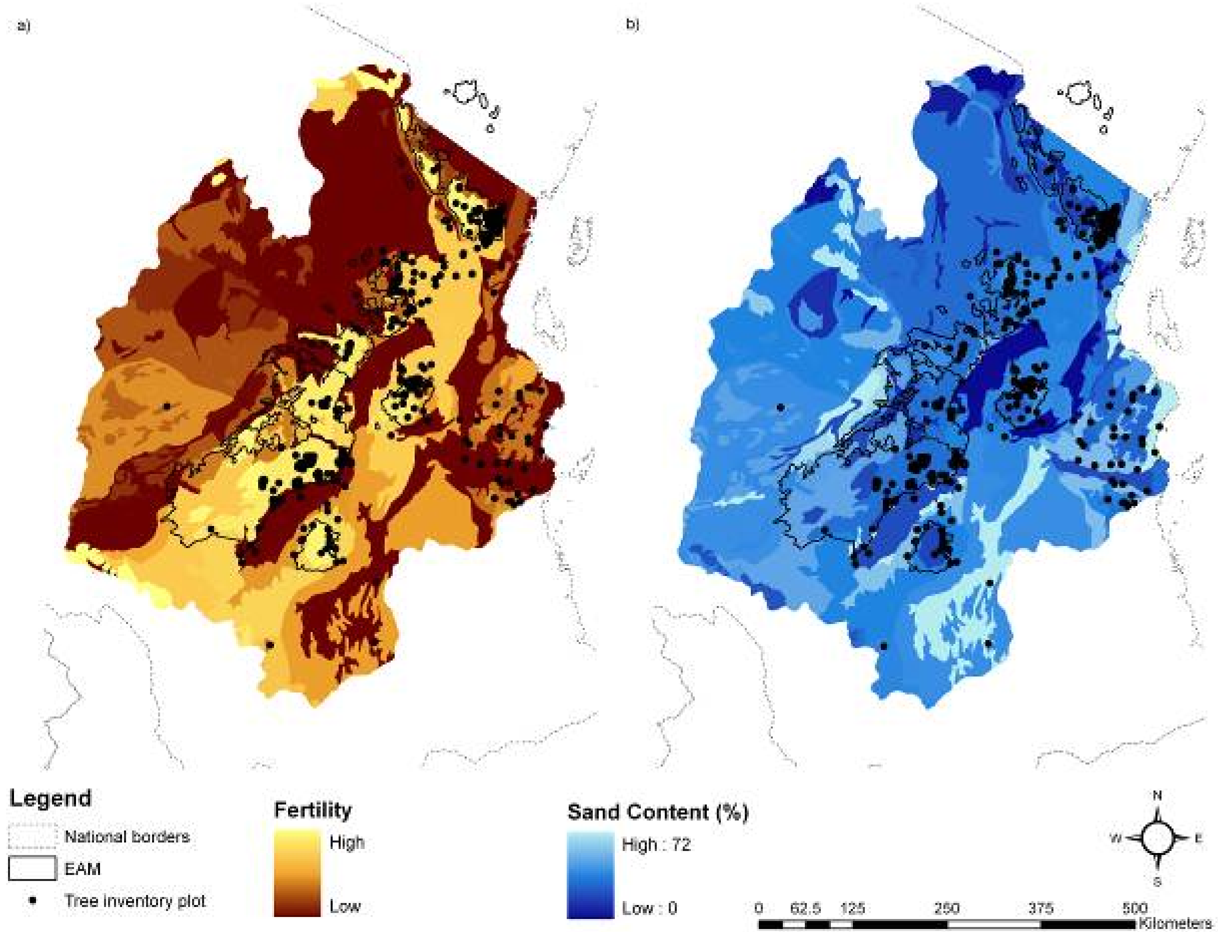


Figure 1.8 Examples of the edaphic heterogeneity of the study area, illustrated using (a) soil fertility and (b) the percentage sand content of the soil (Batjes, 2004, ISRIC, 2010).

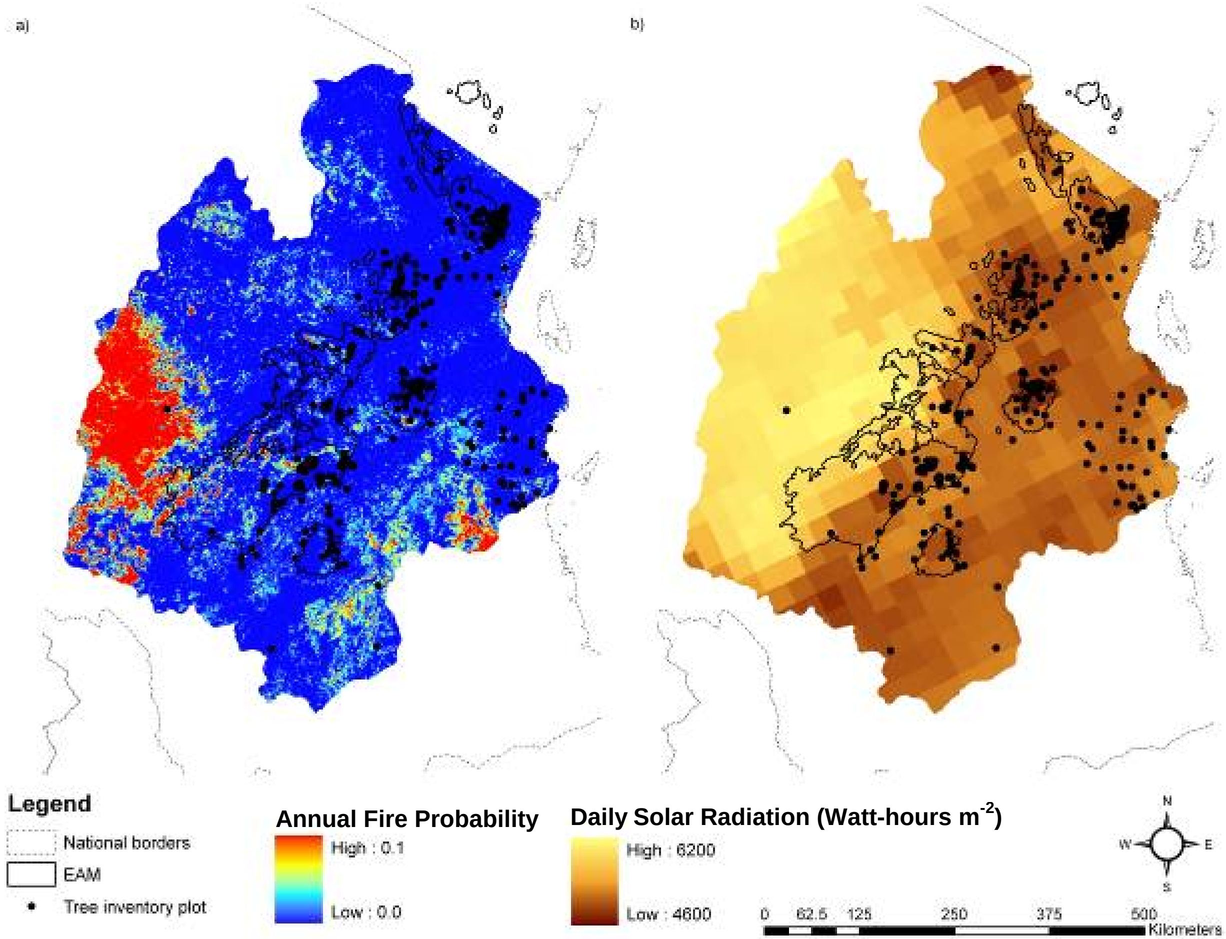


Figure 1.9 Further examples of the heterogeneity of the study area, illustrated using (a) the annual mean burned area probability (Roy et al., 2005) and (b) the mean annual global horizontal solar radiation (Perez et al., 2002, NREL, 2010).

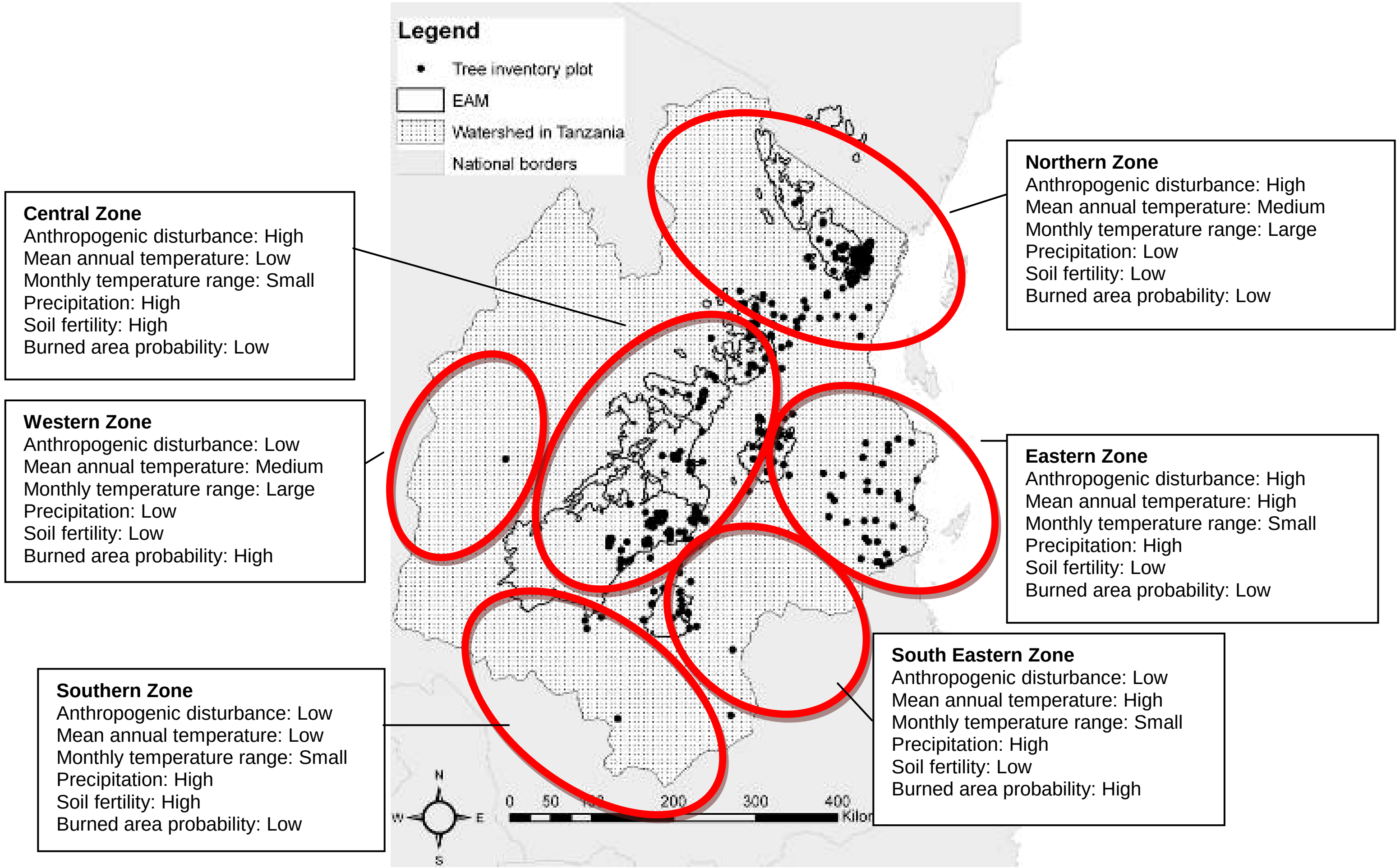


Figure 1.10 The six zones (red) broadly describing the heterogeneity of the Eastern Arc Mountains of Tanzania and Kenya (Platts et al., 2011). The study area is the Eastern Arc watershed in Tanzania (Swetnam et al., 2011).

1.7 The 'Valuing the Arc' Project

The data and analyses in this thesis form a significant part of the research undertaken by the Valuing the Arc (VtA) project (www.valuingthearc.org). VtA was a five-year multidisciplinary project, which commenced in January 2007, and ran until January 2012, and was funded by the Leverhulme Trust (www.leverhulme.ac.uk). Broadly, VtA aimed to address the rapid decline in ecosystems across the EAM landscape in Tanzania by developing a general procedure for analysing and synthesising ecosystem service data. Here, ecosystem services are defined as the benefits, or goods, people obtain from natural systems. VtA collated data locally and internationally, obtaining the information necessary to model many key ecosystem services (listed below). These models could then be used to guide payment for ecosystem service (PES) proposals and policy initiatives, such as REDD+. VtA focussed on three sets of ecosystem services: carbon-related services (including timber provision, carbon storage and carbon sequestration), hydrological-related services (including the provision of water for drinking, irrigation and hydroelectric power generation), and biodiversity-related services (including tourism, the existence value of biodiversity and the sustainable harvesting of non-timber forest products) as preliminary investigations showed these services to represent the most valuable services provided by the study area in eastern Tanzania (FBD, 2003).

VtA aimed to accurately assess the value of carbon, hydrological and biodiversity related ecosystem services by systematically following a series of steps (Figure 1.11). Firstly, an inventory of the ecosystem services delivered to people (ranging from locally to globally) was conducted, assessing the current biological, physical and anthropogenic components. As part of this process, I spent over 1 year in the field establishing 22 plots and recensusing 20 existing plots (Chapter 5). Secondly, spatially explicit models were created, describing the production and flow of these services (Chapters 4 and 5). Thirdly, these models were combined with economic data to quantify the value of each service. Fourthly, the costs associated with maintaining the ecosystem service were mapped in the same manner. Fifthly, ecosystem uses were mapped by allocating goods and services among resource user groups. Sixthly, the maps of benefits, cost and use were combined, illustrating the economic "winners" and "losers" under current conditions. Penultimately, plausible future scenarios were created from projections of LCC, socio-economic development, and climatic changes (Swetnam et al., 2011). The services were then mapped to these scenarios, giving indications of how the flows of ecosystem services, economic benefits, opportunity costs, and how the "winners" and "losers" may change. Finally, policy recommendations and incentives for the conservation of ecosystem services that also address poverty and inequality, both now and in the future, were made (see Chapter 6).

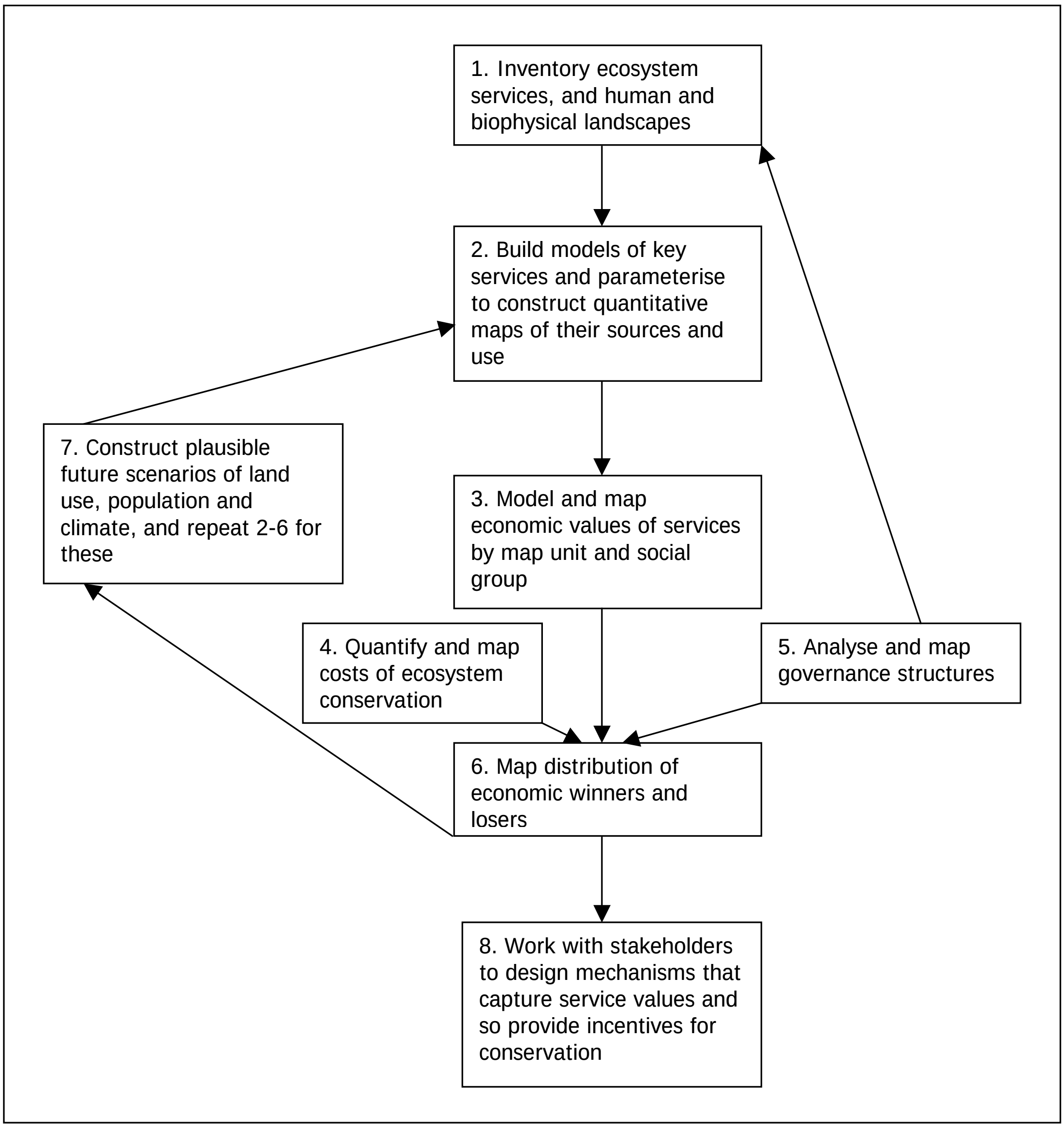


Figure 1.11 The VtA procedure for identifying, quantifying, mapping and conserving ecosystem services (Balmford et al., 2006).

1.8 Thesis Synopsis

In **Chapter 2**, I review the literature, identifying the data needs of REDD+ schemes and evaluating the available methods and data, highlighting key data-deficiencies which this thesis will address. **Chapter 3** investigates LCC within the study area across the twentieth century using historical maps which I sourced and digitised over a 6 month period. My results suggest that a forest transition has occurred in eastern Tanzania and I descriptively analyse the possible pathways of this transition. In **Chapter 4**, I present a repeatable method by which Tier 2-type carbon estimates for land cover classes can be obtained for data-deficient countries. Through use of historical maps digitised in Chapter 3, I estimate the committed carbon emissions from LCC between 1908 and 2000. In **Chapter 5**, I use a newly collected and compiled dataset of forest and woodland inventory plots, including 42 plots which I established and/or remeasured over the period of a year in the field. I investigate the influential natural and anthropogenic variables correlated with aboveground live carbon storage and provide a Tier 3-type estimation of carbon storage and sequestration. Finally, key results are synthesised in **Chapter 6**, highlighting the implications of the findings and identifying emerging research directions.

Chapter 2
Literature Review

2.1 Introduction

In Chapter 1, I illustrate the urgent need and political will to reduce global GHG emissions, describing the progression on UNFCCC negotiations aimed at reducing emissions from deforestation and forest degradation. However, it is immediately evident that any emission reduction scheme possesses substantial data requirements so that those countries reducing emissions can be fairly compensated, whilst also ensuring that realised emission reductions occur.

Here, I discuss these data needs, critically evaluating available information and techniques. Firstly, I evaluate vegetation classification systems, recognising that much of the uncertainty surrounding global trends in forest and woodland cover derives from differing definitions (Putz and Redford, 2010) and that a concise debate on reducing emissions from forested systems cannot be had without first clearly defining land use/cover types. Secondly, I present a review of our current understanding of the variables causing the variation observed in present-day tropical forests and woodlands. A large part of these data is derives from government led forest surveys. However, there is a wide disparity in the capacity of nations to monitor forest area and carbon content. Thus, thirdly, I evaluate current government-led forest monitoring systems, recognising that it is impossible to track changes in land use/cover or the emissions associated with such transitions without this data. Fourthly, I evaluate scientific methods for monitoring and modelling land use/cover change, indicating how the research community plays a vital role in independently verifying government figures and furthering technological abilities, producing best-practice methods and estimating changes in data-deficient nations. Fifthly, I describe the available methods by which the GHG emissions that result from the observed land use/cover changes can be estimated and monitored. Once historical emissions are known, baselines need be created in order to detect any future reduction in emissions. Hence, finally, I evaluate approaches to identify baseline trends, reviewing the scientific literature to suggest methods by which reference levels could be used to assign appropriate compensation in lieu of emission reductions.

2.2 Evolution of Vegetation Classification Systems

The classification of vegetation into discrete units has substantially furthered our scientific understanding of flora, separating flora into communities which can be investigated through focussed studies. However, are the plant communities that result from the classification process natural or artificial units? This question has been key in shaping the evolution of vegetation classification across the past 200 years (Whittaker, 1956, Whittaker, 1962). There are many possible approaches to vegetation classification, with each resulting in different boundaries and divisions (Whittaker, 1973). All approaches may have some validity, but there is merit in a standardised approach, enabling comparison between investigations, although this has yet to be decided upon by the research community. Here, I summarise the evolution of vegetation classification systems, selecting the most appropriate for use in this thesis.

Modern attempts to classify vegetation can be traced back to the beginning of the 19th century. In the early 1800s, Alexander von Humboldt extensively surveyed South America and attempted to explain the distributions of vegetative groups using environmental conditions, particularly those of climate (von Humboldt, 1805, von Humboldt, 1806, von Humboldt, 1807). Von Humboldt (1805, 1806, 1807) expressed the ideas that similar growth-forms of plants could be grouped, forming communities that could be primarily characterised by their dominant species. Since then, numerous studies of vegetation ecology have developed many different approaches to classify vegetation into discrete units. Broadly, the approaches form three separate groups: physiognomic approaches; environmental approaches; and floristic approaches.

Plant physiognomy is the external appearance of vegetation and its attributes. As such, it is comprised of many obvious features (e.g. colour, texture, size) which can usually be rapidly determined by a visual assessment. Physiognomic approaches are primarily determined by growth form and life form (Rübel and Brockmann-Jerosch, 1930, Raunkiaer, 1934) and so frequently include references to communities (e.g. forest, woodland, scrub, savannah, grassland, desert), seasonality (e.g. deciduous, evergreen), dominant organisms (e.g. trees, shrubs, herbs, grasses), and lesser organisms (e.g. bryophytes, epiphytes, lichens, fungi) (Shimwell, 1971). Von Humboldt first employed the physiognomic approach and it has been applied by a wide variety of scientists, often differently between regions (Whittaker, 1973). For much of the nineteenth century, the unit of classification (termed the ‘formation’) was debated, with many scientists using the term in a variety of different ways. For example, von Marilaun (1863) considered formations to be plant groups with regular structure and distinctive compositions, primarily attributed by dominant species. However, Hult (1898) used the term to mean very narrow units defined by stratal structure and Drude (1890) based his definition around floristic composition and habitat. This debate continued into the twentieth century (Warburg, 1900).

Whilst debating the unit of classification, numerous mechanisms by which vegetation could be allocated into discrete groups were developed. An example of this is the leaf-size classification system developed by Raunkiaer (1934). He proposed that leaf size correlated well with water availability and so could be used to classify the climax communities (the final successional state of a region). However, more recent investigations have demonstrated that other factors (e.g. edaphic phosphorus availability) also affect leaf size (Beadle, 1953, Loveless, 1961). Raunkiaer’s method involved the calculation of leaf area using squared paper (although has since been modernised to involve leaf length and breadth measurement only (Cain and Castro, 1959)) and so require intense scrutiny of vegetation. Following the work of Raunkiaer (1934), vegetation classification evolved in two directions: those that used a single characteristic to determine vegetative groups; and those the utilise many aspects of plant morphology.

The formation is usually thought to be determined by macroclimate. This causal relationship between vegetation and environment was refined by Jenny (1941) and Major (1951), although can be dated back to 1899 (Grabherr and Kojima, 1993), and led to the development of several environmental classification systems (Holdridge, 1947, Whittaker, 1973, Box, 1981). A well-known example of this approach is the Holdridge Life Zone model (Holdridge, 1947, Holdridge, 1971). This system is based on Holdridge’s field observations on tropical vegetation, combined with analyses of climatic factors. The model relates potential natural vegetation with climate based on three variables: mean total annual precipitation, mean annual biotemperature and mean annual potential evapotranspiration (Holdridge, 1947, Holdridge, 1971). The climate space provided by variation in these variables is divided into 36 hexagons, each being allocated a vegetation type. In addition, some transitional Life Zones are recognised in the corners of some hexagons. The model is based on annual climate, with no attempt to account for seasonality, although this was incorporated into the framework in 1971 (Holdridge, 1971). Holdridge's Life Zone system has been widely used in the literature (Pyke et al., 2001, Huston and Wolverton, 2009, Cleveland et al., 2011), however, its accuracy when applied to the globe is less than 40% (Prentice, 1990). This is the result of several short-comings: i) altitudinal variation is not considered. Biotemperature does not differentiate between horizontal and vertical change and thus fails to include the difference between daily temperatures and varying hours of daylight (Zhou and Wang, 2000); ii) the frost line placed at an annual biotemperature of 18°C is not appropriate in all regions (e.g. China) (Zhou and Wang, 2000); iii) the anthropogenic impact on vegetation composition and type is ignored; and iv) ecophysiological variation is ignored but can be important in determining the climax community (e.g. leaf succulents are almost entirely absent from the Australian flora but this is thought to be a result of evolutionary isolation and not due to climatic differences when compared to other semi-arid regions) (Grabherr and Kojima, 1993). However, the latter problem can be avoided by classifying life forms by region (Box, 1981).

The final approach to vegetation classification is the floristic approach, developed in the late 19th and early 20th century. As described above, many physiognomically similar communities occur on different continents if environmental conditions are comparable. However, these correlations are imperfect, in part due to the different species found in each region. The absence of a dominant growth form from an environment to which it is well adapted may result in the occurrence of different communities in similar climates (Beadle, 1953, Whittaker, 1956). Thus, species composition is known to be important in determining vegetation type, and this is emphasised by floristic approaches. After early works (Flahault and Schröter, 1910, Schröter, 1894), Braun-Blanquet et al. (1932) proposed a comprehensive floristic approach. The approach analyses the floristic composition of plant communities, grouping according to floristic similarity. Thus, not only are the dominant vegetation types considered, but the entire assemblage. However, detailed botanical surveys are required to support such a data-intensive approach.

The three classification approaches (physiognomic, environmental, and floristic) are not mutually exclusive and can be combined in various ways.

Few attempts to synthesis the various systems were made until the mid-twentieth century (Rübel and Brockmann-Jerosch, 1930, Ellenberg, 1956), although the merit of combining morphological characteristics with functional traits was recognised several decades earlier (Drude, 1890). Today, most classification systems retain elements of all three approaches, although one approach may dominate the others depending on the research agenda (Kuchler, 1955, Mueller-Dombois and Ellenberg, 2003). All approaches of vegetation classification have been applied in the tropics. However, in many tropical regions, the application of the floristic approach is problematic due to high levels of biodiversity and relatively poor botanical knowledge. The physiognomic approach is substantially less intensive and so is very useful for covering large expanses of land but is not very effective in detecting spatial and temporal changes in vegetation, unless the changes are great enough to cause a shift in biome. Finally, the environmental approach, also less intensive, can be flawed in areas under a high influence of local peoples. Both the physiognomic approach and the environmental approach are highly compatible with modern remote sensing technologies (Section 2.5).

Here, I adopt a physiognomic approach to vegetation classification, specifically using the classes proposed by HTSL (1997) (for definitions see Table 1.1). I adopt this approach as it is well established in east Africa, having been applied many times over the twentieth century (Phillips, 1930, Gillman, 1949). It is likely that this approach is favoured in the region as data-deficiency prevents utilisation of the floristic approach, and the high levels of anthropogenic disturbance may produce large uncertainties under the environmental approach. Additionally, whilst there is broad similarity, I find the environmental approaches used in some studies (Brown, 1997, Chave et al., 2005) are not easily applied to East Africa, because of clear bimodal rainfall patterns that dominate tropical African climates but are rarely found elsewhere (Mutai et al., 1998). By adopting the physiognomic approach proposed by HTSL (1997), I ensure my work is compatible with previous studies in the region (Engler, 1908-10, Shantz and Marbut, 1923, Gillman, 1949), as well as being comparable with other approaches using similar systems (Whittaker, 1975).

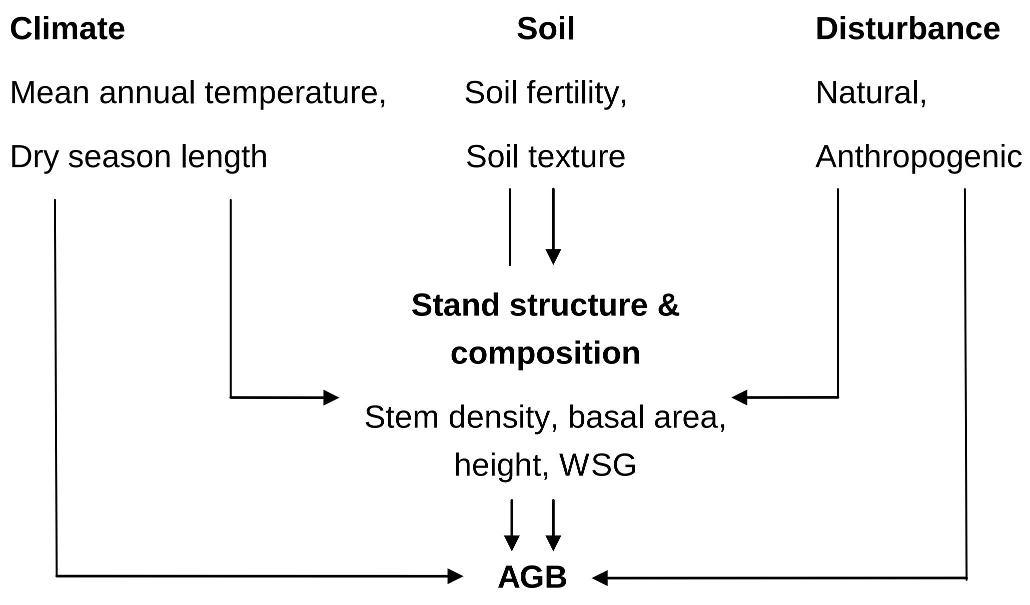
Table 2.1 A summary of variables observed to explain spatial variation in aboveground biomass in tropical forests and woodlands. Effects are shows as a positive correlation (+), negative correlation (-) or contrasting reports (*). Adapted from (Baraloto et al., 2011).

Group	Variable	Effect	References
Climatic	Mean annual precipitation	+	(Malhi et al., 2006, Chave et al., 2004)
	Dry season length	-	(Malhi et al., 2006, Chave et al., 2004)
	Mean annual temperature	+	(Raich et al., 2006, Asner et al., 2009a, Girardin et al., 2010, Quesada et al., 2009b)
Edaphic	Topography	*	(Clark and Clark, 2000, Ferry et al., 2010)
	Texture	*	(Quesada et al., 2009b, Paoli et al., 2008)
	Exchangeable bases	*	(Quesada et al., 2009b, Laurance et al., 1999)
	Labile P	*	(Quesada et al., 2009b, Paoli et al., 2008)
	Type	*	(DeWalt and Chave, 2004)
Disturbance	Fire	-	(Aragão and Shimabukuro, 2010, Cochrane and Schulze, 1999)
	Wind	-	(Laurance and Curran, 2008, Nelson et al., 1994)
	Anthropogenic	-	(ter Steege and Hammond, 2001, Chazdon, 2003)
Stand	Basal area	+	(Baker et al., 2004b, Paoli et al., 2008, Malhi et al., 2006)
	Stem density	+	(Paoli et al., 2008, DeWalt and Chave, 2004, Rutishauser et al., 2010)
	Height	+	(Chave et al., 2005)
	WSG	*	(Baker et al., 2004b, DeWalt and Chave, 2004, Stegen et al., 2009)

2.3 Explaining Spatial Variation in Biomass

Despite broad similarities within the global biomes resulting from vegetation classification systems, regional variations are apparent (Section 1.2.2). For example, several studies have reported spatial patterns in aboveground live biomass (AGB) across the Amazon basin. Broadly, central and eastern parts of Amazonia have higher AGB estimates than in the west (Baker et al., 2004a, Baraloto et al., 2011, Malhi et al., 2006, Quesada et al., 2009b). There is limited understanding on the relative importance of environmental factors resulting in spatial differences in AGB, with the effects of precipitation being the most certain (Table 2.1). The AGB of vegetation is the net result of stand characteristics such as basal area, height, stem density and wood specific gravity (WSG), which in turn are net effects of differences in photosynthesis and respiration of individual stems via growth and mortality. Since AGB is determined by the net effect of several variables, identifying general trends has proven difficult (Figure 2.1). For example, one might hypothesis that highly productive forests are high in biomass, however if the high rates of growth are matched with high mortality rates then these areas may contain lower levels of AGB than slower growing, but less dynamic forest, c.f. eastern and western Amazonia (Phillips et al., 2004, Baker et al., 2004b, Malhi et al., 2006, Malhi et al., 2008). Furthermore, one might expect taller forests to store more carbon than shorter forests. However, if the shorter forests had both higher wood and stem density, then this correlation may not be observed. This study focuses on the effects of variations in climate and soil characteristics on AGB, therefore my discussion here centres on the same variables (see Section 1.3 for discussion of anthropogenic variables).

Figure 2.1 A conceptual framework for studying the relationships between aboveground biomass (AGB) and natural and anthropogenic variables. Adapted from (Baraloto et al., 2011).



2.3.1 Climate

The most studied aspects of climate, with respect to tropical forests and woodlands are those related to precipitation and temperature. Across the tropics, annual precipitation shows consistent positive linear correlations with AGB for a wide range of precipitation levels (1000-5000mm yr^{-1}), however non-linearity is often not investigated (Saatchi et al., 2007, Malhi et al., 2006, Slik et al., 2010, Quesada et al., 2009b) but is suspected as the wettest forests have lower biomass (Chave et al., 2005). Water is vital to plants, as it is for most life-forms, being utilised as solvent or reagent in numerous biochemical reactions (e.g. photosynthesis), as well as being integral to mineral transport and structural support throughout the plant (Dawson, 1993). A plentiful supply of water reduces competition between individuals for water and so may correlate with high stem densities and/or an increased proportion of larger, taller stems. Indeed, increasing levels of precipitation are known to increase both stem density and basal area, causing a concomitant increase in biomass (Phillips et al., 2004, Baker et al., 2004b, Malhi et al., 2006, Malhi et al., 2008, Slik et al., 2010). Conversely, in times of water scarcity, plants close stomata to reduce water loss through transpiration, leading to a reduction in carbon assimilation, and an increase in mortality (Meir and Grace, 2005, Phillips et al., 2009b). Thus, water availability is of particular importance during the dry season, where solar radiation is abundant but precipitation levels may fall below levels of optimal evapotranspiration (Saatchi et al., 2007, Malhi et al., 2006, Slik et al., 2010). It is important to note, that the true driver of these patterns may not be precipitation *per se*. Specifically, it is water availability that is important, which is a combination of precipitation rates, the distribution of precipitation through the year, temperature and soil water availability.

The increase in biomass with increasing water availability may be driven by changes in forest and woodland structure. Forest tree height is known to increase as the length of the dry season experienced decreases (Feldpausch et al., 2011). This pattern is relatively consistent over all tree-dominated biomes, as woodland trees are often present in significantly drier habitats than their forest counterparts but are considerably shorter (Chave et al., 2005). This can be explained theoretically. As previously described, plant stomata close in times of water shortage leading to a reduction in carbon assimilation (Meir and Grace, 2005, Phillips et al., 2009b). Thus, water-limited plants will be shorter than those in areas where water is available as the number of growing days per unit time is reduced. Since wooded areas are often drier than forested regions, this may explain their shorter stature.

Additionally species associated with woodlands have been shown to have WSG values 10-60% higher than moist forests (Barajas-Morales, 1987, Wiemann and Williamson, 1989, Phillips et al., 2009b, Slik et al., 2010). This is thought to be an adaption to water limitation, as these dense timbers have thicker walled xylem vessels and show higher cavitation thresholds (Tyree et al., 1998, Hacke et al., 2001). However, within biomes the effect of precipitation on WSG is unclear. For example, WSG within Amazonian tropical forests have been observed to be positively (Bunker et al., 2005), negatively (Wiemann and Williamson, 2002) and not correlated (ter Steege and Hammond, 2001) with mean annual precipitation, perhaps again illustrating the importance of the accurate representation of water limitation beyond the simplistic use of precipitation measures.

Since water is essential for plant growth (Fitter and Hay, 2002), it would be reasonable to expect the structural changes resulting in biomass increases to be derived from increases in growth. Indeed, physiological evidence suggests that tree growth is limited during periods of low precipitation (Malhi et al., 1998, Williams et al., 1998, da Rocha et al., 2004). However, large-scale studies in Amazonia do not suggest that precipitation is an important driver of AGB and litter production (Malhi et al., 2004, Chave et al., 2010), with some studies indicating an unexpected negative correlation (Schuur, 2003). These unexpected results may be indicative of a lack of large-scale correlation between annual precipitation and water limitation, as well as covariation with variables known to decrease growth (e.g. the increased cloudiness in areas of high precipitation may limit light availability). Further research is required to determine the effects of precipitation on plant productivity. I recommend that future studies focus effort on dry season rainfall (perhaps more indicative of water stress) whilst statistically blocking for the effect of covariates.

The effects of temperature on tropical biomass are also difficult to investigate. There is relatively little latitudinal variation in temperature within the tropics, thus inferences of the effect of temperature are often obtained via altitudinal gradients (Colwell et al., 2008). This has inherent difficulties as one cannot discount the effects of community composition, the partial pressure of CO_2, or any other correlate of altitude. Of the studies that have investigated the effect of temperature, positive correlations with aboveground biomass have been suggested (Raich et al., 2006, Asner et al., 2009a, Girardin et al., 2010, Quesada et al., 2009b). However, this pattern is not consistent across biomes as woodlands, typically hotter than forests, consistently have lower levels of AGB (Brown and Lugo, 1984, Ruesch and Gibbs, 2008). Higher temperatures will result in higher levels of biomass if associated gains in photosynthesis exceed increases in respiration. The potential rate of photosynthesis and respiration are known to increase with temperature due to the increased kinetic energy up to a point of inflection (Dewar et al., 1999, Amthor, 2000), however, the net effect may be determined by differences in water limitation. Under water-stress, plant stomata close, preventing photosynthesis but doing little to slow respiration (Meir and Grace, 2005, Phillips et al., 2009b). Thus, woodlands may contain less AGB than forests because they are water limited and so unable to exploit the higher temperatures available.

Due to the relatively small number of studies available, the effect of temperature on stand characteristics is uncertain. Preliminary investigations show that stems grow taller for a given stem diameter as temperature increases (Way and Oren, 2010). However, there is limited support for this claim as only two studies have investigated how tropical forest height changes over time (Kellner et al., 2009, Dubayah et al., 2010). This is consistent the cohesion-tension theory, whereby negative pressure gradients and surface tension provide the forces necessary to lift water against gravity (Tyree and Zimmermann, 1983). An increase in height as temperature increases is to be expected, provided water is not limiting (Koch et al., 2004). As temperature rises, potential evapotranspiration increases (Hargreaves and Allen, 2003). As a result, the negative pressure gradients within the xylem vessels will increase (Koch et al., 2004), thus providing more force to lift water against gravity and allow trees to increase in maximum height. Since wooded areas are often drier than forested regions, water limitation may explain their shorter stature, despite the higher temperatures they often experience.

The effects of temperature on WSG are debated. WSG has been shown to be positively correlated with mean annual temperature (MAT), although this global correlation may be driven by temperate forests (Wiemann and Williamson, 2002). As previously described, stems with high WSG have thicker walled xylem vessels and are able to withstand higher pressures (Tyree et al., 1998, Hacke et al., 2001). Thus, high WSG species are better able to withstand the high evapotranspiration pressures experienced under higher temperatures (Hargreaves and Allen, 2003), with other stems being forced to close stomata to prevent cavitation. However, studies from the tropics have indicated that the direction of correlation between temperature and WSG is unclear (Slik et al., 2010) or insignificant (Muller-Landau, 2004), perhaps a result of the inability of many studies to separate the often correlated effects of temperature and water limitation.

Where it has been investigated, the temperature range has also been shown to correlate with stand-level characteristics. Both a larger difference in temperature between seasons and a higher monthly temperature range are reported to result in increasing stem densities (Slik et al., 2010). This may result from two different mechanisms. Firstly, large differences in seasonal temperatures may indicate high levels of natural disturbance, resulting in the presence of many small pioneer stems (Hubbell et al., 1999). Secondly, higher monthly temperature ranges may be indicative of favourable growth conditions. Respiration is known to be negatively correlated with low night-time temperatures (Clark et al., 2010) and thus low minimum monthly temperatures. Additionally, high day-time temperatures (and thus high maximum temperatures) may result from high insolation, leading to increased photosynthesis, provided water is not limiting (Graham et al., 2003). Hence, large temperature ranges may indicate a large net difference in photosynthesis and respiration, resulting in ideal growth conditions. The increased growth, even if matched by an increase in mortality, could result in higher stem densities. Substantial further research over several tropical montane systems is required before the true mechanisms are known.

Temperature is expected to affect plant growth as it changes gross amounts and the activity rates of RuBisCo - the key photosynthetic enzyme (Lloyd and Farquhar, 2008). Tree growth is ultimately a derivative of the difference in the carbon gained from photosynthesis minus that lost through respiration. Respiration is known to be positively correlated with temperature (Meir et al., 2001), hence, all else being equal, tree growth may decline under higher air temperature (Clark et al., 2010, Chambers et al., 2000). However, high day-time temperatures (and thus high maximum temperatures) may result from high insolation, leading to increased photosynthesis, provided water is not limiting (Graham et al., 2003). Nevertheless, a positive correlation between temperature and tree growth is not always observed (Wright et al., 2006). This may result as increases in RuBisCo abundance and function are non-linear, increasing steadily up to a threshold temperature before rapidly declining. *In situ* experiments show photosynthesis reduces under high temperatures, possibly as a result of increased evapotranspiration rates causing stomata to close (Lloyd and Farquhar, 2008, Doughty and Goulden, 2008). Meta-analyses suggest higher air temperatures result in high levels of gross primary productivity (Larjavaara and Muller-Landau, 2012), net primary productivity, litter production, decomposition rates, and belowground carbon allocation (Raich et al., 2006). However, as discussed previously, the increased dynamics may not be driving changes in structure or biomass.

2.3.2 Soil

Unlike correlations between AGB and climate, correlations between AGB and soil are somewhat contentious, with conflicting results being reported between AGB and both chemical and physical soil properties. Some studies have suggested AGB is limited by soil nutrient availability, highlighting a positive correlation with soil fertility (de Castilho et al., 2006, Paoli et al., 2008, Slik et al., 2010). However, this has been disputed, with other studies reporting no (Clark and Clark, 2000, Chave et al., 2003) or a negative effect (Quesada et al., 2009b, van Schaik and Mirmanto, 1985). This uncertainty may arise from trade-offs between changes in productivity and in the residence time of wood and/or the differential effects of soil fertility on the individual components of carbon storage. High WSG values are associated with low fertility soils, showing lower levels of adult mortality (Baker et al., 2004b, Muller-Landau, 2004, Slik et al., 2010). Thus, these slow growing species may be better able to exploit the scarce resources in the long-term. However, as resources are scare, competition is high and so lower stem densities and lower basal areas are reported in infertile areas (Slik et al., 2010, Paoli et al., 2008). Hence, it is the net effect of these actions on the components of carbon storage that is important for predicting AGB.

The lack of large-scale correlation between AGB and soil nutrients is perhaps surprising. It is widely accepted that tropical forests and woodlands are phosphorus limited, with nitrogen limitation only occurring in montane or extremely infertile localities (Lal, 2004, Lal, 2005, Vitousek and Sanford, 1986). Hence, large-scale correlations between soil fertility, particularly phosphorus concentration, and aboveground growth rates are expected and, indeed, have been identified in several studies (Malhi et al., 2004, Paoli et al., 2008, Quesada et al., 2009b). Recent fertilisation experiments also support these results (Santiago et al., 2012). However, increased growth rates could be matched by increases in mortality, resulting in no increase in aboveground biomass but an increase in stem dynamics. This effect is observed in the Amazon, with areas of high growth being correlated with high mortality rates (Phillips et al., 2004, Baker et al., 2004b, Malhi et al., 2006, Malhi et al., 2008).

The effects of physical soil properties on AGB are equally disputed. For example, both the clay content and drainage capability of soils has been positively correlated with AGB (Asner et al., 2009a, Laurance et al., 1999). However, other studies identify no such trends (Clark and Clark, 2000, Quesada et al., 2009b). Again, this dispute may arise from the complex interactions of the components of carbon storage. For example, the absence of physical soil constraints results in taller trees as root systems can be more developed and thus provide the support needed for increases in height (Feldpausch et al., 2011). However, high WSG values are associated with coarse soils due to the water limitation often associated with these areas as a result of poor soil water retention (Baker et al., 2004b, Muller-Landau, 2004, Slik et al., 2010). Additionally, positive correlations between soil depth and basal area are known but are countered by negative correlations with both stem density and WSG (Slik et al., 2010, Paoli et al., 2008). The mechanisms behind these complex effects are poorly understood. Hence, the effect of soil properties on tropical forests requires substantial further exploration, particularly the development of well-sampled datasets with high spatial resolution.

2.3.3 Additional Variables

I have previously discussed the effect of climate and soil on AGB, however, other natural variables are also predicted to have an effect, although these are relatively rarely investigated. Additional factors thought to effect plant growth include photosynthetically active radiation and atmospheric carbon dioxide concentrations, both direct inputs to photosynthesis. Whilst atmospheric CO_2 concentrations are relatively uniform globally and so unlikely to result in differences amongst tropical forests and woodlands unless it has differential effects on different plant communities, levels of solar radiation have been positively correlated with AGB, the net effect of increased stem densities but decreased WSG values (Lewis et al., 2009a, Wright and Calderón, 2006, Macpherson et al., 2012). However, differences resulting from increased CO_2 concentrations may be expected due to differences in C3 and C4 plants, resulting in an increase in C3 communities, perhaps indicated by an advance of forests into grassland areas.

As previously discussed, correlations between cloud cover and water availability make investigations into the large-scale effect of light availability on AGB difficult. In addition, clouds alter the direct:diffuse light ratio. Under heavy cloud cover, stems may receive a low level of total solar radiation, however, increases in the amount of diffuse radiation may increase photosynthesis in the canopy as a whole (Mercado et al., 2009, Gu et al., 2003).

The majority of other variables causing differences in AGB amongst forests and woodlands derive from forms of disturbance. Disturbance is known to significantly reduce biomass (Cayuela et al., 2006, Chazdon, 2003) (Table 2.1). This pattern is well established and so will not be discussed in detail here, however, may occur via both natural and anthropogenic (Section 1.3) processes. An example of natural disturbance known to affect AGB is that of natural fires. An increase in the occurrence of fire will result in lower AGB levels (Aragão and Shimabukuro, 2010), driven by a decreasing stem density and basal area (Slik et al., 2008, Balch et al., 2011, Muoghalu, 2007). Overall, burnt areas will show lower rates of growth, but during recovery from a burn, growth rates may be increased (Slik et al., 2008, Balch et al., 2011).

2.3.4 Summary

There is broad consensus as to the effect of climate related variables on tropical forest and woodland AGB. However, the effects of edaphic variables are much more contentious. One reason for this is a distinct lack of data. Relatively few tropical tree-inventory plots include the collection and analysis of high-quality soil data. Whilst the spatial distribution of climate data may be fairly accurately represented using remotely sensed data, soil data collection is far more labour intensive. Many candidate variables are correlated with one another, making it difficult to separate the effects of individual variables or compare their relative importance. In this thesis (Chapter 4), I attempt to use the natural heterogeneity of east Africa to separate the effects of climatic, edaphic and other lesser known variables, examining their effect on AGB and the stand-level characteristics driving it. The justification of study area selection is given in Section 1.6.

2.4 Government National Forest Monitoring Methods

Since the Middle Ages, when intensive forest use led to wood shortages in some regions, decision-makers have had to monitor forests to ensure an adequate supply of resources for future use (Gabler and Schadauer, 2007). Typically, methods to monitor forests include estimates of area and stock (defined here as the supply of trees [typically for timber] available). These parameters can be readily measured and applied to a variety of forest uses (Davis et al., 2001). Broadly, estimates of forest area and stock can be obtained in two ways: single-effort surveys; and aggregation-effort surveys. An intensive effort can be made to collect forest data for an entire country in a single wave. This approach is commonly used to obtain estimates of forest area, with remote sensing (aerial photography or satellite-based imagery) from a specified year being interpreted to map forest cover at a specified time point, typically for a given year. However, single-effort surveys can also be used to estimate forest stock. For example, Nordic countries conduct nationwide inventories of forest stock in one single effort (Lund, 2006). This approach is also taken in many relatively small countries. Alternatively, the inventory data may be collected continuously over an extended period of time, an approach common in Central Europe and larger countries such as Australia, Canada and the USA (Lund, 2006). This approach has advantages in that it reduces costs to the governing body, often by delegating work to smaller parties who are free to carry out the inventories when suitable, but may involves many partners and numerous standards and techniques and so may have higher uncertainties.

Over time, forest monitoring has been adapted to reflect current issues as the role of forests has evolved. In the 1980s, attention turned from managing timber stock to maintaining forest health and conserving biodiversity (CBD, 2012), with methods altering to reflect this. More recently, the UNFCCC has attempted to reduce the impacts from human-induced climate change by reducing GHG emissions (see Chapter 1). Since changes in forest cover are associated with substantial fluxes in GHG (Bonan, 2008, Feddema et al., 2005), many forest monitoring methods now include this component, enabling them to be managed to have a positive effect on the atmospheric GHG balance (Cienciala et al., 2008).

Despite the obvious importance of forest monitoring, the standards and techniques utilised by governments vary widely (see Table 2.2). Here, I focus on the forest monitoring methods of developing countries, using Tanzania, Brazil, China and India as specific examples. These nations were selected as they well represent the range of forest monitoring capacity observed in developing countries (see Table 2.2). I will use these case studies to illustrate the various techniques by which nations monitor forest area and stock, as well as indicating how these data can be used to conform to international requirements such as the FAO Global Forest Resource Assessment (FRA), the Kyoto Protocol and REDD+.

Table 2.2 Summary of country capacities for monitoring forest area and stock for a selection of developing countries (adapted from Herold (2009)).

	Forest area change monitoring

Forest stock inventory	No forest cover map	Single forest cover map (external)	Multiple forest cover maps (external)	Forest cover map (internal) or multiple maps, latest before 2000	Regular forest area mapping, most recent after 2000
No consistent national inventory			Paraguay Tanzania	Congo Ecuador Nepal	Bolivia Colombia Malaysia
One national inventory (external)	Guyana CAR Gabon Nigeria Kenya	Zambia	Liberia	Ghana Panama	Costa Rica Brazil
Multiple inventories (external)			DRC PNG		
One or more inventories (internal), most recent before 2000		Cameroon Suriname	Madagascar	Laos	Indonesia Peru Vietnam
Regular forest inventories (internal), most recent after 2000					China India Mexico

Key:
External – Performed by institutions/individuals that are not native to the focal country
Internal – Performed by institutions/individuals that are native to the focal country
CAR – Central African Republic
DRC – Democratic Republic of the Congo
PNG – Papua New Guinea

2.4.1 Area Survey Methods

Remotely sensed data is commonly used to assess forest area. If these data are collected as a time series, the change in forest cover over time and in response to various socioeconomic and/or climatic changes can be observed. Remotely sensed data can be analysed using geographic information systems to readily provide forest cover estimates (see Chapter 3 for an example method). Currently, Landsat data are the most commonly used remote sensing data for forest area monitoring at the national level, although SPOT and ASTER images are also used. Landsat data are often favoured as the data span the entire globe and is freely available. Although the data are free-of-charge, substantial resources are required to process the data before analysis of forest area change. Firstly, the data are most commonly obtained via the internet, and some countries may experience difficulties when trying to access these large datasets due to the low bandwidth available locally (Herold, 2009). In addition, all remotely sensed data needs to be processed prior to interpretation, including ortho-rectification, geometric corrections and radiometric corrections (see GOFC-GOLD (2008) for details). Furthermore, the data needs ground-truthing to assess the accuracy to which the digitally processed data reflects the on-the-ground patterns of land use/cover. International groups are aware of the capacity deficits that prevent some developing nations from utilising remotely sensed data to assess forest area, and efforts are being made to address this (e.g. through the provision of pre-processed data via DVD). Remotely sensed data are further discussed in Section 2.5.

The development of an understanding of forest area also important for stock estimates. Forest inventories involve labour-intensive study at a local-scale in order to collect detailed data on forest stock, forest health and biodiversity. However, it is rarely feasible for nations to perform such inventories throughout all forests and woodlands, so a sub-sample of these areas is selected, with results being extrapolated to other wooded areas. This is further discussed in Section 2.7.

Tanzania has a long history of mapping natural resources, with land use/cover maps dating back over 100 years (Engler, 1908-10) (see Chapter 3 for full details). However, these surveys were often conducted or supported by other nations. In the early twentieth century, Tanzania was colonised by Germany and, subsequently, by Great Britain. Both these European nations held an interest in the timber stocks of Tanzania and so mapped forest cover on several occasions (Engler, 1908-10, Shantz and Marbut, 1923, Gillman, 1949). Since obtaining independence, Tanzania has not conducted a single national forest area survey without outside assistance. Between 1971 and 1973, the Tanzanian government was supported by the Canadian International Development Agency and instigated a partial survey of forest area, covering five regions (Kilimanjaro, Tanga, Tabora, Kilombero and Mtwara) (FAO, 2009b). In 1996, Hunting Technical Services (a UK-based company) was contracted to map national land use/cover (HTSL, 1997). This study remains the best representation of Tanzanian land use/cover to this day. More recently, a partial survey (covering 11 districts) was conducted by local organisations in 2005, using Landsat data to estimate land use/cover change at five year intervals from 1990 (FBD, 2006b). As a UN-REDD pilot country, Tanzania is currently receiving assistance from UN-REDD, the Finnish government and the government of Norway to increase the capacity of forest area monitoring in Tanzania, and the production of a recent land cover/use map is underway (Tomppo et al., 2010b).

Vegetation mapping is somewhat more established within Brazil and China than in Tanzania. Brazil has established an independent vegetation mapping scheme based on topographic maps and remotely sensed data, to be up-dated every 5 years (Tomppo et al., 2010a). A recent map, known as the PROBIO or Map of Vegetable Cover of Brazilian Biomes, was prepared from Landsat data at a 1:250,000 scale for the year 2002 (FAO, 2009a). This map serves as the first in the anticipated series of land use/cover maps and will be updated using data from Landsat and the China-Brazil Earth Resource Satellite (CBERS) (Tomppo et al., 2010a). Recognising the unique importance of the Amazon region, annual estimates of the forest area are produced by the PRODES program (Project for Gross Deforestation Assessment in the Brazilian Legal Amazon) using MODIS imagery. Similarly, using a combination of Landsat, MODIS and SAR data, China has produced maps of forest area every five years, commencing in 1988 (Tomppo et al., 2010a). These data are now being complemented with data from the collaborative CBERS.

Finally, India has perhaps the best established forest area monitoring system of the case studies presented here, being of both the highest resolution and frequency. In 1982, the National Remote Sensing Agency demonstrated that remotely sensed data could be used to estimate the forest area of India (Herold, 2009). By 1987, the Forest Survey of India was established and was estimating national forest area on a two-year cycle, initially using Landsat data, but shifting to data from the Indian Remote Sensing Satellite (IRSS) in 1995 (Herold, 2009). Until the 4th assessment (in 1993), the processing of remotely sensed data were done manually, visually classifying land use/cover for the entire nation. Due to the labour-intensiveness of this activity, processing was initially done at a 1:1,000,000 scale, although this was reduced to 1:250,000 by 1989 (FSI, 2009). During the 4th and 5th assessments (1995 and 1997 respectively), part of the image processing was done digitally, with digital processing being applied to the entire image from 1999 onwards (FSI, 2009, Rawat et al., 2004). The automation of this procedure has reduced labour requirements and enabled high resolution outputs, at a 1:50,000 scale (Table 2.3). The remotely sensed image is geometrically rectified using topographic maps and then co-registered using panchromatic data, also obtained from the IRSS (FSI, 2009, Rawat et al., 2004). The Normalised Difference Vegetation Index transformations are then used to remove non-vegetative areas, and vegetation categories are assigned using canopy cover thresholds (FSI, 2009, Rawat et al., 2004).

The above case studies clearly demonstrate the range of capabilities of developing countries to monitor forest area (methodologies are discussed in Section 2.4). There are advantages to mapping at higher resolution (capturing smaller fragments of forest and woodland) and higher frequency, creating a time-series by which the trend in forest cover over time can be reliably estimated. However, the capacity for all countries to adopt such monitoring systems is yet to be developed.

Table 2.3 A summary of the Forest Survey of India between 1987 and 2005 (adapted from FSI (2009)).

Cycle	Year	Satellite & Sensor	Resolution (m)	Data Period	Forest Cover Estimate (km^2)	Scale of Map Available	Method of interpretation
First	1987	Landsat-MSS	80	1981-83	640,819	1:1,000,000	Visual
Second	1989	Landsat-TM	30	1985-87	638,804	1:250,000	Visual
Third	1991	Landsat-TM	30	1987-89	639,364	1:250,000	Visual
Fourth	1993	Landsat-TM	30	1989-91	639,386	1:250,000	Visual
Fifth	1995	IRS-1B LISS II	36.25	1991-93	638,879	1:250,000	Visual/digital
Sixth	1997	IRS-1B LISS II	36.25	1993-95	633,397	1:250,000	Visual/digital
Seventh	1999	IRS-1B LISS II IRS-1C&1D LISS III	36.25 23.5	1996-98	637,293	1:250,000	Visual/digital
Eighth	2001	IRS-1C&1D LISS III	23.5	2000	653,898	1:50,000	Digital
Ninth	2003	IRS-1D LISS III	23.5	2002	677,816	1:50,000	Digital
Tenth	2005	IRS-P6 LISS III	23.5	2004	677,090	1:50,000	Digital

2.4.2 Timber Inventory Methods

Although remotely sensed data are being increasingly used in forest monitoring, they are unlikely to completely replace on-the-ground inventories. Current remote sensing capabilities are not sufficient to produce reliable estimates of many important aspects of forests and woodlands, such as biodiversity, deadwood, and soil carbon. Even with substantial technological advancement, it is unlikely that remote sensing will enable the direct measurement of all forest components and so ground sampled data may also be necessary to provide an element of ground truthing. The majority of national forest inventories combine ground sampling approaches with remote sensing, using stratified random sampling techniques to ensure that the sub-sample of forests and woodlands investigated are representative (Tomppo et al., 2010a).

Traditionally, ground sampling techniques were targeted at estimating the quantity of timber resources available, although these have been adapted over time to include a host of other factors such as ground vegetation, deadwood, biodiversity and edaphic characteristics (McRoberts et al., 2010). As previously described, national forest inventories can involve a single intensive effort (e.g. over 1-2 years) and be repeated every 5 to 10 years, or can follow an aggregated-survey design. By measuring 10-20% of plots each year, systematically distributed over the entire nation, up-to-date estimates can be obtained in any year (e.g. the National Forest Inventory of the UK (FC, 2010)). Thus, the ground sampling of forest inventory data can be divided into two distinct parts: 1) the assessment of on-the-ground plots; and 2) the extrapolation of this data to un-sampled sections of forests and woodlands.

The techniques and standards for on-the-ground plot measurement vary, though they are often characterised by the measurement of tree diameter at breast height (DBH; commonly 1.3m above the ground; the minimum diameter recorded may vary between 0 and 40cm), the measurement of tree height, and species identification (see Section 2.7.1). Detailed examples of plot-based techniques are provided in Chapters 4 and 5, and have been thoroughly reviewed in the literature and so will not be discussed here (Shiver and Borders, 1996, Schreuder et al., 1993).

Following the labour-intensive ground survey, the data obtained are extrapolated to un-sampled areas of forests and woodlands. Generally, this extrapolation is carried out via two main processes: extrapolation using mathematical functions; or extrapolation using correlations with variables of known distribution. Mathematical, nearest-neighbour techniques (e.g. inverse distance weighting, kriging, splines) are able to estimate values for the areas between sampled points (Childs, 2004). These mathematical extrapolation techniques assume high spatial correlation, with areas likely to be similar to those nearby. However, plant characteristics are often correlated with environmental conditions (Section 2.3). Thus, un-sampled forest and woodland localities may be better represented by those plots that share a similar environment, as opposed to those that are closer but experience substantially difference environmental conditions, such methods are used in the Finnish National Forest Inventory (McRoberts et al., 2010, Tomppo and Halme, 2004). Thus, correlations with remotely sensed data are often used to extrapolate of plot data to un-sampled areas. For example, plot data on forest biomass can be extrapolated across the globe using

LiDAR data using some known correlations between vegetation height and biomass (Baccini et al., 2012, Saatchi et al., 2011).

Under the 1998 National Forest Policy, the Forestry and Beekeeping Division (FBD) within the Ministry of Natural Resources and Tourism (MNRT) is responsible for forest monitoring in Tanzania (GoT, 2012). However, due to a lack of funds, no National Forest Assessment has been done since Tanzania gained independence, therefore the knowledge of the state and trends of the nation's forests and tree resources is insufficient to ensure sustainable use (FAO, 2009b). Thus, in collaboration with the government of Finland and the FAO, Tanzania launched its first National Forest Resources Monitoring and Assessment (NAFORMA) programme in 2009 (MNRT, 2012). NAFORMA will establish over 32,000 plots, 25% of which will be permanent sample plots, in order to collect data on land use, vegetation type, soil, and forest products and services. In addition, information on shrubs, regeneration, deadwood, stumps, and bamboos will also be collected (Vesa et al., 2010). Furthermore, this data will be complemented by a socioeconomic survey, enabling the drivers of deforestation and forest degradation to be explored (Kessy et al., 2010).

Similar to Tanzania, Brazil possesses little governmental knowledge about the state of nation-wide forest and woodland resources. Brazil has performed a single National Forest Inventory (NFI) to produce information about timber stocks of planted and natural forests (Tomppo et al., 2010a), although, having been performed in the 1980s, this is now considerably out-of-date and may not be applicable to the Brazilian forests and woodlands of today. Since then, only regional forest inventories have been carried out, meeting the demands of information required for specific strategies in some states (Tomppo et al., 2010a). In 2005, Brazil began to design a second NFI, although some states had begun to implement their own inventories in the interim (Tomppo et al., 2010a). The first field test of the methodology was held in the Amazon forest in November, 2007, with the woodland biomes being trialled in 2009 (FAO, 2012a). Once established, Brazil plans to repeat the inventory every 5 years (GoB, 2010).

China, by contrast, has a well-established NFI system, having conducted eight NFI at 3 to 5 year intervals between 1973 and the present day (NFI1 from 1973 to 1976, NFI2 from 1977 to 1981, NFI3 from 1984 to 1988, NFI4 from 1989 to 1993, NFI5 from 1994-1998, NFI6 from 1999 to 2003, NFI7 from 2004 to 2008, NFI8 from 2009 to present [currently on-going]) (Tomppo et al., 2010a). Data from all counties and provinces has been collected from systematically distributed sample plots. Rectangular permanent sample plots (ranging between 0.07ha to 0.1.ha) were established, predominantly during NFI2, and are utilised in a continuous survey (MoF, 1983). Inventories are conducted in one fifth of the provinces every year, collecting data on forest stock, tree growth and mortality, forest health, ecosystem diversity, forest disturbance and forest functions (Tomppo et al., 2010a).

Once again, India's forest survey is perhaps the most well-established and complete. The Forest Survey of India has been conducting field inventories of forest and woodland stock since 1965, and have inventoried >80% of the countries forests (FSI, 2009). Between 2002 and 2007, this programme was extended to include a survey of all vegetation types, as well as data collection on soil carbon in forest and woodland areas. Every two years, India surveys 10% of its districts, collecting data on forest stock, forest biodiversity, herbs, shrubs, forest regeneration, and forest soil carbon. To collect this information, a differentiated sample design is used, recording tree data in a 0.1ha plot, but collecting shrub and herb data from four $9m^2$ and $1m^2$ subplots laid out 30m from the centre of the 0.1ha plot (FSI, 2002). Furthermore, data on forest floor litter are collected from $1m^2$ subplots in the corners of the 0.1ha plot. The results of the survey are considered accurate to ±10%, although the accuracy of each district may vary (FSI, 2009).

Similar to forest area monitoring capabilities, the above case studies clearly demonstrate that the capacity of developing countries to monitor the status of their forests and woodlands vary substantially. Countries use a various standards and techniques each with different advantages and disadvantages (see Section 2.7.1 for a discussion on the effects of varying plot sizes). Furthermore, the survey frequency varies substantially between countries, with higher frequency measurements better able to create a time-series by which the trend in forest characteristics over time can be reliably estimated. The development and standardisation of this capacity is a key issue to resolve if REDD+ is to be successfully implemented.

Previously, this section has focussed on national forest monitoring, however, it is widely recognised that land use/cover change is of global concern (see Chapter 1). In the remainder of this section, I will discuss global efforts to monitor deforestation, forest degradation and their effects. Specifically, I will focus on the FAO FRA and the actions to mitigate the impacts of climate change overseen by the UNFCCC.

2.4.3 Uniform Methods for reporting FAO Forest Resource Assessments

The FAO has been monitoring the world's forests at 5 to 10 year intervals since 1946, initially producing World Forest Inventories in 1948, 1953, 1958 and 1963 (FAO, 2012c). During the 1970s, the FAO did not carry out global surveys but instead undertook a series of regional assessments, sending out surveys to each country region-by-region. By 1980, the need for uniform methods was recognised, using (for the first time) the standard FAO definition of forest (see Section 1.2.1). However, neither this, nor the assessment in 1988, was global and the definition of forests varied between developing and developed countries. Since 1988 the FRA has continued to evolve, with the general trend being one towards uniform methods and increased transparency. Since 1990, the FRA have been conducted every 5 years, with the latest published in 2010 (FAO, 2010d) and the assessment for 2015 already in development (FAO, 2012c).

The FRA 2010 was the most extensive FRA to-date. The FAO sought information on the status of 'forest' and 'other wooded land' area, encouraging countries to also provide data on 'other land with tree cover' (FAO, 2010d). Forests were the categorised into three classes (primary forests, other naturally regenerated forests and planted forests) and area estimates for these sub-categories were also provided (FAO, 2010d). The FRA also collected specific data on the area of mangrove forests, bamboo forests and rubber plantations. In addition, the standing volume of wood (total growing stock in forests and other woodland) was reported, alongside data on forest biomass and the carbon stock contain within this biomass for aboveground live, litter, coarse woody debris (CWD) and soil carbon pools (see Table 2.4 for definitions). The above data were provided by nations and, in addition to this, the FAO conducted a global remote sensing survey (Lindquist et al., 2012).

Broadly, the data provided to the FAO by nations are derived from their respective national forest inventories and must be converted to conform to FAO standards before it meets the FRA reporting criteria. Countries are encouraged to document the original national data used to compile the report, which commonly consists of national inventories and scientific reports (Sections 2.4.1 and 2.4.2), but also to document when there is data-deficiency (FAO, 2008). Data must be calibrated so total land area conforms to the FAO land area estimate. Typically, this is performed using a calibration factor such that all land uses/covers remain in the original proportions, but the total meets FRA reporting requirements (FAO, 2008). Furthermore, national data may not have been collected for the reference years used by the FAO and so the data may have to be interpolated or extrapolate to provide estimates for the required years. Finally, the FAO definitions frequently differ from those used in national forest inventories (Putz and Redford, 2010). In this case, the data must be reclassified using a matrix to assign a percentage of the original land use/cover category to the required FRA category (FAO, 2008). Similar standardisation procedures are required for all FRA reporting requirements (see FAO (2008) for full details), but those related to forest area (described above), biomass and carbon are of particular relevance to this thesis. Biomass and carbon reporting procedures conform to those of the Intergovernmental Panel on Climate Change (IPCC) and so are discussed in Section 2.4.4.

Although most nations are able to complete the majority of the FRA report, the uncertainty of the data provided often reflects that of national inventories. Tanzania provides land use/cover data for only 1984 and 1994, thus the FRA reference years of 1990, 2000, 2005 and 2010 need be assumed by linear extrapolation (FAO, 2010c). Such assumptions are typical of the Tanzanian report to the FRA as a whole, but here I will focus solely on forest area as this has direct relevance to Chapter 3. Similarly, Brazil only presents land use/cover data from 2002, calculating the required data from reference years using linear sub-national deforestation data (FAO, 2009a). The well-established national forest inventory systems in China and India are evident throughout the respective country reports to the FRA, with adequate data provided and so reduced uncertainty (FAO, 2010a, FAO, 2010b).

The data-deficiencies present in most developing countries severely impact the ability of the FAO to produce reliable estimates of global forest area. For example, in the absence of inventory data for the reference dates, the FAO relies upon projections and/or expert opinion (Matthews and Grainger, 2002). This data-deficiency is wide-spread. The FAO acknowledge that estimates of open woodland areas are less accurate than those of closed forest as it is harder to detect open woodland via remote sensing and because government inventories often ignore such biomes (FAO, 2000b). Since open woodlands account for an estimated 40% of tropical forests, it is likely that the uncertainty associated with global estimates is substantial (Matthews and Grainger, 2002). The reliability of FRA has been strongly questioned (Meyer and Turner, 1992, Ramankutty et al., 2007, Grainger, 2008b, Grainger, 2010), and is likely to remain problematic until NFI systems become well-established in all countries across the globe.

2.4.4 Uniform Methods for Reporting to UNFCCC

As a result of the substantial GHG emissions associated with land use/cover change and the likely negative impact of such emissions on the global climate, the UNFCCC has instigated several mechanisms (e.g. the Kyoto Protocol and REDD+) by which to limit these emissions (see Chapter 1). In order to evaluate climate regulation activities associated with these mechanisms and assign the appropriate compensation and/or carbon credits, the UNFCCC require nations to submit standardised reports. Here, I will focus on the IPCC requirements for reporting emissions resulting from land use/cover change to the UNFCCC.

Similar to the FRA, the IPCC require data on land use/cover change. The IPCC require complete national land use/cover vegetation surveys, since all land uses/covers are considered in this reporting process. Nations must ensure that the categories used in national vegetation surveys conform to the IPCC guidelines and so must broadly include forest land (woody vegetation), cropland (arable and tillage land), grassland (including rangeland and pasture), wetlands (land covered or saturated by water for all or part of the year), settlements (all developed land), and other land (e.g. bare rock, ice) (IPCC, 2003). In order to estimate the GHG flux associated with any land use/cover change trends, the IPCC require countries to estimate the emissions resulting from degradation within land use/cover categories (e.g. from forest that remains forest land) and the emissions resulting from land use/cover change (e.g. deforestation). The IPCC guidelines state that the "*fundamental basis for the methodology rests upon two linked themes; i) the flux of* CO_2 *to or from the atmosphere is assumed to be equal to changes in carbon stocks in existing biomass and soils, and ii) changes in carbon stocks can be estimated by first establishing rates of change in land use and the practice used to bring about the change (e.g. burning, clear-cutting, selective cut etc.). Second, simple assumptions or data are applied about their impact on carbon stocks and the biological response to a given land use*" (IPCC, 2003). Thus, by understanding the carbon stored per unit area for each land use/cover and by understanding the rate of carbon flux following land use/cover change or degradation, the associated GHG emissions can be estimated.

Table 2.4 Description of the IPCC carbon pools and general tiers to estimate changes in carbon stocks in biomass in a land cover category, taken from (IPCC, 2006a). Land cover specific tier definitions are also available.

IPCC term	Description
Tier 1	Uses aggregate data and default emission /removal factors
Tier 2	Uses country-specific biomass data and emission/removal factors
Tier 3	Uses detailed data on biomass to estimate changes in carbon stock using dynamic models or allometric equations
Aboveground live carbon	All carbon contained in living vegetation, both woody and herbaceous, above the soil including stems, stumps, branches, bark, seeds, and foliage.
Coarse woody debris carbon	All non-living woody carbon not contained in the litter, either standing, lying on the ground, or in the soil. Dead wood includes wood lying on the surface, dead roots, and stumps, larger than or equal to 10 cm in diameter (or the diameter specified by the country).
Litter carbon	All non-living organic carbon with a size greater than the limit for soil organic matter (suggested 2 mm) and less than the minimum diameter chosen for dead wood (e.g. 10 cm), in various states of decomposition above or within the mineral or organic soil. Live fine roots above the mineral or organic soil (of less than the minimum diameter limit chosen for below-ground biomass) are included in litter where they cannot be distinguished.
Belowground carbon	All carbon contained in live roots. Fine roots of less than (suggested) 2mm diameter are often excluded because these often cannot be distinguished empirically from soil organic matter or litter.
Soil carbon	Includes organic carbon in mineral soils to a specified depth chosen by the country. Live and dead fine roots and dead organic matter within the soil, that are less than the minimum diameter limit specified (suggested 2 mm), are included with soil organic matter where they cannot be distinguished.

Direct measurement of the carbon (and other GHG) stored within biomass and soil is impractical (Woodhouse et al., 2012), and so carbon stock is estimated from direct measurement of other variables (e.g. DBH (Lewis et al., 2009b, Phillips et al., 2009b)). Volume estimates can be calculated from these indirect measurements but it is necessary to convert these volume estimates to units of mass (i.e. carbon content per unit area) using allometric equations (Chave et al., 2005, Brown, 1997). Thus, total carbon flux is equal to the difference between the carbon stock of the original and final land use/cover. The IPCC recognise, however, that GHG flux does not immediately follow land use/cover change nor degradation, and requires that the flux occur gradually over time through the use of emission/removal factors (the average rate of flux of a given GHG for a given source). Furthermore, the IPCC require these calculations be performed for five pools of carbon: aboveground live; CWD; litter; belowground; and soil to achieve the necessary completeness (see Table 2.4 for definitions).

Recognising that the capacity of countries to deliver this data varies substantially, the IPCC adopts a tiered approach, ensuring all countries are able to participate. The most basic method employed is termed the Tier 1 approach and uses globally standard values provided in the IPCC Guidelines (IPCC, 2003). For this tier, some land use/covers and pools are assumed to have zero emissions or removals due to data-deficiencies. Tier 2 approaches use the same methodology as Tier 1 approaches, but apply emission factors that are more appropriate for the climatic regions and land use/cover systems in the country of study. Finally, Tier 3 approaches are the highest order methods, and require the use of models and inventories tailored specifically to national circumstances and repeated over time. Tier 3 methods demand a high level of spatial and temporal resolution. As nations progress from a Tier 1 approach to a Tier 3 approach, the GHG flux estimates they produce become more representative of their country and, as such, uncertainty reduces by an order of magnitude (from approximately ±90% to ±10%) (GOFC-GOLD, 2010).

Since IPCC requirements share similarities with those of the FAO, the capacity of nations to deliver the necessary data somewhat reflects the stage of development of their respective NFI. In 2003, Tanzania submitted its sole National Communication to the UNFCCC, containing two GHG inventories (dated 1990 and 1994), although these used a Tier 1 approach and so can be substantially improved (Government of Tanzania, 2003). Brazil submitted its initial National Communication to the UNFCCC in 2004, providing a GHG inventory (MCT, 2004), and followed that with a second in 2010 (MCT, 2010). Within Brazil, locally derived allometric biomass equations are available to calculate the carbon stock, although these were derived by an external agency (Herold, 2009). Thus, the carbon stock values reported to the IPCC and FRA use a Tier 2 approach. China has also submitted two National Communications to the UNFCCC, dated 2000 and 2011 (PRC, 2004, PRC, 2011). China predominantly uses a Tier 2 approach for estimating GHG flux following land use/cover change and degradation, but adopts some Tier 1 IPCC defaults (PRC, 2004, PRC, 2011). Finally, India submitted its National Communication to the UNFCCC in 2004 but did not include GHG emissions from forestry (MEF, 2004), however this was rectified by the second National Communication in 2012 (MEF, 2012). In both National Communication documents, carbon emissions were estimated using a Tier 2 approach (MEF, 2012). Given India's capacity for NFI, it is likely that a Tier 3 approach will be followed in the near future (Herold, 2009). All case studies highlight data-deficiencies in the capacity to undertake a national GHG inventory. However, those nations with well-established NFI, once again, are best placed to deliver the required data to global institutions. Substantial capacity building is required in some developing nations before they are ready for REDD+ (see Chapter 1).

2.5 Scientific National and International Forest Area Monitoring Methods

Complementing national forest inventories, science has had, and continues to have, a role to play in the monitoring of national and international forest area. I have previously described the variation in capacity of nations to monitor forest area, detailing how some developing nations (e.g. Tanzania) are aided in forest monitoring by external organisations (see Section 1.4.2). Whilst the external organisations that contribute to forest monitoring in low-capacity nations vary widely, including the private sector and foreign governmental organisations, science has been integral in developing and applying many of the technologies and methodologies used. It is this scientific contribution to forest area monitoring that I will focus on in this section.

Multiple methods for monitoring deforestation have been developed. These methods include: 1) visual interpretation of remote sensing (aerial photos or satellite imagery). This process is labour intensive but can typically be performed without extensive computational capacity (Skole and Tucker, 1993); 2) wall-to-wall monitoring, whereby automated or semi-automated procedures are utilised to map forest area using remotely sensed images that capture the entire area of interest (INPE, 2005); 3) hot-spot analyses – using high resolution data to monitor deforestation in locations of rapid change (Achard et al., 2002). These three approaches can be followed using a variety of techniques, from relatively simple technologies (such as historical land use/cover maps and aerial photography) to more complex procedures (e.g. satellite imagery derived over varying resolutions and differing spectral ranges). Each approach must be suitable to the task at hand, with the most appropriate approach and technology being decided upon using the following selection criteria: a) Costs and technological constraints – where either finances and/or technological capabilities limits apply, best-practice recommendations cannot be followed and so visual interpretation of remotely sensed images may provide the only feasible source of data; b) deforestation patterns and rates – in areas of rapid deforestation there is a need for data with high temporal resolutions, whilst in areas where deforestation typically occurs in small sections, data of higher spatial resolution are required; c) seasonality – annual variation may lead to misclassification of land use/cover type, particularly for deciduous forests and woodlands whose characteristics can change dramatically through the year. Seasonality must also be considered in evergreen regions, as cloud cover may prevent the classification of land use/cover using visual spectra (Sánchez-Azofeifa et al., 2009, Asner, 2001); d) the area of interest – forest area monitoring in large countries and at global or continental levels may require the use of lower resolution data in order to reduce costs and computational requirements, whilst also ensuring image consistency over the entire study area. Thus, although science strives for best-practice standardisation of data collection, no single method is appropriate in all circumstances and methods must be adapted to local conditions (DeFries et al., 2007, Rogan and Chen, 2004).

Whilst satellite data have only been available for the past few decades (Lambin, 1997), historical maps and aerial photography have been used to determine the spatial extent of vegetation for many years. Historical maps can be of relatively low resolution, but are useful for monitoring changes in forest area that occurred prior to the availability of satellite data as they may be the only direct data source capable of monitoring forest area over a century-long time scale in some regions (Börjeson, 2009). However, due to low technological capacity and the need to standardise land use/cover categories across maps (see Chapter 3 for further discussion), there is a trade-off between the temporal span of study and the resolution of area change detection (Petit and Lambin, 2002). By comparison, aerial photography can provide data of very high resolution, typically from aeroplanes (Waser et al., 2008). However, aerial photography is more time-consuming and expensive to obtain than some satellite data and so it is often impractical to collect these data over vast areas, and so this technique is only particularly efficient for estimating forest area and biomass in small regions (Brown et al., 2005).

In the mid-1980s, Tucker et al. (1985) and Townshend et al. (1987) used 4km spatial resolution imagery to demonstrate that is was possible to map land use/cover over and entire continent in a consistent manner. Since this achievement, scientists have been testing and adapting satellite technologies, increasing both scope and resolution. For example, by the following decade, Loveland et al. (1999) published the first pan-continental map of forest cover at an improved 1.1km resolution, using a single data source over a fixed time period (April 1992 until December 1993). These medium resolution data sources have been continually developed and are still utilised today. Most notably, AVHRR, MODIS (the Moderate Resolution Imaging Spectroradiometer) and SPOT data have been particularly important for monitoring forest area and these will be discussed in turn.

AVHRR data have repeatedly been utilised for mapping forest area (Achard et al., 2001, Mayaux et al., 1999), with products well received by the scientific community (Mayaux et al., 2005). Work funded by NASA investigates the extent of forest area in the tropics at a 8km resolution using the Pathfinder dataset of AVHRR (DeFries et al., 2002). For each year from the early 1980s to the late 1990s, the percentage tree cover in each pixel was estimated, allowing the forest area (under various definitions) to be mapped. AVHRR data are the only data set capable of covering both this time-span and the entire global area. Although the AVHRR provided an important source of temporally and spatially continuous data, other data sources began to be favoured, most notably MODIS (Townshend and Justice, 2002) and SPOT Vegetation (Mayaux et al., 2004). Both sensors offered improved geo-location and calibration relative the AVHRR data (Fuller, 2006). MODIS in particular has proven exceedingly popular.

MODIS instruments provide consistent daily coverage of the entire globe at a 250m to 1km resolution, with 36 bands of spectral information (Justice et al., 2002). MODIS products provide varying types of data for the monitoring of forest area. For example, Surface Reflectance (MOD09) data and Vegetation Indices (MOD13) are provided in near-real time (a maximum of every 16 days), allowing for rapid detection of changes in forest area (Morton et al., 2005). However, MODIS also provides quarterly or annual products such as the Vegetation Cover Conversion (MOD44A) and Vegetation Continuous Fields (MOD44B) which can be used to periodically estimate deforestation and forest cover respectively (Morton et al., 2005), although this dataset only extends back to 2000. MODIS is widely utilised by both scientific and governmental communities, particularly as the data are freely available to download via the internet.

The Vegetation sensors on board SPOT4 and SPOT5 have a 1km spatial resolution and four spectral bands (two in the visible range, and one in both the near infrared and shortwave infrared bands). Similar to MODIS, SPOT Vegetation data are also supplied to end-users via the internet and is delivered in a series of standardised products: atmospheric reflectance; canopy reflectance; and the Normalised Difference Vegetation Index (NDVI) (Vegetation, 2011). NDVI data are supplied every 10-days and higher values typically indicate the presence of high-biomass land uses/covers (i.e. forests and woodlands). For example, Mayaux et al. (2004) used the NDVI data to map land use/covers across Africa for the year 2000. Additionally, Global Land Cover 2000 used the same data to produce a global land use/cover map for the same year (Bartholomé and Belward, 2005).

AVHRR, MODIS and SPOT Vegetation data have high temporal resolution and so there is high probability of obtaining cloud-free images from which land use/cover data can be derived. Furthermore, the relatively coarse spatial resolution of these data has cost advantages, reducing the amount of data that needs to be processed whilst still ensuring wall-to-wall coverage. However, the AVHRR, MODIS and SPOT Vegetation datasets are limited in resolution and can only provide general indications of trends in forest area change at a national or continental scale (Mayaux et al., 2005, Rogan and Chen, 2004).

Advances in science and technology enabled the more recent development of satellite sensors capable of acquiring satellite imagery at a high spatial resolution. The improved spatial detail of such images enables forest area to be estimates with increased certainty over national and international scales (Mayaux et al., 2005). High resolution data with nearly complete global coverage are available at low (or no) cost for the early 1990s to present day. However, countries are limited by the high cost of data processing required for this data, plus the reduced temporal resolution (decreasing the likelihood of cloud-free images – the primary data limitation in the humid tropics (Asner, 2001, Helmer and Ruefenacht, 2005, Ju and Roy, 2008), when compared to medium resolution data. In particular, the Landsat dataset has been frequently used to monitor forest area (Mollicone et al., 2003). For example, Brink and Eva (2009) have used Landsat images to monitor land use/cover change in Africa between 1975 and 2000.

The Landsat programme began in 1972, and made high resolution study of forest area change possible via satellite data. The first Landsat satellites held a Multispectral Scanner System (MSS) capable of delivering data from four spectral bands (two in visible light and two in near infrared) at a spatial resolution of 80m. The Landsat system was continually improved. In 1984, the Landsat Thematic Mapper (TM) was launched, providing higher spectral and spatial (30m) resolution data. Whilst the Landsat MSS sensors were specially designed to map vegetation and geological features, with Landsat TM was tailored to investigate vegetation type, soil moisture and other key landscape features (Jensen, 2007). Generally, Landsat imagery provides clear distinction between forest and non-forest cover, enabling both manual (Townshend and Justice, 2002) and semi-automated interpretation (Achard et al., 2002). The full Landsat archive (Landsat 1-5 MSS [1972-1994], Landsat 4 TM [1982-1985], Landsat 5 TM [1984-present] and Landsat 7 [1999-present; but developing a fault in 2003]) is available free of charge via the internet, with scenes covering 170km squares.

There are two principle limitations of the Landsat data. Firstly, many scenes are required to cover large areas (e.g. 215 scenes are required to provide wall-to-wall coverage for the Amazon forest in Brazil (Fuller, 2006)). The large numbers of scenes require high computational capacity to process the data. To reduce this cost, Tucker and Townshend (2000) established a strategy by which a sub-sample of Landsat scenes could be processed, estimating deforestation with a ±20% accuracy 90% of the time. Such an approach has been successfully implemented in the Brazilian Amazon (Fearnside and Barbosa, 2004) and the Congo (Hansen et al., 2008a). Secondly, the spectra used by Landsat sensors cannot penetrate clouds, which persist over many parts of the tropics during the wet season and throughout the year in many upland and montane environments. This can dramatically reduce the availability of usable images in cloud-prone areas to one every few years (Trigg et al., 2006).

High resolution satellite data has been used to map global forest resources by two main programmes: TREES, and the FAO. Initiated in the early 1990s, TREES aims to map forest cover throughout the tropics using extensive sets of satellite data (Achard et al., 2002). The programme uses stratified sampling, visually interpreting Landsat imagery, focussing particular attention on deforestation hotspots (Mayaux et al., 2005). Over the same period, the FAO have run a similar scheme, using a sample of 117 multi-date Landsat TM scenes, visually interpreted using a 2km grid cell, to map forest into four classes: closed forest (canopy cover >40%); open forest (canopy cover 10-40%), long fallow (forest affected by shifting cultivation) and fragmented forest (forest/non-forest mosaics) (Lindquist et al., 2012).

The new survey scheme FAO and TREES have adopted uses far more, but smaller, sample sites, with 9000 anticipated (Eva et al., 2010). The survey will sample 20km square units at the point where each degree of latitude and longitude intersect every 5 years using satellite imagery of 30m spatial resolution, detecting current forest cover, deforestation and forest regeneration (Eva et al., 2010).

Furthermore, very high resolution satellite data are available (e.g. Hyperian, IKONOS, ALI, ETM+, Quickbird, SPOT, ASTER, CBERS, IRSS), although these have been more recently developed and so there is less scope to use them for identifying changes in forest area over time. Here, I will focus on the CBERS and IRSS as these are relevant to two of the case study nations used in Section 2.4. The CBERS programme consists of two satellites, the earliest of which was launched in 1999. They carry a high resolution (20m) sensor capable of detecting visible and near infrared spectra, as well as those of lower resolution (80m and 260m) capable of using shortwave and thermal infrared spectra (Wulder et al., 2008). The data from CBERS is freely available to developing nations and can be purchased by developed nations with no redistribution fee. However, the quality of the CBERS satellites is still under investigation (Wulder et al., 2008). The IRSS was launched in 2003 and also detects a range of spatial resolutions (5.8m to 56m) with visible and near infrared spectra detected at high resolutions and short wave spectra being added to lower resolution data. The IRSS shares similar qualities to the Landsat satellites, but with higher resolution. However, IRSS lacks a comprehensive ground station network and only carries 15GB of on-board memory (c.f. with nearly 50GB for Landsat 7), limiting its ability to routinely acquire global data (Wulder et al., 2008).

Very high resolution systems are unlikely to meet the needs for routine monitoring of cloud-prone regions or nations of low capacity as they suffer the same general limitations as high resolution systems, namely a low temporal resolution and a relatively small area of coverage. Thus, researchers are increasingly turning to cloud-penetrating imagery to provide forest area estimates in these regions. Although active microwave remote sensing (i.e. radar) technology has been available for more than 50 years, it is only relatively recently that this technology has been used to detect forest and woodland area. These radar-type systems can be utilised on-board aeroplanes (thus sharing many disadvantages with aerial photography) but has been increasing used in satellite systems (termed synthetic aperture radar [SAR] system).

A SAR is an active sensor, transmitting pulses of polarised microwaves to the ground, and receiving the reflected radiation. The microwaves used by SAR sensors (typically between 3 and 25cm wavelength) are able to penetrate clouds, dry snow and, to some extent, rain, thus observations can be made 24 hours a day, even in cloud-prone areas (although intense rain can cause major difficulties) (Balzter, 2001). The microwaves also partially penetrate vegetation, with reflectance occurring at both the canopy top and ground level. As a result, SAR can be used to provide estimates on forest height as well as forest area. However, the analysis of the reflected spectra is of limited use as ecological factors may cause ambiguities in the signal (Balzter, 2001). Thus, two SAR images should be used, eliminating random scatters through the subtraction of the two signals (Balzter, 2001). Although SAR imagery does not provide as much spatial detail as very high resolution satellites using visible spectra, Sgrenzaroli et al. (2002) and Podest and Saatchi (2002) have reported that SAR data are able to provide acceptable forest area estimates at the continental scale. However, at present, relatively few satellites operate with this technology, making the data and its processing costly. LiDAR sensors use similar technologies but, at present are predominantly mounted on aeroplanes and so best suited for analyses of small areas (see Section 2.7.2 for a detailed discussion).

It is apparent that early applications of remote sensing technology for forest and woodland area estimation were largely experimental, and that science has played a critical role in standardising techniques of data collection and processing, as well as estimating uncertainty. It is also evident that there is no best-practice with regards to methods of forest area estimation, with numerous trade-offs evident: historical maps provide the longest temporal scale, but both temporal and spatial resolution are often poor; aerial photography requires low processing capacity, but is expensive for investigations over large areas; medium resolution images provide wall-to-wall coverage at high temporal resolution, but does not have sufficient spatially resolution for national forest area estimates; high and very high resolution images provide the spatial resolution required at a national-scale, but show poor temporal resolution and require extensive processing capabilities; and active microwave remote sensing can provide temporal resolution in cloud-prone areas, but are of poor spatial resolution and expensive. Thus, nations and scientists must select the approach that is most appropriate for their area of interest, or adopt a combination of methods (e.g. the combination of temporally high resolution satellite imagery with those derived from very high resolution satellites). Due to the variety of appropriate methods available, science has an important role to play in closely scrutinising the government-sponsored national forest monitoring schemes (Kummer, 1992, Kummer, 1994), independently verifying results. However, there seems to be geographic bias in the scientific application of remote sensing in tropical regions, with nearly two-thirds of studies between 1995 and 2003 being focused on the Amazon, with the remainder divided equally between Central Africa and Southeast Asia (Fuller, 2006). Furthermore, like many nations, researchers often use the data they can afford, not the data they truly need (Hansen et al., 2008a). The inadequate funds available for forest area estimation substantially limit the ability of scientists to estimate forest area. The lack of long-term funding is particularly concerning, as it inhibits the establishment of independent scientific centres of excellence capable of monitoring change in global forest area over time, thus rates of tropical deforestation remain somewhat uncertain.

2.6 Modelling Land Use/Land Cover Change

As is evident above, LCC has been of interest to researchers for some time (Otterman, 1974, Charney et al., 1975, Sagan et al., 1979, Woodwell et al., 1983, Houghton et al., 1985). Over the last few decades, researchers have improved measurements of LCC, as well as developing an increased understanding of the causes of LCC and increasing the certainty of predictive models, in part due to the technological and methodological advancements described in Section 2.5. Over this time period, theories of spatially homogenous, linear patterns of the conversion of pristine environments have evolved, becoming increasingly complex, and land change science has developed into a discipline it its own right.

In this section, I will discuss the theory and techniques surrounding the short-term and long-term modelling of LCC, before discussing a recent development in land change science that is particularly relevant to REDD+ activities – the Forest Identity (see Section 2.6.3). However, there are several over-arching key issues in land change science that are relevant to all these discussions, centring on how and why LCC occurs. Firstly, should land change science focus on shifts from one land use/cover to another (termed conversions; e.g. deforestation), or should subtle changes within land use categories (termed modifications; e.g. forest degradation) also be of interest? The study of land use/cover conversions has the advantages of concision and clarity (Lambin et al., 2003), with the categorisation of land uses/covers into discrete units is a relatively simple process (Loveland et al., 1999, DeFries et al., 1995), enhancing our ability to monitor the change in area of these categories. However, although more difficult to detect, land use/cover modifications can still have a substantial effect on the character of the landscape. For example, declines in tree density and species richness (without changes in land use/cover) have been used to indicate deforestation in Senegal (Gonzalez, 2001), although no such declines are associated with desertification in the Sudan (Schlesinger and Gramenopoulos, 1996), indicating that multiple factors may be driving desertification and that it my occurs via numerous possible pathways. Secondly, what should be the time-scale of focus? LCC can occur progressively, with one land use/cover being slowly converted to another over time, but the converted state may not be permanent and land use/cover may revert back to its original state. Such LCCs and reversions may occur periodically as a result of regular anthropogenic (e.g. repeated cycles of slash and burn agriculture (Tschakert et al., 2007)) or natural (e.g. El Niño–Southern Oscillations effecting forest characteristics (Phillips et al., 2009b)) processes. Finally, what processes drive LCC? Land change science contains two mutually exclusive explanations of the causes of LCC: 1) LCC is caused by a single factor (Myers, 1993, Ranjan and Upadhyay., 1999, Allen and Barnes, 1985, Cropper and Griffiths, 1994, Ehrhardt-Martinez, 1998, Mather and Needle, 2000); 2) LCC is the result of many varying causative factors (Rudel and Roper, 1996, Bawa and Dayanandan, 1997, Mather et al., 1998, Geist and Lambin, 2002). Both single and multiple causal factors can act at different scales, i.e. proximate causes and underlying causes (see Section 1.3). Thus, land change science is continually evolving. Below I document the progress to date, focussing on deforestation and forest degradation as these are of particular relevance for REDD+.

2.6.1 Short-Term Regression Modelling of Land Use/Land Cover Change

Some trends of changes in forest area over time are apparent from national, global, and scientific monitoring of forest area (see Sections 2.4 and 2.5) and some of the causative factors driving these patterns are described in Section 1.3. Here, I will evaluate the techniques used to explore and understand such LCCs over the short-term. I discuss six broad categories of model (system models, empirical models, economic models, cellular-based models, hybrid models, and agent-based models), highlighting key variables important in driving and controlling tropical deforestation and forest degradation.

Systems models represent stocks, flows and sinks of information and/or resources, through differential equations and structural ontologies. Socioeconomic structures (e.g. governments, communities, markets) interact at numerous spatial and temporal scales and cumulatively provide many of the factors on which an individual's land use/cover decisions are based. Time is divided into discrete steps of varying lengths, allowing feedback loops to be included in the system. Furthermore, human and ecological interactions can be represented in these models, although such approaches require specific datasets that are often deficient and so poorly represent the apparent spatial variation (Baker, 1989, Parker et al., 2003). By modelling human behaviour directly, rather than the outcome of human behaviour, multiple factors driving LCC decisions can be considered (Irwin and Geoghegan, 2001). Thus, the systems approach represents the socioeconomic-environment linkages in a dynamic manner at a designated spatial scale, highlighting the complex mechanisms driving LCC decisions and revealing the underlying drivers involved. Lambin et al. (2003) provide an example of this, describing how institutional barriers (e.g. poor land tenure, inaccessible finance systems) may lead to the marginalisation of the rural poor, and mass migration into inadequately protected forested areas as modernised agriculture develops.

Empirical models differ from systems models in that they are not derived from an understanding of the underlying socioeconomic pressures but are typically developed using remotely sensed data on LCC. Empirical models are often simple correlations between LCC and explanatory variables also derived from remotely sensed data (e.g. distance measures and biophysical variables; see Chapter 3 and Chapter 5). These models are readily applied in areas were detailed data are lacking and, as such, there are numerous examples in the literature (Mertens and Lambin, 1997, Andersen, 1996, LaGro and DeGloria, 1992, Ludeke et al., 1990). In many cases, these models fit the LCC data well, explaining a large amount of the observed spatial variation. However, caution must be applied when interpreting these models as correlations identified do not prove causation. Thus, empirical models are less successful at identifying the drivers involved or at explaining the human decisions associated with such patterns. This short-coming derives from the fact that these analyses are performed at the pixel-level, rather than that of the individual decision-maker. For example, whilst soil fertility, distance to market and regional poverty measures of a pixel may be considered, studies may neglect social aspects such as the family size, education and/or ability to bear risk of specific households (Irwin and Geoghegan, 2001). However, empirical approaches can overcome this limitation by adopting theoretical frameworks that help explain decision-making and other social characteristics (Geoghegan et al., 1997, Leggett and Bockstael, 2000). Due to data constraints, empirical models are most commonly developed for a single point in time, focussing on the spatial variation of LCC. As my study area (the watershed of the EAM in Tanzania) is data-deficient, I adopt this approach in Chapters 3 and 5, although by creating numerous empirical models for different time-points, I was able to investigate some aspects of temporal variation in LCC in Chapter 3.

Economic models of LCC can be broadly divided into two subcategories: microeconomic models that describe equilibrium patterns within a local context; or regional economic models that encompass the flows of various resources and goods across regions. Microeconomic models typically use simple theory (e.g. the bid-rent theory) to develop models of land use/cover (Mills, 1967). Similarly, regional economic models also involve gross simplifications, modelling the socioeconomic interactions between discrete zones (see Wegener (1994) for a review). Thus, regional economic models suffer similar limitations to empirical models as decisions occur at the pixel and not individual scale. Due to over-simplification, neither microeconomic nor regional economic models capture the complex spatial and temporal patterns of LCC well (Anas et al., 1998). As described above, the limitations of economic models can be somewhat avoided by combining this approach with empirical models, using socioeconomic theory to provide a sound basis by which remote sensing data is used to explain the variation in LCC observed (Pfaff, 1999, Nelson and Hellerstein, 1997).

Cellular models include both cellular automata and Markov models, and operate over a network of similar cells. Cellular automata characterise the behaviour of the system using a set of deterministic or probabilistic rules to assign the state of a cell based on the state of its neighbours, although non-local neighbours (Takeyama and Couclelis, 1997) and networks can also be used (O'Sullivan, 2001). The system is fully homogenous, with each cell capable of being assigned all states and the same transition rules apply to each cell (Parker et al., 2003). Markov models, adopt a similar approach, but cell states depend on temporally-lagged transition rules. Thus, Markov models and cellular automata can be combined to model LCC (Balzter et al., 1998). Despite the simplicity of transition rules, these models can yield complex patterns and thus have been widely used in LCC modelling (Silvertown et al., 1992, Hogeweg, 1988, Alonso and Solé, 2000). However, again, this approach is limited as it cannot fully incorporate human decision making, and thus may prove erroneous in predicting the effects of various social phenomena (e.g. migration) (Hogeweg, 1988).

Hybrid models, as the name suggests, combine any of the above-mentioned approaches. By using a combination of approaches many of the limitations discussed above can be overcome. Examples of hybrid models include the LUCAS model (Berry et al., 1996) and the CLUE model (Veldkamp and Fresco, 1996). Both LUCAS and CLUE model LCC using a combination of geographic, edaphic, climatic and socioeconomic variables to simulate future land use/cover under different scenarios (e.g. logging and road-building, or urbanisation and protected area network planning respectively). However, such models are still limited to the degree to which individual decision-making can be evaluated (Irwin and Geoghegan, 2001).

The agent-based modelling approach takes a different perspective to the above techniques, focussing on individual decision-making rather than landscape variation and transitions. Agent-based modelling represents the motivations behind decisions and identifies the external factors that influence these decisions through the use of autonomous agents. Each agent represents a social unit (e.g. an individual or household) which can act intelligently to achieve desirable goals (e.g. increased household income or food security). As a minimum, agent-based model can be used to test reactions to environmental shocks or policy decisions. For example, Bilsborrow (1987) analysed the demographic responses to land shortage and declining yields in developing countries. Furthermore, agent-based modelling can be used to test rational choice theory, whereby land use/cover decisions are cumulative result of numerous rational analyses of socioeconomic and/or biophysical factors. However, it is debated whether , in practice, human decision-makers make fully rational decisions (Selten, 2001).

Thus, there are a wide variety of approaches available for modelling short-term LCC, however each has associated drawbacks. Hybrid cellular models successfully represent socioeconomic and biophysical phenomena, but do not also fully encompass human decision-making. Agent-based modelling approaches show promise in their ability to fully represent the complex process of decision making, and so future efforts should focus on combining cellular- and agent-based approaches to further our understanding of LCC (Parker et al., 2003).

Numerous driving factors (those causing LCC; e.g. firewood demand) and controlling factors (those restricting LCC; e.g. laws restricting development activities in protected areas) have been identified using the approaches, and various combinations of the approaches, outlined above. These have been briefly described in Section 1.3 and many examples are apparent in the literature (Verburg et al., 1999, Verburg and Overmars, 2009, Matthews et al., 2007, Overmars and Verburg, 2005, Long et al., 2007, Veldkamp et al., 1992, Serneels and Lambin, 2001, Pontius Jr et al., 2001). However, these factors are often specific to the local situation and not widely applicable to other geographic areas where socioeconomic and biophysical variables may greatly differ, even between sites that are geographically adjacent (Homewood et al., 2001, Serneels and Lambin, 2001), thus it is not fruitful to discuss these patterns here. Of greater interest are the factors common to many situations, as these provide directions in which to develop policies in order to reduce deforestation and forest degradation. Meta-analyses have identified a limited number of high-level causative factors: resource scarcity; changing market conditions; policy interventions; risk management; and social change (Geist and Lambin, 2002, Lambin et al., 2003). These high-level drivers are applicable to both short-term and long-term LCC patterns and warrant further investigation under REDD+ readiness activities (Table 2.5).

2.6.2 Long-Term Modelling – the Forest Transition Model

In addition to the above modelling techniques, a specific model detailing the long-term changes in forest area over time (termed the forest transition model) has been developed over the past 20 years (Mather, 1992). Forest transition models demonstrate that long-term changes in forest cover can be broadly described using a U-shaped curve. However, the curve is actually the net effect of two separate LCC curves: the decline in forest area (termed national land use transition) and the recovery in forest area (the forest replenishment period) (Grainger, 1995) (Figure 2.2). The two components of this curve should be considered separately as different factors drive forest

Table 2.5 Common drivers of tropical LCC (adapted from Lambin et al. (2003)).

Temporal scale	Resource scarcity	Changing market conditions	Policy interventions	Risk management	Social change
Short-term	• Spontaneous migration, forced population displacement, refugees • Decrease in land availability due to encroachment by other land uses (e.g. protected areas)	• Capital investments • Changes in national or global macro-economic and trade conditions that lead to changes in prices (e.g., surge in energy prices or global financial crisis) • New technologies for • intensification of resource use	• Rapid policy changes (e.g., devaluation) • Government instability • War	• Internal conflicts • Illness (e.g., HIV) • Risks associated with natural hazards (e.g., leading to a crop failure, loss of resource, or loss of productive capacity)	• Loss of entitlements to environmental resources (e.g., expropriation for large- scale agriculture, large dams, forestry projects, tourism and wildlife conservation), which leads to an ecological marginalization of the poor
Long-term	• Natural population growth and division of land parcels • Domestic life cycles that lead to changes in labour availability • Loss of land productivity on sensitive areas following excessive or inappropriate use • Failure to restore or to maintain protective works of environmental resources • Heavy surplus extraction away from the land manager	• Increase in commercialisation and agro-industrialisation • Improvement in accessibility through road construction • Changes in market prices for inputs or outputs (e.g., erosion of prices of primary production, unfavourable global or urban- rural terms of trade) • Off-farm wages and employment opportunities	• Economic development programs • Perverse subsidies, policy- induced price distortions and fiscal incentives • Frontier development (e.g., for geopolitical reasons or to promote interest groups) • Poor governance and corruption • Insecurity in land tenure	• Impoverishment (e.g., creeping household debts, no access to credit, lack of alternative income sources, and weak buffering capacity) • Breakdown of informal social security networks • Dependence on external resources or on assistance • Social discrimination (ethnic minorities, women, members of lower classes or castes)	• Changes in institutions governing access to resources by different land managers (e.g., shift from communal to private rights, tenure, holdings, and titles) • Growth of urban aspirations • Breakdown of extended family • Growth of individualism and materialism • Lack of public education and poor information flow on the environment

decline and forest recovery (Barbier et al., 2010). For example, in most countries the rising population and food demand resulting from economic development results in a considerable loss in forest area (Mather, 1992). However, more intensive farming practises and an increased demand for wood product may lead to forest replenishment.

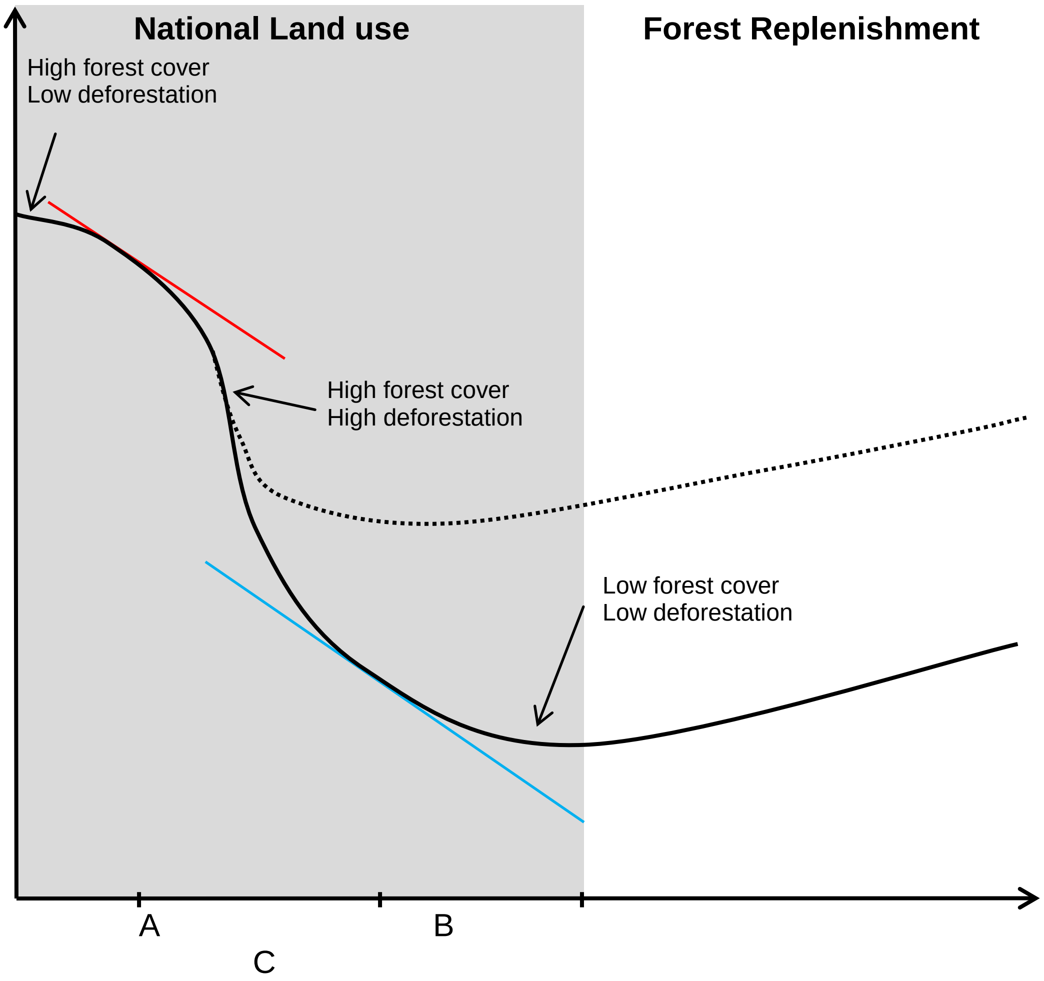


Figure 2.2 The trend of changing forest cover over time as described by the forest transition theory (Mather, 1992). The potential for linear baselines to both overestimate and underestimate deforestation rates is illustrated by red (time point 'A') and blue (time point 'B') respectively. Forest transition occurs at time point 'C'. The potential for REDD+ policies to alter trends in forest cover is shown as a dashed line.

Traditionally, forest transition was thought to occur via two broad mechanisms, the forest scarcity pathway and the economic development pathway. The forest scarcity pathway relies on relative isolation. In areas with stable or increasing populations and little ability to import forest products, the profitability of forest products increases as forest area decreases. As a result, once a threshold value is passed, it becomes profitable for farmers to plant trees instead of crops or pasture grasses

(Rudel et al., 2005). The same type of pathway can be reached with an increased appreciation for all forest-related ecosystem services. For example, reforestation policies in China were not only aimed at increasing the availability of forest products, but were also designed to reduce the impacts of flooding and soil erosions. Similar mechanisms are thought to have acted in other montane regions at risk from these environmental disasters (e.g. Europe, Thailand and the Philippines (Mather and Fairbairn, 2000, Mather, 2007)).

The economic development pathway operates via independent drivers, being dominated by the process of urban migration. Polanyi (1944) describes how, under urbanisation and economic development, farm labourers are lost as part of a ‘great transformation’. The labourers leave rural areas in search of better paid employment, leaving rural labourers in higher demand. As a result, the wages of farm labourers increase, making agriculture less profitable and so less productive fields are abandoned and regenerate to forest (Rudel et al., 2005). Within the tropics, the economic development pathway more frequently occurs in isolated sparsely populated countries (e.g. the Americas (Rudel et al., 2005)), whereas the forest scarcity pathway is more prominent in densely populated Asian countries (Mather and Fairbairn, 2000, Mather, 2007). However, Meyfroidt and Lambin (2011) cite recent examples of forest transition (Mather, 2007, Hecht, 2010) for which the explanation offered by these pathways is insufficient.

In light of these recent exceptions, Lambin and Meyfroidt (2010) proposed three additional forest transition pathways: state forest policy; globalisation; and smallholder, tree-based land use intensification. The state forest pathway uses national policy to initiate forest transition. These policies may be driven by forestry and non-forestry related factors, for example, modernising the economy, or promoting tourism (Lambin and Meyfroidt, 2010). REDD+ policies aim to reduce emissions by initiating forest transition in this manner (dashed line in Figure 2.2). Several examples of governments promoting activities that increase forest cover can be found in Asia (Mather, 2007). For example, decentralisation of forest management through a joint forest management system encouraged communities to manage forest and woodland resources in a sustainable manner, restoring degraded areas to meet their growing demand (Foster and Rosenzweig, 2003, DeFries and Pandey, 2010). In other areas (e.g. Japan and South Korea) the state took a more active role, implementing active reforestation and forest restoration policies (Meyfroidt and Lambin, 2011, Mather, 2007).

The globalisation pathway is similar to the economic development pathway. Forest cover may be affected through increased connectedness to global markets as a result of globalisation, for example: farm labourers may migrate to another country; aid agencies may enforce conservation ideals or economic reforms; and/or immigration and land acquisition by wealthy foreigners may all lead to increasing forest cover (Kull et al., 2007). In Costa Rica, increased access to global markets reduced beef prices (Daniels, 2009) and promoted conservation ideologies via increased eco-tourism (Kull et al., 2007), thus resulting in increases of forest cover. Further evidence is available from Puerto Rico, where increased trade with the US drove both urbanisation and industrialisation, resulting in urban migration and allowing forests to recover (Rudel et al., 2000, Grau et al., 2003). However, increased connectedness with global markets can result in increased deforestation. Since 1990, timber exports from Brazil have increased (FAO, 2012b), as countries protect their own forest resources and seek to import increasing amounts from other nations (Meyfroidt et al., 2010).

Finally, forest transition can occur through the increases in tree cover associated with agricultural diversification (e.g. the expansion of fruit orchards, agroforestry or alley cropping (Hecht et al., 2006)). This form of forest transition need not be driven by conservation ideals but may evolve slowly through farmer’s attempts to protect themselves from climatic and economic shocks (Lambin and Meyfroidt, 2010). In 1989, the International Centre for Research in Agroforestry (now the World Agroforestry Centre) initiated research on 20 indigenous fruit trees in five sub-Saharan African nations, with aim of increasing rural income (Akinnifesi et al., 2004). Uptake of this practice in some countries (e.g. Zimbabwe) has led to the domestication of these wild crops, and the increased development of agroforestry (Akinnifesi et al., 2006). Similar patterns have been documented in the Ecuadorian Amazon, with smallholders converting roadside pastures into agroforestry systems producing high-value crops whilst retaining soil fertility (Rudel et al., 2002).

Thus, forest transition models reflect the general changes in tree cover over time, as a result of globalisation, industrialisation, economic development and urbanisation (Rudel et al., 2010). However, forest transition theory has received criticisms that draw on its similarities to the largely discredited modernisation theory (Perz, 2007, Robbins and Fraser, 2003). Modernisation theory seeks to explain the process of social evolution, but frequently ignores the cultural differences between nations and peoples, promoting western values that may increase the wealth disparity within nations (Bernstein, 1971, Tipps, 1973). However, the forest transition theory does not apply western ideals in the same way. Similarly, the forest transition model has drawn comparisons with the environmental Kuznets curve (EKC; a theory predicting an inverted U-shaped relationship between deforestation and income (Stern, 2004)). Although, both theories have common underlying ideas, EKC relates change in forest cover to income, whereas the forest transition model focusses on the change in forest cover with time. As such, there are two key differences: 1) EKC hypothesis that deforestation is increasing rapidly at early stages of development, whilst forest transition theory begins with low deforestation rates in developing nations; 2) EKC does not anticipate reforestation as an economy develops, merely a reduction in deforestation, thus no forest transition is expected (Culas, 2012).

Whilst the forest transition model provides useful theory with which to investigate long-term trends in forest area change, caution should be applied when interpreting forest area trends before a forest transition can be declared. Firstly, although displayed as a smooth curve (Figure 2.2), in reality forest cover may fluctuate, reflecting changes in national policy or market trends, and, in the future, deforestation trends may once again dominate afforestation trends. The change in forest cover over time in France provides a detailed example of the ability of socioeconomic conditions to reverse forest transition (Mather and Needle, 2000). Prior to the Black Death, forest cover in France was rapidly decreasing, however, a net gain in forest cover can be seen between the years 1300 and 1400 as human populations reduced as a result of disease. However, this forest transition was reversed by the year 1500, with rapid deforestation widespread throughout the nation once again (Mather and Needle, 2000). Secondly, small-scale studies may convincingly demonstrate forest transition, however resource demand may not have slowed as demands may be met by other regions. For example, small regions in Brazil (e.g. Santa Catarina State) are suggested to have undergone forest transition (Baptista, 2008, Baptista and Rudel, 2006) but this is not evident at a national scale (Meyfroidt and Lambin, 2011) perhaps because the net afforestation in these regions is fuelled by rapid deforestation of Amazonian land (Walker, 2012) (see Grainger (2008a) for further examples). As a result of globalisation, the same effect can be observed between nations. For example, the rapid gain in forest area in Vietnam since the early 1990s has been associated with an increase in timber imports from neighbouring countries (Meyfroidt and Lambin, 2009). Despite these limitations, forest transition theory has proven indispensable in understanding LCC over the past few centuries (Rudel et al., 2010) and is supported by a large number of studies (Mather, 1992, Grainger, 1995, Houghton and Hackler, 2000, Angelsen, 2007, Meyfroidt and Lambin, 2011).

2.6.3 Forest Identity – Integrating Carbon into the Forest Transition Model

In 2006, Kauppi et al. recognised that the forest transition model, although well representing forest area, provided a somewhat incomplete analysis of the state of a nation's forests and woodlands (Kauppi et al., 2006). He asserted that, given global REDD+ negotiations, many forest characteristics were of interest to decision-makers on top of forest area, such as forest carbon stock (see Section 1.4). Thus, he developed the Forest Identity method (Kauppi et al., 2006), which was later refined (Waggoner and Ausubel, 2007, Waggoner, 2008). Here, I describe the development and evolution of the Forest Identity, critically evaluating its usefulness to REDD+ schemes.

The Forest Identity states that a nation's forests and woodlands are best described using a single variable (carbon stock [Q]), which can be calculated from the measurement of four variables: forest area (A); forest growing stock density (D); the conversion ratio of forest biomass to growing stock (B); and the carbon concentration (C) (Figure 2.3). Kauppi et al. (2006) began with the widely available variable of forest area (A), but recognised that it could be converted to the volume (V) of living trees larger than a threshold diameter (i.e. the stock) through multiplication with forest density. Thus:

$$V\ (m^3) = A\ (ha) \times D\ (m^3\ ha^{-1})$$

which is equivalent to:

$$\ln(V) = \ln(A) + \ln(D)$$

and can be followed over time via:

$$\frac{d\ln(V)}{dt} = \frac{d\ln(A)}{dt} + \frac{d\ln(D)}{dt}$$

allowing change to be displayed as a percentage per unit time:

$$v = a + d$$

where the upper case letters are replaced with the respective lower case letter to indicate the new proportional unit.

Reverting to the original equation, the aboveground biomass in living trees (M) can be calculated given the biomass per unit volume of the growing stock (B; biomass m^{-3}):

$$M\ (Mg) = A\ \times D \times B$$

Allowing biomass to be converted to carbon stock (Q), given knowledge of the carbon content of vegetation (C):

$$Q =\ A\ \times D \times B\ \times C$$

and

$$q = a\ \times d\ \times b\ \times c$$

if percentages per unit time are applied.

Thus, assuming 'b' is equivalent to $-0.3\ \times d$ and that the carbon per ton of dry biomass (c) changes negligibly (a constant of ~0.5), then the sequestered carbon (q) can be calculated from the changes in 'a' and 'd' via the following equation:

$$q = a\ \times d\ \times d\ \times (-0.15)$$

Hence, the Forest Identity allows for the calculation of change in carbon stock over time from the readily reported estimates of forest area and forest growing stock density provided in FRA country reports (FAO, 2010d). A further advantage of this concept is the ability to display this information on a single output, enabling for rapid communication to both researchers and decision-makers alike (Figure 2.3). By plotting the relative change in forest area (a) on the horizontal axis, and the relative change in growing stock density (d) on the vertical axis, nations of increasing volume can be indicated as they will be above the diagonal line $a =\ -d$ (Kauppi et al., 2006) and nations of increasing biomass and carbon stock will be above the line $a = (-d)\ \times 0.7$ (Waggoner and Ausubel, 2007), illustrated in Figure 2.3 by the red and green lines respectively.

The Forest Identity, therefore, represents a more complete forest transition model, adding a new dimension by accounting for changes in forest growing stock density as well as forest area. Kauppi et al. (2006) interpreted Figure 2.3 to show four groups of countries: 1) those countries where forest area has expanded, typified by an increasing relative forest volume but low growing stocks per unit area as the forests are young (e.g. China and India); 2) those countries showing an increased forest volume dominated by relative increases in growing stock but little change in forest area (e.g. Europe and the US). These countries may have limited space for forest expansion, but have developed sufficient to reduce demand on local forest resources; 3) those nations with a slowly changing area and volume per unit area (e.g. Gabon and Angola). It is likely that these nations are nearing forest transition; and 4) those nations whose forests are heavily exploited (e.g. Indonesia, where both area and density shrank, and Nigeria and the Philippines, which show a substantial reduction in forest area) (Kauppi et al., 2006). These results indicate that deforestation and forest degradation are evident in approximately half of the 50 nations with most forest in the year 2005, but that 36% of these nations show increased forest area and 44% show increased forest volume per unit area (Kauppi et al., 2006).

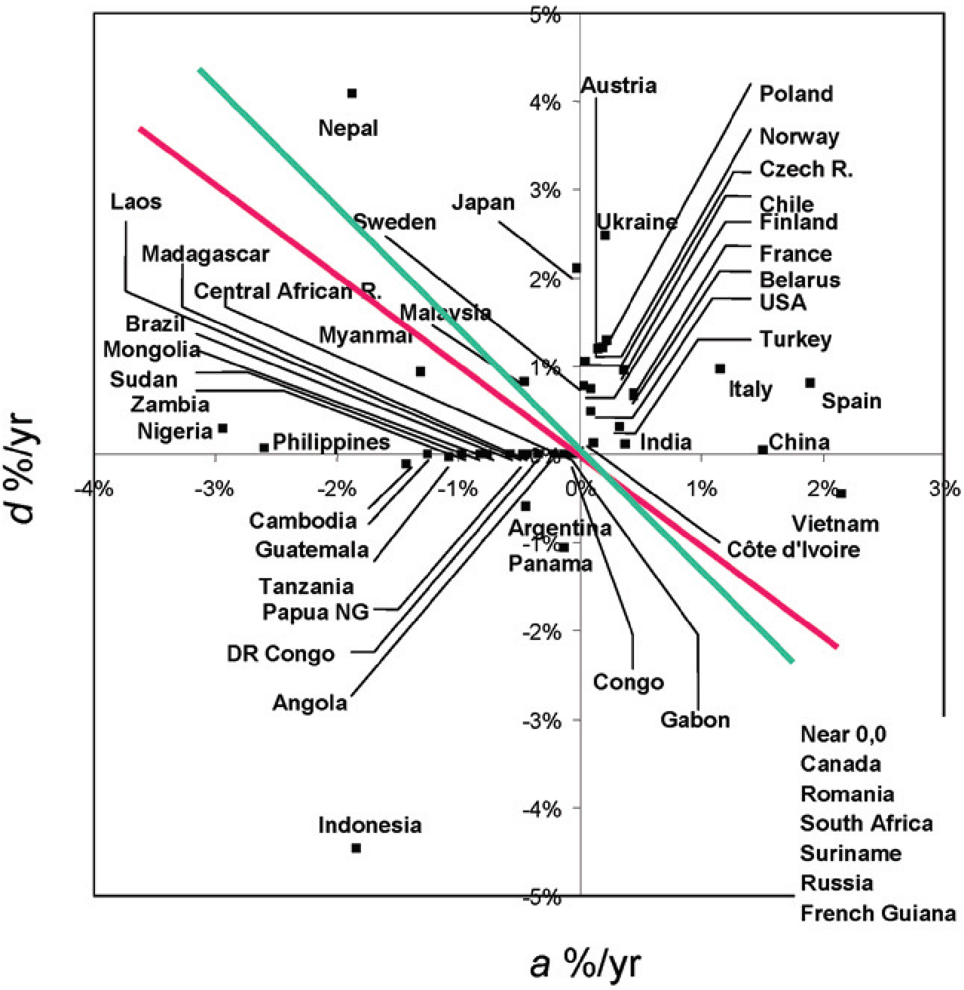


Figure 2.3 The changing area (a) and density (d) in 50 nations with the largest volumes of forest and woodland trees in 2005. The red line represents unchanging volume, and the green line illustrates unchanging biomass and sequestered carbon (taken from Waggoner and Ausubel (2007)).

The Forest Identity concept has obvious advantages over the traditional forest transition model and has been well received in the literature. Using this concept, it has been demonstrated that the forest area and growing stock density of China increased by 0.51% and 0.44% annually over the past three decades, while the conversion ratio of forest biomass to growing stock has declined 0.10% annually (Shi et al., 2011). Similarly, these patterns are reflected sub-nationally, with most provinces showing the same results but eight provinces arid provinces (Ningxia, Gansu, Xizang, Jilin, Heilongjiang, Shaanxi, Inner Mongolia and Shandong) showed declining forest areas due to climate change, and a further eight provinces forest-rich provinces (Ningxia, Gansu, Xizang, Jilin, Heilongjiang, Shaanxi, Inner Mongolia and Shandong) showed a decline in forest density indicating forest degradation is likely occurring in these regions (Shi et al., 2011). Continental analyses have also been conducted. Between 1990 and 2000, Asian and North American forests changed little in area but increased in density, European forests increased in both area and density (Rautiainen et al., 2011). Furthermore, African and South American forests showed reductions in area (and ultimate carbon stock) despite increase in carbon density (Rautiainen et al., 2011). The above patterns were similar between 2000 and 2010 in all regions except Asia, where a great loss of both forest area and density in Indonesia shifted the region from a carbon sink to a carbon source (Rautiainen et al., 2011).

The development of the Forest Identity is timely considering the evolution of REDD+, and may contribute significantly to negotiations on MRV techniques (see Chapter 1). However, I urge caution in adopting this approach as, although the results are displayed in a manner that is easily interpreted, the uncertainties involved are not. Since, the volume of growing stock (V) is equal to the multiplication of forest area (A) by forest density (D), there are no additional errors in calculating volume than already present in current estimates of forest area and density (Waggoner, 2008). Similarly, the assumption of constant carbon concentrations per unit biomass across vegetation types seems to hold true as the carbon content of vegetation varies relatively little across a wide variety of plant and tissue types (Schlesinger, 1991, Martin and Thomas, 2011) . However, the inclusion of a biomass ratio (B) carries with it uncertainties that propagate through biomass (M) and carbon (Q) estimates (Waggoner, 2008). Whilst it is accepted that the conversion ratio of forest biomass to growing stock (B) declines with increasing forest growing stock density (D) (Schroeder et al., 1997), the gradient of this relationship shows substantial variation (Smith et al., 2003), ranging an order of magnitude from -0.05 to -0.4 according to IPCC estimates, depending on forest type (IPCC, 2006b). Hence, although a gradient of -0.3 is most frequent (Smith et al., 2003), the assumption that this is globally constant is likely to be false. I recommend that uncertainty be indicated within the Forest Identity by making small alterations to Figure 2.3. I propose that the substantial uncertainty surrounding forest area and density estimates known to exist (Grainger, 2008b, Grainger, 2010) be illustrated by increasing the size of the country marker (black squares on Figure 2.3) accordingly. Furthermore, I advise that the additional uncertainty included in biomass (M) and carbon (Q) be indicated by inclusion of a green shaded area beneath the current green line, to better illustrate the 95% confidence intervals surrounding the conversion ratio estimation (B).

The Forest Identity provides a valuable tool through which the trend of forest carbon flux can be illustrated, however it does not incorporate all the requirements of REDD+. Negotiations for REDD+ have moved beyond isolated emission reduction activities as social development, the protection of vulnerable groups (e.g. forest dwelling peoples) and the safeguarding of biodiversity are also considered of high importance (see Section 1.4.1). Whilst the Forest Identity illustrates well the shift in carbon stored within a nation's forests and woodlands, countries that show increasing forest area and/or density may still show a dramatic decline in natural forest and woodlands if plantations drive this forest trend. This criticism also applies to the forest transition model. It is considered vital that REDD+ schemes do not compound the global extinction crisis (Thomas et al., 2004), as a result of replacing the unique biodiversity values of old-growth tropical forests and woodlands with low biodiversity plantations (Brooks et al., 2006). The Forest Identity, and the forest transition model, could move to incorporate the protection of natural forests and woodlands by analysing natural and production forest separately, thus highlighting these important trends. Furthermore, the social aspects of REDD+ are also not illustrated with the Forest Identity. I propose that land change scientists work in close collaboration with social scientists to create an index of social development, characterised by variables highlighted in REDD+ negotiations as of high importance (Section 1.4.1). The nations' social development over time could then be illustrated alongside the Forest Identity, e.g. by colour-coding the country markers (black squares on Figure 2.3). For example, those nations showing an increased social development over time may be indicated by having a green country marker, with colours graduating so that those nations showing worsening social conditions are illustrated with a red country marker. With these additions, I believe the Forest Identity could signal a new era in land change science and have substantial impact on REDD+ practices.

2.7 Scientific International Forest Carbon Monitoring Methods

The Forest Identity provides a framework through which the carbon flux of forests and woodlands can be monitored (see Chapter 1). The estimation of the carbon flux of forests and woodlands by scientific community can be divided into two broad groups: monitoring – typically via ground-based plots and/or remote sensing (reviewed by Gibbs et al. (2007) and summarised in Table 2.6); and modelling – commonly via book-keeping or process-based modelling (see Ramankutty et al. (2007) and Houghton (2010); Table 2.7). Broadly, ground-based methods are thought to be the most certain, but are labour intensive and these data are often sparse, and so large uncertainties can arise when extrapolating data to a large area. Remote sensing methods are often globally available but can be expensive, requiring both expertise and ground-truthing. Thus, plot-based methods (which can provide carbon data currently unobtainable from remote sensing instruments) and remote sensing methods (which cover large areas) are commonly combined to estimate carbon storage and sequestration within forests and woodlands. Modelling techniques are useful to estimate the carbon flux associated with forests and woodlands on a global/continental scale, providing indications of long-term changes and forming the basis of scenarios estimating future changes. Here, I discuss plot-based methods, remote sensing, book-keeping methods and process-based models in turn.

2.7.1 Plot-Based Methods

I have previously described how forest inventory methods have been adapted over time to incorporate the measurement of new variables of interest (e.g. carbon) (see Section 2.4.2). Furthermore, I provide detailed descriptions of examples of plot-based methods in Section 2.4.2, Section 4.5.3.3 and Section 5.5.1.2, and so in this section I will focus on the uncertainties surrounding such methods rather than the techniques themselves. First, I discuss the uncertainty associated with AGB estimation, dividing this into the tree measurement uncertainty, the allometric equation uncertainty and the sampling uncertainty. I then describe the methods and uncertainties associated with the estimation of the remaining IPCC carbon pools (CWD, litter, belowground, and soil carbon; Table 2.4).

The first potential source of uncertainty in estimating aboveground live carbon (ALC) storage is in the tree measurement process. Typically, within a plot of known area, stems of a DBH of 10cm or over at 1.3m above the ground are located, identified to species level, and their DBH (and sometimes height) are recorded. The trees are then tagged with a unique identity so that these data can be recollected over time, providing information on carbon sequestration as well as carbon stock. However, stems are often irregular, for example with a trunk deformity at 1.3m above the ground, and early work (Phillips and Gentry, 1994, Phillips et al., 1998) has been criticised as being methodologically (Clark, 2002) and statistically (Sheil, 1995) flawed. Potential methodological biases include site selection bias, tree deformities as a result of the monitoring process, poor measurement of buttresses, and ignoring any records of negative growth (Phillips et al., 2002). However, many of these errors have since been investigated and either demonstrated to be negligible or resolved, having little impact on results (Baker et al., 2004a, Chave et al., 2008, Phillips et al., 2002). For example, tree deformities, often localised swelling, may result from the use of nails to tag trees. If in close proximity to the point of measurement, this could artificially increase the diameter recorded. Whilst this is unlikely to affect biomass estimates arising from the first census, this effect could drive an increase biomass observed over time. Should this be true, biomass would increase over time, at a similar increasing rate, on average across all plots. However, this is not observed (Phillips et al., 2002). Further uncertainties and potential biases associated with plot-based measurement are discussed in (Phillips et al., 2002).

The most important source of uncertainty associated with plot-based techniques is the estimation of stem volume from the DBH measurements described above (Chave et al., 2004). This estimation is performed using allometric equations with, ideally, each species having its own relationship (Ter-Mikaelian and Korzukhin, 1997). However, due to data limitations and high biodiversity levels, species specific allometric equations are unrealistic for tropical forests and woodlands. Thus, general allometric equations are used in high biodiversity regions, but these suffer from three main shortcomings: 1) they are developed from limited (and perhaps biased) samples; 2) they may only be valid within a certain DBH range; and 3) depending on available data, the goodness of fit of these models can vary widely (Chave et al., 2004).

Published allometric equations are usually based on a small number of directly harvested trees. Allometric equation production is often associated with planned logging activities and thus may show a bias towards marketable stems with few deformities, over-estimating the biomass of a general tree stand which likely contains a proportion of deformed stems. Furthermore, despite large stems contributing most to stand-level biomass (Chave et al., 2001, Alves et al., 1997), relatively few large stems are included in the production of allometric equations. For example, from a database of 454 US hardwood trees used to create a general allometric equation, only 16 had a DBH of over 60cm (Schroeder et al., 1997). Furthermore, the mostly widely used allometric equations include no biomass data from Africa (Chave et al., 2005, Chambers et al., 2001) and may bias carbon stock estimates in African tropical forest if allometry in Africa is fundamentally different to Amazonia and tropical Asia. Recent evidence suggests that forest height for a given diameter varies significantly amongst continents (Banin, 2010, Banin et al., 2012) and so continental differences in allometry may be likely. Thus, regional tree harvesting is necessary to develop African based allometric models. This process has already begun across the continent (Djomo et al., 2010, Henry et al., 2010, Ebuy et al., 2011), although early indications show few signs of geographical bias (Djomo et al., 2010, Henry et al., 2010). Finally, many studies differentiate forest types based on precipitation categories (Brown, 1997, Chave et al., 2005) that are not easily applied to all parts of the world and are somewhat arbitrary.

These uncertainties result in large differences in stand-level carbon estimation when alternative allometric equations are used (Brown, 1997, Clark and Clark, 2000, Chave et al., 2004) and are the most important source of error when estimating AGB (Chave et al., 2004). However, this uncertainty can be reduced by utilising as much of the available data as possible (e.g. including tree height and WSG as additional parameters in allometric equations is known to reduce the estimation error (Djomo et al., 2010, Chave et al., 2005)), reducing uncertainty to between 0.5% and 6.5% (Chave et al., 2005). Despite this, allometric equations could be improved substantially (Brown, 2002a). To decrease uncertainty of stand-level carbon estimates in mature forests and woodlands, more large diameter trees need to be destructively harvested and their biomass directly measured. In addition, robust equations should be developed for unique forest types (e.g. mangroves), further reducing stand-level uncertainty in some biomes. Furthermore, many of the allometric equations were developed based stems harvested several decades ago (Brown, 2002a). Allometric equations need to be continually updated to address any shifts in stem resource allocation occurring over time (e.g. as a result of CO_2 fertilisation). Whilst the above changes will require a large, sustained effort by the scientific community, efforts to collate current allometric data and make this freely available could begin immediately.

Using the above methods, tropical forest and woodland inventory networks have been developed, including RAINFOR (http://www.rainfor.org/), AFRITRON (http://www.geog.leeds.ac.uk/projects/afritron/), TROBIT (http://www.geog.leeds.ac.uk/groups/trobit/), TEAM (http://www.teamnetwork.org/) and CTFS (http://www.ctfs.si.edu/). Whilst these networks span much of the world's tropical forests, it has been suggested that, as a result of a site selection bias, the plots show a clustered distribution (primarily focused on pristine forest), meaning that important ecological phenomena (e.g. rare, large mortality events) may not be sampled and so the representativeness of these plot networks to the forest/woodland as a whole has been questioned (Wright, 2006, Fisher et al., 2008). Such bias occurs if ecologists preferentially locate plots within tropical forest, avoiding areas of disturbance, and would result in elevated carbon storage estimates, but over time, decreased sequestration rates as these forests are thought to be in a steady-state. At the first census, majestic forest bias can be detected using size-frequency distributions. Size-frequency distributions of forests worldwide have been suggested to conform to a -2 power law (Enquist and Niklas, 2001). However, it has been argued that this rule is not globally applicable (Li et al., 2005, Muller-Landau et al., 2006a, Muller-Landau et al., 2006b), containing a tendency for the over-prediction of large stems (Enquist et al., 2009, Coomes, 2006). Thus, any majestic forest bias of an ecologist might be indicated by a significantly shallower gradient than -2. Over time, a decrease in the abundance of larger stems would be expected, in contrast to the increasing dominance of large stems observed in long-term plot data, given the biomass of trees increasing at a faster rate than the rate of increase in the number of stems within a given forest plot (Lewis et al., 2004b, Phillips et al., 2004).

One obvious way of reducing the uncertainty in biomass estimates would be to increase the number of plots and their geographical spread. With limited resources available, plot size could be reduced in order to obtain a network of increased density and heterogeneity. Landscape scale efforts to quantify forest biomass would benefit from extensive rather than intensive sampling, focussing on many separate geographical areas with a few plots in each area (Nascimento and Laurance, 2002). Smaller plots have been shown to produce reliable estimates of forest traits and, while there is a tendency for smaller sampled areas to yield larger biomass estimates, this has been shown to be insignificant, with plots as small as 0.2ha providing accurate estimates of biomass (Houghton et al., 2001, Chave et al., 2004). Small plots provide similar estimates to larger ones when, overall, sampled areas of land within the landscape are comparable (Clark and Clark, 2000). Whilst smaller plots may be suitable for studies of forest biomass, larger plots provide further information on biodiversity (Barlow et al., 2007). Tropical forests support such high levels of biodiversity, comprising many rare species, that species-area curves only begin to saturate when much larger areas are sampled, for example at Pasoh, Malaysia, species-area curves saturate at ~8ha (Plotkin et al., 2000). Thus, compositional changes within tropical forests may go unnoticed if smaller plots are used, leading to large uncertainties in future carbon estimates.

Additionally, to decrease the investment required to establish and maintain dense tropical tree inventory networks, the threshold DBH at which trees are sampled could be increased. A DBH threshold of 10cm was a common standard for traditional forestry and so is widely used in the literature, maximising the amount of long-term data (Lewis et al., 2009b, Phillips et al., 2009b). Trees with a DBH ≥30cm only account for 20% of the trees but contribute about 80% of the above ground biomass (Chave et al., 2001, Alves et al., 1997). Larger size classes, DBH ≥ 45cm, only account for 45% of the total basal area (Alves et al., 1997). Hence, sampling only larger size classes may enable for rapid assessment by greatly reducing the number of trees that need be sampled whilst not greatly affecting the basal area estimate that results. Therefore it may be possible to sample only trees above a higher threshold to reduce the costs of acquiring data while only marginally increasing uncertainty. However, errors on individual large stems are much larger than those with a narrower DBH (Chave et al., 2004). In addition, overall diversity is higher in tree samples including smaller individuals as not all tree species reach the larger size classes even when fully mature (Hardy and Sonke, 2004). Thus, once again, there is a trade-off between an increased confidence of the spatial distribution of carbon storage and biodiversity monitoring and conservation.

As described above, the measurement of AGB is relatively well established, however, the carbon estimation of other pools generally has higher levels of uncertainty. For example, CWD often accounts for 10-20% of the aboveground biomass (Delaney et al., 1998, Harmon et al., 1995) but tends to be ignored from many forest inventory surveys. Methods have been developed for measuring biomass in CWD and require volume estimation, using tested techniques, followed by sampling to determining decomposition class and wood density (Baker and Chao, 2008). This method assumes that the state of decomposition is correlated with its density, a relationship that may not be upheld in many tropical species, where resistant heartwood can still be very dense, despite advanced states of decomposition (Delaney et al., 1998, Harmon et al., 1995). Similar protocols can be followed for the estimation of litter carbon. However, both CWD and litter are investigated much more rarely than AGB, leading to substantial data deficiency.

Similarly, belowground and soil carbon are relatively rarely sampled. Root biomass is often estimated from root:shoot ratios, as the direct measurement is difficult and time consuming (Kurz et al., 1996, Cairns et al., 1997). Cairns et al. (1997) reviewed more than 160 studies that reported aboveground and belowground biomass, indicating a mean ratio of 0.26, but with substantial variation and thus high uncertainty. I propose that belowground allometric equations be developed in a similar manner to those used to estimate AGB. These equations could be developed for a variety of stem diameters, ages, and forest types, substantially reducing the uncertainty associated with this carbon pool. The techniques to measure soil carbon pools are well established and documented (Post et al., 1999), however, this process is labour intensive and so neglected in most studies (Brown, 2002b).

2.7.2 Remote Sensing methods

The carbon stored within tropical forests can be estimated using remotely sensed data (those data collected from instruments mounted on satellites or aeroplanes). As stated above, remote-sensing can only be used in combination with plot-based data as it cannot be used to directly measure carbon stocks (Rosenqvist et al., 2003, Drake et al., 2003). However, remote sensing provides a tool by which ground-based measurements can be extrapolated across landscapes, on both national and global scales. It must be noted that, combining these techniques compounds the errors associated with plot-based methods (described above) with those associated with remote sensing (see Section 2.5). Here, I will briefly discuss the two main methods (biome-based methods and correlation-based methods) by which remote sensing can be used for forest and woodland carbon monitoring, expanding on limitations and uncertainties specific to carbon stock estimation that have not been previously discussed in Section 2.5.

The earliest compilations of biome averages were made decades ago, and have been continuously updated by the research community (Brown and Lugo, 1984, Whittaker and Likens, 1973). Biomes likely represent the most important source of variation in landscape carbon stocks, thus the application of plot-derived carbon estimates to biome area obtained via remote sensing (see Section 2.5) is perhaps the simplest way to estimate forest and woodland carbon storage. Biome averages are currently freely available and are currently the only source of globally consistent forest carbon information (e.g. IPCC Tier 1 values; Section 2.4.4). However, forest carbon stocks vary within each biome (e.g. according to temperature, precipitation, soil; Section 2.3) and so an average value cannot adequately represent this variation, leading to high uncertainties in carbon flux estimations associated with LCC, particularly if deforestation primarily occurs in forests and woodlands that systematically differ from biome averages (Houghton et al., 2001).

To better represent variation within biomes, regression models can be used to correlate remotely sensed data with plot-based carbon estimates. This approach is similar to the IPCC Tier 3 methods described in Section 2.4.4 and shows reduced uncertainty when compared to biome-based (Tier 1) estimates (GOFC-GOLD, 2010). Similar to monitoring forest area, several satellite sensors are available, broadly falling into four categories: medium and high resolution optical data; very high resolution optical data; microwave or radar data; and LiDAR data.

Present optical satellite sensors (e.g. Landsat, MODIS) cannot be used to estimate carbon stocks of tropical forests and woodlands with high certainty (Thenkabail et al., 2004). Correlations have been developed between plot-based carbon estimates and vegetation indices (e.g. NDVI) (Lu, 2005, Foody and Cutler, 2003). However, optical satellite sensors tend to saturate in high biomass regions (Sánchez-Azofeifa et al., 2009, Thenkabail et al., 2004, Waring et al., 1995) and may be of limited availability due to cloud cover (Sánchez-Azofeifa et al., 2009, Asner, 2001). Furthermore, the correlations developed are often regionally specific and so not transferable between studies or applicable across the globe (Waring et al., 1995). Very high-resolution images can be collected, typically from aeroplanes, and used to directly measure tree height and crown area. However, due to the high cost, it is often impractical to collect these data over vast areas, and so this technique is only particularly efficient for estimating biomass in small regions (Brown et al., 2005).

Table 2.6 Benefits and limitations of available methods to estimate national-level forest carbon stocks (reproduced from Gibbs et al. (2007)).

Method	Description	Benefits	Limitations	Uncertainty
Biome averages	Estimates of average forest carbon stocks for broad forest categories based on a variety of input data sources	Immediately available at no cost Data refinements could increase accuracy Globally consistent	Fairly generalised Data sources not properly sampled to describe large areas	High
Forest inventory	Relates ground-based measurements of tree diameters or volume to forest carbon stocks using allometric relationships	Generic relationships readily available Low-tech method widely understood Can be relatively inexpensive as field-labour is largest cost	Generic relationships not appropriate for all regions Can be expensive and slow Challenging to produce globally consistent results	Low
Optical remote sensors	Uses visible and infrared wavelengths to measure spectral indices and correlate to ground- based forest carbon measurements e.g. Landsat, MODIS	Satellite data routinely collected and freely available at global scale Globally consistent	Limited ability to develop good models for tropical forests Spectral indices saturate at relatively low carbon stocks Can be technically demanding	High
Very high-resolution airborne optical remote sensors	Uses very high-resolution (10–20 cm) images to measure tree height and crown area and allometry to estimate carbon stocks e.g. Aerial photos, 3D digital aerial imagery	Reduces time and cost of collecting forest inventory data Reasonable accuracy Excellent ground verification for deforestation baseline	Only covers small areas (10,000s ha) Can be expensive and technically demanding No allometric relations based on crown area are available	Low to medium
Radar remote sensors	Uses microwave or radar signal to measure forest vertical structure e.g. ALOS PALSAR, ERS-1, JERS-1, Envisat	Satellite data are generally free New systems launched in 2005 expected to provide improved data Can be accurate for young or sparse forest	Less accurate in complex canopies of mature forests because signal saturates Mountainous terrain also increases errors Can be expensive and technically demanding	Medium
Laser remote sensors	LiDAR uses laser light to estimates forest height/vertical structure e.g. Carbon 3-D satellite system combines Vegetation canopy LiDAR (VCL) with horizontal imager	Accurately estimates full spatial variability of forest carbon stocks Potential for satellite-based system to estimate global forest carbon stocks	Airplane-mounted sensors only option Satellite system not yet funded Requires extensive field data for calibration Can be expensive and technically demanding	Low to medium

In contrast to the above optical techniques, microwaves, radar and LiDAR signals are able to detect the top of the canopy, whilst also penetrating down to the underlying terrain. Thus, data on canopy height are collected and used to estimate carbon storage. Recent studies (Baccini et al., 2012, Saatchi et al., 2011) have tended to use LiDAR data over microwave and radar techniques as they are less likely to saturate in high-biomass regions (Means et al., 1999, Lefsky et al., 1999, Drake et al., 2003). However, due to the scattering of reflectance beams, these techniques have higher uncertainties for taller canopies and in montane regions, where terrain is more rugged (Reutebuch et al., 2003, Means et al., 1999). Despite this drawback, large-footprint LiDAR remote sensing far exceeds the capabilities of radar and optical sensors to estimate forest and woodland carbon stocks (Means et al., 1999, Lefsky et al., 1999, Drake et al., 2003). However, currently aeroplane-mounted LiDAR instruments are too costly for use at large scales, and satellite based LiDAR systems are not yet widely available (Hese et al., 2005, Gibbs et al., 2007). In addition, techniques that use height as a proxy for AGB have high uncertainty in regions that obtain maximum height rapidly but continue to accumulate biomass for many years (Feldpausch et al., 2011, Banin et al., 2012).

In this thesis, I utilise both the biome-based and correlation-based techniques. Firstly, I apply plot-derived carbon estimates of differing land cover types to land cover maps; and secondly, I correlate the ground based data with remotely sensed candidate variables, providing proxy data for climatic, edaphic and anthropogenic variables. This second technique has an advantage over the detection methods described above in that it provides indications as to what influential variables likely effect carbon storage (Sánchez-Azofeifa et al., 2009). Furthermore, both these forms of remotely sensed data are freely available, increasing the accessibility of methods developed here to less economically developed countries (LEDC).

2.7.3 Book-Keeping Methods

Over the past three decades, Houghton and colleagues have combined LCC data from various national inventories within a simplistic carbon-cycle model to estimate emissions, typically at a national or global scale (Houghton et al., 1983, Houghton, 2003, Houghton et al., 2000). This model is referred to as a book-keeping model as it estimates the carbon flux associated with LCC with high temporal resolution. Book-keeping models account for deforestation and forest regeneration by tracking the immediate release of carbon during deforestation, the slower release of carbon resulting from the

LCC, the accumulation of carbon as a result of regrowth, and the soil carbon flux (Achard et al., 2004). The book-keeping model tracks the carbon in living vegetation, dead organic matter, wood products and soils for each hectare of land that undergoes a change in use/cover. As such, book-keeping models require similar data to that submitted to the UNFCCC GHG inventories, including rates and dynamics of LCC, initial carbon stock data, data on methods of LCC and data describing the time-span associated with each carbon flux.

Changes in land use/cover are simplified within book-keeping models to a limited number of possibilities including: the clearing of lands for cultivation and pastures; the abandonment of agricultural lands and associate regeneration of natural biomes; the harvesting of wood (including deforestation); reforestation; afforestation; and shifting cultivation. Rates and types of LCC are generally obtained from agricultural statistics, forestry statistics, historical accounts and national handbooks, such as those data collected via national forest area monitoring and forest inventories and submitted to the FAO within the FRA country reports. However, as previously described, the availability of land use/cover data, particularly as a time series, varies by region. In addition to the nationally reported data, the wide variety of satellite data has also been previously discussed. Estimates of the rates and dynamics of LCC within book-keeping models are similarly uncertain, with a wide variety of methods used. For example, Fearnside (2000) and Houghton (2003) estimated LCC using the deforestation statistics provided in the FAO FRA. Similarly, McGuire et al. (2001) derived deforestation estimates from data on the expansion of agriculture from the FAO's FAOSTAT database and other subnational statistics (Ramankutty and Foley, 1999). Other researchers have utilised remote sensing to estimate deforestation. For example, DeFries et al. (2002) used AVHRR data to indicate deforestation at an 8km spatial resolution by documenting when pixels decreased in tree cover below 14%. The inability of the national inventories, FRA data and remotely sensed data to describe global LCC with high certainty have been previously described but should be noted here as they are compounded by further assumptions. To accurately estimate carbon fluxes from LCC, book-keeping models require data on the method used to convert the land to a different cover/type, and also on the fate of the land following this conversion. For example, was the forest burnt and converted to permanent agriculture, or was the LCC a result of gradual encroachment by pastoralists? Tracking LCC at this level requires data of both high temporal and spatial resolution and this is not always available.

For example, using the 8km AVHRR data, DeFries et al. (2002) was not able to include these LCC in their model. By contrast, Achard et al. (2002) used 30m Landsat imagery to detect LCC between 1990 and 1997 and well captured these changes for tropical regions, though used a hot-spot analysis and so lacked wall-to-wall coverage. National inventory data are also uncertain as it is thought to underestimate the transitions between forest, agricultural land and secondary regrowth (Ramankutty et al., 2007).

Once again, to associate the LCC with a carbon emission, the carbon stock of each biome must be estimated. The uncertainties associated with estimating present day carbon stocks have been previously described. These uncertainties explain the wide variation in book-keeping model estimates (Achard et al., 2002, Achard et al., 2004, DeFries et al., 2002, Houghton, 2003, Fearnside, 2000) but are, once again, compounded. Whilst the estimation of carbon stocks described in Section 2.7.2 often includes a spatial component, this is rarely possibly when using book-keeping models to estimate historical carbon fluxes due to data-deficiencies. Whilst spatial detail is available from some satellite data, historical data are often tabular and so lack any spatial component (Houghton, 2003), although this can be modelled (see Section 2.8). Further uncertainty is included as not only is the carbon stock of interest, but the rate of change of carbon stock over time is also required. For example, in an area of forest regrowth, the rate of growth and accumulation of carbon in all carbon pools need be understood. Similarly, after deforestation events, for example when forest is replaced by agricultural land, not only is the carbon stock of both land covers required, but the rate of change is also important. For example, Houghton (2003) modelled deforestation events by clearing the land for timber, but ensuring that a set percentage of the carbon was released into the atmosphere as a result of burning, whilst another portion was left *in situ* and decayed in the soil carbon pool at varying rates. The timber removed was allocated to various product pools, with different decay time-scales, ranging from 1 to 1,000 years (Houghton, 2003). Similar methods are used by other researchers and so it is unlikely that these assumptions result in the large differences between carbon flux estimations, although they are a substantial cause of uncertainty (Achard et al., 2002, Achard et al., 2004, DeFries et al., 2002, Houghton, 2003, Fearnside, 2000). Given the possible delay in emissions following LCC events, it is critical to include historical LCC when estimating carbon flux as a result of anthropogenic activities over a defined time period. Whilst this may be possible for studies using national inventories, those utilising satellite-derived data may lack this crucial information (Ramankutty et al., 2007). Finally, it is important to note that the calculated flux of book-keeping models are not equivalent to the net flux of carbon between terrestrial and atmospheric pools, as the analysis is primarily concerned with those emissions/absorptions resulting from direct human activity.

The ambition of book-keeping models is clear. Currently, book-keeping models are the only method by which long-term inventories of the carbon flux resulting from anthropogenic activities can be tracked directly. Due to data-deficiencies, these models include a large amount of uncertainty but illustrate a very clear recent trend (Table 2.7). For example, estimates of carbon emissions for the 1980s vary between 0.6 and 2.4 Pg C yr^{-1} (Achard et al., 2002, Achard et al., 2004, DeFries et al., 2002, Houghton, 2003, Fearnside, 2000) so, whilst the exact carbon emission as a result of anthropogenic activities is unclear, it is relatively certain that these activities resulted in a substantial carbon emission. The improvement of LCC monitoring and carbon inventories will greatly reduce the uncertainty associate with these models.

2.7.4 Process-based Methods

In Sections 2.7.1 and 2.7.2, I described how empirical models can be used to estimate carbon storage at varying spatial scales, however, processed-based modelling offers and alternative approach. As described above, a major advantage of the empirical approach is that readily available data can be used to establish simple correlations and provide best-fit relationships for present day estimates. However, these models are not robust for estimating historical or future carbon stocks if conditions change significantly over time, as expected under many climate change scenarios. Whilst book-keeping models provide a method by which historical carbon fluxes can be understood, only process-based models provide us with an indication of future conditions.

Unlike empirical models and book-keeping methods, process-based models attempt to describe the key mechanistic processes that determine the variable of interest. For example, process-based models estimating carbon stock may simulate a number of interacting processes, such as photosynthesis, respiration, decomposition, and nutrient cycling (Peng et al., 2002). By understanding the underlying mechanisms, process-based models are able to examine long-term hindcasting and forecasting patterns for which empirical model estimates are highly uncertain due to data deficiency (Peng, 2000). Process-based methods can be used to model a wide variety of mechanistic processes. The modelling of forest and woodland characteristics and LCC are particularly relevant to this thesis and so will be discussed in detail here.

The process-based modelling of forest and woodland characteristics can be divided into two main approaches: stand-level approaches – where the forest is modelled as horizontally homogenous canopy layers; and tree-level approaches – whereby individual trees are modelled, allowing for heterogeneity in responses between species and/or functional groups (Porté and Bartelink, 2002). Each approach can be subcategories into distance-dependent and -independent methods.

In the distance-dependent stand models, the forest/woodland stand is described as a mosaic of forest patches, with each patch being characterised by its location in the stand and having its own dynamics that interact with those of neighbouring patches. Distance-dependent stand models are similar to the cellular-based models described in Section 2.6.1, whereby there are a set number of states for each forest patch (typically successional stages) and the probability of transition from one state to another is estimated using the probabilities depending on the state of neighbouring cells. For example, FORMIX2 represents the vertical and horizontal structure of a forest stand, with growth modelled using transitions from one canopy class to another (Bossel and Krieger, 1991). By contrast, distance-independent stand models describe stand-level variables (e.g. carbon storage) using averaged characteristics, which can incorporate some natural variation (Porté and Bartelink, 2002). Distance-independent stand models are common, being used by foresters for several decades through yield tables (Payandeh and Wang, 1996). Such approaches typically model forest growth and thus the change in carbon storage through time-steps in which DBH data, tree number and density are altered in accordance with empirically derived relationships.

Tree-level approaches model individual trees in entire stands and are thus more computationally complex. Using modelled mechanistic processes, the individual tree is recruited, grows and dies. Models can be regarded as distance-dependent if the spatial location of the stem is specified, or distance-independent if it is not, although gap models bridge this divide, as the presence of gaps in the canopy are important, but the individual trees do not have specific spatial coordinates (Liu and Ashton, 1995). In all tree-level approaches, the unit of interest is the individual tree and not the cell nor the stand and so tree-level approaches are similar to the agent-based approaches described in Section 2.6.1.

As with LCC modelling, the modelling of forest carbon involves trade-offs. Besides the common issues of data-deficiency, it is not possible to model interactions at all spatial and temporal scales. Stand-level cellular-based models poorly explain the heterogeneity observed in tropical forests, but can be feasibly applied on large spatial scales and over long time frames (Mladenoff, 2004). By contrast, tree-level agent-based models better represent the mechanisms and interactions that influence the growth of individual stems, but as a result can only be used to model small areas over relatively short time-frames (Mladenoff, 2004). Thus, the appropriate modelling technique often depends on the aim of the investigation.

A common use for process-based carbon models is to estimate the future carbon flux of terrestrial pools under climate change. However, these models should be applied with caution as they are highly uncertain. Examples of these process-based ecosystem models are the High Resolution Biosphere Model (HRBM (Esser et al., 1994)), the Integrated Biosphere Simulator (IBIS (Foley et al., 1996, Kucharik et al., 2000)), the Lund-Potsdam-Jena Dynamic Global Vegetation Model (LPJ (Prentice et al., 2000)) and the Terrestrial Ecosystem Model (TEM (Tian et al., 1999)). All four models simulate the exchange of carbon between terrestrial carbon pools and the atmosphere, but each emphasises different aspects of ecosystem dynamics. For example, the vegetation distribution within HRBM and TEM is defined by input data, whereas IBIS and LPJ predict mosaics of plant functional types based on mechanistic relationships with environmental conditions. Furthermore, the models calculate carbon flux differently. HRBM models the carbon flux of vegetation using known correlations between net primary productivity and climatic conditions (see Section 2.3). By contrast, IBIS, LPJ and TEM individually model gross primary productivity and respiration (both affected by climatic variables) and assumes carbon flux to correlate with the difference between these two processes (McGuire et al., 2001). Continued monitoring of forest plots to collect data on plant growth and the response to disturbance and climate change will substantially reduce the uncertainty associated with such models. However, it must be noted that these models describe natural vegetation and so do not include anthropogenic LCC and its associated carbon emissions.

Combining historical land use/cover products with process-based ecosystem models enables historical carbon fluxes to be estimated. Typically, two input datasets are used to model long-term anthropogenic LCC: the History Database of the Global Environment (HYDE) and the reconstruction of global cropland developed at the Centre for Sustainability and Global Environment (SAGE). Here, I critically evaluate both products.

The HYDE database contains global maps of land use/cover between 1700 and 1990 (Goldewijk, 2001). At a 1° spatial resolution, terrestrial crop and pasture area were estimated (along with 13 other land covers) for each year by linearly interpolating between the values provided in the HYDE database, with data from 1990 to 2000 being added from FAO data. By contrast, the SAGE dataset is of higher spatial resolution (5min), spanning annually between 1700 and 1992 (Ramankutty and Foley, 1999). Ramankutty and Foley (1998) calibrated the IGBP 1km resolution Global Land Cover Classification dataset to the FAO categories, working backwards to 1700 assuming that cropland area did not alter, merely a change in percentage cover. Deviations from this assumption were included if available data indicated otherwise. Hurtt et al. (2006) extended the dataset to the year 2000, and combined both models, creating a HYDE-SAGE model including the cropland data from SAGE, but the pasture data from HYDE. In addition, Hurtt et al. (2006) added wood harvesting and shifting cultivation to the SAGE and HYDE datasets by combining these land cover change models with book-keeping approaches. There is broad consistency between the HYDE and SAGE datasets, with differences predominantly attributed to uncertainty in the spatial patterns of historical LCC (Klein Goldewijk and Ramankutty, 2004). A recent review by Klein Goldewijk and Ramankutty (2004) recommended that local and regional datasets be incorporated into these LCC products to address this uncertainty, although this is a difficult task as these data sources will be time-consuming and labour intensive to obtain and analyse.

LCC products such as HYDE and SAGE can be associated with carbon values using biome-based and process-based methods, allowing the carbon flux associated with historical LCC to be estimated semi-independently from book-keeping models and in a spatial explicit manner. For example, Strassmann et al. (2008) used an update version of HYDE (HYDE 3.0) in combination with LPJ to calculate carbon emissions between 1700 and 2000, estimating total emissions to be ~188 Gt C, of which have was caused by LCC. However, this analysis did not include shifting cultivation or wood harvest, and may overestimate emissions as it is likely that pasture preferentially expanded into grasslands rather than being equally partitioned over all land uses/covers (Houghton, 2010).

Table 2.7 Average annual emissions of carbon from global land use/cover change.

1700-1990 (Pg C yr^{-1})	1850-2000 (Pg C yr^{-1})	1980-1989 (Pg C yr^{-1})	1990-1999 (Pg C yr^{-1})	Data source	Reference
0.5[1]	0.7	0.7	1.1	SAGE-HYDE	Pongratz et al. (2009)
0.6[2]	n/a	1.4	1.3	HYDE3.0	Strassmann et al. (2008)
0.8	1.1	1.0	1.1	HYDE (Hurtt et al., 2006)	Shevliakova et al. (2009)
1.0	1.3	1.4	1.3	SAGE (Hurtt et al., 2006)	Shevliakova et al. (2009)
n/a	1.0[3]	1.5	1.6	Houghton and Hackler (2006) & FAO (2006)	Houghton (2010)
n/a	1	2	2.2	Houghton (2003) & FAO (2000b)	Houghton (2003)
n/a	n/a	0.6	0.9	AVHRR	DeFries et al. (2002)
n/a	n/a	0.9-1.6	n/a	Cropland inventory	McGuire et al. (2001)
n/a	n/a	2.4	n/a	FAO (1993)	Fearnside (2000)
n/a	n/a	n/a	1.1	Landsat	Achard et al. (2004)

1: from 1700 to 2000
2: from 1700 to 1999
3: from 1850 to 2005

2.7.5 Summary

The ability of the scientific community to monitor forest carbon is, at present, limited, predominantly due to data-deficiency. Methods to monitoring ALC pools have developed rapidly in recent decades, with the standardisation of plot-based methods and the development of remote sensing approaches. Whilst historical data may always be data-deficient, book-keeping and process-based approaches have enabled historical carbon fluxes to be estimated, albeit with large uncertainty. Future effort should be directed towards expanding and regularly monitoring the forest plot network, providing up-to-date information by which remote sensing and modelling approaches can be continually improved.

2.8 Methods for Identifying Baseline Trends for REDD+ Reference Levels

As discussed in Section 1.4.3, the development of historical baselines of carbon emissions is crucial before an effective REDD+ mechanism can be established. Emission reduction activities, such as REDD+, must prove that carbon expected to be emitted to the atmosphere was retained. To show this, future projects of emission pathways without any mitigation measures must be developed (GOFC-GOLD, 2010). Under REDD+, it is likely that realised emissions will be compared to these baseline scenarios to evaluate country performance and allocate compensation. Thus, obtaining reliable data on the recent change in forest cover is critical for REDD+ activities (Romijn et al., 2012).

Broadly, the proposed methodology for baseline calculation can be divided into three groups: the strict historical approach, the adjusted historical approach, and the simulation model approach (Gutman and Aguilar-Armuchastegui, 2012). Strict historical approaches develop a baseline scenario based on the mean annual rate of change in forest cover over a relatively recent time period (typically >10 years) (Santilli et al., 2005). Such approaches are transparent and practically feasible, despite current data-deficiencies. However, strict historical approaches are over-simplified and may result in spurious baseline estimations. This can be illustrated by comparing forest transition theory (an example of an adjusted historical approach; see Section 2.6.2) to the four country types proposed by da Fonseca et al. (2007): 1) low forest cover and high rates of deforestation; 2) low forest cover and low rates of deforestation; 3) high forest cover and high rates of deforestation; and 4) high forest cover and low rates of deforestation. Forest transition theory can be used chronologically link the types of countries identified by da Fonseca et al. (2007). Deforestation rates increase in countries with high forest cover by low deforestation rates (Fonseca Type 4; e.g. Colombia, the Democratic Republic of the Congo) as development progresses (Fonseca Type 3; e.g. Brazil, Cameroon, Indonesia), but eventually reach a transition point where the trend in forest cover shifts due to forest regeneration (Fonseca Type 2; e.g. China, India, UK) (see point ‘C’ in Figure 2.2). Prematurely inducing the shift from net deforestation to forest regeneration would result in significantly reduced emission (Culas, 2012, Dudley, 2010) (dashed line in Figure 2.2). The over-simplicity of strict historical baseline approaches is apparent when considering the linear rates of deforestation that would be estimated at each stage in the forest transition model. High forest, low deforestation countries would have a very low deforestation baseline, however forest transition predicts that this is an underestimate of emissions expected under the forest transition model as deforestation is expected to increase in upcoming years. This is illustrated at time point ‘A’ in Figure 2.2. Similarly, baselines for low forest, high deforestation countries that are nearing forest transition would be overestimates of emissions expected under the forest transition mode as deforestation in these countries is expected to decrease in the near future (see point 'B' in Figure 2.2).

Adjusted historical approaches also depend upon historical forest cover data, but consider other country circumstances (e.g. the stage in the forest transition curve) to improve predictions. As such, baseline scenarios estimated using this approach are often non-linear, frequently fitting an quadratic relationship (Umemiya et al., 2010). The development of a national forest transition model can be regarded as an adjusted historical baseline. Typically, adjusted historical baselines are thought to more reliably represent likely emissions (Umemiya et al., 2010). However, whilst strict historical estimates can be developed from freely available Landsat imagery or FAO national statistics (Olander et al., 2007), the development of non-linear forest transition models is more data intensive. In well documented regions, such as Eastern USA, the increased data requirements of adjusted historical approaches is not problematic as observational time-series of LCC span several centuries (Hall et al., 2002). However, in the tropics, analysis is normally limited to a period of a few decades as determined by the availability of remotely sensed data (Lambin, 1997), although historical maps should be utilised, where they are known to exist, to explore patterns before the satellite era (Börjeson, 2009). Despite this, forest transitions have been identified in numerous tropical countries, particularly those in Asia (Mather, 2007). There is no well documented case of forest transition in Africa, although a few smaller, poorly documented countries do provide indications of this shift within the FAO data (Meyfroidt and Lambin, 2011).

Simulation models have high potential to accurately predict changing forest cover. These models come in several forms (Huettner et al., 2009) but typically relate to key socioeconomic, technical and political drivers of deforestation (e.g. increases in food demand) rather than relying on historical deforestation rates. For example, Soares-Filho et al. (2006) developed a simulation model for the Amazon basin using satellite based deforestation maps between 1997 and 2002. However, the increased complexity of these models does not ensure more accurate baseline prediction as uncertainty is high when extrapolating to possible future conditions. Tropical LCC is affected by numerous drivers, including population growth and global economic markets (Veldkamp and Lambin, 2001, Lambin et al., 2001, Mather and Needle, 2000, DeFries et al., 2010) but significant uncertainty remains in the quantity of LCC and the implications of such changes (Grainger, 2008b, Grainger, 2010). In data-deficient areas, the assumptions and extrapolations associated with simulation models may result in increased uncertainty when compared to simpler adjusted historical baselines (Herold et al., 2012). Hence, many studies suggest that relatively simple historical-based approaches be followed until enough capacity is developed for more advanced approaches, and REDD+ policies are advocated to adopt a tiered system of baseline estimation (Sloan and Pelletier, Huettner et al., 2009).

If nations were awarded REDD+ payments for reducing emissions below these historical baselines, then their ability to share the cost of their own emission reductions is being ignored (see Section 1.4.3). Typically, LEDC are less able to share the costs of emissions reductions and most in need of economic development. As nations develop, they exploit natural resources and so, as countries become more economically developed, deforestation and forest degradation occurs on a larger scale (Rodrigues et al., 2009). However, many more economically developed countries have already proceeded down this path and so there is an ethical dilemma in restricting deforestation, and thus perhaps development, in LEDC. Whilst some LEDC show rapid rates of deforestation, fuelling development, others have yet to begin this process (da Fonseca et al., 2007). Thus, LEDC showing low rates of deforestation would have a low baseline, which could perhaps limit their development, violating the social aspects of REDD+. Using simulation and adjusted historical approaches helps to solve this problem, but many developing nations are data-deficient and unable to estimate deforestation rates beyond strict-historical approaches (FAO, 2010d). The UNFCCC must ensure that these nations (often amongst the poorest in the world) are not penalised due to this data-deficiency. I propose a method by which these data-deficient LEDC are evaluated against regional standards. These standards could be calculated centrally by the UNFCCC using adjusted historical and/or simulation approaches. For example, countries emissions could be evaluated against a regional forest transition curve calculated by averaging the forest transition curves present in neighbouring countries that show a similar level of economic development. Further debate centres on whether or not countries exceeding the baseline should be penalised. If countries are not penalised for exceeding the baseline, financial incentives may be delivered for the service of climate change mitigation through avoided deforestation without the service actually being delivered. This may occur if deforestation avoided during one time period is simply temporarily postponed, and occurs later. This is an example of temporal leakage (see Section 1.4.4 for a full discussion).

Table 2.8 Proposed baseline methodologies (adapted from Griscom et al. (2009)).

Proposal	Historical or projected?	Historical time period used	Includes Degradation?	Debits	Recalculated over time?	Provisions for country circumstances
Combined incentives	Historical	Not specified	No	Proposes no debits, although could allow a debit system to be incorporated	Global diminishing baseline could be established	The use of the global emission rate is an incentive for these countries
Compensated reductions	Historical	5-10 years	Yes	"Once in, always in" clause. Banking of some credits occurs to ensure this	Adjusted downwards over time	Includes a stabilisation fund and/or allows countries to negotiate a "growth cap"
Corridor approach	Historical	5-10 years	Yes	Variant 1: countries are debited for surpassing the upper reference level Variant 2: none.	No	No
Joint Research Centre	Historical and projection	1990-2005	Yes – divides into intact and non-intact forests	No penalties for exceeding the baseline	Adjusted downwards over time	Global average used for countries with high forest cover but low emissions rates
Stock-Flow	Historical and projection	Not specified	Yes	If a country exceeds its historical emissions rate, the country's dividends will be reduced accordingly. If these costs exceed the dividend then this is carried over and discounted from future revenues	Not specified	Dividends are provided for maintaining carbon stocks
Terrestrial carbon group	Neither, but informed by historic rates and projection of threats	20-30 years	Yes	If emissions have increased over the crediting period, the difference is converted into and amount to be debited from future revenues	The National Terrestrial Carbon budget can be adjusted due to unexpected events (e.g. war)	A variety of alternatives

Six mechanisms have been developed to calculate REDD+ reference levels from historical baselines. These proposed mechanisms consider the above debates, aiming to allow economic development whilst ensure emissions reductions are realised and appropriately compensated. The mechanisms are: combined incentives, compensated reductions, corridor approach, joint research centre, stock flow and terrestrial carbon group (Table 2.8). Negotiations as to which mechanism will be used are on-going, so all mechanisms are briefly described here.

1. Combined incentives – the baseline of a country is determined by a combination of their performance against their own baseline, as well as how it relates to the global baseline (Strassburg et al., 2009). The weighting of this model is negotiated on a country by country basis, but carbon stock emissions higher than the baselines are not penalised.

2. Compensated reductions – the baseline is determined from the historical deforestation rate (over a period of no less than five years) and estimating the associated carbon emissions (ED and IPAM, 2007). LEDC would be able to negotiate a baseline that is higher than their realised historical deforestation rate in order to allow for economic development.

3. Corridor approach – two historical baselines are generated (JR, 2006). If a country reduces emission below the lower baseline then it is entitled to receive carbon credits. However, these may be lost if future emissions rise over the upper baseline.

4. Joint research centre – The Joint Research Centre proposal allows for economic development of LEDC by dividing nations around the global average deforestation rate. Countries with baselines over half the global average must reduce deforestation below their historical rate, whilst remaining countries will receive compensation if they are able to maintain baselines less than half the global average (Mollicone et al., 2007).

5. Stock-flow – countries receive financial incentives via two mechanisms, both reductions of emissions and maintenance of carbon stocks are rewarded (Woods Hole Research Center and Amazon Institute for Environmental Research, 2008).

6. Terrestrial carbon group – The Terrestrial Carbon Group propose that carbon stocks are divided into those under threat of exploitation and

those whose risk of deforestation and degradation is negligible (TCG, 2008). Under the proposal 2% of at risk carbon stocks can be compensated annually if emissions are avoided. However, all credits sold must be removed from the at risk group, preventing temporal leakage.

Currently, negotiations surrounding the calculation of baselines and the mechanism by which they will be applied are on-going (see Chapter 1). Busch et al. (2009) evaluated the impacts of six possible reference levels, including using strict historical and adjusted historical approaches directly as crediting baselines, the combined incentives approach and the terrestrial carbon group approach. Simulating the responses given the different methods of compensating emissions reductions, Busch et al. (2009) demonstrated that a REDD+ mechanism could decrease emissions by between 73% and 84% relative to business-as-usual, but that the difference between each reference level approach was relatively small. Using strict-historical baselines was discouraged, as LEDC with low deforestation rates were excluded from REDD+ payments, but the direct application of adjusted-historical baselines as reference levels was encouraged as it is extremely cost effective (Busch et al., 2009). Similarly, Griscom et al. (2009) evaluated the combined incentives, compensated reductions, corridor approach, joint research centre, stock flow and terrestrial carbon group approaches, suggesting that all approaches matched emissions with appropriate compensation measures reasonably well, although many produced similar outcomes as when using a simple historical baseline as the crediting threshold. However, it is evident that the terrestrial carbon group approach has a tendency to over-compensate and so would not provide a credible compensation system. Again, low deforestation LEDC are only adequately compensated under systems that use an adjusted historical baseline or simulation approach (Griscom et al., 2009). Ensuring the participation of low deforestation LEDC is vital to the success of global emission reductions schemes as emission reductions are anticipated to be significantly greater given greater global participation (Busch et al., 2009, Griscom et al., 2009).

Given the adequacy of using adjusted historical baselines as crediting reference levels and the need to transparency within REDD+, I would encourage UNFCCC negotiators to focus on this simple mechanism to encourage wider global participation and thus a greater total emissions reductions. By ensuring the participation of all nations, spatial leakage can be prevented, and the inclusion of a debit system (where emission increases are penalised) would help to prevent temporal leakage. Nations are well prepared to produce forest transition curves, adding carbon stock information as indicated in the Forest Identity. The ability of nations to share their cost of emissions reductions could be allocated *en masse* via applying a standard to each Fonseca type. This simple mechanism is feasible given current data-deficiencies; however, until policy-makers have selected an appropriate mechanism, it is difficult to make any firm conclusions about how nations can best produce and analyse the data required for reference level estimation.

2.9 Conclusions

It is evident a reduction in global emissions is of critical importance, however the capacity of nations to monitor emissions and deliver such reductions varies widely. Both governments and the scientific community have invested heavily in monitoring LCC. With further targeted efforts, those regions considered data-deficient can be assisted to produce the required data, namely estimates of forest and woodland loss and the associated carbon emissions. The forest transition model provides a simple framework by which adjusted historical baselines can be created for each nation. Although long-term data on LCC in the tropics are typically thought to be sparse, I suggest that an independent expert body be created by the UNFCCC to lead a concerted central effort to digitise historical maps. This work may address current data-deficiencies as my preliminary investigations indicate that these maps are available in many parts of the world (Kuchler, 1970). Since this process can be centralised, results can be standardised and independently verified with relative ease. Nations should continue to be supported by the World Bank, UN-REDD, the scientific community and non-governmental institutions to establish national forest inventories. The data collected through plot-based methods can be combined with remote sensing and modelling methods to estimate the carbon emissions that accompany any observed LCC. It is not feasible to centralise plot-based data collection, and so I feel that the scientific community has a key role to play in independently validating the data provided by governments, who may be considered to have a vested interest. The establishment of on-going national inventories and centralised forest area monitoring will provide much of the data required by REDD+, as well as reducing uncertainty when estimating future emission.

Having identified Tanzania to be a data-deficient country in great need of such support, I substantially advance the data and analyses available for this region in my thesis. I provide an adjusted historical baseline against which future emission reductions can be evaluated and appropriate compensation given (Chapter 3). I then collate available plot-based data to provide and refine carbon estimates in this region (Chapters 4 and 5), identifying areas in need of further improvement (Chapter 6).

Chapter 3
A Century of Land Cover Change Within A Tropical Biodiversity Hotspot

3.1 Abstract

Land cover has changed rapidly across the tropics over the past century, particularly expansion of agricultural land. However, detailed historical information is widely lacking, despite its importance for climate change mitigation and biodiversity conservation. Here, I constructed a 20th century history of land cover change and resulting forest area estimates for the Tanzanian river catchments of the Eastern Arc Mountains (EAM; a global biodiversity hotspot). I geo-referenced and digitised historical land use maps dated 1908, 1923 and 1949 and obtained a contemporary map from 2000, showing that 2.79 million ha of forest cover and a further 2.91 million ha of savanna were lost from the 33.9 million ha watershed over 92 years, driven by a five-fold increase in cropland area. I demonstrate that the EAM watershed underwent a forest transition between 1960 and 1990. This trend is supported by changes in forest cover within the nested study area of the EAM themselves (where additional data from 1891, 1955, 1970, 1990, 2000 and 2007 are available). This is the first time a forest transition in Africa has been convincingly demonstrated, however, it must be noted that forest transition detection is highly dependent on the definition of forest used. Using descriptive analysis, I suggest that the forest transition predominantly occurred via the state forest policy pathway, with the increasing amount of protected land being vital in shifting net deforestation trends to those of forest regeneration. Additionally, I provide first-order estimates of the historical baseline rates of deforestation in the EAM. Finally, I provide preliminary evidence that a new ‘forest-favourable climate’ pathway may influence forest transitions under future climate change. Analysing long-term land cover trends using historical maps is encouraged as, in this study, forest loss predominantly occurred prior to remote sensing capabilities.

3.2 Introduction

Land cover is part of a constantly evolving dynamic anthropogenic-environment system with numerous complex drivers and impacts. Evidence of land cover change (LCC) is present in almost every landscape on earth (Houghton, 1994), contributing to biodiversity loss and climate change (Malhi et al., 2008). The most extensive LCC has been the increase in agricultural area, resulting in approximately one-third of the terrestrial land surface being classified as under this land use today (Houghton, 1994, Ellis et al., 2010). It is estimated that half of this long-term increase occurred in the last 100 years, although the majority of change within tropical regions has typically been estimated to have occurred within the last 50 years (Gower, 2003). Understanding LCC and its drivers is important for biodiversity conservation and climate change mitigation policies (Chapter 1 and 2). However, historical records in the tropics are rare, so where, when, why and how past LCC occurs is very uncertain for low latitude regions of the world.

LCC can contribute both to climate change, via changes to the global carbon cycle, and biodiversity loss (Kalnay and Cai, 2003, Lindblade et al., 2000, Thomas et al., 2004). Such impacts underpin several global initiatives, such as REDD+ (UNDP, 2009) and the Nagoya Convention on Biological Diversity agreement, that are aimed at altering LCC patterns and their impacts. However, the success of such initiatives, in part, rests on robust scientific information on the rates of LCC in tropical regions and how they change over time, yet quantitative data on LCC are typically incomplete and/or unreliable (Meyer and Turner, 1992, Ramankutty et al., 2007, Grainger, 2008b, Grainger, 2010).

As described in Sections 1.4.3 and 2.8, one of the main ecological challenges remaining before an effective REDD+ mechanism can be established is the methodology via which a baseline or reference scenario can be set. Several studies simulating the effectiveness of various reference level mechanisms have concluded that adjusted historical crediting baseline enables wide ranging participation and may result in substantial emission reductions (Busch et al., 2009, Griscom et al., 2009). The forest transition model is an example of an adjusted historical baseline (Section 2.6.2; Figure 2.2). However, the capacity for nations to monitor their progress along the forest transition curve varies greatly, as many countries lack this data due to poorly established national forest monitoring surveys (Section 2.4.1). For example, in the tropics, baseline analyses are normally limited to a period of a few decades as determined by the availability of remotely sensed data (Lambin, 1997). These data-deficient countries tend to rely on strict historical approaches to provide baseline rates of deforestation, although this method is known to be highly uncertain (Section 2.8). However, by combining the available satellite data with historical maps, it may be possible to create long-term baselines of changes in forest cover (Börjeson, 2009).

Here I investigate historical deforestation rates for the Tanzanian drainage basin of the Eastern Arc Mountains (EAM), a global biodiversity hotspot (Myers et al., 2000), using a century of LCC data. I develop both strict and adjusted historical baselines and identify the influential variables correlated with deforestation, paving the way for future development of simulation models. I provide evidence that the EAM watershed has gone through a forest transition and investigate the pathway through which the net deforestation trend shifted to one of net forest regeneration.

3.3 Definitions

3.3.1 Land use and Land cover

In order to detect LCC it is necessary to divide the landscape into different categories (often termed land covers or land uses) and observe the change in these categories over time. Here, I adopt the definitions of both terms from the IPCC (2000). I define land cover as “the observed physical and biological cover of the Earth’s land as vegetation or man-made features” and land use as “the total of arrangements, activities and inputs undertaken in a certain land cover type (set human actions)” (IPCC, 2000). Thus, land use describes the socioeconomic purposes for which the land is managed (e.g. farming, grazing, timber extraction), whilst land cover is a categorisation of the vegetation (or the lack of it). It must be noted that there is ambiguity in the IPCC documentation, with cropland being deemed a land cover by some definitions (IPCC, 2000) but a land use by others (IPCC, 2003). To avoid confusion, I will refer to all land categories used in this chapter (described in Chapter 1) as land covers, despite the fact that they may be deemed by some to be a mixture of land cover (e.g. forest, grassland) and land use (e.g. cropland).

3.3.2 Forest establishment

Whilst deforestation has previously been defined (Section 1.3.1), LCC may also occur through the development of forest on land that previously belonged to another land cover category. There are 3 ways in which this can occur:

1) Afforestation – the conversion of land that has not been forested (for at least 50 years) into forested land. This may occur via human-

induced planting, seeding and/or promotion of natural seed sources (IPCC, 2003).

2) Reforestation – the conversion of non-forested land into forested land (through planting, seeding and/or the human-induced promotion of natural seed sources) on land that was previously forests within the last 50 years (IPCC, 2003).
3) Regeneration – the natural regeneration of forest on land that was previously non-forest. This process is not human induced, often occurring via succession.

Using historical land cover maps, it is not possible to reliably differentiate between the effects of afforestation, reforestation and regeneration as the motives driving the increase in forest cover are unknown. Thus, in this chapter, I refer to forest establishment to describe the combined effects of afforestation, reforestation and/or regeneration.

3.3.3 Protected areas

In an effort to slow human-induced LCC, many nations have a dedicated protected area network. In this chapter I will examine the effectiveness of Tanzania's protected area network between 1949 and 2000. To do this, I adopt the International Union for Conservation of Nature (IUCN) definition of a protected area – "an area of land and/or sea especially dedicated to the protection and maintenance of biological diversity, and of natural and associated cultural resources, and managed through legal or other effect means" (Dudley, 2009). This definition is broad and encompasses a wide variety of activities including strict protection (i.e. strict nature reserves and wilderness areas), ecosystem conservation and protection (i.e. national parks), conservation of natural features (i.e. natural monuments), conservation through active management (i.e. habitat/species management areas), landscape/seascape conservation and recreation (i.e. protected landscapes/seascapes), and sustainable use of natural resources (i.e. managed-resource protected areas) (Dudley, 2009).

3.4 Background

3.4.1 History of Forest Protection for Timber Production and Conservation in Tanzania

It is likely that the forests and woodlands of Tanzania have been exploited for several thousands of years (Hamilton and Bensted-Smith, 1989). However, due to low population densities, this resource was not substantially diminished. Although not protected by written laws, the forests enjoyed a level of cultural protection, as well as protection via limited technology (i.e. local populations lacked the capacity to rapidly modify large areas of land). The forests and woodlands were sites to honour ancestors and perform initiation rituals (Swantz, 1995). Local peoples believed that forest spirits could possess people, with several principle timber species (e.g. African teak [*Milicia excelsa*]) believed to be likely sites for possession (Sunseri, 2009). As such, society's rules prevent the felling of these trees. It is likely that the enforcement of informal forest protection fell on tribal chiefs called *mapazi* (Klamroth, 1910). Their title stemmed from the term for a ceremonial ace (*mhaazi* or *mabazi*) (Steere, 1869), symbolising authority over forests and woodlands (Swantz, 1970).

In the 19th century, traders identified the presence of copal in the forests near Dar es Salaam. Copal was highly valued by Europeans and used as a varnish, whose hardness and quality rivalled Asian lacquers (Trotter, 1912). The wealth generated by the copal trade resulted in increased forest exploitation, attracting the attention of wild rubber traders (Sunseri, 2009). By the late 19th century, German had declared Tanzania a colony (termed *Deutsch-Ostafrika*), eager to exploit the valuable natural resources. In 1891, before much of the mainland had been conquered, the new German government issued an ordinance that regulated tree cutting throughout the colony (Sunseri, 2009). The Germans aimed to manage forests in order to maintain adequate long-term wood supplies and make colonisation profitable (Sunseri, 2009). The views are well summarised by the Chief Forester, Otto Eckbert, in 1903 who said "the view of the forest administration is that all these primeval forests are ripe for harvest. Postponing their exploitation until a later date thus means a loss of state property" (Sunseri, 2009). Thus, numerous forests and woodlands (most notably coastal forests and mangroves) were deforested during this period. The rate of deforestation was so great, with little or no effort of reforestation, that missionaries raised concerns with the foreign office (FO, 1903). In response, the German authorities declared the 1904 Forest Protection Ordinance, allowing creation of legally protected areas for the first time in Tanzania (Sippel, 1996). In 1904, all mangroves of coastal Tanzania were declared forest reserves, and district officers were instructed to remove any peoples residing within them (Sunseri, 2009). Alongside forest reserves, large wildlife reserves were also created (Gißibl, 2006). Africans were not permitted to reside within the borders of protected areas and their access was restricted. This enabled German authorities to profit from the forest resources, but the law required reforestation to follow exploitation. The sudden restriction on the local people's access to natural resources caused great conflict and as such poaching and illegal harvesting were frequent (Sunseri, 2009).

The gazetting of public lands into protected areas prioritised montane forests and mangroves as both were known to harbour valuable timbers. However, laws also called for the protection of trees on mountain ridges and near water courses to prevent soil erosion and moderate climate (Sunseri, 2009). However, there was little concern for preserving species diversity, with the colonialists keen for reserves to be as productive and as profitable as possible. In 1902, a biological and agricultural research station was founded at Amani to trial numerous crops. The trials showed particular success with Ceará rubber (*Manihot glaziovii*), Teak (*Tectonis grandis*) and Oil Palms (*Elaeis sp.*) thus, many native species were replaced with exotic plantations containing these species (Hamilton and Bensted-Smith, 1989).

During World War One, the forests and woodlands were readily exploited to aid the war effort, providing timber for town defences and/or fuel. As a result of this conflict, Tanzania changed hands, becoming a British colony known as Tanganyika. Initially, British authorities followed the same template as the Germans, being advised by the same scientists based at Amani (Sunseri, 2009). In 1920, the British founded the Forestry Department in Tanzania but it was substantially understaffed (consisting of only 11 European foresters and 100 African forest guards) and so any reserves not containing valuable timber species were de-gazetted, especially if the land would support cash crop production (FD, 1923-1931). Much like under German rule, the British were initially concerned with trying to expand timber production (FD, 1935). However, preservation of forests to regulate climate, soils and water supplies was also evident (FD, 1928). The British neglected woodlands due to the lack of marketable timber, the open nature of the canopy and the presence of the Tsetse fly (a vector of sleeping sickness) (Sunseri, 2009). However, woodlands were heavily exploited by the local peoples.

After 1926, British policy was to create African authorities with legislative and administrative powers under colonial supervision (Iliffe, 1979). This marked the beginning of the transfer towards the independence of Tanzania. This period was marked by a dramatic increase in protected area (from 1% of total land in 1914 to 8% in 1956 and 14% by 1961) accompanied by an increase in exploitation (Sunseri, 2009). Hardwood timbers were now held in higher regard and so all forests and woodlands were regarded as valuable resources that could be exploited (Eggeling, 1951). The economic boom that accompanied World War Two drove increased rates of deforestation. For example, in 1941 military orders doubled Tanzania's timber exports when compared to the previous year (Sunseri, 2009). The increase in international demand was followed by an increase in local demands, with population doubling between 1943 and 1952 (Sunseri, 2005). Although residing within forest reserves remained illegal, they were opened up to allow for charcoal production to meet the nation's fuel requirements. For example, over the same time period (1943-1952), it is estimated that ~400ha of forest near Dar Es Salaam was removed for fuelwood alone (Sunseri, 2009).

Tanzania achieved independence in 1961 and took over the Forestry Division in the middle of the decade, but British foresters remained for much of the 1960s (Hurst, 2004). Incoming political figures attempted to increase their popularity by appeasing local demands for agricultural land. Decision makers often readjusted protected area boundaries to allow for some encroachment, or simply failed to punish offenders. For example, the 1986-87 forest division/FINNIDA forest inventory showed that Kilanda and Lutindi forest reserves had become extensively cultivated and there were illegal villages within both reserves, despite at least two efforts (in 1979 and 1987) to remove them (Hamilton and Bensted-Smith, 1989).

The Arusha Declaration resulted in significant change in Tanzania. The Forest Division was required to contribute to national economic development (WyA, 1967). For example, the second five year plan in Tanzania (1969-74) provided funds to increase the extent and efficiency of charcoal production, with its export to Europe and the Middle East providing significant economic gain (Edvingstone, 1969). The Forest Division was also actively establishing plantations. Between 1961 and 1984, 1,756ha of Teak (*Tectona grandis*) and 24ha of *Terminalia sp*. were established in Longuze and Kihuhwi-Sigi forest reserves (FINNIDA, 1985). Logging activities took place in numerous reserves, including Kwamkoro forest reserve in 1958 and Kwamsambia forest reserve in 1987 (Hamilton and Bensted-Smith, 1989). Foreign aid agencies supplemented these activities by providing funds for state-owned saw mills (e.g. Sihk Saw Mills in the east Usambaras) (Hamilton and Bensted-Smith, 1989). Protected areas generated further income via tourism activities. Between 1969 and 1976 visitor bednights in Tanzania grew by 10.6% per year (from 295,000 to 564,000 yr^{-1}) and national park visits rose from 136,000 to 285,000 yr^{-1} (with >90% of this in northern Tanzania) (Curry, 1982).

The Arusha Declaration also required people to concentrate in planned villages, relocating some 11million people by 1976 (Sunseri, 2009). During this process some forest reserves were created, providing a legal basis by which people could be evicted. In other areas, villagisation took precedence and protected areas were de-gazetted to provide land for new villages. This vast migration greatly increased the pressure on forest and woodland resources local to newly formed villages, but allowed abandoned areas to regenerate. Villagisation mandated that each community tend woodlots to provide for their own domestic needs. As a result, 25,000ha of forest was planted between 1975 and 1979; however self-sufficiency was never obtained (Sunseri, 2009).

Tanzania was forced to abandon its previous path of economic development following fluctuations in oil prices and several droughts in the 1970s and a global debt crisis in the early 1980s (Tripp, 1997). These market conditions led to a reliance on numerous aid agencies and donors, whose ideals had shifted towards sustainable development and biodiversity conservation. In the 1990s, several conservation NGOs, supported by donor funding, pressurised the state into implementing measures designed to conserve biodiversity (Woodcock, 2002) that was now acknowledged to be of global significance and under threat (Myers, 1988, Myers, 1990). In order to reduce the century-long conflict between conservation activities and local livelihoods, Tanzania included participatory forest management in its National Forest Programme (2001-2010), attempting to balance people's needs with the reduction of deforestation and the conservation of biodiversity (Goldman, 2005). This policy shift is well illustrated by Hangani forest. The British authorities tried to make Hangani a state forest reserve after World War Two but were opposed by local villagers and so abandoned these plans (Sunseri, 2009). In 1996, Liwale subdistrict authority planned to declare Hangani a district forest reserve. Again local villagers protested, fearing being excluded from the forest (de Waal, 2001). After much negotiation, Hangani was declared a community forest reserve, with management of the forest shared between district governors and 13 surrounding villages (Sunseri, 2009). However, not all conflicts were solved as harmoniously. In 1997, the High Court of Tanzania heard the case of pastoralist communities who believed they had been unlawfully evicted from Mkomazi game reserve in 1988. The court ruled in favour of the pastoralist communities and assigned minimal compensation, but did not allowed them to return to their ancestral lands (Juma, 1999).

Today, the network of areas with some form of legal protection in Tanzania covers ~30% of total land area, although not all of these reserves are recognised by IUCN classification criteria (FBD, 2006a). These areas are protected by ten current policies and laws, namely: the Wildlife Conservation Act No. 12 of 1974; the National Parks Ordinance No. 412 of 1959; the Ngorogoro Conservation Ordinance No. 413 of 1959; the National Policies for Wildlife Conservation of 1997; the Forest Policy of 1998; the Forest Act No. 14 of 2002; the National Forest Policy of 1998; the Fisheries Act No. of 1972; the Marine Parks and Reserves Act No. 29 of 1994; and the National Fisheries Policy of 1998 (FBD, 2006a). As a result, protected areas in Tanzania have a tiered system, with restrictions on forest resource use increasing from forest reserves, through catchment forest reserves and nature reserves, to national parks. Some 3.7million ha of forests and woodlands (mostly in the form of forest reserves) are under various forms of participatory or community based management. Under these schemes, villages gain the right to harvest timber and forest products from the forest, but are responsible for its day-to-day management (FBD, 2006a). The management of catchment forests are similar to that of forest reserves, but with priorities focused on biodiversity, water and soil conservation. In both forest reserves and catchment forests, it is legal to collect dead wood, but permission should be sought (although it rarely is). The removal of live trees is prohibited, except with permission and on payment of a fee (Hamilton and Bensted-Smith, 1989). However, again, permission is rarely sought and the gathering of poles is extensive and evident in all but the most remote locations of forests (Ahrends et al., 2010). A forest nature reserve is the highest level of protection under the Forest Act and is entirely state managed. In recent years, eight catchment forests were up-graded to nature reserves across the EAM (Amani, Nilo, Magamba, Uluguru North, Uluguru South, Mkingu, Kilmbero, and Rungwe). It is illegal to harvest timber inside a nature reserve without expensive permits, although prices are reduced if local peoples can demonstrate significant need for the resource (Engh, 2011). However, illegal pole and timber collection is common. National parks are the highest protection category present in Tanzania. However, even these forests and woodlands are not exempt from exploitation. For example, within the last 3 years, almost 7,000 teak (*Tectona grandis*) trees have been clear-felled from the eastern section of Udzungwa Mountains National Park (TANAPA, 2009). Further timber removal is planned for deeper within this protected area in future years (Banga, 2010). In addition, although the collection of dead wood is limited to one day of the week and only by women, it is still permitted and is proving difficult to prohibit, despite numerous attempts (Nyundo et al., 2006).

In summary, it is evident that there is a long history of implementing protected areas in Tanzania. However, these protected areas were often subjected to high levels of use, involving substantial deforestation and forest degradation. This extraction of natural resources from protected areas continues today and so local evaluation of the long-term effectiveness of this management strategy is urgently needed.

3.4.2 Review of Government Estimates of National Forest Area in Tanzania in the 20th Century

Very little is known about the trend in forest area within Tanzania, although the FAO provides forest area estimates between 1990 and 2009. In 1990, there was an estimated 41.5million ha of forest in Tanzania (Figure 3.1). It must be noted, that this area estimate is based on the FAO definition of forest, namely land, over 0.5ha, with a tree crown cover of over 10 percent and trees that (when mature) reach over 5m in height (FAO, 2000a). Between 1990 and 2009, the FAO estimated that forest area declined linearly, at a rate of ~0.4 million ha yr^{-1}, to 33.8 million ha (FAO, 2012b). However, there are large uncertainties associated with the forest area estimates and the trend of forest decline. According to FAO (2012b), the trend is estimated from only three data points from the years 1990, 2000 and 2005. However, on examination of the Global Forest Resource Assessment Country Report from which this data is derived, it is evident that the values for these years are also estimates. Two sources of forest area data are presented in the Country Report. The first, dated 1984, is derived from the Millington et al. (1989) assessment of woody biomass in Southern Africa and the second derived from HTSL (1997) (see Section 3.5.3.7) (FAO, 2010c). Both estimates are deemed high quality. However, it is highly questionable whether an accurate deforestation trend can be derived from only two data points. Other government estimates of deforestation are also highly uncertain. The National Forest programme in Tanzania estimates a deforestation rate between 0.1 and 0.5million ha yr^{-1} (FBD, 2001) and the Centre for Energy and Environment, Science and Technology (CEEST) estimate that 24.4% of original tropical closed forests were either deforested or degraded by 1990 (totalling ~0.1million ha deforested and ~0.2million ha degraded) (CEEST, 1999). In summary, while national estimates of forest area in Tanzania are highly uncertain, it is widely suspected to be in decline, although estimates of the rate of decline vary over five orders of magnitude.

3.5 Methodology and Methods

3.5.1 Methodology

3.5.1.1 Land Cover Classification System

A consistent collection of land cover categories did not exist in the twentieth century, and still does not exist today. Most modern land cover maps depict different categories (e.g. NLCD (2010), GLCF (2010)) and the differences are often more substantial with historical maps (Engler, 1908-10, Shantz and Marbut, 1923, Gillman, 1949, Swetnam et al., 2011). Even when land cover maps use categories of identical name (e.g. forest), the definitions of the categories often differ so the categories may not be directly comparable (Putz and Redford, 2010). In order to investigate trends of LCC over time, a chronosequence of land cover observations is required. To reduce uncertainty, the entire chronosequence should use the same land cover categories. If land cover categories differ between maps then it is necessary to harmonise the categories to provide continuous estimates of LCC. For example, under the Global Forest Resource Assessment programme, individual countries are permitted to use a wide range of definitions of ‘forest’. However, in order to investigate deforestation trends it is necessary for the data provided under the county’s definition to be converted to the standard FAO forest definition (FAO, 2000a, FAO, 2010d, FAO, 2010c). It must be noted that, LCC data is lost when categories are combined into harmonised groups as LCC within a land cover category will not be detected using the methods described here. Thus, the broader the categories, the greater the potential for substantial change within each category to occur before it is detected as LCC (i.e. the category is reallocated to another land cover type). Hence, the harmonised categories chosen should be the narrowest possible groupings of land cover categories that are continuous over all land cover maps of interest.

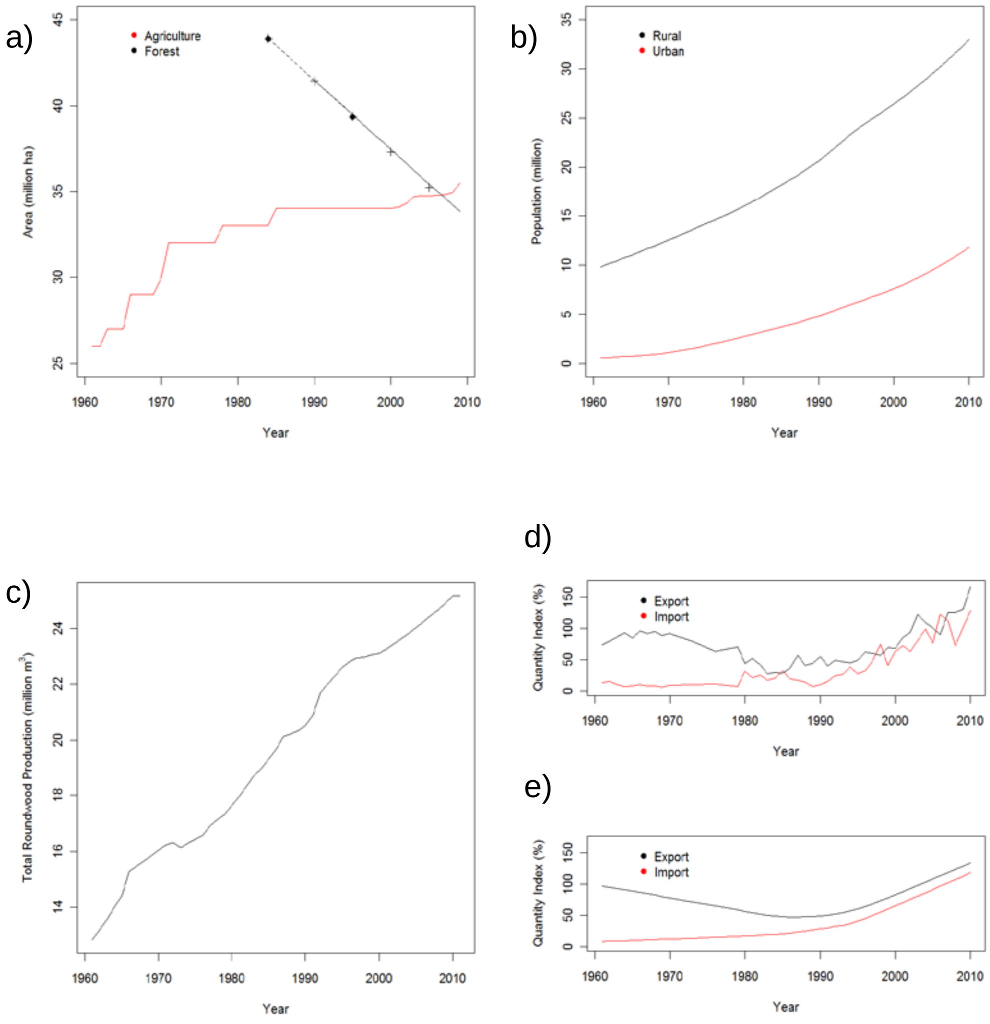


Figure 3.1 Trends in Tanzania between 1960 and 2010 for: a) forest area (black; country-indicated data points shown as solid point (FAO, 2010c), FAO-indicated data points shown by + (FAO, 2012b)) and agricultural area (red); b) the rural (black) and urban (red) population over time; c) Total roundwood production over time; d) the quantity of imports (red) and exports (black) over time; and e) the trend of the quantity of imports (red) and exports (black) over time illustrated using a locally-weighted polynomial Lowess regression (smoother span of 2/3). All data extracted from FAOSTAT except where otherwise indicated (FAO, 2012b).

3.5.1.2 Forest Transition Model

Forest transition models demonstrate that long-term changes in forest cover can be broadly described using a U-shaped curve (see Section 2.6.2). In this chapter, I focus on the last century, testing if a forest transition forest is evident during this period and, if it is, identify the possible pathway that brought about this transition.

Forest transitions are theorised, by Meyfroidt and Lambin (2011), to occur via five main pathways: the economic development pathway; the forest scarcity pathway; the state forest policy; the globalisation pathway; and the smallholder, tree-based land use intensification pathway (see Section 2.6.2 for a detailed description). In addition to these, I propose an additional pathway. Climatic conditions and events may affect both deforestation and forest establishment, and so these biophysical impacts should not be ignored in tropical regions (Perz, 2007). A forest-favourable climate pathway could be imagined under several scenarios. These actions could be: a) direct, whereby climate changes result in a critical transition to/from forest. For example, precipitation change is a key variable that may lead to transition between the stable states of forest, savannah and grassland (Hirota et al., 2011); or b) indirect, whereby climate changes result in abandonment of agricultural land. For example, a series of droughts over a short time span may lead to abandonment of agriculture after crop failure over successive years. Furthermore, heavy rains may lead to waterlogged soils and, ultimately, landslides. Thus, both increased and decreased precipitation can be theorised to result in agricultural abandonment and forest recovery. Additionally, edaphic conditions may also fall under this pathway. Agricultural fields may be abandoned as a result of impoverished soil and declining yields, however, forest regeneration may be able to occur even under these extreme conditions.

In this chapter, I will investigate whether the long-term changes in forest cover in Tanzania follow the U-shaped curve expected under the forest transition theory. If forest transition is detected, I will descriptively analyse the forest replenishment period and evaluate the ability of the economic development pathway, the forest scarcity pathway, the state forest policy pathway, the globalisation pathway and the proposed forest-favourable climate pathway to explain this transition. Due to data-deficiency, evaluation of the smallholder tree-based land use intensification pathway is beyond the scope of this study.

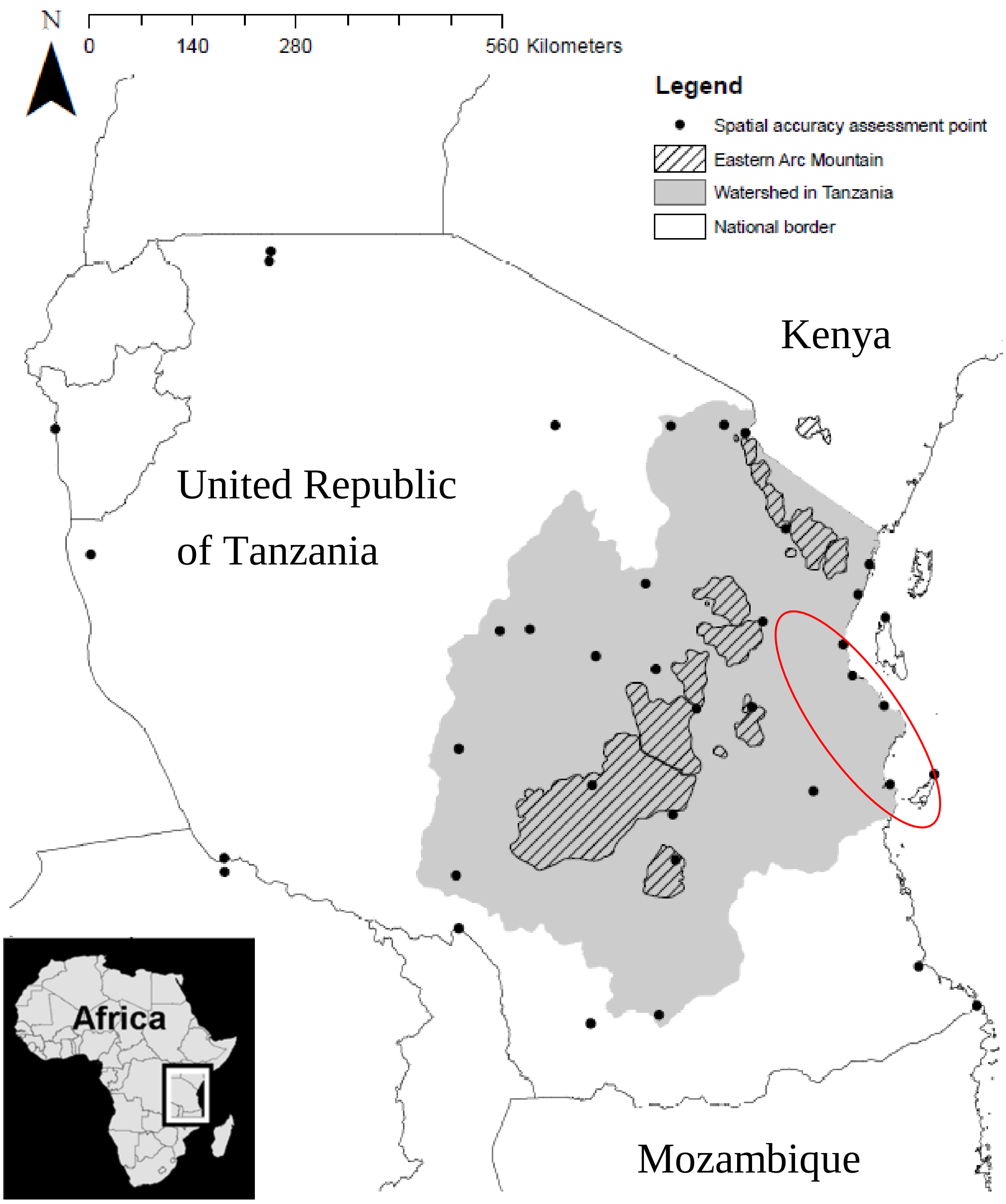


Figure 3.2 Region for land cover change analysis is the Eastern Arc Mountain watershed in Tanzania (shaded) (Swetnam et al., 2011). Additional analyses were conducted for the mountain blocs themselves (striped), and for just the northernmost blocs (circled). Points locate towns and geographical features used to assess the spatial accuracy of historical maps.

3.5.2 Study Area

In order to maximise the historical land cover data available, I focus on two nested study areas: the Eastern Arc Mountains (hereafter, EAM) and their Tanzanian watershed, which cover 5.2 and 33.9 million ha, respectively (Figure 3.2; see pages 46-48 and Swetnam et al. (2011) for further details). The EAM are defined as ancient crystalline mountains within Tanzania and Kenya, under the climatic influence of the Indian Ocean (Lovett, 1990). Their watershed is a heterogeneous mix of cropland, savanna, miombo and forest, and contains the administrative and commercial capitals of Dodoma and Dar es Salaam. Ecosystems within the EAM are considered a global priority for biodiversity conservation, with high levels of plant and animal endemism (Burgess et al., 2007, Platts et al., 2008, Myers et al., 2000). The region provides numerous critical ecosystem services including timber, fuel, carbon storage, water provision and regulation, maintenance of soil quality, reduction of erosion, stabilisation of local climate, conservation of cultural values (including traditional medicine), hydroelectricity generation and nutrient cycling (Economic Research Bureau, 2006, FORCONSULT, 2005, Pfliegner and Burgess, 2005, Marshall, 1998). At the time of the last national census, the population of Tanzania was 34.4 million people (NBS, 2006), of which 2.2 million lived in the EAMs and 12.9 million lived within the wider watershed catchment. Over the last 14 years, the national population growth rate has been 2.9 % yr^{-1}, increasing pressure on land and resources (NBS, 2006).

3.5.3 Data

3.5.3.1 1891 Map

In the late 19th century Dr Oscar Baumann was tasked by the Deütschostafrikanischen Society to map the topography and vegetation of northern Deutsch-Ostafrika. The 1891 map produced by Engler (1908-10) shows the location and extent of forest in the Usamabara and Pare mountains in the late 19th century at a scale of 1:2,000,000. I find the map to be highly accurate, showing the names and locations of settlements in areas where they still persist today. Prominent natural features of Tanzania (northern EAM [namely North Pare, South Pare, West Usambara and East Usambara] and Lake Jipe) are also identifiable on the map in the correct spatial location. In addition, national borders and coastlines are accurately illustrated. I categorise the reliability of the 1891 map as high, having been well validated on-the-ground by extensive German exploration in this region of Tanzania.

3.5.3.2 1908 Map

In the early 20th century Engler and Drude produced a series of works summarising the flora and ecological conditions of Africa. Engler's area of expertise encompassed the tropical flora contained within German territories (which, at this time, Tanzania was) (Cowles, 1910). The 1908 map produced

Table 3.1 Land cover categories originally reported in maps and their coercion into the harmonised land cover categories (Forest, Savanna-spectrum, Crop, Other).

Harmonised category	1908 map legend	1923 map legend	1949 map legend	2000 map legend
Forest	• 5 Tropical rainforests of the flat plains and the mountains • 6 Cloud or high altitude forest • 7 Park-like grove of the coastlines with high tree and shrub diversity • 4 Alluvial land in rain-poor areas, often park-like • 2 Mangrove and Creekland	• Tropical rain forest • Temperate rain forest • Mangrove	• 1 Forest • 1b Forest/woodland intermediate	• 22 Montane Forest 1500-2000m • 21 Sub-montane forest 1000-1500m • 2 Lowland Forest <1000m • 23 Upper-montane forest >2000m • 11 Mangrove forest • 15 Plantation Forest • 27 Teak plantation • 26 Rubber plantation
Savanna spectrum	• 1 Dry forest (forest -steppe, Miombo forest) or tree-steppe with few grasses with low tree diversity (few dominating species) often growing in single-species patches) • 8 Dry woody scrub bush and mountainous bush, sometimes with evergreen species, in some places with trees and often merging into bust-tree and grass steppe • 9 Individual mountains with bush-kind vegetation	• Dry forest • Thorn forest • Acacia tall grass savanna • High grass low tree savanna • Alpine meadow • Mountain grass	• 2 Woodland • 5 Closed Woodland • 3 Bushland and Thicket • 3b Specialised thickets of regional extent • 2b Woodland/Bush intermediate • Ugogo catena • Central plateau catena • 4 Wooded grassland • Rain-pond catena • 5 Valley grassland • 5b Ridge and slope grassland • 6 Permanent swamp vegetation	• 5 Closed Woodland • 0.5*(19 Woodland with scattered cropland) • 3 Bushland • 0.5*(4 Bushland with scattered cropland) • 7 Forest mosaic • 13 Open Woodland • 8 Grassland • 14 Permanent Swamp • 0.5*(9 Grassland with scattered cropland)

	• 12 Open grass prairies, with only very few trees or shrubs • 11 High altitude grassland and high mountain steppe alongside alpine scrub and rock in high altitude regions		• 8 Grassland	
Crop			• 8 Actively induced vegetation by natives • 8b Actively induced vegetation by aliens	• 24 Sisal plantation • 25 Tea plantation • 6 Cultivation • 0.5*(19 Woodland with scattered cropland) • 0.5*(9 Grassland with scattered cropland) • 0.5*(4 Bushland with scattered cropland) • 28 Rice plantation • 29 Monocrop unspecified • 3 Sugarcane plantation
Other	• 13 Steppe with few grasses, often with rocks, sometimes also with low, mostly thorny shrubs and trees, then orchard steepe with few grasses	• Acacia desert grass savanna	• 7 Desert/Semi desert	• 1 Unclassified • 2 Bare Soils • 1 Ice • 12 Ocean • 16 Rock outcrops • 17 Urban Area • 18 Water

by Engler (1908-10) to identify the spatial location of natural resources in Tanzania was widely considered at the time as both reliable and accurate (Cowles, 1910). The map illustrates land cover within the whole of Tanzania at a scale of 1:6,000,000, using a biome-type classification system consisting of 13 different land covers (Table 3.1). I find the 1908 map to be highly accurate, showing the names and locations of settlements in areas where they still persist today. Prominent natural features of Tanzania (EAM, Kilimanjaro, Lake Nyasa, Lake Tanganyika and Lake Victoria) are also identifiable on the map in the correct spatial location. Figure 3.3 shows that, prior to geo-referencing, the map image corresponded well to the digitised study area boundary, with national borders and coastlines accurately illustrated. I categorise the reliability of the 1908 map as high, having low spatial errors (maximum spatial error of <14km [Figure 3.4]; see Section 3.5.4.5).

3.5.3.3 1923 Map

Shantz and Marbut (1923) presented a generalised map of the vegetation in Africa at a 1:10,000,000 scale. The map uses a biome-type classification system consisting of 10 different land covers within my study area (Table 3.1), but 20 in total. The 1923 map was the first such continental estimate (Whitlow, 1985) but was criticised in the literature for the broad land cover categories used during the mapping process. Michelmore (1934) felt that land covers grouped together by Shantz and Marbut (1923) were in fact very different and distinct due to wide geographical separation and thus should not grouped. I find the 1923 map to be reasonably accurate, showing the names and locations of settlements in areas where they still persist today, as well as accurately representing the railway network present in Tanzania at the time. Prominent natural features of Tanzania (Kilimanjaro, Lake Nyasa, Lake Tanganyika and Lake Victoria) are also identifiable on the map in the correct spatial location. Figure 3.5 shows that, prior to geo-referencing, the map image corresponded well to the digitised study area boundary, although the national border with Kenya shows minor discrepancies. I categorise the reliability of the 1923 map as medium, having medium spatial errors throughout my study area (maximum spatial error of <23km [Figure 3.4]; see Section 3.5.4.5).

3.5.3.4 1949 Map

In 1943, Gillman was appointed to prepare a map of the vegetation of Tanganyika Territory (Gillman, 1949). Gillman had visited the territory regularly during the 30 year period leading up to this, accumulating a wealth of land cover data and combined these with detail reconnaissance (Gillman, 1949). The 1:2,000,000 map illustrates land cover within the whole of Tanzania to a high resolution, identifying many small fragments of isolated land covers, and uses a biome-type classification system consisting of 16 different land covers (Table 3.1). The 1949 map does not illustrate the names or locations of settlements, but does accurately represent the railway network present in Tanzania at the time. Prominent natural features of Tanzania (EAM, Kilimanjaro, Lake Nyasa, Lake Tanganyika, Lake Rukwa and Lake Victoria) are also identifiable on the map in the correct spatial location. The author provided spatially explicit indications of map reliability which were, on the whole, favourable (with 55% of the map classed as of 'high reliability', 25% as 'medium reliability and 20% as low reliability (Gillman, 1949)). Figure 3.6 shows that, prior to geo-referencing, the map image corresponded well to the digitised study area boundary, with national borders and coastlines accurately illustrated. I categorise the reliability of the 1949 map as high, having low spatial errors (maximum spatial error of <18km [Figure 3.4]; see Section 3.5.4.5).

3.5.3.5 1955 Map

I obtained digitised estimates of forest cover in the EAM in 1955 from Hall et al. (2009). These estimates were derived from the 'Tanganyika First Series' 1:50,000 topographic maps and had been digitised by the Tanzanian National Resource Information Centre. The data are regarded to be of high reliability, however, may be slightly erroneous for the Nguru mountains due to data deficiency (it was not possible to obtain this sheet of the map and so the data were substituted with 1970s Landsat MSS land cover). Substituting 1970 land cover into this 1955 map was appropriate as experts believe most of the forest clearing in this area occurred prior to 1955 (Hall et al., 2009).

3.5.3.6 1970, 1990, 2000 and 2007 Maps

Similarly, I obtained digitised estimates of forest cover in the EAM in 1970, 1990, 2000 and 2007 from Hall et al. (2009). These maps were produced for the Tanzanian government from Landsat MSS and ETM+ satellite images by the Sokoine University of Agriculture using standard classification protocols (Harper et al., 2007). Cloud cover prevented land cover classification in the Uluguru, East Usambara and Nguru mountains and so SPOT images were used in these areas (see FBD (2006b) for a full description of methods). These maps are spatially accurate to 30m and so are regarded as very reliable.

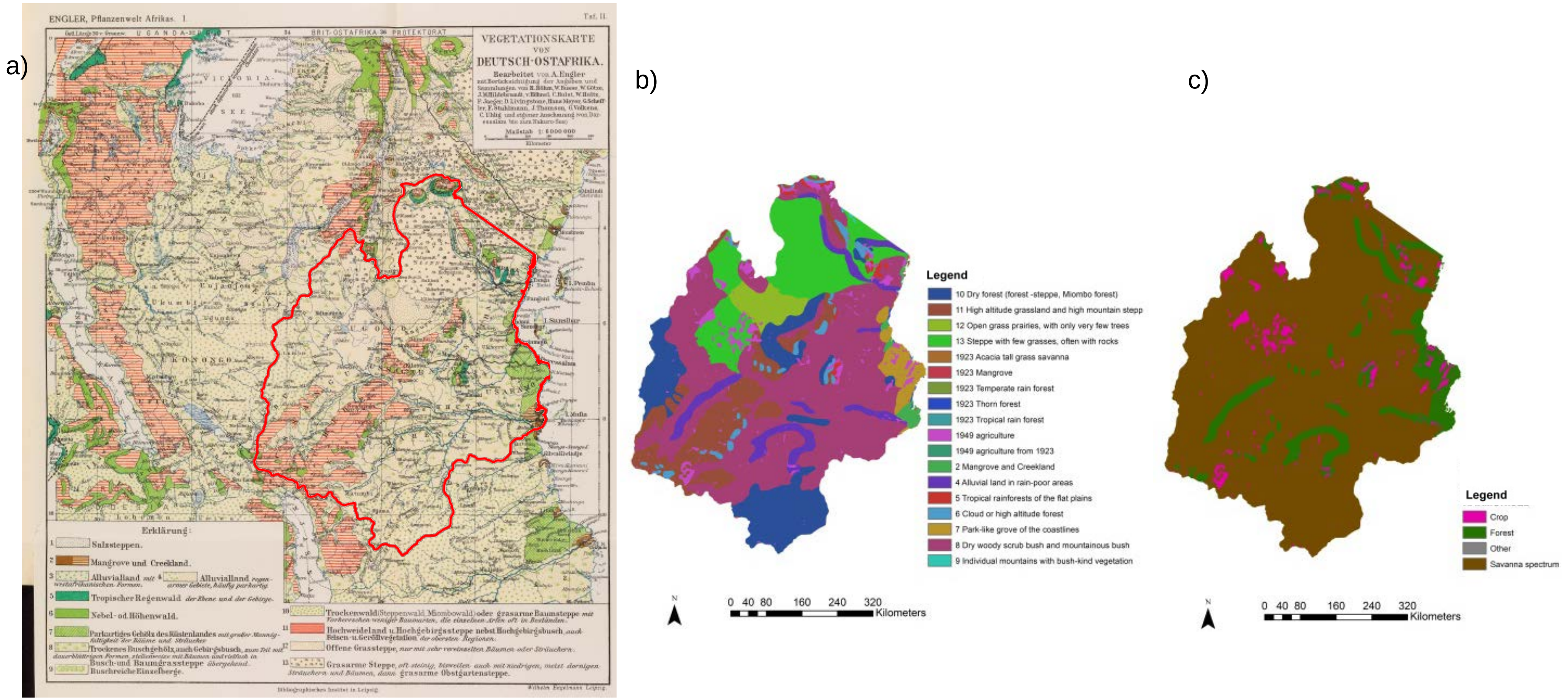


Figure 3.3 The 1908 land cover map: a) shows the original map image, with my study area illustrated by a red outline; b) shows the error corrected digitised map using original land cover categories; and c) shows the error corrected digitised map using harmonised land cover categories.

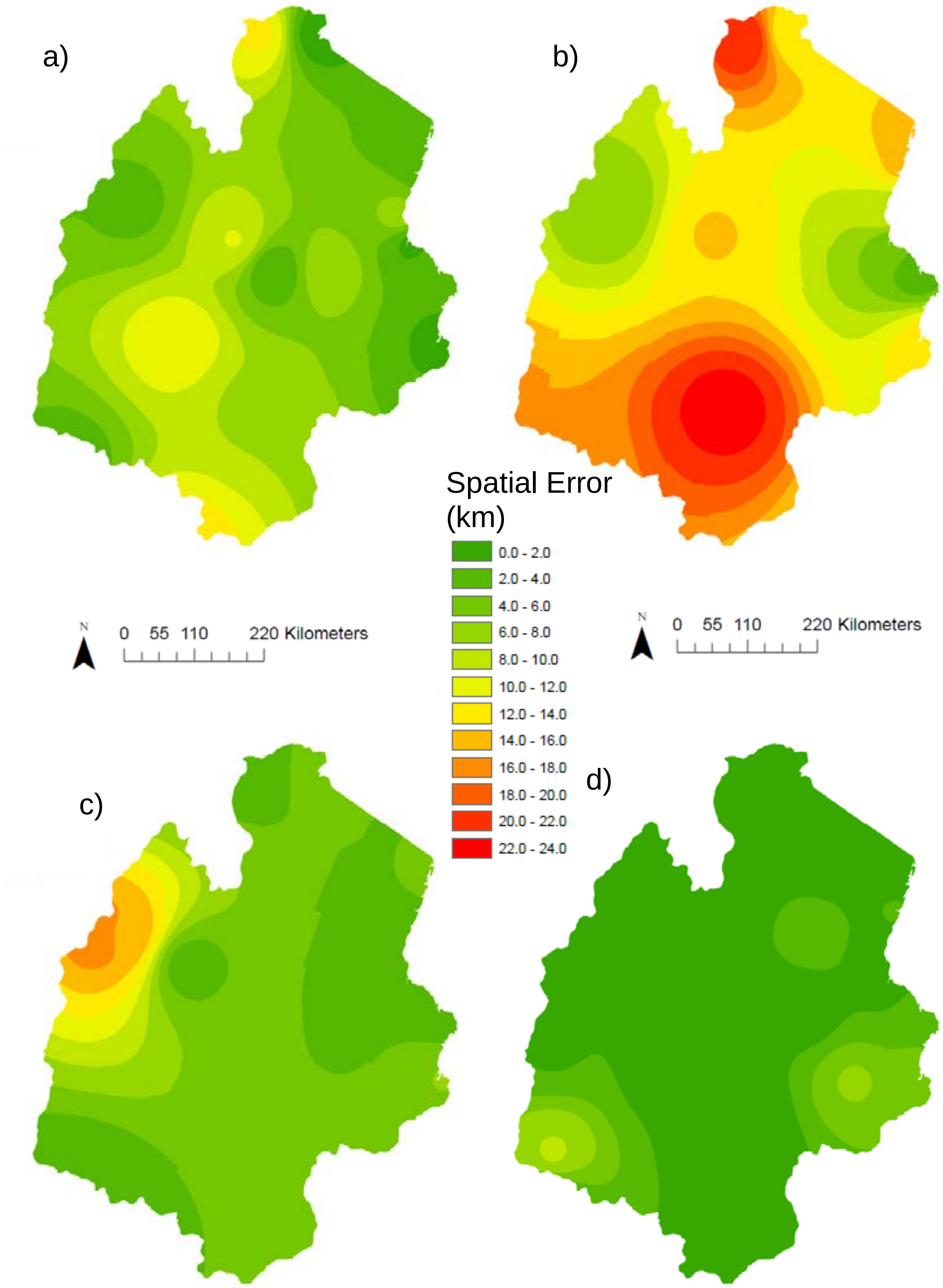


Figure 3.4 The spatial displacement of the digitised geo-referenced maps of the EAM watershed from a) 1908; b) 1923; c) 1949; and d) 2000 when identifiable points are compared to the same points on an independently derived map (Earth Tools, 2010).

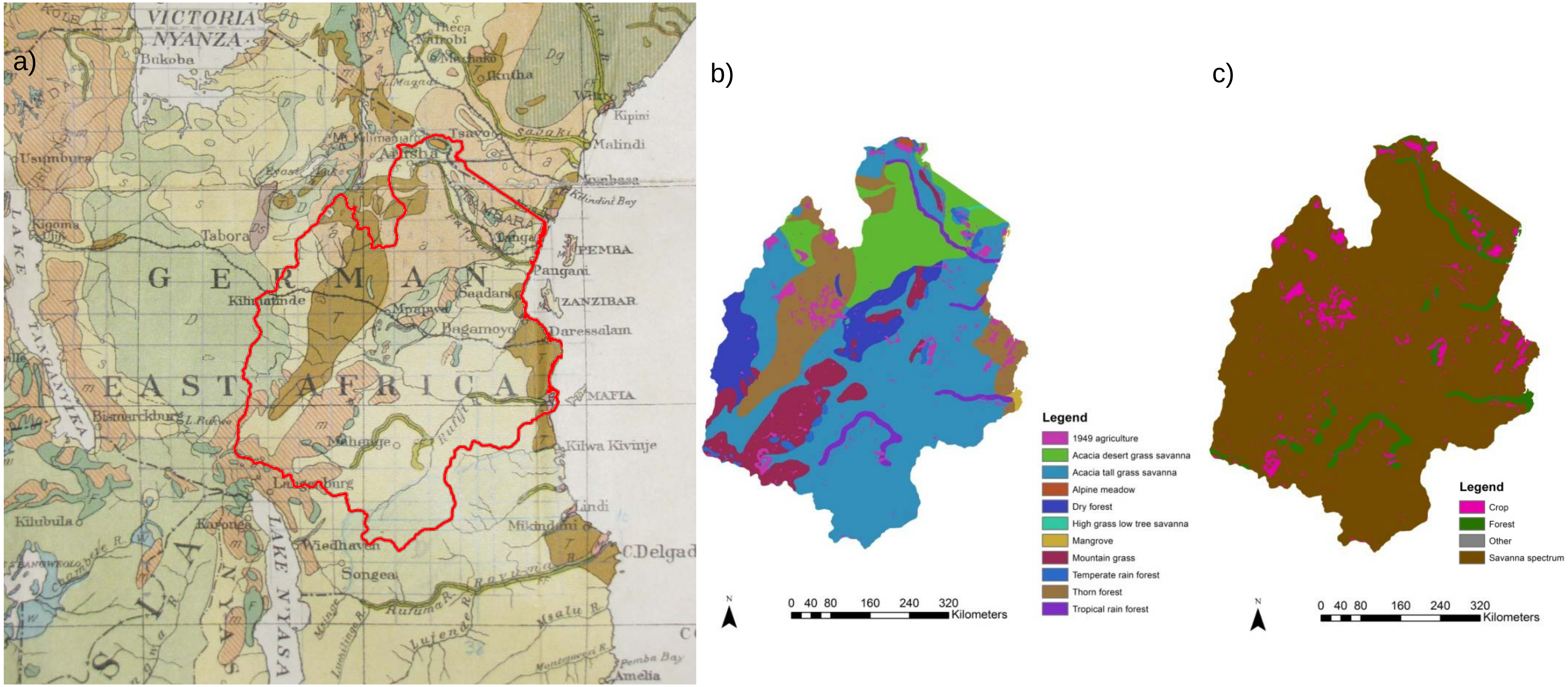


Figure 3.5 The 1923 land cover map: a) shows the original map image, with my study area illustrated by a red outline; b) shows the error corrected digitised map using original land cover categories; and c) shows the error corrected digitised map using harmonised land cover categories.

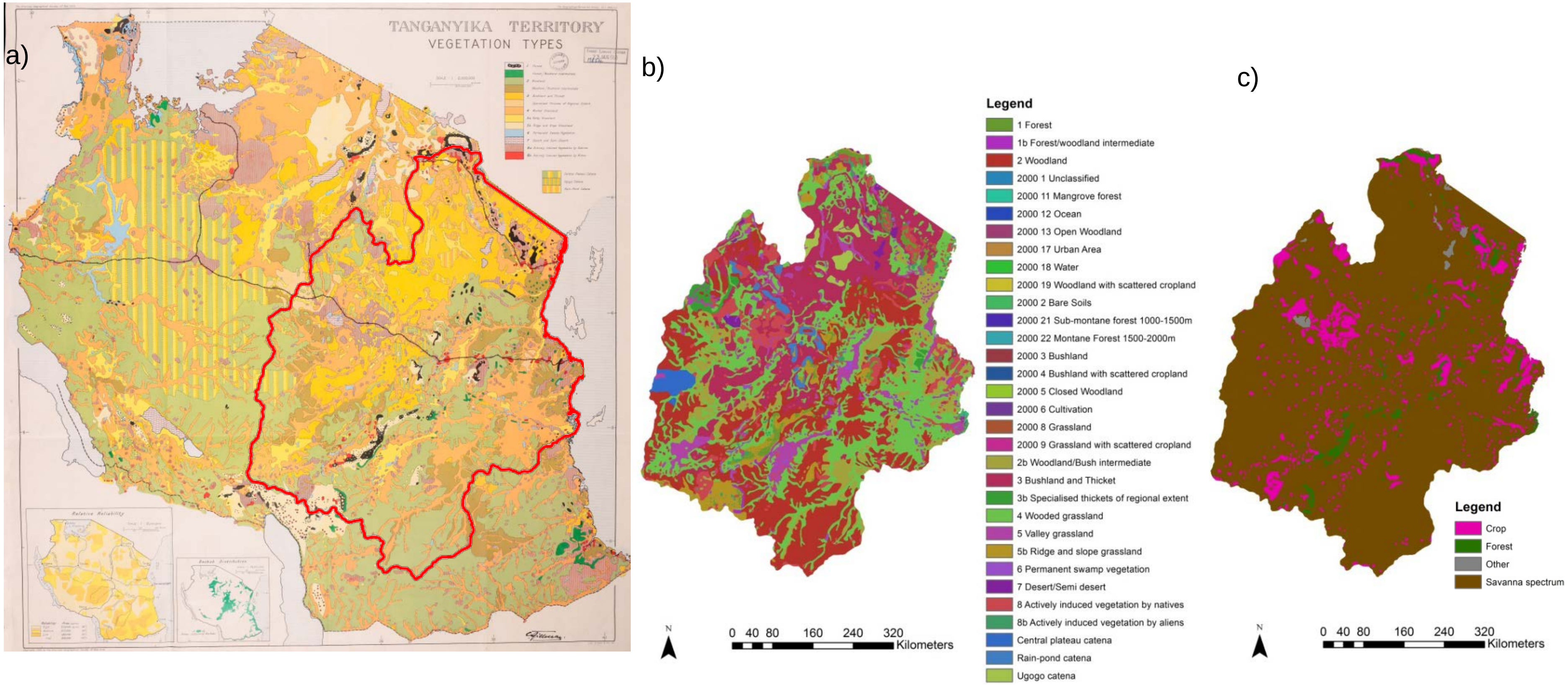


Figure 3.6 The 1949 land cover map: a) shows the original map image, with my study area illustrated by a red outline; b) shows the error corrected digitised map using original land cover categories; and c) shows the error corrected digitised map using harmonised land cover categories.

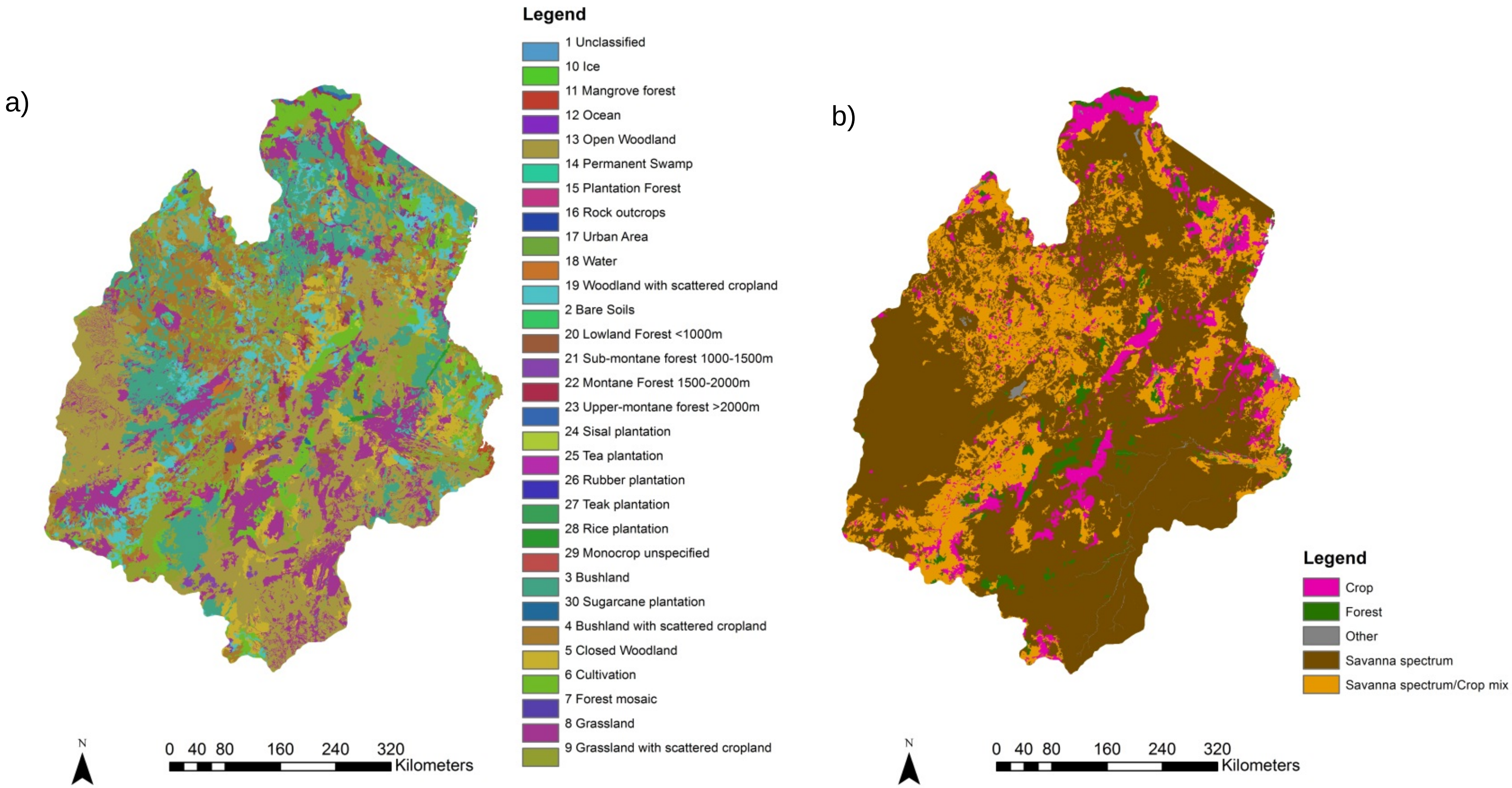


Figure 3.7 The 2000 land cover map: a) shows the error corrected digitised map using original land cover categories; and b) shows the error corrected digitised map using harmonised land cover categories.

3.5.3.7 2000 Map

An additional 2000 map illustrates land cover within the whole of Tanzania to a high resolution, identifying many small fragments, and uses a biome-type classification system consisting of 30 different land covers (Table 3.1, Figure 3.7). The 2000 map was derived from an estimate of land cover in 1995 (produced at a 1:250,000 scale by combining satellite based assessment with rigorous on-the-ground validation (HTSL, 1997)). The 1995 map was produced by Hunting Technical Services by analysing mosaics of Landsat Thematic Mapper and SPOT images acquired between May 1994 and July 1996 and is thought to be accurate to the nearest 100ha (Wang et al., 2003). This original map was updated by local experts and tropical biologists, taking into account any land cover changes that had occurred between 1995 and 2000 (Swetnam et al., 2011). I categorise the reliability of the 2000 map as very high, having very low spatial errors (maximum spatial error of <9km [Figure 3.4]; see Section 3.5.4.5).

3.5.4 Methods

3.5.4.1 Geo-referencing and Digitising Maps

I geo-referenced and digitised the 1891, 1908, 1923 and 1949 maps in ArcGIS Desktop version 9.2 using the following method. The relevant map image was loaded into ArcMap alongside digitised data providing the locations of villages and national and sub-national boundaries (obtained from Swetnam et al. (2011)). As shown in Figures 3.3-3.6, the map images corresponded very well to the existing digital maps. Following this, numerous control points were added where areas of known coordinates could be identified on the images. For example, the national borders and coastlines shown in the images could be linked to the digital maps using the geo-referencing tool. Further links could be created using other anthropogenic or natural features if they were indicated on the original maps (see above). Using national boarders in combination with other features within the interior assured that the best results possible were obtained. Once the links had been created, the map image was transformed using a first order polynomial transformation based on a least square fitting algorithm. Although there is no co-registration (perfect pixel alignment of two images) tool in ArcGIS, this minimal transformation was adequate to ensure near perfect correspondence between the image and the digital maps, with root mean square errors approaching zero. All geo-referenced datasets were the projected into UTM 37 South using a WGS 1984 geographic coordinate system (Swetnam et al., 2011).

Once the map image had been geo-referenced, interactive digitisation was performed. The image was displayed as a basemap, and land cover categories were traced to create a digital vector map indicating each land cover. Digitisation occurred at the highest possible resolution, typically ~1:30,000. At this scale, it was possible to distinguish between individual pixels of different land cover, thus the boundary between land covers was digitised as the boundaries between these pixels. For map boundaries that were indicated by a solid (black) line, the digital boundary was located at the halfway point of this line. Finally, all vector datasets were re-sampled to a common spatial resolution of a 100m grid, with each grid cell receiving the land cover classification most that covered the largest area within the cell.

3.5.4.2 Simulating Agricultural Area in the 1908 and 1923 Maps

The 1908 and 1923 maps do not include an agricultural land cover category and I have derived it as follows: firstly, I estimated population in 1908 and 1923 within my study area. To do this I created a relationship describing population growth over time by combining data on the total population of Tanzania (World Bank, 2010) with older census results of the mainland (Boesen et al., 1986) (Table 3.2; p-value < 0.001, R-sq = 99.97%). Secondly, I calculated the ratio between known agricultural area and population in 1949 and 2000, and used this to estimate the area under agriculture in 1923 and 1908, based on the population in these two years (Figure 3.8, Table 3.2). This relationship assumes that there has been no change in yield over time, a reasonable assumption based on current assessments of agricultural productivity in Tanzania today (Paul et al., 2002, FAO, 2012b) and from regional studies of farming yields that show a modest positive trend (Tarimo and Takamura, 1998). Thirdly, I assume that agricultural land is created adjacent to past areas of agricultural land. I progressively removed agricultural land at random from the margins of land cover marked as agriculture on the 1949 land cover map, until the relevant agricultural area for 1923 and 1908 was obtained. Although I may not have exactly replicated the true size and distribution of past agricultural land, failing to add it to older maps would have resulted in an over-estimation of LCC. In my attempt to model past agricultural area, I ensured that my LCC estimates are conservative. For older maps, areas that lacked land cover data were filled with the land use type from the subsequent map (required for 3.7% [1.25 million ha] of the 1908 map; 4.2% [1.42 million ha] of the 1923 map; and 0.2% [0.07 million ha] of the 1949 map).

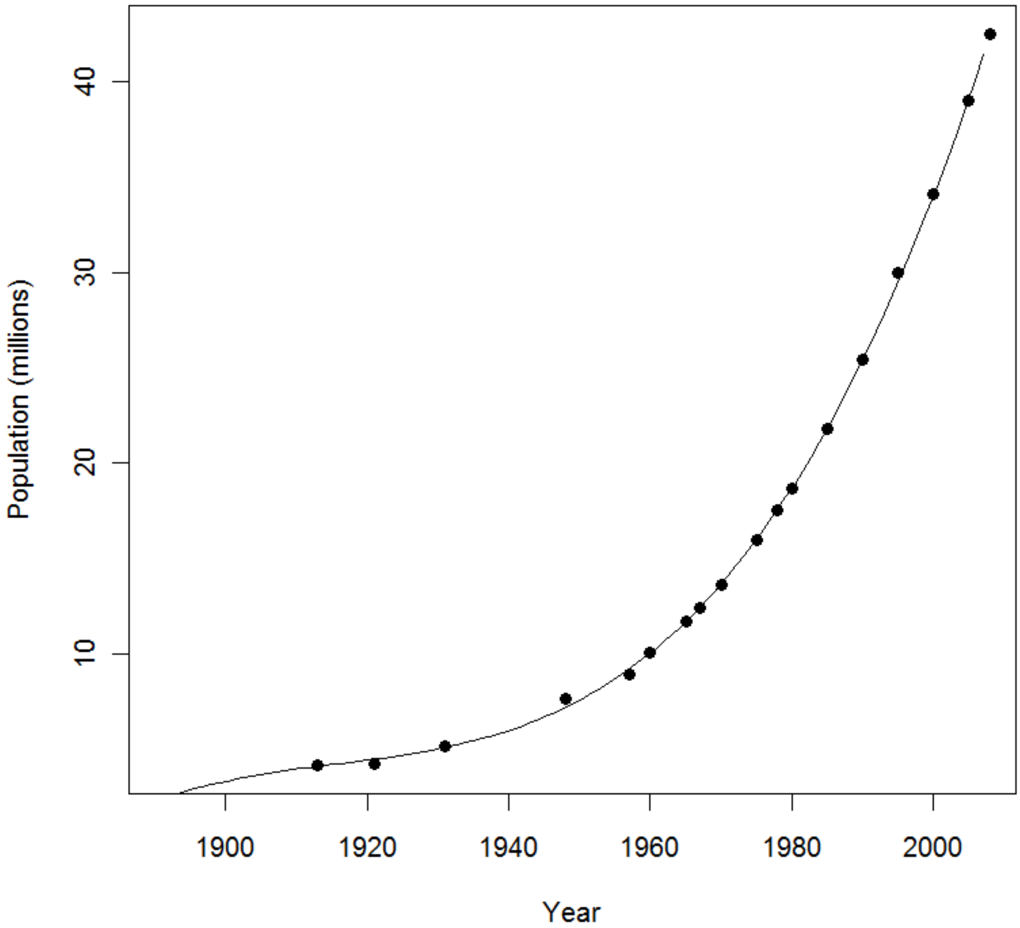


Figure 3.8 The modelled population of Tanzania between 1900 and 2000 (modelled population = -305287.934660931 + (477.954124067276 * Year) + (-0.249447122059476 * YEAR^2) + (0.0000434002810672193 * YEAR^3) [p<0.001]). Data (show as solid points) was obtained from Table 3.2. The modelled population of Tanzania was utilised to create the estimated agricultural area for 1908 and 1923 via the mean of the known ratios (1949 and 2000; a mean of 0.308).

3.5.4.3 Harmonising Land Cover Categories

Each watershed map had different land use categories, termed ‘original land use categories’ (11 categories in the 1908 map; 10 categories in the 1923 map; 16 categories in the 1949; and 30 categories in the 2000 map - giving a total of 67 categories). For consistency across maps, I allocated each of these original land use categories to one of four ‘harmonised land cover categories': forest (high carbon density tree-dominated systems, including montane forest, coastal lowland forest, mangroves and tree plantations), savanna spectrum (medium carbon density mixed tree and grass systems, including miombo woodland, Acacia savanna, bushland/thicket and grassland), crop (anthropogenic arable systems) and 'other' (largely dominated by low carbon systems, such as semi-desert and snow) (Figure 3.9, Table 3.1).

All historical land cover maps used in this chapter adopted a biome-type approach (Engler, 1908-10, Shantz and Marbut, 1923, Gillman, 1949, Swetnam et al., 2011). The harmonised classification categories I have selected follow a biome-type classification system, differentiating between the forest and woodland ecosystems due to differences in structure, function and physiognomy (Whittaker, 1975, Haxeltine and Prentice, 1996, Woodward et al., 2004, Lomolino, 2010). Whilst forests and woodlands in Tanzania often occupy a similar climate niche, they show marked differences in structure and species composition (Lovett, 1990, Platts et al., 2008), with woodland sharing more similarities with savanna-type systems and so being grouped within the 'savanna spectrum'. Thus our approach is consistent with previous land cover maps of the region, forming the narrowest possible groupings that are continuous over all maps.

Whilst anthropogenic agricultural systems form a relatively narrow harmonised category (crop), I recognised that the other harmonised categories (forest, savanna-spectrum, and other) are somewhat broader. It was not possible to further subdivide these categories into more specific groups. For example, forest may be divided into montane forest, coastal forest, mangrove forest and plantation forest. However, it was not possible to distinguish these categories across all maps. Specifically, the 1949 map indicated none of these forest sub-groups, whilst both the 1923 and 1908 maps did not differentiate between natural forest and plantation forest. The savanna-spectrum category was amalgamated because, although maps shared similar categories (i.e. woodland, bushland, savanna, and grassland), no two categories shared the same definition. The tree height threshold differentiating between woodland and bushland varied between all maps. Similarly, there was no agreement in the canopy cover thresholds separating woodland and bushland from savanna nor savanna from grassland. Thus, the narrowest category common to all maps was the savanna-spectrum category (Figure 3.9, Table 3.1). Although the 'other' grouping is exceedingly broad, it consists of land covers with a very

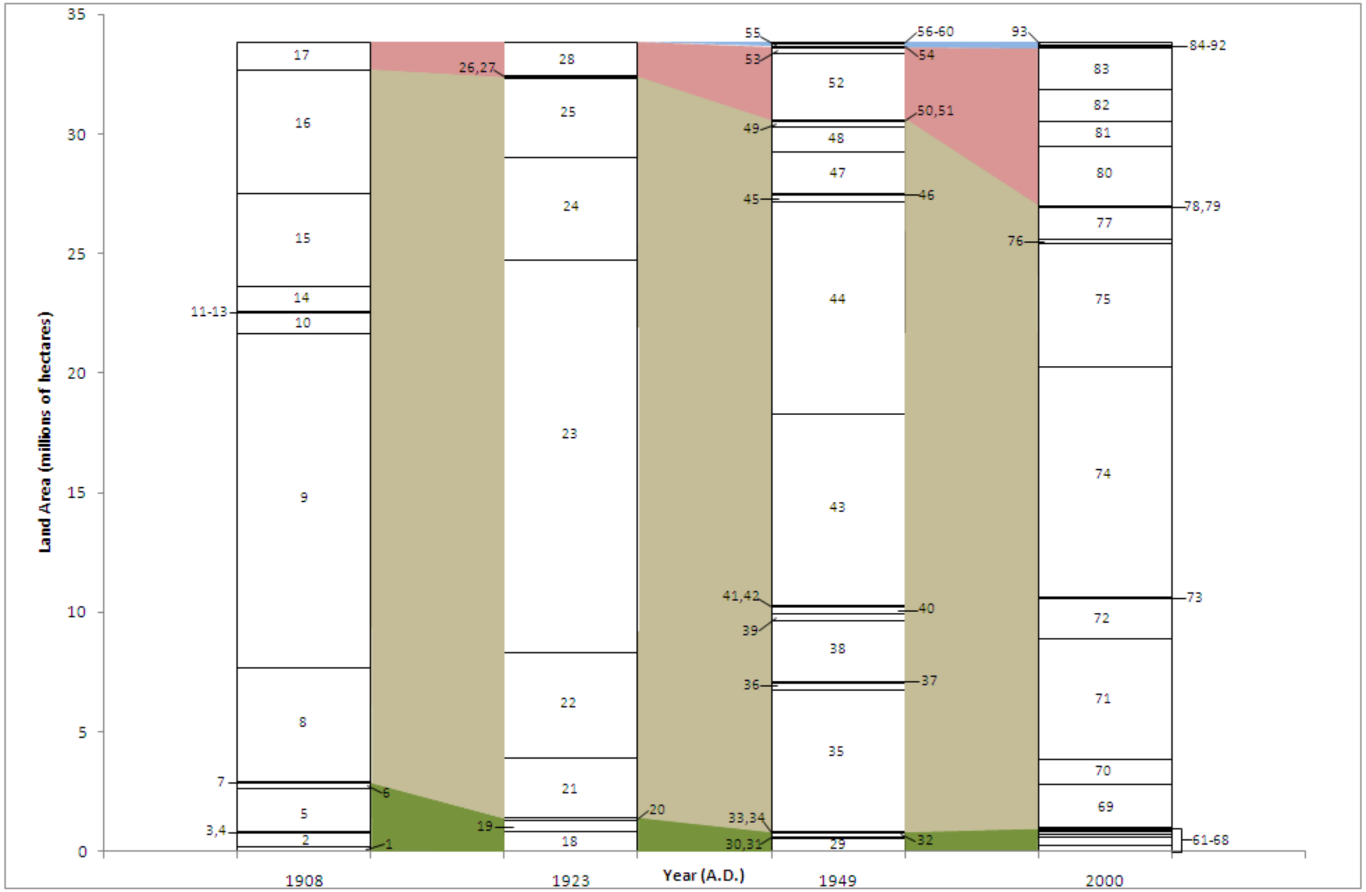


Figure 3.9 Four harmonised land use categories (forest, green; savanna spectrum, brown; crop, red; other, blue) show land cover change for the Eastern Arc Mountain watershed between 1908 and 2000. Also indicated are the original land use categories (white) and how they were harmonised (for key to numbers, see App. 2.1).

restricted range, occupying <0.6% of the study area, and thus is not of interest in this investigation.

3.5.4.4 Error Correction

Error-corrected maps were created by considering each hectare over time and assessing if the LCC documented is physically possible, and likely, and modifying the land cover as necessary. I proceeded as follows: Assuming a pixel is unlikely to have grown from a non-forest harmonised land cover category into my harmonised forest land cover category between 1908 and 1923, then forest identified as present in 1923 and 1949 is very likely to have been present in 1908. As such, if forest was present in both the original 1923 and 1949 maps then it was assigned as forest in the error-corrected 1908 map. If this was not the case, the land use category from the original 1908 map was retained. For later years, it was assumed that LCC is usually unidirectional and a given land cover category is unlikely to change to another category only to revert back. For example, a given hectare being forest (1908) then agriculture (1923) then forest (1949) is likely to be an error in 1923, as would the inverse sequence (agriculture-forest-agriculture). Error-corrected maps for 1923 and 1949 were created by assigning the category present in the previous and following maps in the chronosequence if both the land uses indicated in these were identical. If this was not the case, the land use category from the original 1923 map and 1949 map, respectively, was used. In total, 7.2% of the 1908, 0.2% of the 1923 and 2.8% of the 1949 maps were error-corrected in this manner. It must be noted that, these rules do not allow for agricultural abandonment and reestablishment of forest or savanna over short time spans. Hence, it is unlikely that all the changes made during this process were necessary and, in fact, some true change may have been masked. However, utilisation of the error-corrected maps in combination with the original (uncorrected) maps provides a range of estimates of past LCC, encompassing the likely true extent.

3.5.4.5 Spatial Accuracy

For each map, the locations of towns and permanent geographical features were identified and compared to independently derived locations of the same features (Figure 3.2) (Earth Tools, 2010), which were assumed to be spatially accurate. Spatial errors for each point were interpolated using inverse distance weighting, providing an indication of spatial error for the entire watershed. In total, 30 locations were used for validation; 27 for the

1908 map, 23 for the 1923 map, 20 for the 1949 map and 28 for the 2000 map. The largest spatial displacement recorded was 25km, with the southern section of the 1923 map being the most spatially erroneous and the others having a much higher degree of precision (Figure 3.4).

3.5.4.6 Analysing Correlates of Land Use/Land Cover Change

In order to investigate forest transition in the EAM and their watershed, I observe the LCC between 1891 and 2007 using the harmonised land cover categories for both the original and error-corrected maps, creating linearly, quadratic and locally-weighted polynomial Lowess (smoother span of 2/3) regressions using R 2.11.1. I descriptively analyse the change in forest cover that occurs during this period, evaluating the effect of four pathways to forest transition by critically comparing modernisation trends linked to forest cover change under each of the pathways. Firstly, I evaluate the economic development pathway by investigating whether any change in forest area is correlated with an increase in urban populations and a simultaneous decrease in rural populations. Declining availability of farm labourers is a key component of forest transitions occurring via this pathway. Secondly, using total roundwood production as a proxy to indicate scarcity of forest-related products, I assess the likelihood of the forest scarcity pathway in driving the observed change in forest area. Thirdly, I investigate the correlation between forest-related state policy (e.g. protected areas) and forest cover, so determining if forest transition occurred via the state forest policy pathway. Fourthly, I evaluate the globalisation pathway, using total agricultural export and import quantity indices as a proxy for global interconnectedness and trade. Finally, I investigate long term climatic trends, using month mean temperature and precipitation data, to evaluate the impact of my proposed forest-favourable climate pathway. All of the proxies I use to descriptively analyse the forest transition are mostly derived from the FAO (2012), with protected areas being obtained from IUCN and UNEP-WCMC (2010) and climate data from Mitchell and Jones (2005).

To investigate the different correlates of the two deforestation and forest recovery curves that underlie forest transitions, the relationships between deforestation or forest establishment and possible spatial, environmental, and anthropogenic factors were identified at each step in the chronosequence between 1908 and 200. I included many candidate socioeconomic and environmental variables that, individually, have been shown to be correlated with LCC (Veldkamp et al., 1992, Lung and Schaab, 2010, Southworth and Tucker, 2001). These included slope (derived from

Table 3.2 The population increase of Tanzania from 1913 to 2008

Year	Population of Tanzania (million)	Reference
1913	4.20*	(Boesen et al., 1986)
1921	4.24*	(Boesen et al., 1986)
1931	5.19*	(Boesen et al., 1986)
1948	7.66*	(Boesen et al., 1986)
1957	8.95*	(Boesen et al., 1986)
1960	10.07	(World Bank, 2010)
1965	11.68	(World Bank, 2010)
1967	12.40	(World Bank, 2010, Boesen et al., 1986)
1970	13.60	(World Bank, 2010)
1975	15.97	(World Bank, 2010)
1978	17.54	(World Bank, 2010, Boesen et al., 1986)
1980	18.66	(World Bank, 2010)
1985	21.81	(World Bank, 2010)
1990	25.45	(World Bank, 2010)
1995	29.97	(World Bank, 2010)
2000	34.13	(World Bank, 2010)
2005	39.01	(World Bank, 2010)
2008	42.48	(World Bank, 2010)

*The data were for populations of the mainland only. A conversion factor of 1.03323 was applied to these data to estimate the total population. This conversion factor was created using the mean of the ratio between the mainland and total values in years of overlap between the two datasets.

Table 3.3 The trend in land cover in the EAM watershed from 1908 to 2000.

Harmonised Land Cover Category	Area in 1908 (million ha)	Area in 1923 (million ha)	Area in 1949 (million ha)	Area in 2000 (million ha)
Forest	3.75	1.38	0.82	0.96
Savanna spectrum	28.92	31.06	29.77	26.02
Crop	1.18	1.41	3.08	6.69
Other	n/a	n/a	0.08	0.30

the USGS Shuttle Topography Radar Mission (Farr et al., 2007)), current protection (derived from the latest version of the World Database of Protected Areas (IUCN and UNEP-WCMC, 2010)), distance to major settlements (namely Arusha, Bagamoyo, Dar es Salaam, Dodoma, Iringa, Kalema, Kilosa, Morogoro, Moshi, Muhanga, Nondoto, Pangani and Tanga, digitised from 1:50,000 topographic maps), soil fertility (from the Southern Africa SOTER database (Batjes, 2004, ISRIC, 2010)), local population density (derived from the LANDSCAN dataset (LGPD, 2008)) and climate regimes (extracted from CRU 3.0 (Mitchell and Jones, 2005) and used to calculate the mean annual temperature and the mean maximum cumulative water deficit (Phillips et al., 2009)). Using R 2.11.1, generalised linear models were found for the relationships of each time step, taking into account the binomial distribution. The best fit models were chosen using forward-backwards and backward-forward stepwise selection, resulting in a final model with the lowest possible Akaike information criterion. All second-order interactions were included in the stepwise selection process. Spatial autocorrelation was accounted for by including a trend surface in the model (Chapman, 2010). The trend surfaces used were latitude, longitude and the interactions between them.

3.6 Results

3.6.1 Temporal and Spatio-Temporal Trends in Land Use/Land Cover

Considering the harmonised land cover categories across the 33.9 million ha watershed, forest area declined 74% from 3.75 to 0.96 million ha between 1908 and 2000, across the 33.9 million ha study area (Figure 3.10, Table 3.3). Using my definition of forest (Table 1.1), forest transition is apparent across the watershed, with a net loss of forest cover (2.9 million ha) over the first half of the twentieth century being followed by an increase of forest cover (0.1 million ha) by the year 2000. The savanna-spectrum category showed a decline from 28.9 to 26.0 million ha over the same period but showed an inclined transition, with the majority of area loss taking place over the second half of the twentieth century following savannah establishment in the between 1908 and 1923. In total, forest and savanna decreased by 4.7 million ha and, when considered together, forest transition is not apparent. Meanwhile, the cropland area increased from 1.2 million ha in 1908 to 6.7 million ha in 2000.

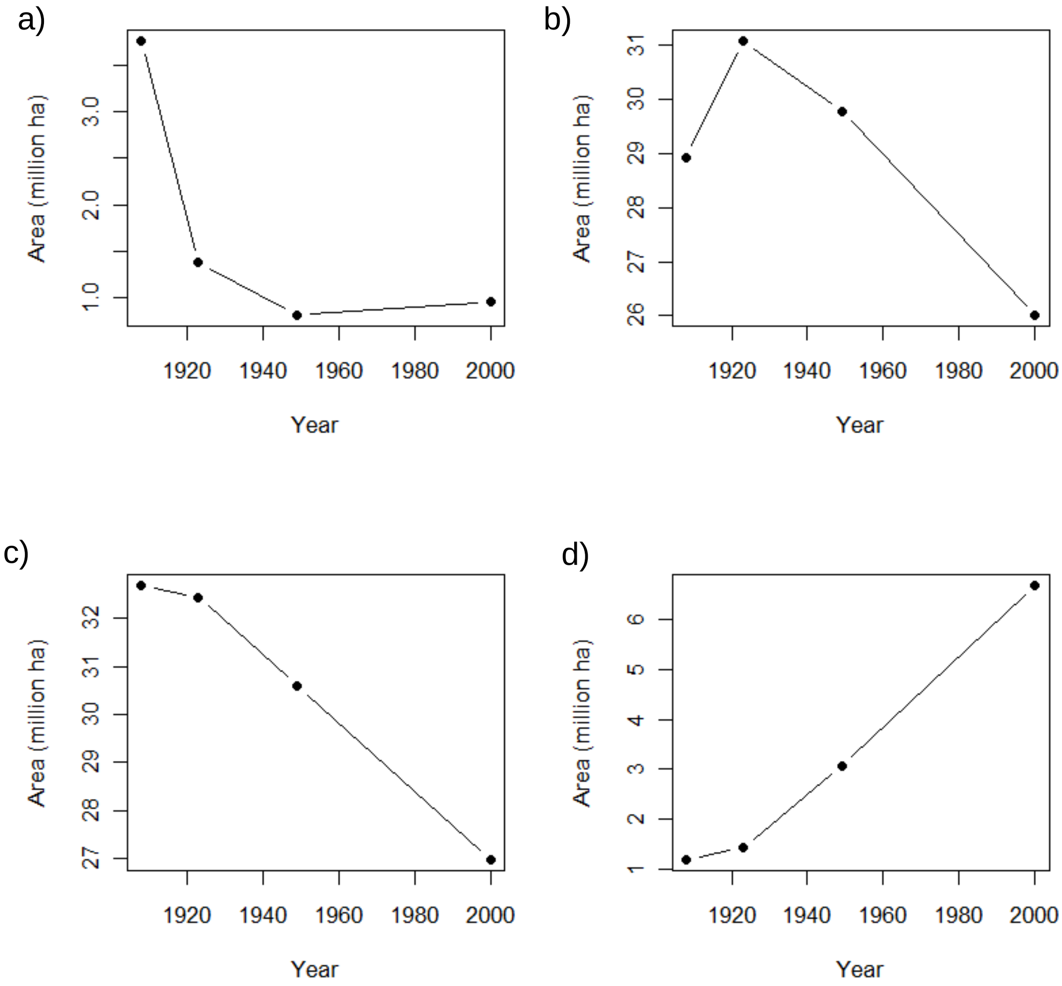


Figure 3.10 The trend in LCC between 1908 and 2000 for the EAM watershed using harmonised land cover categories: land covers are separated into a) forest; b) savannah; c) forest and savannah combined; and d) crop.

From 1891 to 2007, the northern EAM lost forest at a linear rate of 935 ha yr^{-1} (p-value < 0.01) (Figure 3.11). This compares to the rate over the entire EAM of 1,306 ha yr^{-1} (p-value < 0.05; 1923 is anomalous in this analysis due to large spatial error for the southern EAM and so excluded [Cook's distance > 0.90]). However, the smoothed data indicates that the trend in forest cover is non-linear. Similar to the watershed, both the northern EAM and the EAM as a whole show high rates of deforestation in the first half of the twentieth century. Using a second order polynomial regression and a locally-weighted polynomial Lowess regression (smoother span of 2/3) indicate that forest transition occurred between 1960 and 1990. The second order polynomial regression is significant in the northern EAM (p-value < 0.05) and almost significant for the EAM as a whole (p-value < 0.16). The non-linearity of the

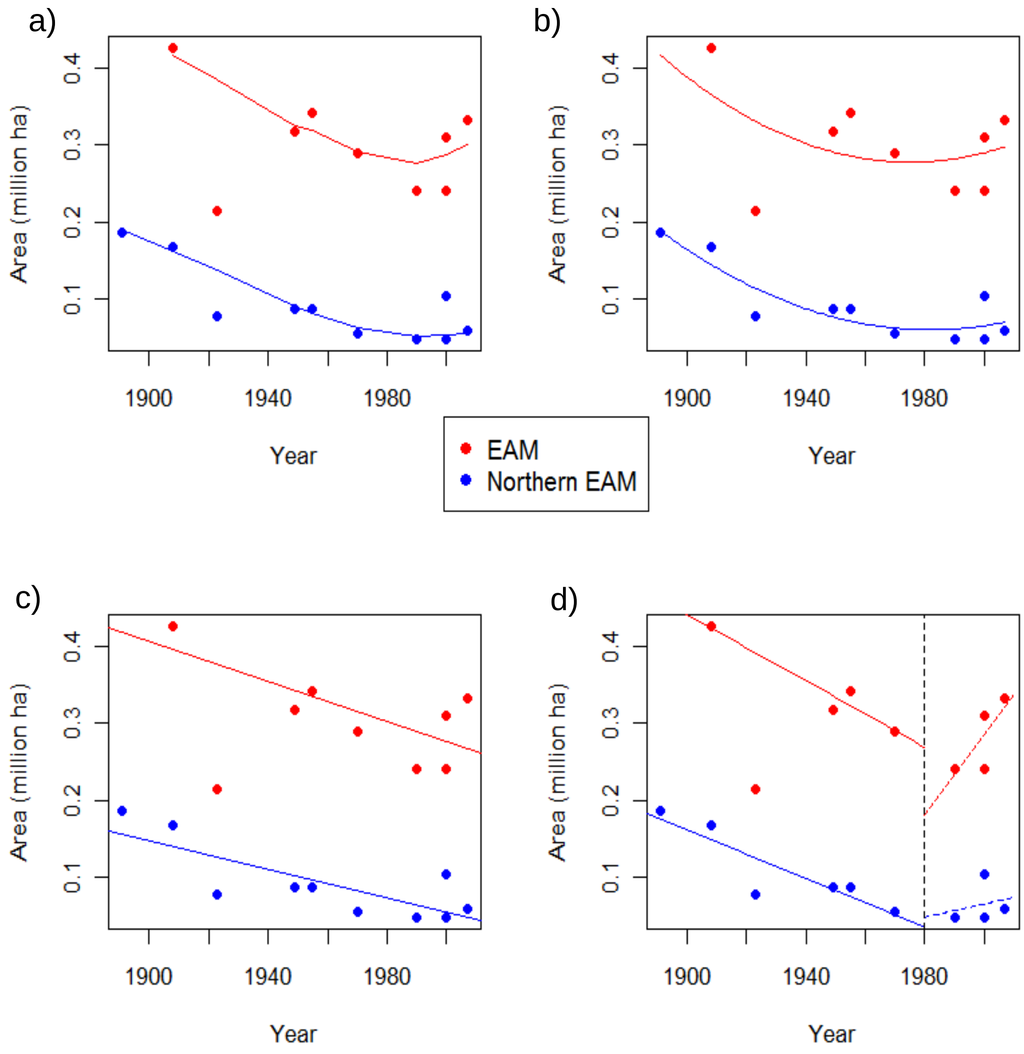


Figure 3.11 The trend in forest cover between 1891 and 2007 for the EAM using harmonised land cover categories. Data from the entire EAM is shown in red, whilst the separate trend for the combined Usambara and Pare mountains is shown in blue. a) Illustrates the trend using a locally-weighted polynomial Lowess regression (smoother span of 2/3). b) Illustrates the trend using a quadratic regression (EAM: forest area = 9.216809e+01 + -9.242581e-02 * Year) + (2.324246e-05 * Year^2) [p-value < 0.16]; northern EAM: forest area = 6.123227e+01 + (-6.173154e-02 * Year) + (1.557393e-05 * Year^2) [p-value < 0.05]). c) Illustrates the trend using a linear regression (EAM: forest area = 2.888614329 + (-0.001306170 * Year) [p-value < 0.05]; northern EAM: forest area = 1.924533838 + (-0.000935435 * Year) [p-value < 0.01]). d) Illustrates the trend using a segmented linear regression with a break point at 1980 (illustrated with a black dashed line (EAM prior to 1980 [solid line]: forest area = 4.523023098 + (-0.002148226 * Year) [p-value < 0.24]; EAM post 1980 [dashed line]: forest area = -10.138161735 + (0.005211568 * Year) [p-value < 0.05]; northern EAM prior to 1980 [solid line]: forest area = 3.154636357 + (-0.001575383 * Year) [p-value < 0.78]; northern EAM post 1980 [dashed line]: forest area = -1.6630645792 + (0.0008640664 * Year) [p-value < 0.05]).

trend is support by a segmented linear regression, my data clearly indicates an increase in forest area after 1980 of 1,575 ha yr-1 for the EAM (p-value < 0.05) and 864 ha yr-1 for the northern EAM (p-value < 0.05), in stark contrast to the decline in forest area evident before this time point.

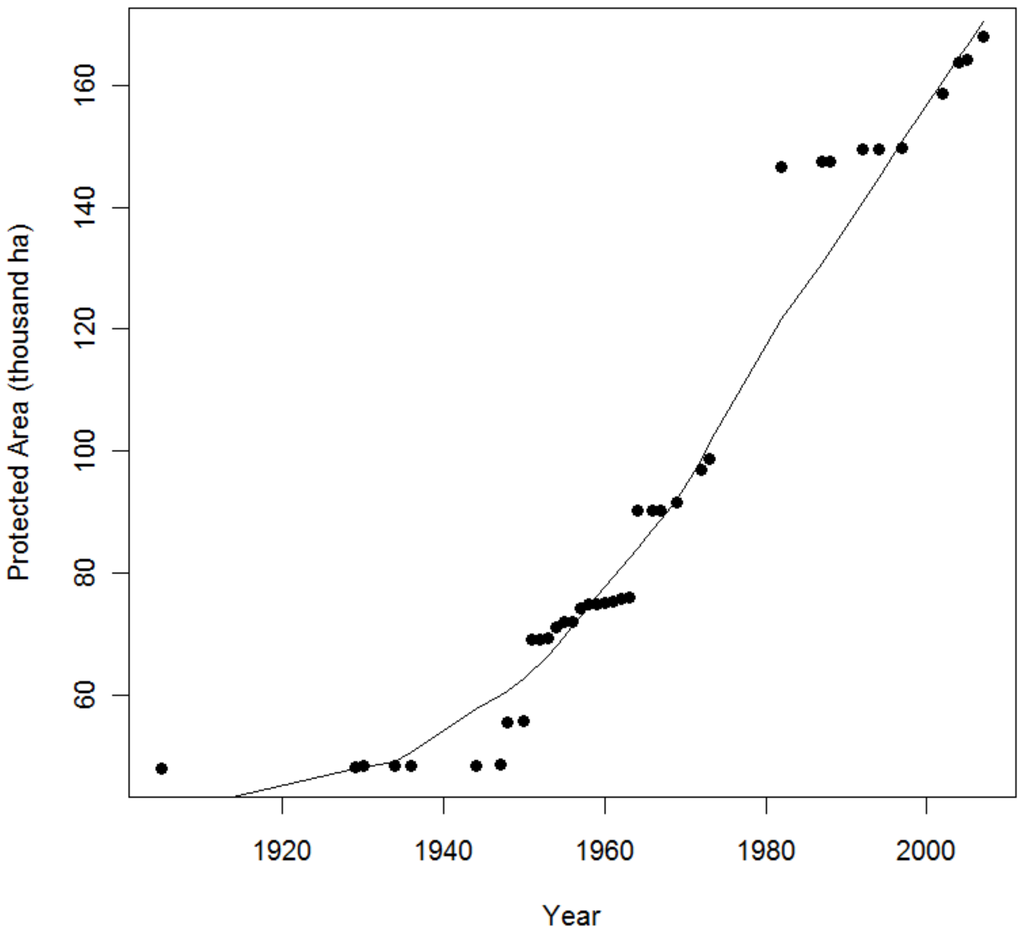


Figure 3.12 The increase in the area of the Tanzanian protected area network between 1900 and 2010 (IUCN and UNEP-WCMC, 2010). The trend is illustrated using a locally-weighted polynomial Lowess regression (smoother span of 2/3).

3.6.2 Explaining the Forest Transition Curve

Rapid population growth is evident over the entire twentieth century (Figure 3.8, Table 3.2) and it is likely that this was a major driver of deforestation. However, my results show that forest transition occurred in the EAM region

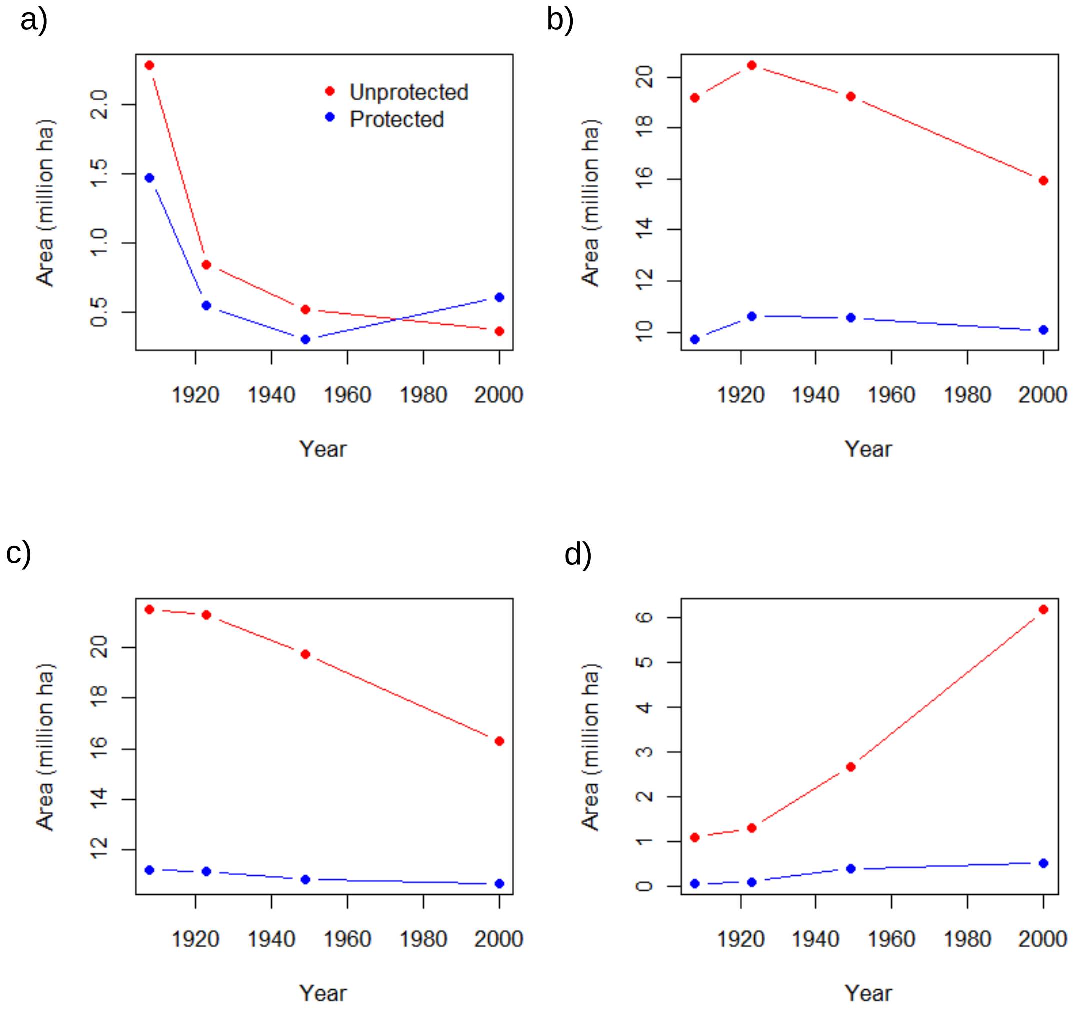


Figure 3.13 The trend in LCC between 1908 and 2000 for the EAM watershed using harmonised land cover categories: land covers are separated into a) forest; b) savannah; c) forest and savannah combined; and d) crop. Land covers currently within legally protected areas are indicated by blue lines and unprotected areas in red.

between approximately 1960 and 1990 (Figure 3.10, Figure 3.11), as forest establishment rates exceeded those of deforestation. The following FAOSTAT data covers this period and can be used to suggest the pathway to transition. Between 1961 and 1990, both urban and rural populations increase, with rural population rising over two-fold, from 9.8 million to 20.7 million (Figure 3.1). This increase is matched by an 8 million ha increase in agricultural area, from 26 million ha to 34 million ha (Figure 3.1). Over the same time period, total roundwood production shows a similar increase, from 12.8 million m^3 in 1961 and 20.5 million m^3 in 1990 (Figure 3.1). The extent of protected areas also increased substantially during this period, almost doubling from 75.1 million ha in 1960 to 149.5 million ha in 1992

(Figure 3.12). In addition, it is apparent that whilst forest in protect areas have undergone a transition from net deforestation to net forest establishment, those forests not legally protected have yet to do so (Figure 3.13). The impact of protection on transition is emphasised by savanna, with unprotected savanna showing high deforestation rates and those within protected areas showing lower reduction and likely being closer to transition (Figure 3.13). The forest area increased by 0.3 million ha between 1949 and 2000, compared with a decrease of 0.16 million ha in unprotected regions. Savanna decreased by 0.47 million ha inside current protected areas and by 3.29 million ha in unprotected regions over the same period. Between 1961

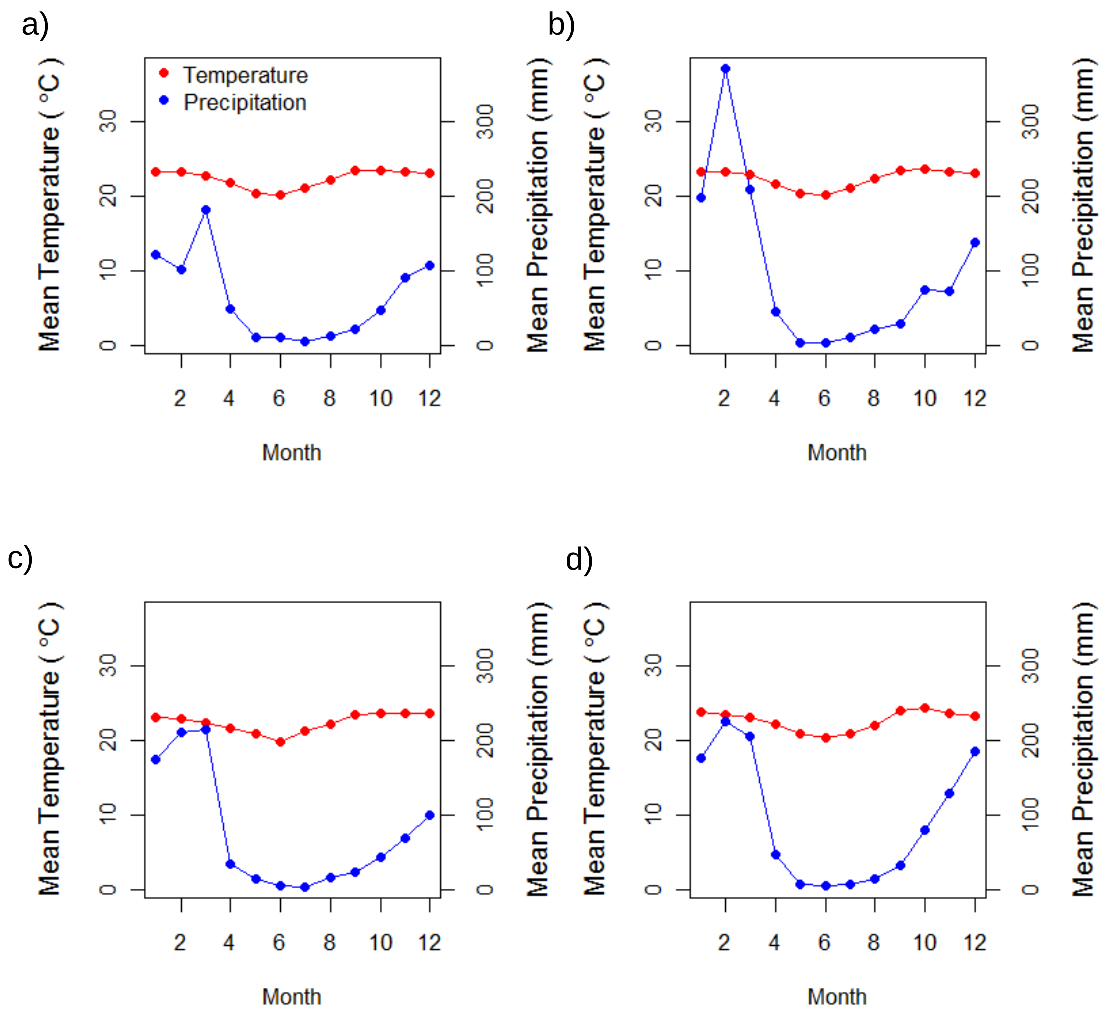


Figure 3.14 Long term climatic trends in Tanzania between 1900 and 2009. The mean temperature (red) and mean precipitation (blue) is shown for a) 1900-1930; b) 1930-1960; c)1960-1990; and d) 1990-2009. Months are number sequentially from January through to December. All data are derived from CRU 3.0 (Mitchell and Jones, 2005).

and 1990 there was little net change in the connectedness with global markets and traders. Total agricultural import and export quantity showed a slight decrease from 14% to 11% and 74% to 55% of the values shown in 2004-2006 respectively (Figure 3.1). However, smoothed Lowess regressions (smoother span of 2/3) show that the trend was for increasing imports and decreasing exports, with little net change (Figure 3.1). Finally, there has been little long-term fluctuation in the Tanzanian climate over the twentieth century, although precipitation during the wet-season was lower between 1900 and 1930 but higher between 1930 and 1960 (Figure 3.14). Thus, only the change in protect areas seems to correlate with the change in forest cover observed in this study.

3.6.3 Correlates of Deforestation and Forest Establishment

Soil fertility and distance to major settlements were also positively correlated with deforestation over the 20th century (Table 3.4). Additionally, slope and mean annual temperature were positively correlated over the first half of the century but negatively correlated over the second half; mean maximum cumulative water deficit was negatively correlated between 1908-1923 and 1949-2000 but positively correlated between 1923 and 1949; and local population density was positively correlated from 1923 to 1949. The results show that deforestation occurred first in areas with wet, warm environments with fertile soils before occurring within infertile, unprotected, dry, lowland forests (high temperature) in densely populated areas by the mid-20th century. In the second half of the century, deforestation moved upslope to cooler, flatter and wetter areas. P-values have not been given for the main effects as they are known to be significant due to the significance of the interacting terms (Table 3.4). If any time period between 1908 and 2000 is not listed here then the direction of the correlation was not consistent across original and error-corrected maps and thus is not robust.

Over the 20th century, soil fertility and local population density were negatively correlated with forest establishment (Table 3.5). Additionally, mean maximum cumulative water deficit and mean annual temperature were positively correlated from 1923-1949 but negatively correlated over the second half of the century; and slope was positively correlated from 1923-2000. The distance to major settlements was also found to be an influential variable explaining forest establishment but the direction of the correlation was not consistent across original and error-corrected maps. The strongest two-way interactions amongst variables were between slope and mean annual temperature (positively correlated from 1923-2000, p-value <0.001)

(Table 3.5). The results show that forest establishment occurred first in unfertile, protected areas with low population density before occurring in warmer, drier, more sloped environments by the mid-20th century. In the second half of the century, forest establishment moved to cooler, drier areas.

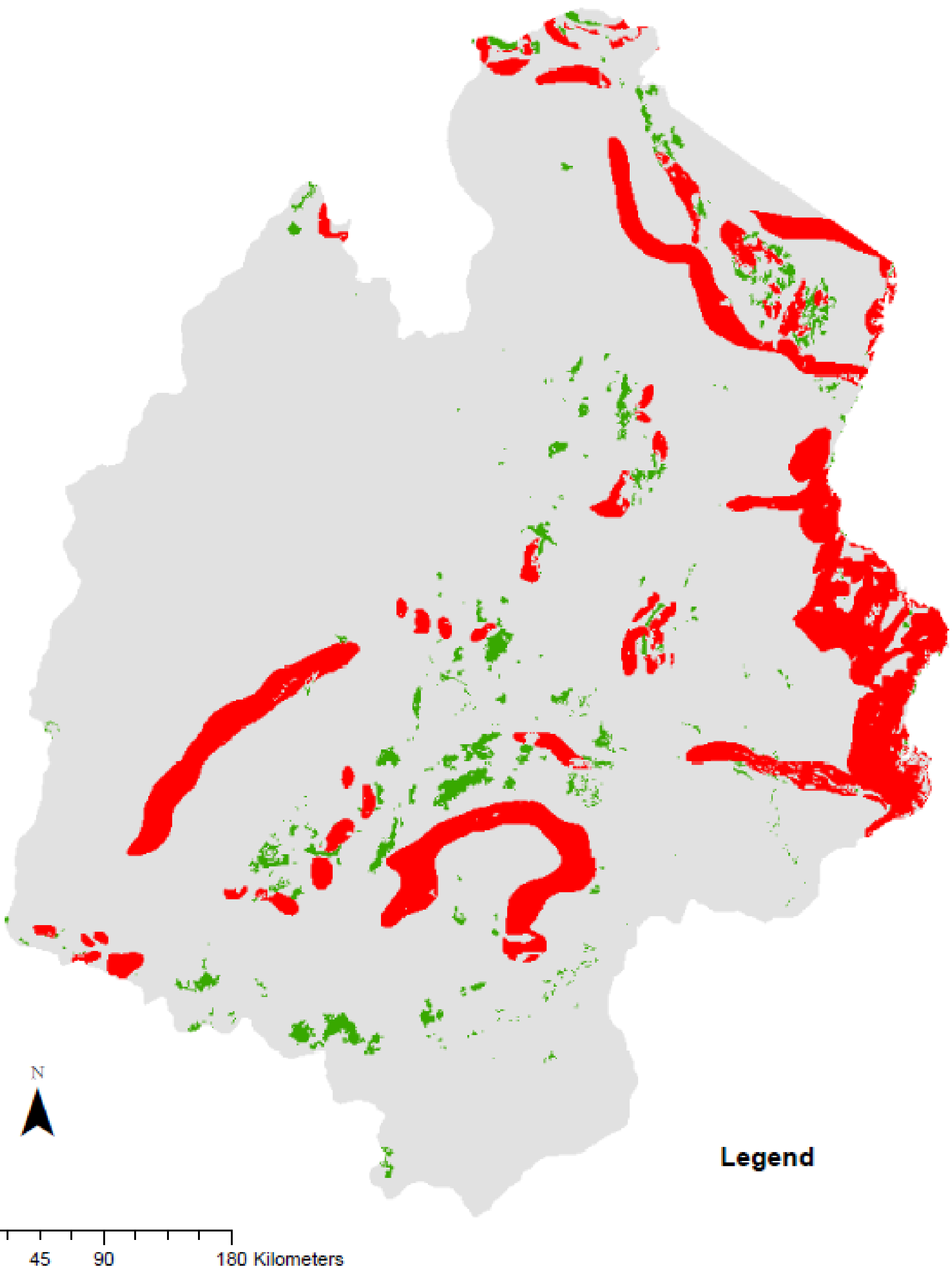


Figure 3.15 The overall change in forest cover observed in the watershed from 1908 to 2000.

Table 3.4 The best fit models describing how the candidate variables effect deforestation at a 1km resolution. Variables not included in the final model are indicated by N/A (see Section 3.5.4.6 for a description of the variables).

Variable	Original land-use categories						Harmonised land-use categories					
	1908-1923		1923-1949		1949-2000		1908-1923		1923-1949		1949-2000	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
(Intercept)	-6.13E-01	0.429	-1.51E+01	0.001	7.24E+00	0.001	-3.28E-01	0.695	-1.36E+01	0.001	1.75E+01	0.001
Spatial component	-2.26E-21	0.001	3.59E-21	0.001	-4.75E-21	0.001	-2.63E-21	0.001	2.31E-21	0.030	-1.23E-20	0.001
Soil fertility	1.38E-01	0.001	2.73E-01	0.001	3.60E-02	0.110	1.61E-01	0.001	1.78E-01	0.001	1.66E-01	0.001
Local population density	-4.27E-03	0.001	1.93E-02	0.001	-4.71E-04	0.181	9.87E-04	0.596	1.01E-02	0.003	6.53E-03	0.057
Slope	8.85E-02	0.004	4.72E-01	0.001	-1.71E-01	0.001	6.13E-02	0.069	2.05E-01	0.001	-4.34E-02	0.340
Mean maximum cumulative water deficit	-7.67E-03	0.001	6.63E-03	0.016	-1.42E-02	0.001	-1.18E-02	0.001	4.14E-05	0.976	-3.51E-02	0.001
Mean annual temperature	1.31E-01	0.001	4.89E-01	0.001	-5.10E-02	0.464	1.41E-01	0.001	5.43E-01	0.001	-5.84E-02	0.506
Protected area	-1.62E+00	0.002	-1.06E+01	0.001	-8.70E+00	0.001	1.67E+00	0.001	-7.14E+00	0.001	-6.32E+00	0.001
Distance to a major town	3.85E-02	0.001	4.64E-02	0.001	6.98E-02	0.001	4.65E-02	0.001	1.30E-01	0.001	4.51E-02	0.004
Soil fertility*Local population density	3.40E-05	0.001	-1.40E-04	0.001	-5.94E-05	0.003	2.80E-05	0.015	-7.55E-05	0.004	-7.90E-05	0.001
Soil fertility*Slope	N/A	N/A	N/A	N/A	N/A	N/A	3.79E-04	0.084	9.49E-04	0.008	1.62E-03	0.001
Soil fertility*Mean maximum cumulative water deficit	2.85E-05	0.002	2.99E-04	0.001	1.77E-04	0.001	N/A	N/A	3.43E-04	0.001	9.28E-05	0.002
Soil fertility*Mean annual temperature	-6.34E-03	0.001	-1.35E-02	0.001	-4.20E-03	0.001	-7.34E-03	0.001	-1.11E-02	0.001	-8.48E-03	0.001
Soil fertility*Protected area	-3.13E-02	0.001	N/A	N/A	N/A	N/A	-2.91E-02	0.001	-1.53E-02	0.011	-3.46E-02	0.001
Soil fertility*Distance to a major town	-8.31E-05	0.001	-5.37E-04	0.001	N/A	N/A	N/A	N/A	-3.98E-04	0.001	N/A	N/A
Local population density*Slope	-2.10E-04	0.001	-2.05E-04	0.001	N/A	N/A	-1.28E-04	0.001	N/A	N/A	N/A	N/A
Local population density*Mean maximum cumulative water deficit	1.21E-05	0.001	-2.21E-05	0.001	N/A	N/A	2.00E-05	0.001	-1.05E-05	0.016	N/A	N/A
Local population density*Mean annual temperature	N/A	N/A	-4.06E-04	0.004	N/A	N/A	-3.05E-04	0.001	-2.31E-04	0.043	-2.58E-04	0.046
Local population density*Protected area	-1.28E-03	0.002	-6.99E-04	0.128	-1.74E-03	0.038	-4.79E-04	0.155	2.01E-03	0.057	N/A	N/A

Local population density*Distance to a major town	-8.77E-06	0.005	-7.39E-05	0.001	7.30E-05	0.001	-6.94E-06	0.069	-8.34E-05	0.001	2.50E-05	0.003
Slope*Mean maximum cumulative water deficit	N/A	N/A	-3.62E-04	0.001	N/A	N/A	N/A	N/A	-3.62E-04	0.001	N/A	N/A
Slope*Mean annual temperature	-7.14E-03	0.001	-1.63E-02	0.001	5.49E-03	0.002	-6.71E-03	0.001	-7.33E-03	0.001	-2.88E-03	0.111
Slope*Protected area	-3.58E-02	0.001	-4.93E-02	0.001	N/A	N/A	-1.02E-02	0.053	3.96E-02	0.001	-1.45E-02	0.092
Slope*Distance to a major town	7.05E-04	0.001	N/A	N/A	N/A	N/A	8.56E-04	0.001	N/A	N/A	5.13E-04	0.001
Mean maximum cumulative water deficit *Mean annual temperature	4.80E-04	0.001	-3.36E-04	0.004	6.24E-04	0.001	7.09E-04	0.001	N/A	N/A	1.29E-03	0.001
Mean maximum cumulative water deficit *Protected area	5.85E-03	0.001	1.06E-02	0.001	N/A	N/A	4.32E-03	0.001	7.11E-03	0.001	2.74E-03	0.001
Mean maximum cumulative water deficit *Distance to a major town	-2.76E-05	0.001	N/A	N/A	-2.36E-05	0.034	-3.00E-05	0.001	3.76E-05	0.001	2.91E-05	0.021
Mean annual temperature*Protected area	-4.40E-02	0.008	2.87E-01	0.001	2.22E-01	0.001	-1.66E-01	0.001	1.31E-01	0.001	1.02E-01	0.002
Mean annual temperature*Distance to a major town	-1.44E-03	0.001	-7.98E-04	0.023	-2.84E-03	0.001	-1.94E-03	0.001	-5.02E-03	0.001	-2.59E-03	0.001
Protected area*Distance to a major town	5.82E-03	0.001	-1.27E-02	0.001	1.05E-02	0.001	8.79E-03	0.001	N/A	N/A	6.88E-03	0.001

Table 3.5 The best fit models describing how the candidate variables effect forest establishment at a 1km resolution. Variables not included in the final model are indicated by N/A (see Section 3.5.4.6 for a description of the variables).

Variable	Original land-use categories						Harmonised land-use categories					
	1908-1923		1923-1949		1949-2000		1908-1923		1923-1949		1949-2000	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
(Intercept)	-6.21E-01	0.726	-3.03E+00	0.001	6.89E+00	0.001	7.78E+00	0.001	4.17E+00	0.001	4.09E+00	0.001
Spatial component	1.19E-20	0.001	N/A	N/A	-6.81E-22	0.035	-6.71E-21	0.001	-5.82E-21	0.001	-5.31E-22	0.085
Soil fertility	-1.61E-01	0.001	-2.18E-01	0.001	-1.32E-01	0.001	-1.76E-01	0.001	-8.54E-02	0.001	-1.50E-01	0.001
Local population density	8.81E-05	0.232	-1.03E-02	0.001	-1.41E-02	0.001	-2.48E-03	0.001	-1.29E-02	0.001	-9.93E-03	0.001
Slope	8.94E-02	0.001	-2.59E-01	0.001	-2.37E-01	0.001	1.88E-01	0.001	-1.95E-01	0.001	-2.00E-01	0.001
Mean maximum cumulative water deficit	-7.45E-03	0.001	2.73E-02	0.001	-1.25E-02	0.001	1.20E-02	0.001	5.80E-03	0.001	-4.51E-03	0.002
Mean annual temperature	-5.49E-01	0.001	1.79E-01	0.001	-3.15E-01	0.001	2.57E-02	0.462	1.22E-01	0.001	-1.92E-01	0.001
Protected area	5.31E+00	0.001	8.95E+00	0.001	1.11E+01	0.001	-1.24E+00	0.001	9.80E+00	0.001	1.18E+01	0.001
Distance to a major town	-1.18E-01	0.001	-1.86E-02	0.001	1.22E-02	0.003	-1.47E-01	0.001	1.42E-02	0.001	-2.99E-03	0.018
Soil fertility*Local population density	N/A	N/A	4.50E-05	0.001	-2.85E-05	0.046	N/A	N/A	3.37E-05	0.001	N/A	N/A
Soil fertility*Slope	4.16E-04	0.140	N/A	N/A	3.13E-04	0.012	4.16E-04	0.013	6.51E-04	0.001	N/A	N/A
Soil fertility*Mean maximum cumulative water deficit	N/A	N/A	6.21E-05	0.001	1.24E-04	0.001	-6.32E-05	0.001	N/A	N/A	7.61E-05	0.001
Soil fertility*Mean annual temperature	3.39E-03	0.044	7.66E-03	0.001	3.85E-03	0.001	5.98E-03	0.001	3.09E-03	0.001	5.40E-03	0.001
Soil fertility*Protected area	3.07E-02	0.001	1.59E-02	0.001	-1.18E-02	0.001	4.39E-02	0.001	7.61E-03	0.002	-1.18E-02	0.001
Soil fertility*Distance to a major town	7.86E-04	0.001	2.36E-04	0.001	-2.02E-04	0.001	7.03E-04	0.001	9.62E-05	0.001	-8.11E-05	0.001
Local population density*Slope	N/A	N/A	N/A	N/A	-7.29E-05	0.001	N/A	N/A	3.18E-05	0.016	-6.90E-05	0.001
Local population density*Mean maximum cumulative water deficit	N/A	N/A	N/A	N/A	8.78E-06	0.001	4.19E-06	0.001	N/A	N/A	6.40E-06	0.001
Local population density*Mean annual temperature	N/A	N/A	3.77E-04	0.001	4.01E-04	0.001	N/A	N/A	4.74E-04	0.001	2.77E-04	0.001
Local population density*Protected area	-3.95E-03	0.002	N/A	N/A	3.84E-03	0.001	2.74E-03	0.001	1.68E-03	0.001	3.63E-03	0.001

Local population density*Distance to a major town	N/A	N/A	2.39E-05	0.001	2.28E-05	0.001	2.05E-05	0.001	2.60E-05	0.001	1.63E-05	0.001
Slope*Mean maximum cumulative water deficit	-7.31E-05	0.053	1.78E-04	0.001	1.04E-04	0.001	-8.93E-05	0.001	2.00E-04	0.001	8.88E-05	0.001
Slope*Mean annual temperature	N/A	N/A	1.23E-02	0.001	1.21E-02	0.001	-6.31E-03	0.001	6.62E-03	0.001	1.13E-02	0.001
Slope*Protected area	-3.96E-02	0.007	N/A	N/A	-1.18E-02	0.001	2.37E-02	0.001	N/A	N/A	-7.81E-03	0.005
Slope*Distance to a major town	N/A	N/A	-1.44E-04	0.002	1.13E-04	0.001	1.66E-04	0.001	1.40E-04	0.001	7.67E-05	0.002
Mean maximum cumulative water deficit *Mean annual temperature	N/A	N/A	-1.75E-03	0.001	1.18E-04	0.074	-1.05E-03	0.001	-7.33E-04	0.001	-2.42E-04	0.001
Mean maximum cumulative water deficit *Protected area	-1.03E-02	0.001	-3.66E-03	0.001	-2.88E-03	0.001	N/A	N/A	-4.83E-03	0.001	-3.05E-03	0.001
Mean maximum cumulative water deficit *Distance to a major town	9.26E-05	0.001	N/A	N/A	1.22E-05	0.001	7.14E-05	0.001	N/A	N/A	1.75E-05	0.001
Mean annual temperature*Protected area	N/A	N/A	-2.64E-01	0.001	-2.77E-01	0.001	3.16E-02	0.035	-2.88E-01	0.001	-3.04E-01	0.001
Mean annual temperature*Distance to a major town	2.91E-03	0.001	4.06E-04	0.011	-5.21E-04	0.001	4.49E-03	0.001	-1.12E-03	0.001	N/A	N/A
Protected area*Distance to a major town	-9.02E-03	0.007	-1.08E-02	0.001	-1.52E-02	0.001	-4.49E-03	0.001	-9.88E-03	0.001	-1.55E-02	0.001

3.7 Discussion

3.7.1 Evaluation of Forest Transition

During the 20th century, I estimate that 4.7 million hectares of forest and savanna vegetation was converted to other land cover types, overwhelmingly to croplands. This LCC shows a clustered distribution (Figure 3.15). Broadly, areas that underwent the most deforestation are those (1) near the Indian Ocean, where the proximity of export markets makes timber exploitation favourable; (2) near to the most populous city within Tanzania, Dar es Salaam, from which waves of degradation have previously been identified (Ahrends et al., 2010), and (3) the mountainous regions, areas that harbour valuable timbers and climates favourable for European colonists' agriculture. My estimate of the 92-year decrease in forest area of 74%, occurring mostly between 1908 and 1923, is consistent with previous studies which estimate between 70% and 96% of the original forest cover to have been lost (Newmark, 2002, Hall et al., 2009).

My results indicate that eastern Tanzania underwent a forest transition from net deforestation to net forest establishment between 1960 and 1990. If this transition was echoed across the Tanzanian landscape, it would provide the first convincing evidence of a national forest transition in Africa. However, it is apparent that the trend of forest cover over time is dependent on the definition of forest. For example, my result is in stark contradiction to the trend in forest cover illustrated by FAO data. Using FAO data, the forest cover in Tanzania between 1990 and 2009 shows a linear decline, although, as previously discussed, this trend is derived from only two actual data points, one in 1984 and the other in 1995 (FAO, 2010c) (Figure 3.1). It is widely acknowledged that trends illustrated by the FAO data are highly uncertain due to data deficiencies (Grainger, 2008b, Grainger, 2010) and ambiguity in the definition of forest (Putz and Redford, 2010), whereby nations often use different land cover categories to those advocated by the FAO (FAO, 2010d, FAO, 2000a). Thus, while recent publications using FAO data suggest that Tanzania has not undergone forest transition (Meyfroidt and Lambin, 2011), the results I present here may indicate otherwise. The difference between my results and the FAO data arises due to two main reasons. I analyse long-term changes in forest cover and my data indicates that the highest rates of deforestation proceed the years included in the FAO data (1960-present), although the linear trend shown since 1980 in my dataset differs from that of the FAO data. The differences between my data and that of the FAO predominantly arise as my definition of forest differs to that used by the FAO (see Section 1.2.1). The FAO forest definition contains forest, woodland and savanna, and so may be more comparable to a combination of my forest and savannah categories. My results show that woodland and savanna are still undergoing rapid deforestation and that, when forest and savannah spectrum are combined, a transition is not evident (Figure 3.10c), although a transition is indicated within protected areas (Figure 3.13c). This result highlights the importance of establishing a standardised definition of forest that is used in all REDD+ monitoring assessments as, depending on definition, my study area shows positive or negative deforestation rates.

The state forest policy pathway is the likely mechanism for transition as the shift occurs during a period of rapid increase in protected areas. As previously described, Tanzania's legally protected areas are not devoid of resource use, however, rules surrounding resource extraction are sufficiently stringent to shift net deforestation trends to net forest establishment patterns. Although protected areas are underfunded (Green et al., 2012), some studies have also identified their success in slowing and, in some cases, reversing LCC (Bruner et al., 2001, Defries et al., 2005, Pfeifer et al., 2012).

It is likely that the state forest policy pathway has acted in Tanzania through several additional practices on top of the creation and policing of protected areas. In Asia, forest policies encouraging the restoration of degraded forests and afforestation have had considerable impact (Démurger and Yang, 2006, Foster and Rosenzweig, 2003, Mather, 2007). The villagisation that took place in Tanzania encouraged communities to tend woodlots to meet the needs of domestic use (Sunseri, 2009). This process was on-going throughout the transition period identified in this study and likely contributed to the net shift from deforestation to forest establishment. Furthermore, it has been suggested that community ownership of forests is likely to lead to improvements in forest conservation and management (Barbier et al., 2010, Chhatre and Agrawal, 2009). As previously described, participatory or community based management is extensively performed throughout Tanzania, and this may have also contributed to the forest transition. Finer scaled data, both spatially and temporally, are required to more accurately identify specific policies that effected forest transition, but the results present here (and those from across the tropics) are encouraging to those attempting to reduced global carbon emissions by reducing deforestation through policy changes, such as those associated with REDD+.

My results do not show strong support for the other transition pathways investigated (the economic development pathway, the forest scarcity pathway, the globalisation pathway, and the forest-favourable climate pathway). Under the economic development pathway, forest transition occurs as a result of the succession of agricultural land following abandonment due to the lack of available farm labour. My results contradict those expected for this pathway, illustrating a rise in both rural population (labour force) and agricultural area. Similarly, my results show little support for the forest scarcity pathway. The total roundwood production showed consistent increase with time, and provided no indications that a period where forest resources were scarce occurred. It is likely that the vast areas of woodland were able to provide timber, non-timber forest products (NTFP) and forest-related ecosystem services to such a degree that, despite the dramatic reduction in forest area, there was not a scarcity of forest products and so little increase in the perceived value of forests. Furthermore, my results provide little support for the globalisation pathway. If an increase in global connectedness caused the transition then I would expect to observe a substantial increase in the quantity of products traded. No such increase was apparent in my results. In addition, my data provide little support for the proposed forest-favourable climate pathway, although a peak in wet-season precipitation between 1930 and 1960 could have resulted in increased forest regeneration between 1960 and 1980 assuming a lag of ~30 years for tree growth. Finally, although, due to data deficiency, I did not specifically investigate the smallholder tree-based land use intensification pathway, preliminary evidence suggests that this pathway may have contributed to forest transition. This potential effect is suggested through examination of the original land cover categories used in each map. In the 2000 map, several land cover categories are described as a natural-crop mix (e.g. woodland and scattered cropland, forest mosaic) (HTSL, 1997, Swetnam et al., 2011). The integration of small woodlots and agriculture is not suggested by any other map legend, perhaps indicating that this practice emerge within my study area between 1949 and 2000, coinciding with the period of forest transition.

Whilst this study does not provide strong support for any pathway other than the state forest policy pathway, I cannot rule out the possibility that other pathways contributing the forest transition evident in the EAM region. The proxies available to assess the effect of each pathway are limited due to data-deficiency and it is possible that many pathways not supported here did affect forest transition. For example, the economic development pathway need not be tightly coupled with rural population. If other sources of rural income displaced farm labourers into another revenue stream then the economic development pathway could act without a decline in rural population. In addition, the forest scarcity pathway is known to act via non-marketable ecosystem services as well as traditional forest-based products. Tanzania has long valued ecosystem services, creating forest reserves to protect watersheds for almost a century (Sunseri, 2009) and has recently instigated several PES mechanisms (Branca et al., 2011). Furthermore, the globalisation pathway may act through a shift in global attitudes, as well as an increase in interconnectedness. Such a shift of attitudes amongst influential global partners is evident in Tanzania. Between 1960 and 1980, foreign aid agencies in Tanzania subsidised logging activities (Hamilton and Bensted-Smith, 1989). However, in the 1980s and 1990s, aid agencies pressurised the state to conserve local biodiversity (Woodcock, 2002). These global pressures may have contributed to forest transition in the EAM region and is an example of how the pathways are not mutually exclusive, with the global pathways interacting with the state forest policy pathway in this example.

Whilst the evidence I present strongly indicates that forest transition has occurred in the EAM watershed, as well as within the EAM themselves, it is possible that this has not occurred in other regions of Tanzania and thus is not typical of the nation as a whole. For example, the transition observed within our study area may not indicate increasing sustainability within the region if it depends on forest losses in other regions (i.e. leakage). This spatially constrained forest recovery has been illustrated elsewhere in the tropics. For example, small regions in Brazil are suggested to have undergone forest transition (Baptista, 2008, Baptista and Rudel, 2006) but this is not evident at a national scale (Meyfroidt and Lambin, 2011) (see Section 2.6.2 for full details). Furthermore, whilst it is fairly certain that the EAM region has undergone forest transition, this should be viewed with caution as forest cover may fluctuate, reflecting changes in national policy or market trends, and, in the future, deforestation trends may once again dominated afforestation trends. The change in forest cover over time in France provides a detailed example of the ability of political and economic conditions to reverse forest transition (Mather and Needle, 2000) see Section 2.6.2 for full details).

3.7.2 Evaluation of Deforestation and Forest Establishment Correlations

The different correlations identified with deforestation and forest establishment highlight the assertion that forest transition curves consist of two separate underlying relationships (Grainger, 1995). My results confirm population pressure, infrastructure and access to markets are influential variables in determining deforestation patterns (Angelsen, 2007). Furthermore, my results support suggestions in forest transition theory that reforestation begins on less fertile soils, usually away from roads (Rudel et al., 2002). Finally, my results emphasise the importance of biophysical impacts in tropical regions (Perz, 2007). I have shown that climatic conditions and events may affect deforestation and forest establishment, both directly and indirectly. As a result, these effects should not be ignored in forest transition theory, and the forest-favourable climate pathway should be considered in future studies as this pathway is likely to become more prominent under climate change.

Soil fertility was a key determinate of deforestation, with higher amounts of deforestation occurring in areas with fertile soils. Soils of greater fertility are likely to provide higher agricultural yields and as such provide greater rewards for the area of land disturbed. This result is supported in the literature (Veldkamp et al., 1992), though other studies have found soil fertility to have no effect (Laurance et al., 2002).

Deforestation is also shown to have occurred with increasing distance from major settlements. This pattern could arise if land near major settlements was favoured but has already undergone deforestation. There is evidence that the coastal areas (where many of Tanzania’s major settlements are situated) had indeed undergone logging prior to the earliest land cover maps considered here (Schabel, 1990). Other studies have found deforestation to occur closer to major settlements (Southworth and Tucker, 2001) but some have indicated that this relationship is non-linear (Mertens and Lambin, 1999).

Higher amounts of deforestation are shown to have occurred in areas with a higher local population density between 1923 and 1949. High populations exhibit higher levels of demand on local resources and also possess the availability of labour required to cause substantial deforestation. Population pressure is known to be correlated with deforestation in eastern Africa (Lung and Schaab, 2010). However, other studies show how the effect of population pressure is complicated due to the interaction of rural and urban populations (Laurance et al., 2002). My study may have been unable to identify consistent trends related to population density as the modern population distribution was used as a surrogate for past distribution, whereas in reality rural settlements may have been established and abandoned depending on resource availability and depletion over time.

The direction of the effect of some of the variables has been shown to change over time, highlighting the importance in both the temporal resolution and span for studying LCC. In the early 20th century, steep lowland forests that experience little drought show the most deforestation. This may be due to the fact that many early colonialists preferred crops such as tea, for which these growing conditions are ideal (Iliffe, 1971). These sites are highly productive and are unlikely to be abandoned and so, by the mid-century, droughted areas were being deforested. This is consistent with previous understanding (Newmark, 2002, Lovett, 1993a). A constant demand for timber and land led to conversion of the suboptimal mountain tops. These areas are often remote and so the extraction of timber and agricultural products is difficult, but made profitable by the large demand. Similar waves of degradation have previously been observed in Tanzania (Ahrends et al., 2010).

Forest establishment, although intrinsically more complicated due to the inability to separate afforestation and reforestation as well as natural regeneration and tree planting, showed some clear patterns. First, higher amounts of forest establishment occurred on infertile soils, suggesting that (i) poor agricultural yields lead to abandonment and natural succession and/or (ii) active tree planting occurred, which is more common on marginal infertile soils (Thacher et al., 1996). Second, areas with a low local population density showed more forest establishment. It is likely that this is due to the decreased anthropogenic disturbance allowing succession to proceed (Elmqvist et al., 2007). Third, from 1923 to 2000, steeper slopes were more likely to show forest establishment, again these are more likely to be abandoned due to top soil erosion and inaccessibility, as shown elsewhere (Matlack, 1997).

Both mean annual temperature and mean maximum cumulative water deficit were positively correlated with forest establishment from 1923 to 1949 but negatively correlated from 1949 to 2000. This suggests that hotter, drought impacted land was left to regenerate, or even actively afforested with eucalyptus plantations (Iliffe, 1971), in the first half of the 20th century, perhaps because this land was not optimal for agricultural use. In the second half of the century, colder areas experiencing little drought showed more forest establishment. This, again, could be the result of the abandonment of suboptimal land or the establishment of plantations, such as teak. For example, the Kilombero Valley Teak Company was established in 1992 and now controls over 28,000 hectares in montane habitats (KVTC, 2012).

3.7.3 Study Limitations

It is important to note the limitations and uncertainties involved in this study. Spatial errors by the cartographers and digitising errors may result in land use types being displaced geographically. If the displacement is within the area of interest then it does not affect the results as the extent of the land use in question has not decreased. However, as the size of the area of interest decreases (e.g. from the watershed to the EAM), there is an increased chance that any displacement would result in data shifting out of the area of focus. This effect gave rise to the anomalous amount of forest recorded within the EAM in 1923 (Figure 3.11); with the high spatial error shown on this map for the southern EAM causing the land use recorded for this small area to be unreliable (Figure 3.4). All analyses of the harmonised land cover categories from error-corrected maps (which minimise error) produced similar results to those derived from the original maps, suggesting that the results found in this study are robust and not greatly affected by the errors involved.

The use of FAO forest cover data has been widely criticised in the literature as it is thought to be highly uncertain (Grainger, 2008b, Grainger, 2010). In this chapter, I have demonstrated that the trend illustrated for Tanzania by the FAO data are highly dependent on definition and so this scepticism is well founded. Although I do not utilise FAO data for forest area estimation, I use FAOSTAT data (specifically: agricultural area; urban and rural population; total roundwood production; and import and export quantity) as proxies to investigate the pathways of forest transition. Uncertainty in my descriptive analysis increases if my chosen proxy does not accurately represent all aspects of the relevant pathway (previously discussed). In addition, there is likely to be uncertainty associated with the data from which each proxy is derived. If the trend in the proxy is uncertain then the descriptive analysis presented here is flawed. However, the modernisation proxies used in this study are of high quality, although uncertainty is higher in historical estimates (FAO, 2005). A further limitation of this study is that I have not been able to investigate the effect of pathways that involve a substantial (>20year) lag between the impact of the pathway and the change in forest cover as, although I estimate forest transition to have occurred between 1960 and 1990, the proxy data are not available before 1960. Since ecosystems require substantial time to pass from one successional stage to another (Finegan, 1996), it is likely that such a lag exists. Future effort should focus on uncovering historical data allowing the descriptive analysis of the national land cover transition as well as any lagged effects that may bring about the forest regeneration period.

Finally, although I clearly indicate that the EAM region has proceeded through the forest transition, little can be said about the quality of the remaining forests. Forest transition theory describes the trend in forest cover following conversion to the land cover category to/from another. Hence, any degradation that occurs within the forest land cover category is ignored, despite being known to occur (Ahrends et al., 2010, Lambin et al., 2003). In addition, it is likely that there is a general trend from natural forest to agroforestry and/or plantation forestry over time. However, as previously described, it was not possible to separate natural and managed forests in this study. This trend may have impacts on biodiversity conservation and the delivery of ecosystem services and should be investigated in future studies.

3.8 Conclusions

I show dramatic changes in land cover over a century across a 33.9 million ha area of Tanzania. Forest area declined rapidly in the first half of the twentieth century but went through a transition between 1960 and 1990, leading to forest regeneration in the second half of the twentieth century. This is the first time a forest transition has been convincingly demonstrated in Africa. It is likely that this forest transition was driven by a substantial increase in the extent of protected areas, via the state forest policy pathway. However, this study indicates that while forests have regenerated between 1949 and 2000, savanna area decreased rapidly, suggesting forest product needs may now be met by exploitation of this biome. Despite this, the historical rates of deforestation that I provide may be of use in producing preliminary estimates of the baseline scenarios needed for REDD+. However, there is potential for deforestation to once again exceed forest regeneration and so these baselines should be re-evaluated when more data becomes available.

Chapter 4
Towards Regional, Error-Bounded Landscape Carbon Storage Estimates For Data-Deficient Areas Of The World

4.1 Abstract

Monitoring landscape carbon storage is critical for supporting and validating climate change mitigation policies. These may be aimed at reducing deforestation and degradation, or increasing terrestrial carbon storage at local, regional and global levels. However, due to data deficiencies, default global carbon storage values for given land cover types such as ‘lowland tropical forest’ are often used, termed ‘Tier 1 type’ analyses by the Intergovernmental Panel on Climate Change (IPCC). Such estimates may be erroneous when used at regional scales. Furthermore uncertainty assessments are rarely provided, leading to estimates of land cover change carbon fluxes of unknown precision which may undermine efforts to properly evaluate land cover policies aimed at altering land cover dynamics. Here, I present a repeatable seven-stage method to estimate carbon storage values and associated 95% confidence intervals (CI) for all five IPCC carbon pools (aboveground live carbon [ALC], litter, coarse woody debris [CWD], belowground live carbon and soil carbon) for data-deficient regions, using a combination of existing inventory data and systematic literature searches, weighted to ensure the final values are regionally specific. The method meets the IPCC ‘Tier 2’ reporting standard. I use this method to estimate carbon storage over an area of 33.9 million hectares of eastern Tanzania, reporting values for 30 land cover types. I estimate that this area stored 6.33 (5.92-6.74) Pg C in the year 2000. Carbon storage estimates for the same study area extracted from six published Africa-wide or global studies show a mean carbon storage value of only ~50% of that reported using my regional values, with five of the six studies reporting lower carbon storage values. This suggests that carbon storage has been underestimated from this region of Africa. My study demonstrates the importance of obtaining regionally appropriate carbon storage estimates, and shows how such values can be produced for a relatively low investment. Applying my carbon storage estimates to historical land cover maps implies that, between 1908 and 2000, a total committed carbon release of 0.94 (0.37-1.50) Pg C occurred as a result of land cover change, at an average rate of 0.3 [0.1-0.4] Mg ha^{-1} yr^{-1}.

Between 1949 and 2000, legally protected areas led to local expansions of forested area, resulting in committed carbon absorption of 4.77 (3.84-5.70) Mg C ha^{-1} compared to a committed carbon emission of 11.89 (7.21-16.57) Mg C ha^{-1} from unprotected areas.

4.2 Introduction

Land use/cover change (LCC) is known to make up a significant proportion of global GHG emissions. For example, anthropogenic destruction of tropical forests is responsible for between 10% and 28% of global carbon dioxide emissions, depending, in part, upon definitions (Achard et al., 2004, IPCC, 2007, Gullison et al., 2007, van der Werf et al., 2009, Pan et al., 2011, Harris et al., 2012). In response to this, a broad agreement within the United Nations Framework Convention on Climate Change (UNFCCC) was reached to implement a scheme titled ‘Reducing Emissions from Deforestation and Forest Degradation’ (REDD) as a means to encourage the reduction of these emissions, later expanding the schemes’ scope to include the sustainable management of forests and the conservation and enhancement of forest carbon stocks, termed REDD+ (Burgess et al., 2010).

To have the opportunity to receive potential financial incentives through mitigation schemes such as REDD+, countries must estimate carbon storage and rates of loss, following guidance materials (Penman et al., 2003a, IPCC, 2006a, Penman et al., 2003b, GOFC-GOLD, 2010). However, many developing countries lack the data to perform some of the recommended carbon accounting methods (Burgess et al., 2010) and as such often resort to so-called ‘Tier 1’ analyses using global default carbon storage values for given land cover types (Ruesch and Gibbs, 2008, IPCC, 2006a). However, carbon stocks are known to vary greatly on local (Sierra et al., 2007) and global scales (Phillips et al., 2008, Lewis et al., 2009b). Thus, regionally appropriate values, indicating uncertainties (‘Tier 2’), and those derived from intensive multiple census inventory data (‘Tier 3’) are preferable (Gibbs et al., 2007, IPCC, 2006a). This tiered approach has the advantage of enabling participation of all countries, despite varying data availability (Table 4.1). Here, I focus on the differences between Tier 1 and Tier 2 methods; see Chapter 5 for discussions on Tier 3 methods.

Current Tier 1 and Tier 2 guidelines set out the methods by which carbon balance can be calculated. These are separated into the carbon flux (the net balance between emission and absorption) as a result of land remaining in the same land cover category and the carbon flux resulting from LCC (e.g. non-forest land being converted to or from forest) (IPCC, 2006a). The latter (carbon flux resulting from LCC) are the focus of this chapter and so will be discussed. In Tier 1 methods, the carbon flux resulting from LCC is calculated using the difference between the carbon stock of the two land covers. Using default growth rates or mean carbon residence times this carbon flux can be allocated temporally over the years following the LCC event (IPCC, 2006a). However, it must be noted that the current default value for CWD and litter carbon stock in non-forest land cover types is zero, with any changes in carbon stock increasing linearly over a 20 year period (IPCC, 2006a), and many studies omit these carbon pools from their inventories (Hurtt et al., 2006, Houghton, 2003). Due to data deficiency, carbon fluxes as a result of changes in organic soil carbon stock are not calculated using Tier 1 methods (unless land is drained), however, changes in the mineral soil carbon can be calculated using the Tier 1 method, with the difference between the mineral soil carbon stored under the first land cover and the second being emitted/absorbed at a calculated rate (default is linearly over 20 years) (IPCC, 2006a). Tier 2 methods improve on Tier 1 methods in that they are considered to be more representative of true carbon stocks and fluxes occurring over the landscape in question (GOFC-GOLD, 2010). Estimation using a Tier 2 approach involves country- or region-specific carbon stock estimates and/or stock change factors (IPCC, 2006a). In both Tiers 1 and 2, the size of CWD, litter and belowground carbon pools is often estimated from ratios relating each pool to aboveground carbon stock (IPCC, 2006a, Mokany et al., 2006, Lewis et al., 2009b). Furthermore, effort should also be made to capture an estimate of the uncertainty in values (GOFC-GOLD, 2010), although many studies omit this crucial step (Baccini et al., 2008, Ruesch and Gibbs, 2008).

When, estimating carbon emissions, a selective or partial accounting system can be used. When full carbon accounting is not feasible (common in many LEDC often as a result of low capacity (Romijn et al., 2012)), a partial system must include all carbon pools that are expected to decrease, whilst only a sample of those expected to increase need be included (Hamburg, 2000), ensuring carbon emissions are not under-estimated, but potentially over-estimating them. Currently, sampling effort is largely focussed on ALC pools (Lewis et al., 2009b, Phillips et al., 2009b). However, the importance of the remaining IPCC carbon pools (litter, CWD, belowground, and soil carbon – see Table 4.1) is being increasingly recognised (Guo and Gifford, 2002, DeFries et al., 2010, García-Oliva and Masera, 2004, Ramankutty et al., 2007).

The fluxes of all five terrestrial carbon pools are often predicted to change as a result of a LCC event. For example, following the creation of a forest on previously cultivated land, ALC is expected to increase as a result of tree growth. This process may take several decades but will eventually reach a stable maximum (Vanclay, 1994, Putz et al., 2008b). Due to the growth of tree roots, belowground live carbon is expected to show a similar pattern. As a result of increased AGB and the natural turnover in leaves and branches that occurs throughout the life cycle of each stem, the carbon found in litter and CWD are also expected to increase over time. Finally, soil carbon is expected to increase, but over a longer time frame, ranging from decades to centuries (O'Connell and Sankaran, 1997). The opposite trend (i.e. a net carbon emission from all five carbon pools) is expected following a deforestation event in which forested land is replaced by agriculture. Similar to the net absorption described above, each carbon pool responds over a different time span due to the differences in the mean carbon residence time of each pool (Harrison et al., 1997, Trumbore et al., 1996). If carbon accounting does not include all five pools (i.e. does not show full completeness) then there is potential for emissions to be underestimated. For example, if belowground carbon pools are not included in carbon inventories following deforestation events then carbon emissions would be under-reported (IPCC, 2000).

I present a method of obtaining improved regional (Tier 2) estimates of carbon storage for all five IPCC carbon pools in data-sparse regions. Using a case study in eastern Tanzania I apply the resultant median values and 95% confidence intervals (CI) to a recent land cover map to calculate carbon stock for the year 2000. These figures are then compared to published estimates of carbon storage produced for the same study area in the same year. My results suggest that by adopting the method presented here, countries currently using Tier 1 values may be able to generate Tier 2 values which can be easily updated and improved, incorporating inventory data as and when available, until data are sufficient to progress to a Tier 3 method (see Chapter 5). Furthermore, I use my Tier 2 carbon estimates in combination with historical land cover maps (Chapter 3) to estimate the carbon emissions resulting from LCC in the twentieth century.

Table 4.1 Carbon stored within the study area for the year 2000 as estimated by this and previous studies (95% CI given in brackets).

Study	Aboveground live carbon storage, Pg (95% CI range)	Litter carbon storage, Pg (95% CI range)	Coarse woody debris carbon storage, Pg (95% CI range)	Belowground live carbon storage, Pg (95% CI range)	Aboveground live and belowground live carbon storage, Pg (95% CI range)	Soil carbon storage, Pg (95% CI range)	Total carbon storage, Pg (95% CI range)
Original	1.58 (1.56-1.60)	0.15 (0.14-0.15)	0.25 (0.24-0.25)	0.60 (0.59-0.61)	2.18 (2.15-2.21)	3.74 (3.43-4.05)	6.33 (5.92-6.74)
Harmonised	1.64 (1.52-1.76)	0.16 (0.15-0.17)	0.28 (0.26-0.30)	0.51 (0.47-0.55)	2.15 (1.99-2.30)	3.80 (3.77-3.82)	6.38 (6.33-6.43)
Baccini *et al* (2012)	2.03	N/A	N/A	N/A	N/A	N/A	N/A
Hurtt et al. (2006) HYDE-SAGE	0.63	N/A	N/A	N/A	N/A	N/A	N/A
Hurtt et al. (2006) HYDE	0.41	N/A	N/A	N/A	N/A	N/A	N/A
Baccini et al. (2008)	0.34	N/A	N/A	N/A	N/A	N/A	N/A
Ruesch & Gibbs (2008)	N/A	N/A	N/A	N/A	1.61	N/A	N/A
Saatchi et al. (2011)	0.83	N/A	N/A	0.26	1.09	N/A	N/A

4.3 Definitions

4.3.1 IPPC carbon pools

I define a carbon pool as a system which has the capacity to accumulate or release carbon. Specifically, the IPCC define five terrestrial carbon pools. These are: aboveground live carbon (ALC); litter; coarse woody debris (CWD); belowground; and soil (Table 2.4). ALC is defined as all carbon contained in living vegetation, both woody and herbaceous, above the soil including stems, stumps, branches, bark, seeds, and foliage (IPCC, 2006a). Litter carbon is defined as all non-living organic carbon with a size greater than the limit for soil organic matter (suggested 2 mm) and less than the minimum diameter chosen for dead wood (e.g. 10 cm), in various states of decomposition above or within the mineral or organic soil (IPCC, 2006a). All non-living woody carbon not contained in the litter, either standing, lying on the ground, or in the soil is termed CWD, whilst all carbon contained in live roots is defined as belowground carbon (IPCC, 2006a). Finally, soil carbon includes organic carbon in mineral soils to a specified depth chosen by the country (IPCC, 2006a).

4.3.2 Timber volume, biomass stock and carbon stock

It is often not practical to directly measure the carbon stock within many carbon pools (Table 2.4). Direct measurement can only be said to have occurred when the object in question has been physically compared to an internationally acceptable standard (Woodhouse et al., 2012). Thus, the carbon held within vegetation would have to be extracted and its mass recorded. In forest inventory plots, the carbon stock can be estimated via direct measurement of other variables, most commonly diameter (Lewis et al., 2009b, Phillips et al., 2009b), that are correlated with mass. Thus, to estimate carbon stocks in forested land cover types, data on the volume of stems per unit area are required. This is termed the ‘timber volume’. Measurements of tree diameter (and occasionally height) are converted into units of mass using allometric equations (Chave et al., 2005, Brown, 1997). An estimate of biomass stock (the absolute biological mass of a pool per unit area at a specified time) is obtained by summing the estimated tree mass to obtain a stand level estimate. Finally, the biomass stock needs to be converted to an estimate of carbon stock (the absolute mass of carbon held within a pool per unit area at a specified time). Typically, carbon stock is assumed to be ~50% of the estimated biomass stock (GOFC-GOLD, 2010).

4.3.3 Carbon flux

Thus, carbon stock refers only to the carbon contained within a pool per unit area at one point in time. However, the carbon cycle is dynamic and there is a near constant exchange of carbon between pools (Bonan, 2008). Since REDD+ in primarily concerned with carbon emissions to the atmosphere (as opposed to exchanges between terrestrial carbon pools), I define carbon flux as the transfer of carbon between terrestrial carbon pool and the atmosphere. This process can occur in both directions, with terrestrial pools emitting and removing carbon from the atmosphere (van der Werf et al., 2009).

4.3.3 Committed carbon source

Carbon fluxes between terrestrial pools and the atmosphere sometimes occur after LCC (e.g. deforestation (van der Werf et al., 2009)). However, there may be a lag between the LCC event and the associated emission/absorption of carbon into/from the atmospheric pool. Typically, ALC pools are thought to release carbon to the atmosphere almost immediately following LCC, often as a result of burning (Fearnside, 2000). CWD and litter are thought to have a longer half-life, persisting in longer after the LCC event, whilst belowground and soil carbon pools are regarded as being the most stable, often showing a lag time of several years or decades (Fearnside, 2005). Thus, some carbon emissions today could be a result of land cover change several decades previously. To couple periods of LCC with the concomitant carbon emission, I use the term committed carbon source to refer to the total expected carbon emission from the terrestrial pool to the atmosphere following a LCC event. For example, if a forest was converted to grassland in 1930, I allocate the committed carbon emission to 1930 rather than calculating the lag time and estimating how the true carbon emissions vary over time. Conversely, I define committed carbon absorption as the total expected carbon absorption from the terrestrial pool to the atmosphere following a land cover change event.

4.4 Carbon stocks in Tanzania Since 1980

I use the watershed of the Eastern Arc Mountains in Tanzania (EAM), spanning 33.9 million ha, to derive regional carbon storage estimates using my method, as well as estimates of the carbon flux resulting from LCC between 1908 and 2000. Tanzania has a focused on reducing atmospheric emissions for over a decade. For example, the Vienna Convention for the Protection of the Ozone Layer, the Montreal Protocol (1987) and the London Amendment (1990) were all acceded in 1993 (UN, 2002). The UNFCCC was signed by Tanzania on 12 June 1992, but not ratified until March 1996 (UN, 2002).

Given the political will present in Tanzania, various studies have been undertaken by the Centres for Energy, Environment, Science and Technology (CEEST) on behalf of the Tanzania Government, including inventories of Tanzania GHG fluxes in 1990 and 1994 (Government of Tanzania, 2003, CEEST, 1994, CEEST, 1996). The 1990 GHG inventory was developed from 1993 to 1994, following the IPCC guidelines of 1991 (Government of Tanzania, 2003). The inventory was based on data obtained between 1988 and 1990, although most sectors were regarded as data-deficient due to the lack of up-to-date, continuously collected data (CEEST, 1994). As a result, much of this report relies on Tier 1 methods using the default values provided by the IPCC (Government of Tanzania, 2003). According to this report, land use and forestry were the major emitter of GHG (~91% of which are CO_2), producing ~87% of all GHG emissions and ~96% of all CO_2 emissions (CEEST, 1994). The land use and forestry sector were also reported as being the only sink of CO_2, absorbing CO_2 from the atmosphere through afforestation and reforestation. In 1990, the land use and forestry sector is estimated to have emitted 53Tg CO_2, the net effect of a 57Tg emission and 4Tg absorption (CEEST, 1994). Even with this preliminary information, it was evident that human activities were primarily responsible, resulting in ~93% of total emissions. A second GHG inventory was performed for the year 1994. However, no forest inventories had been carried out in the years separating the two reports, nor had any new forest policies or interventions been developed (Government of Tanzania, 2003, CEEST, 1994, CEEST, 1996). Hence, most estimates remained the same, using Tier 1 methods. Both the GHG inventories for 1990 and 1994 were submitted to the UNFCCC by Tanzania in 2003 as part of Tanzania’s Initial National Communication, with the 1990 report being used as baseline data (Government of Tanzania, 2003). Despite almost a decade having passed, Tanzania’s Initial National Communication contained no new data when compared to the 1990 and 1994 GHG inventories. This report remains the sole national communication Tanzania has submitted to the UNFCCC.

In parallel to reports submitted to the UNFCCC, Tanzania has collated forest area and LCC data for the FRA (Section 3.4.2). Table T8 of the national reports to the FRA details estimates of carbon stored in forest and other wooded land cover categories between 1990 and 2010 (FAO, 2010c). These estimates are provided in Table 4.2, however it must be noted that the term ‘forest’ here refers to land as described under the FAO definition of forest and thus differs from the definition of forest used in this thesis (Section 1.2.1). Broadly, forest (as defined by the FAO (2000a)) encompasses both forest and woodland land covers (as defined in this thesis). Other wooded land (as defined in the FRA reports (FAO, 2008)) is comparable to bushland as defined in this thesis. Uncertainty in the definition of forest (Putz and Redford, 2010) is just one of many sources of uncertainty in national forest area estimates (Grainger, 2008b). The uncertainty in forest area estimates has been previously discussed in Chapter 3, so here I will focus on the uncertainty in the carbon estimates. The latest report to the FRA contains a critical evaluation of the quality of the carbon estimates (FAO, 2010c). This situation in Tanzania is that, for all five terrestrial carbon pools, “no [any] serious study has ever been done that can provide reliable country information” (FAO, 2010c). The timber volume (termed growing stock by the FRA) is derived from a single report conducted by CEEST in 1999, providing limited, medium quality data detailing the volume per unit area for each vegetation class (CEEST, 1999). These aboveground live volume estimates are converted to timber volumes using Tier 1 methods. Specifically, it is assumed that forests have a timber volume of $37m^3$ ha^{-1}, with shrubs and thickets containing $10m^3$ ha^{-1} (FAO, 2010c). These are then converted to AGB estimates using expansion factors developed for the humid tropical zone (namely 2.8 for forest and 9.0 for other wooded land) (FAO, 2008). Finally, biomass estimations are converted to estimates of ALC stock and the remaining terrestrial carbon pools estimated using default values provided by the IPCC (2006a). Thus, the carbon estimation submitted by Tanzania to the FRA is highly uncertain. The data are of low quality and rely heavily on Tier 1 methods that could be substantially improved through the development of reliable in-country data collection.

Over the past 6 years, actions have been taken to begin to address the issue of data-deficiency. In 2007, regional estimates suggested that deforestation in the EAM resulted in emissions of ~16Mt CO_2 per year (Hall et al., 2009, Scharlemann et al., 2010). However, data-deficiencies exist in several other regions, with estimates of deforestation rates highly uncertain as no detailed study has occurred (FBD, 2008) and with data-deficiencies reported for several forest types (Burgess et al., 2010). As a result, the carbon stock held within difference forest types in Tanzania is only partially known (FBD, 2008). Thus, global default (Tier 1) values used to estimate the national distribution of carbon storage. The carbon map currently used by the Tanzanian government was developed in 2009 following a workshop by the UNEP World Conservation Monitoring Centre. During the production of this map, no new data were collected, relying solely on Tier 1 methods, bringing together data from three published carbon maps (fully described below). The aboveground carbon estimates were derived from Baccini et al. (2008) (described below), using default IPCC conversion factors (IPCC, 2006a) to calculate belowground carbon from the aboveground live estimates (Miles et al., 2009). In areas of low carbon density (<4.5 Mg ha^{-1}), ALC estimates were based on global estimates provided by Ruesch and Gibbs (2008). Soil carbon to a depth of 1m was mapped using the SOTER database (Batjes, 2004, ISRIC, 2010). Thus, the map currently used by Tanzanian officials omits both CWD and litter carbon pools, and relies on Tier 1 methods for all other pools. Thus, uncertainty in carbon estimation arise through data deficiency via both incompleteness (i.e. data deficiency for some carbon pools) and representativeness (i.e. the global default values for each land covers may not be representative of the carbon stored within land covers in this region of the world).

Table 4.2 Estimates of carbon stock in Tanzania forests (woodland and forest combined as defined here) and other wooded land (bushland) between 1990 and 2010 (FAO, 2010c).

Carbon Pool	Carbon Stock (Pg)							
	Forest				Other Wooded Land			
	1990	2000	2005	2010	1990	2000	2005	2010
Aboveground live	2.02	1.82	1.73	1.63	0.77	0.63	0.56	0.49
Belowground	0.49	0.44	0.41	0.39	0.19	0.15	0.13	0.12
CWD	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Litter	0.09	0.08	0.07	0.07	0.04	0.03	0.03	0.02
Soil	2.00	1.76	1.67	1.57	0.86	0.70	0.62	0.55

Including those used in the above UNEP World Conservation Monitoring Centre maps, six previously published scientific estimates, using a wide variety of methods, give a wide range of carbon storage estimates for my study area (Table 4.1). The lowest value given is derived from MODIS (1 km^2 resolution) and LiDAR data plus limited ground observations, used to estimate the distribution of ALC stored in Africa in 2000, giving a Tier 1 estimate of 0.34 Pg C for my study area (Baccini et al., 2008). This estimate is for ALC only, omitting the other four IPCC carbon pools, and utilises continental, not country, specific data and allometric equations. Following a critique of these methods (Mitchard et al., 2011), a recent revision has been published that fully accounts for disturbance, using inventory data, MODIS imagery and GLAS LiDAR data at a 500m resolution to, surprisingly, provide the highest estimate of 2.03 Pg C for aboveground carbon for my study area (Baccini et al., 2012).

Two carbon model outputs (HYDE and HYDE-SAGE) were presented by Hurtt et al. (2006). The HYDE-SAGE model, which uses cropland data of higher spatial resolution than HYDE, produced an estimate of 0.63 Pg C for the study area (0.41 Pg C for the HYDE model) (Hurtt et al., 2006). Through the use of the Miami LU ecosystem model, these estimates account for disturbance. These dynamic models could be used to provide Tier 3 estimates, however, the models do not utilise data or equations specific to my study area, instead using global (Tier 1) values to provide carbon estimates. Additionally, these models only provide estimates of ALC storage.

The global vegetation map from the Global Land Cover 2000 Project (GLC2000; 100 ha resolution derived from SPOTVEGETATION satellite imagery (GLC, 2003)) is used in combination with carbon values produced by the IPCC to estimate Tier 1 carbon stock (Ruesch and Gibbs, 2008). This approach accounted for disturbance only where vegetation categories were identified as disturbed (for example, burnt forests or cropland mosaics), but does present results for aboveground live and belowground carbon pools combined, estimating that 1.61 Pg C is stored within my study area (Ruesch and Gibbs, 2008). CWD, litter and soil pools are omitted. Saatchi et al. (2011) using MODIS, SRTM and QSCAT to extrapolate inventory plot and GLAS LiDAR data, produces an estimate of 0.83 Pg C (Table 4.1). They provide estimates for aboveground live and belowground carbon pools, omitting CWD, litter and soil, but accounting for disturbance. Estimates provided utilise continental data and allometric equations and so result in Tier 1 estimates. Both the GLC2000 based values and the Saatchi values are in the middle range of the six estimates.

Considering all the previously published studies together, none give estimates for all five IPCC carbon pools, and while some utilise local remotely-sensed data, they mostly do not include local data from on-the-ground. The result is that estimates for ALC storage across the EAM range six-fold from 0.34 Pg C to 2.03 Pg C (Table 4.1), a clearly unsatisfactory basis on which to develop policy. The limitations of these Tier 1 estimates are widely recognised and several on-going activities are currently taking place to reduce data-deficiencies. For example, Tanzania's National Forestry Resources Monitoring and Assessment project (NAFORMA) commenced in 2009. NAFORMA is Tanzania's first comprehensive national forest inventory programme, and plans to implement a total of ~3,400 plots, 25% of which will be permanent (and thus able to be recensused in the future) (FBD, 2010). Within the permanent inventory plots established by NAFORMA, soil samples are being taken, in what is the most comprehensive soil survey in Tanzania to-date. Thus, although plans are underway to reduce the data-deficiencies surrounding carbon estimation within Tanzania, the method, maps and estimates I present here are a significant advance on the data and estimates currently available.

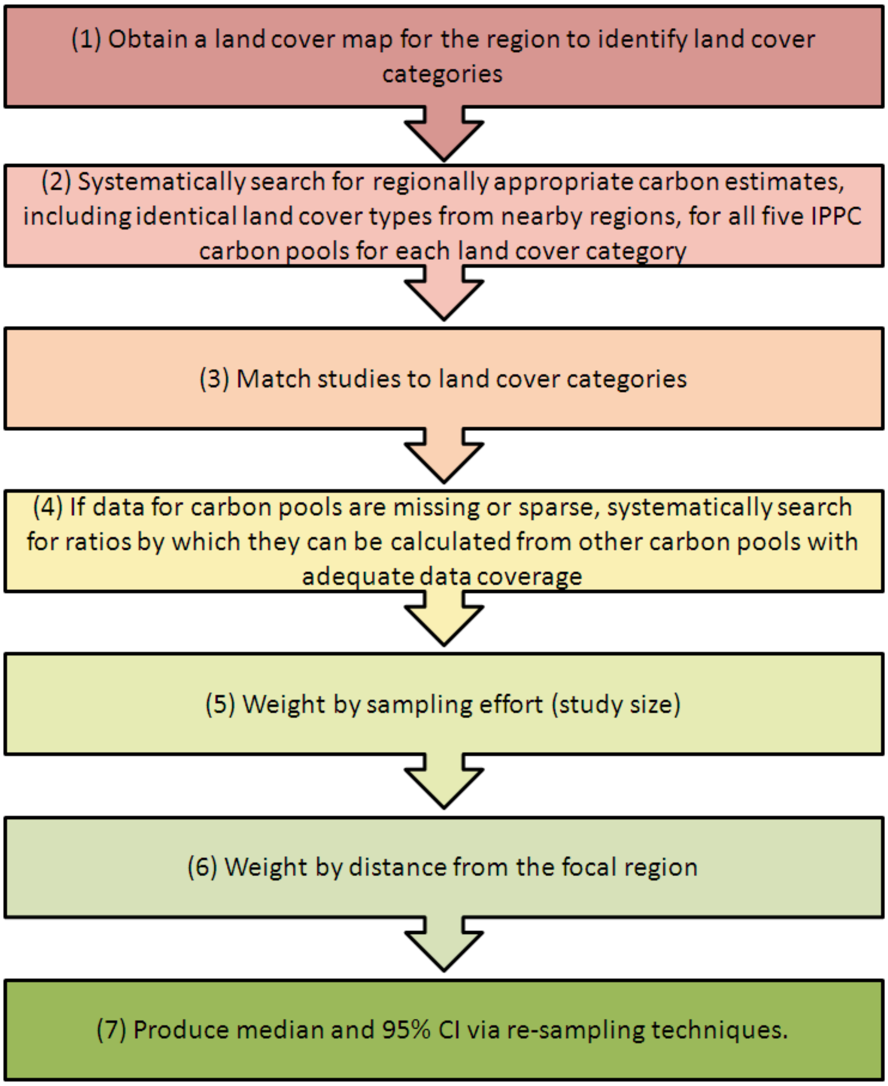


Figure 4.1 A summary of the seven stage method utilised here to produce regionally appropriate carbon estimates and 95% CI.

4.5 Methodology and Methods

4.5.1 Methodology

The method follows seven stages (Figure 4.1), summarised here and described in detail below: (1) Obtain a land cover map for the region to identify land cover categories; (2) Systematically search for regionally appropriate carbon estimates, including identical land cover types from nearby regions, for all five IPCC carbon pools for each land cover category; (3) Match studies to land cover categories; (4) If data for carbon pools are missing or sparse, then systematically search for ratios by which they can be calculated from other carbon pools with adequate data coverage; (5) Weight by sampling effort (study size); (6) Weight by distance from the focal region; (7) Produce median and 95% confidence intervals (CI) using re-sampling techniques.

4.5.1.1 Conceptual Framework for Selecting Substitute Carbon Density Values

The seven-stage method involves weighting by sampled area, as well as by the distance of the sampled area from the site of interest. Confidence in biomass estimation increases with the number of hectares surveyed and thus studies that sampled a larger area should be favoured. However, due to the law of diminishing returns, this relationship is non-linear, i.e. as sampled area increases, the reduction in uncertainty resulting from further increases in sampling area decreases. Empirical evidence suggests that uncertainties in changes of AGB are well described by a square-root of plot area (Houghton et al., 2001, Clark and Clark, 2000, Lewis et al., 2009b). Additionally, I theorise that, due to biogeographic differences, estimates derived from sampled areas near to the study area will better represent the true values found in the study area than those estimates derived from a more distant site. This is likely due to a decreasing likelihood of shared species and/or processes with increasing geographic separation, although some similarities may remain (Prance, 1994, Gentry, 1988). Empirical evidence also supports this assumption, suggesting similarities between forests follow a non-linear distance decay function (Phillips et al., 2003). Thus, weighting against distant studies will likely maximise the local representativeness of the estimates made for the study area, decreasing uncertainty. It is for similar reasons that Tier 2 and 3 type studies are preferred to those using Tier 1 methods (GOFC-GOLD, 2010). It is likely that, as distance from the area of interest increases, the reduction in representativeness resulting from further increases in distance decreases. Thus, a square-root function may adequately function to represent this.

4.5.2 Study Area

My study area is the watershed of the EAM in Tanzania, covering 33.9 million hectares (Figure 1.4; see pages 46-48 and Swetnam et al. (2011) for further details). The EAM themselves (5.2 million ha, as delimited Platts et al. (2011)) are nested within the broader study area and are considered a global priority for biodiversity conservation (Myers et al., 2000), with high levels of plant and animal endemism (including at least 96 vertebrate species and 471 vascular plant species) (Lovett, 1990, Burgess et al., 2007, Platts et al., in press). The watershed is a heterogeneous mix of cropland, savanna, miombo woodland and forest, and contains the administrative and commercial capitals of Dodoma and Dar es Salaam, respectively. The region provides numerous ecosystem services including carbon storage, water provision and regulation, maintenance of soil quality, reduction of erosion, regulation of run-off, stabilisation of local climate, conservation of cultural values (including traditional medicine), hydroelectricity generation and nutrient cycling (Economic Research Bureau, 2006, FORCONSULT, 2005, Pfliegner and Burgess, 2005, Marshall, 1998). As a United Nations REDD+ pilot country (Burgess et al., 2010), a better understanding of the current carbon stock and distribution in Tanzania will likely inform policy choices.

4.5.3 Data

4.5.3.1 Land cover map

I obtained a land cover map of 1ha resolution, derived from a 1995 survey of LANDSAT and SPOT images undertaken for the Tanzanian government (HTSL, 1997), with validation by local experts to ensure the map was applicable for the year 2000 (Swetnam et al., 2011). This map (and all other land cover maps used in this chapter) has been previously described and evaluated in Chapter 3. The map recognised 30 land cover classes, termed hereafter ‘original land cover categories’. Since globally available land cover products (e.g. GlobCover, MODIS etc.) typically describe fewer and/or different land cover categories, I investigated the effect an alternative

Table 4.3 Tier 2 carbon values for all five IPCC carbon pools using the harmonised land cover categories. Confidence limits, percent error and sample size (n) are shown in brackets. Confidence intervals were calculated via sampling with replacement (see text for details). Original land cover categories estimates are shown in App. 3.4.

Description	Area (M ha)	Aboveground live (Mg ha^{-1})	Litter (Mg ha^{-1})	Coarse woody debris (Mg ha^{-1})	Belowground live (Mg ha^{-1})	Soil (Mg ha^{-1})	TOTAL (Mg ha^{-1})	References
Forest	0.96	221.9 (209.1-236.5; 8.7%; n = 1703)	10.9 (10.3-11.6; 8.6%)	13.1 (12.3-13.9; 8.7%)	54.2 (51.1-57.8; 8.7%)	116.8 (113.7-119.9; 3.7%)	416.9 (396.5-439.6; 7.3%)	(Chamshama and Philip, 1980, de Boer, 2000, Glenday, 2006, Glenday, 2008, Kairo et al., 2008, Kaonga, 2005, Kraenzel et al., 2002, Lewis et al., 2009b, Michelsen et al., 2004, Munishi and Shear, 2004, Nunifu, 1997, Schroeder, 1994, Slim et al., 1996, Steinke et al., 1995, Twilley et al., 1992, Unruh J.D. et al., 1993, Wauters et al., 2008, Zahabu, 2006a, Batjes, 2004) & unpublished data
Savanna spectrum	26.02	28.6 (19.8-43.9; 61.5%; n = 185)	3.0 (2.0-4.7; 65.5%)	5.1 (3.5-7.9; 62.5%)	9.1 (6.4-13.8; 59.4%)	116.2 (112.6-120.2; 4.6%)	162.1 (144.4-190.5; 20.6%)	(Deshmukh, 1986, Ek, 1994, Glenday, 2008, Hartemink, 2004, Jones MB and Muthuri FM, 1997, Lal, 2005, Lioubimtseva et al., 1998, Manlay et al., 2002, Mills et al., 2005, Michelsen et al., 2004, Prentice, 2001, Rutherford, 1993, Saunders et al., 2007, Scholes and Walker, 1993, Stromgaard, 1985, Tothill and Mott, 1985, Woomer, 1993, Zahabu, 2006b, Batjes, 2004) & unpublished data
Crop	6.69	3.3 (1.9-5.8; 86.3%; n= 14)	0.1 (0.1-0.2; 83.0%)	0.3 (0.2-0.5; 85.8%)	0.9 (0.5-1.6; 86.2%)	123.3 (118.8-128.1; 5.3%)	127.9 (121.5-136.1; 8.2%)	(Lal et al., 2001, Kamau et al., 2008, Prentice, 2001, Schroth and Zech, 1995, Stoorvogel et al., 1993, Batjes, 2004)
Other	0.19	2.0 (2.0-4.9; 148.9%; n = 6)	0.6 (0.6-1.6; 151.5%)	0.8 (0.8-1.9; 148.9%)	0.0 (0.0-0.0; 0.0%)	97.2 (92.5-102.3; 7.1%)	100.6 (95.9-110.7; 11.0%)	(Lioubimtseva et al., 1998, Prentice, 2001, Batjes, 2004) & unpublished data

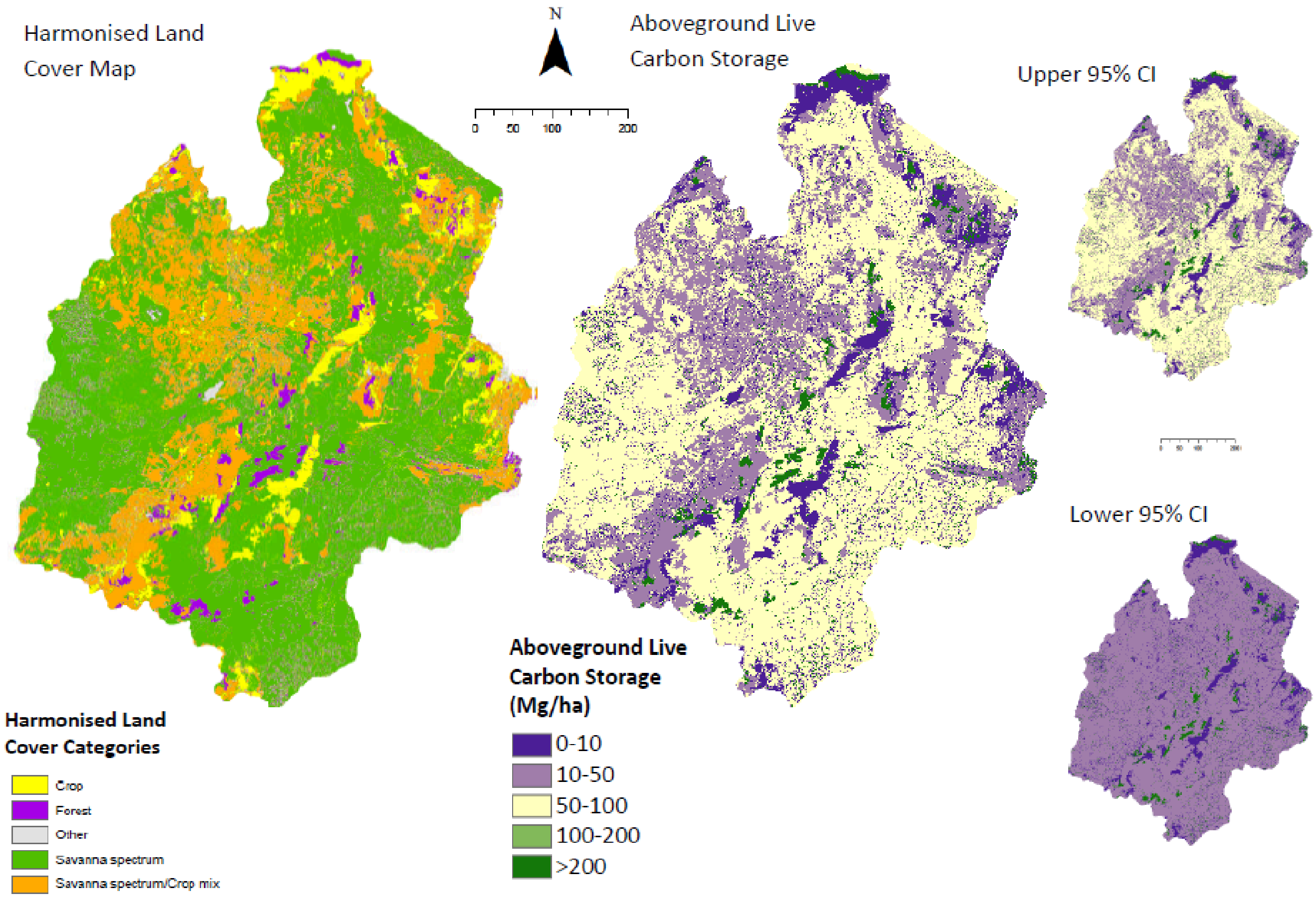


Figure 4.2 The spatial distribution of aboveground live carbon storage and associated pixel errors within the study area, based on combining the harmonised land cover map with my regionally appropriate carbon values (Table 4.3). Maps derived from the original land cover categories are shown in App. 3.1.

categorisation had on the resulting carbon estimates. I therefore reclassified regional land cover according to four major categories that all land-cover schemes conform to, termed hereafter 'harmonised land cover categories'. I opted to use the same harmonised land cover categories as previously used in Chapter 3. These are: forest (high carbon density tree-dominated systems, including montane forest, coastal forest, mangroves and tree plantations), savanna spectrum (medium carbon density mixed tree and grass systems, including miombo woodland, savanna, bushland and grassland), crop (anthropogenic arable systems) and other (largely dominated by low carbon systems, such as semi-desert and snow) (Figure 4.2, App. 3.1, App. 3.2). Any mixed crop system category (grassland with scattered cropland or bushland and woodland equivalents) was split equally between crop and savanna-spectrum categories.

4.5.3.2 Published Carbon Data

Through a literature search, I obtained 62 published papers for use in this study (Table 4.3, App. 3.3, App. 3.4). These papers were independent studies, published by 55 different lead authors in 53 separate peer-reviewed journals. The publications span two decades, from 1985 until 2009, and provide data from 49 different land cover categories, from more than 27 countries and from all five IPCC carbon pools. The data were collected using repeatable scientific methods and the quality of the analyses had been approved by the peer-review process. As a result, I concluded that all the published data collated during the literature search were of high quality and included in the study.

4.5.3.3 Unpublished Carbon Data

The unpublished data used in this study was obtained from the York Institute for Tropical Ecosystems (KITE) database, collated by Dr Antje Ahrends. The KITE database is a large collaborative collection, predominantly made up for plots created by Frontier Tanzania (1,164), Dr Andrew Marshall (648), Prof Jon Lovett (375), and Dr Antje Ahrends (30). Frontier Tanzania created permanent sample plots of 50m by 20m every 450m along transects placed 900m apart (Frontier-Tanzania, 2005). The diameter and species of every woody stem with a DBH over 10cm whose base fell within the designated plot area was recorded. For those stems whose base was bisected by the plot boundary, the data were recorded if more than half of the base lay within the plot. Height of the stem was recorded using a clinometer (whereby the angle to the top of the tree canopy was measured in accordance with

Chave (2005) and the height calculated using trigonometry) for a random subsample of stems (approximately 10 from each of the following size classes: 10-20cm, 20-30cm, 30-40cm and >40cm) (Frontier-Tanzania, 2005). These plots were measured by volunteers (mainly from the UK) supported by local botanists from the Tanzanian Forestry Research Institute (TAFORI) and experienced fieldwork coordinators. Dr Marshall and Dr Ahrends utilised the Frontier methodology when establishing a further 648 and 30 permanent sample plots respectively. The remainder of the plots were established by Prof Jon Lovett (375 plots) and Mr Roy Gereau (85 plots). Prof Lovett established 113 plots of 100m by 25m, recording the DBH, height and species of all woody stems over a 3cm DBH threshold (Lovett et al., 2006). Of these stems, only those over 10cm DBH were included in the KITE dataset. The remainder of the plots established by Prof Lovett (262 plots), and those established by Mr Gereau were done using the 20-tree variable-area plotless technique (Hall, 1991). The nearest 20 trees of over 20cm DBH to an objectively chosen point were identified and DBH was recorded (Lovett, 1996, Lovett, 1999). Distance to the 21^{st} most distance tree was also recorded and half this distance can be considered to be the plot radius (Lovett, 1996, Lovett, 1999). However, this is a crude estimate and so I did not include these 347 plots in my analyses.

Excluding the variable area plots, the unpublished data are deemed of high quality, with many of the principal data collectors regularly publishing in peer-reviewed journals. Biomass estimates resulting from small plots are known to suffer from a left-hand skew, leading to high uncertainties (Chave et al., 2003). However, as the number of plots increases, the confidence also increases (Chave et al., 2003). Thus, results obtained from the extensive network of small plots used here are likely robust.

4.5.4 Methods

4.5.4.1 Seven-Stage Survey Method

4.5.4.1.1 Matching Regional Data to Land Cover Classes

Data from the literature were obtained by systematically entering search terms into Google Scholar, JSTOR and ISI Web of Knowledge search engines. The search terms combined the 34 (original and harmonised) land cover category and carbon pool names (above ground, CWD, litter, root, belowground, soil, biomass, carbon, yield) plus geographical terms (Eastern Arc Mountains [EAM], Tanzania, East Africa, Africa). The bibliographies of all the sources I used for carbon data were checked for additional relevant references and data. To be included, carbon storage or biomass estimates must be reported, with studies excluded if the land use type was absent from my study site (e.g. temperate grasslands). For some agricultural land covers, yield data were more widely available and these were converted to standing crop biomass using published equations (Smidansky et al., 2003, Cadavid et al., 1998, Mshandete et al., 2008), the exception being sugarcane, where almost the entire crop is utilised (so annual yield was assumed to be equal to the AGB). In total, 45 published papers fulfilled the search criteria (Table 4.3, App. 3.3, App. 3.4).

These published data were supplemented with unpublished data. Local and international agencies working in the EAM region were contacted and written memoranda of understanding were agreed (outlining the investigations to be undertaken and the data sharing procedure), enabling a total of 2,462 tree inventory plots to be sourced.

Aboveground live tree biomass (≥10cm diameter) was estimated using an allometric equation for woodland (‘dry forest’) and forest (‘moist forest’) which uses estimates of diameter, wood density (from a global database (Zanne et al., 2009) matched to stems using standard taxon-based procedures (Baker et al., 2004b)) and tree height (using a height:diameter relationship from African forest (Lewis et al., 2009b)) to determine dry mass (Chave et al., 2005). The carbon content of vegetation varies relatively little across a wide variety of plant and tissue types (Schlesinger, 1991, Martin and Thomas, 2011). As such, carbon was assumed to be 50% of dry biomass, consistent with other studies conducted in Africa (Lewis et al., 2009b). Additionally, it was assumed that the carbon values reported in published and unpublished studies were representative of the appropriate land cover category regardless of the date of measurement within the year.

Each data point was assigned to the appropriate land cover category by matching the site description in the carbon data with the land cover categories present in this study (Table 4.3, App. 3.4). After this process, it was evident that most studies (91.8%) considered ALC storage only. This resulted in 63.3%, 36.7% and 30.0% of land cover categories containing more than five data points for aboveground live, belowground and soil carbon pools respectively.

4.5.4.1.2 Finding Substitute Data

Hence, despite a wealth of aboveground live inventory data for forest land cover categories, there are very few data for many land cover types in my study area (Table 4.3, App. 3.4). Furthermore, of the studies reporting ALC storage, most (90.8%) reported only the *measured* ALC storage (for example, the carbon stored in trees with a diameter over 10cm). In order to estimate the total ALC value for these studies, it is necessary to estimate the unmeasured aboveground live component. Thus, I undertook a second systematic literature search (in the same manner) to locate the ratios between ALC storage and the other pools (including unmeasured ALC but excluding soil carbon, which does not scale with aboveground carbon). Measured and unmeasured aboveground carbon pools were combined additively to give the traditional IPCC ALC pool.

I obtained soil carbon values from the Southern Africa SOTER database (Batjes, 2004, ISRIC, 2010). SOTER was chosen because it is freely available and contains regionally obtained data to a standard depth of 1m. Values from the literature were also available (Hartemink, 1997, Rossi et al., 2009, Glenday, 2006), but the varying depths of each study made comparisons difficult. SOTER data were extracted by spatially matching the soil characteristics with the original and harmonised land cover categories of my land cover map. This procedure was followed for all vegetation types except for permanent swamp, because the SOTER database did not contain any appropriate regional cores and so a locally derived value of 683 Mg C ha^{-1} was used (Jones MB and Muthuri FM, 1997).

In order to combine the carbon estimates from individual studies into a single value for each land cover category, each carbon value was weighted by the square root of the sum of number of hectares surveyed, ensuring that larger, studies contribute more to a final best estimate carbon value. Studies were weighted by sampling effort because confidence in biomass estimation increases with the number of hectares surveyed (Houghton et al., 2001, Clark and Clark, 2000). If information on the study area was unavailable then I assumed the study had the same sample size as the median of those studies from the same land cover type. When fewer than five studies with sample sizes were available, the study size was assumed to be one hectare (this assumption was required for the mangrove, savanna, wetland and 'other vegetation' types).

Mean carbon storage for each land cover class was further weighted by the distances of individual carbon estimates from my study area. I first defined a hierarchy of four non-overlapping regions: my study area, outside my study area but within East Africa, elsewhere in Africa, and elsewhere in the world. Second, I took a square root weighting approach to the four regions. I took the square root of the weighting given to an area at the higher level in the hierarchy of regions, i.e. a carbon storage value from East Africa but from outside my study region was given the square root of the weighting of a study inside my study region. Then carbon storage value from outside East Africa, but inside Africa was given the square root of the weighting given to a value from inside East Africa, but outside my study region. Finally, a study from outside Africa was assigned the square root of the weighting of a study from Africa, but outside East Africa. The relative weightings are therefore 256:16:4:2 for plots within the four areas and thus plots within my study area are weighted much more heavily than those studies from further afield. This technique also ensures that data from outside the region are not completely ignored, which is helpful as some land cover classes have few or no regional data. For ALC storage values, 24 of the 34 land cover categories had less than five sample specific to my site. This reduced to 16, 13 and 11 land cover types respectively as data from the other regions were added. Hence, using all data in this way allowed carbon values and 95% CI to be obtained for all land cover types. These regional and previously described study size weightings were combined multiplicatively.

Derivation of carbon estimates occurred in two stages: (1) the production of carbon estimates and associated confidence intervals for each land cover type, and (2) the application of these values to my land cover map to produce landscape scale estimates of carbon storage. Firstly, the carbon value inputs into each land cover were sampled with replacement 10,000 times to produce the median weighted carbon value and 95% confidence limits (using R 2.12.1 (R Development Core Team, 2010)). These were mapped at a one hectare resolution in ArcGIS v9.3.1 (ESRI, 1999-2009) (Figure 4.2, App. 3.1). Secondly, estimates of total landscape carbon storage were made by allocating each pixel in the map a randomly selected value within the appropriate pixel 95% CI. This process was performed 10,000 times and the median landscape carbon storage value and 95% CI were obtained.

4.5.4.2 Carbon Flux Estimation Method

The above method was repeated for three historical land use maps dated 1908, 1923 and 1949 (Chapter 3; (Engler, 1908-10, Shantz and Marbut, 1923, Gillman, 1949)). In Chapter 3, these maps were harmonised, thus, using my seven-stage method, the carbon storage values for all five IPCC carbon pools (total aboveground live, CWD, litter, belowground and soil) were estimated for each of the original and harmonised land cover categories (App. 3.3; App. 3.5; App. 3.6; App. 3.7; see Chapter 2 for full details). The LCC inferred from these historical maps and my 2000 land cover map (described in Chapter 3) could then be associated with a concomitant carbon flux. This was done by subtracting the estimated carbon storage across the landscape in one land cover map from the estimates derived from the previous map in the time series. Here, my definition of committed carbon emissions should again be emphasised. Whilst there is likely a lag between LCC and the resultant carbon flux, data on the half-lives (or mean residence time) of each carbon pool are both wide ranging and highly uncertain (Fearnside, 2005, Harrison et al., 1997, Trumbore et al., 1996). I elect not to estimate the half-lives of the respective carbon pools within my study for two main reasons. Firstly, the addition of this temporal uncertainty may disrupt the simplicity of my seven-stage method, somewhat decoupling carbon emissions from the LCC events and hindering the ability of decision makers to comprehend the results. Although it is possible within this study to indicate historic carbon emissions as a result of LCC, the exact date of the LCC event is unknown. For example, any LCC observed from the historical maps dated 1949 and 2000 (see Chapter 3) could have occurred at any time during that 51 year period and cannot be accurately attributed to a single time point. Secondly, data on the half-life of carbon pools are deficient within my study area, within east Africa, and even within Africa as a whole (Gaston et al., 1998). Thus, in order to estimate the delay in carbon emissions, I would have to rely mostly on Tier 1 estimates of the rates of change of the carbon stock. Hence, calculating the lag in carbon emissions using Tier 2 mean residence times after known LCC events is beyond the scope of this study.

4.6 Results

4.6.1 Carbon Stocks Using the Seven-Stage Survey Method

4.6.1.1 Original Land Cover Categories

Best estimate carbon values from my methodology are given in Table 4.3 and App. 3.4. Using my approach, sub-montane forest is calculated to contain the most ALC per unit area (283 [252-329] Mg ha^{-1}), followed by montane forest (228 [190-286] Mg ha^{-1}), lowland forest (207 [195-220] Mg ha^{-1}), upper montane forest (202 [73-332] Mg ha^{-1}) and forest mosaic (187 [174-201] Mg ha^{-1}) (App. 3.4). This pattern was consistent when all carbon pools were combined, except that permanent swamp became the most carbon-dense land cover due to its large pool of soil carbon.

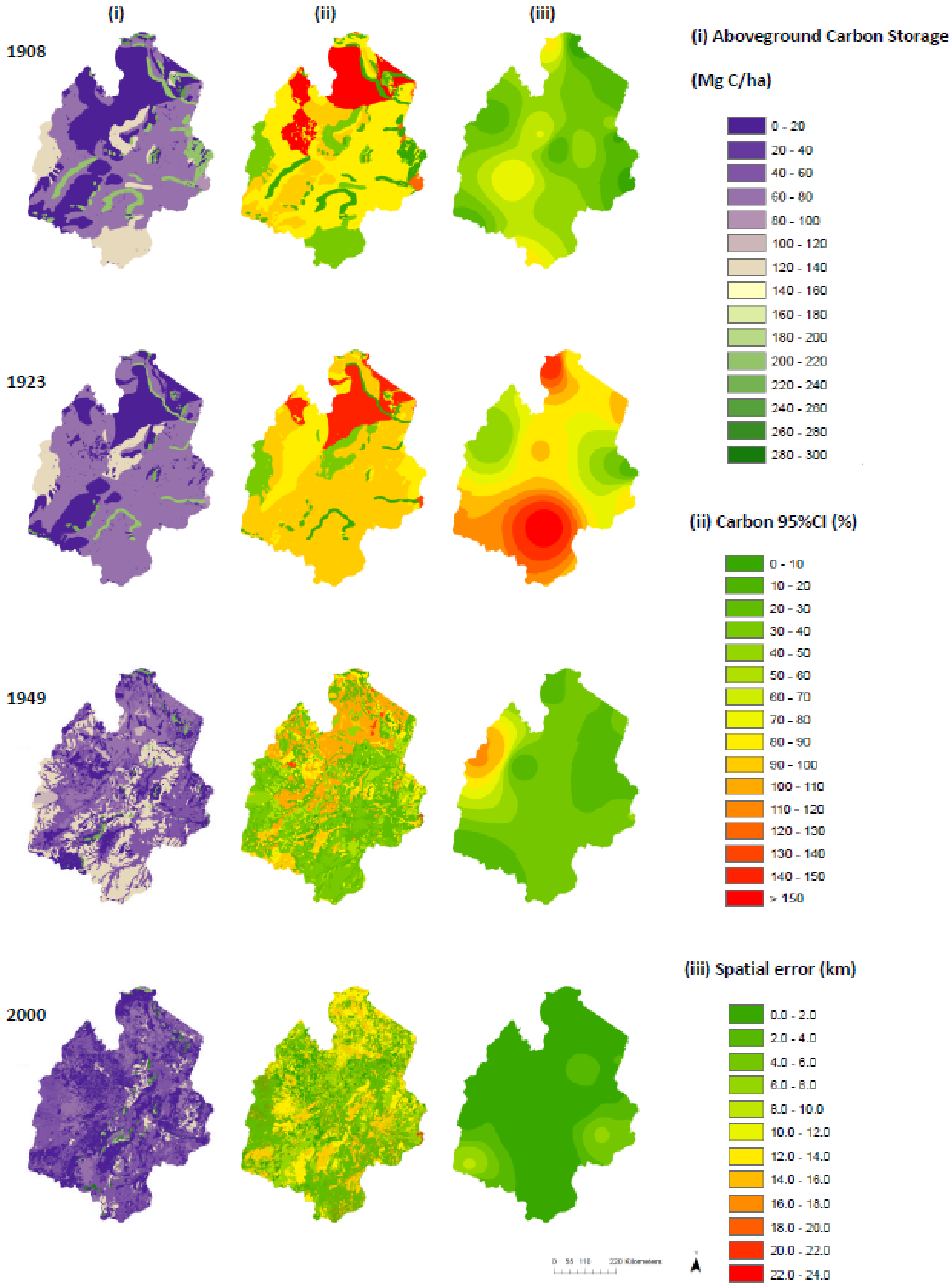


Figure 4.3 The spatial distribution of (i) aboveground carbon storage, (ii) the 95% confidence intervals, based on regionally appropriate values and (iii) spatial errors within the watershed for the years 1908, 1923, 1949 and 2000.

For the 30 original land cover categories, the ALC pool had a mean percentage error of 44±15%. Some land cover categories have high levels of uncertainty for total carbon values (most notably mangroves [±103%], sugar cane [±70%] and upper montane forest [±68%]), and some showed lower uncertainty (permanent swamp [±7%], bushland with scattered cropland [±9%] and lowland forest [±10%]) (Figure 4.3, Table 4.3, App. 3.8, App. 3.4).

Assigning the carbon values to the land cover map indicates that 1.58 (1.56-1.60) Pg C was stored in the aboveground live vegetation in the year 2000 in the study region using the original land cover categories (Figure 4.2; Table 4.1). Woodland and bushland contributed most to the total stored ALC in the study region. Specifically, open woodland stored the most ALC (0.54 [0.45-0.65] Pg C over 9.6 million ha); followed by bushland (0.32 [0.16-0.55] Pg C over 5.0 million ha) and closed woodland (0.23 [0.15-0.28] Pg C over 1.8 million ha). However, when all carbon pools are considered the total carbon storage across the Eastern Arc drainage basin is 6.33 (5.92-6.74) Pg C (Table 4.1). Considering the 30 original land cover classes, and all five carbon pools combined, the land cover were still dominated by open woodland (1.89 [1.67-2.12] Pg C) and bushland (1.07 [0.75-1.52] Pg C); now followed by grassland (0.79 [0.54-0.84] Pg C over 5.2 million ha).

4.6.1.2 Harmonised Land Cover Categories

Using harmonised land cover categories, I estimate that forests contain the most ALC per unit area (221.9 [209-237] Mg ha^{-1}), followed by much smaller values for savanna (28.6 [19-44] Mg ha^{-1}) and cropland (3.3 [1-6] Mg ha^{-1}) (App. 3.4). This pattern was also consistent when all carbon pools were combined. The mean percentage error was 63±9%, higher than that for the original land cover categories (44±15%) as a result of the smaller number of broader categories.

Within forest, the ALC pool was the largest pool, representing 53% of the total carbon stored in this ecosystem. Soil and belowground carbon pools were also substantial in forest ecosystems, containing 28% and 13% of total carbon stored respectively (Table 4.3). In savanna ecosystems, the soil carbon pool was most substantial, representing 72% of the total carbon stored. Crop and ‘other vegetation’ ecosystems store over 96% of their total carbon within the soil (Table 4.3).

Assigning the carbon values to the land cover map indicates that 1.64 (1.52-1.76) Pg C was stored in the aboveground live vegetation in the year 2000 in the study region using the harmonised land cover categories (Figure 4.2; Table 4.2). Savanna contributed most to the total stored ALC in the study region (0.74 [0.51-1.15] Pg C over 26.0 million ha); followed by forest (0.21 [0.20-0.23] Pg C over 0.96 million ha) and cropland (0.02 [0.01-0.04] Pg C over 6.7 million ha). However, when all carbon pools are considered the total carbon storage across the Eastern Arc drainage basin is 6.38 (6.33-6.43) Pg C for the harmonised land cover categories (Table 4.2). Considering the four harmonised land cover classes, and all five carbon pools combined, the land cover were still dominated by savanna (4.21 [3.76-4.96] Pg C) and forest (0.40 [0.38-0.42] Pg C).

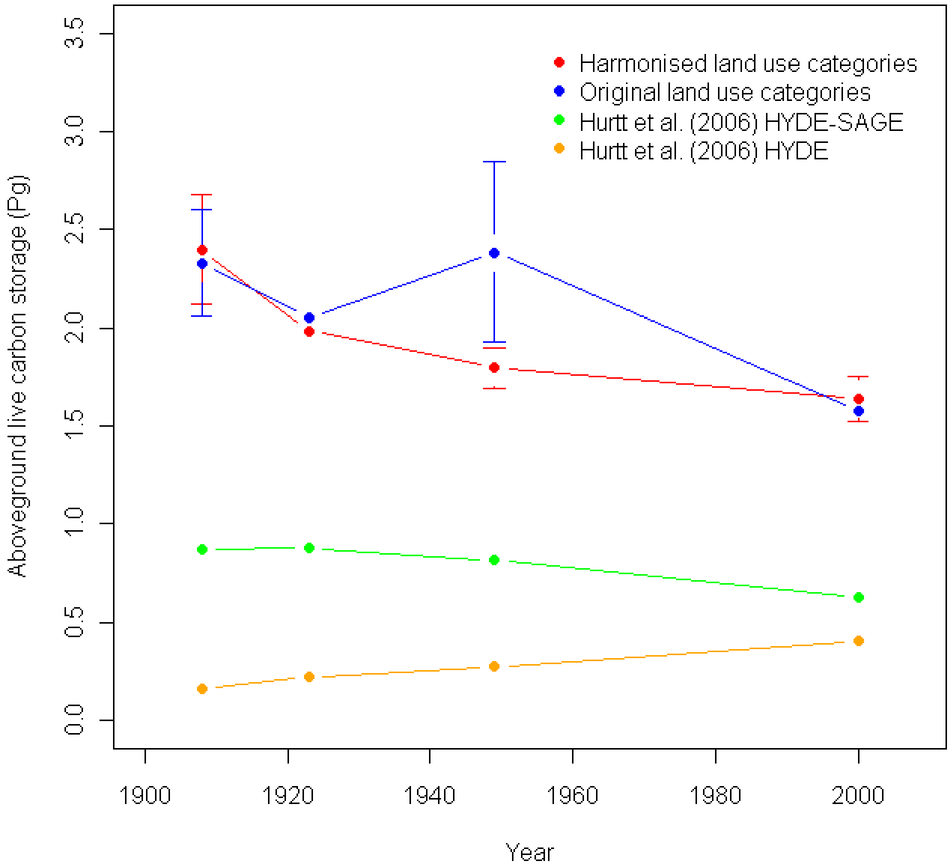


Figure 4.4 The change in aboveground live carbon storage (±95% CI) within the Eastern Arc Mountain watershed during the 20th century.

4.6.2 Carbon Fluxes 1908-2000

The total carbon impact of the LCC across the entire watershed represented a committed net source of 0.94 (0.37-1.50) Pg C when comparing year 2000 carbon storage with that in 1908 for all five carbon pools combined (Figure 4.4; Table 4.4; 1.01 [0.86-1.16] Pg C using harmonised categories). This figure is dominated by the ALC pool which showed a net source of 0.75

Table 4.4 Carbon storage in the Eastern Arc Mountain watershed over time for all five IPPC carbon pools, shown for original land use categories and harmonised land use categories (the latter in bold).

Year	Aboveground carbon storage, Pg (95% CI)	Litter carbon storage, Pg (95% CI)	Coarse woody debris carbon storage, Pg (95% CI)	Belowground carbon storage, Pg (95% CI)	Soil carbon storage, Pg (95% CI)	Total carbon storage, Pg (95% CI)
1908	2.33 (2.06-2.60) **2.40 (2.12-2.68)**	0.24 (0.21-0.27) **0.21 (0.19-0.23)**	0.36 (0.32-0.40) **0.34 (0.30-0.38)**	0.78 (0.69-0.87) **0.71 (0.63-0.80)**	3.56 (3.50-3.62) **3.74 (3.71-3.77)**	7.27 (7.12-7.42) **7.39 (7.29-7.49)**
1923	2.05 (2.04-2.06) **1.99 (1.98-2.00)**	0.20 (0.19-0.20) **0.20 (0.19-0.20)**	0.34 (0.33-0.34) **0.33 (0.32-0.33)**	0.71 (0.70-0.71) **0.61 (0.60-0.62)**	3.59 (3.58-3.59) **3.73 (3.72-3.73)**	6.89 (6.88-6.90) **6.86 (6.85-6.86)**
1949	2.38 (1.92-2.84)* **1.80 (1.70-1.90)**	0.24 (0.19-0.29)* **0.18 (0.17-0.19)**	0.41 (0.33-0.49)* **0.31 (0.29-0.32)**	0.81 (0.65-0.97)* **0.56 (0.53-0.59)**	3.78 (3.48-4.06)* **3.74 (3.65-3.83)**	7.62 (6.40-8.86)* **6.60 (6.28-6.92)**
2000	1.58 (1.56-1.60) **1.64 (1.52-1.76)**	0.15 (0.14-0.15) **0.16 (0.15-0.17)**	0.25 (0.24-0.25) **0.28 (0.26-0.30)**	0.60 (0.59-0.61) **0.51 (0.47-0.55)**	3.74 (3.43-4.05) **3.80 (3.78-3.82)**	6.33 (5.92-6.74) **6.38 (6.33-6.43)**

*Carbon storage estimated from the 1949 original map legend is anomalously high due to the misclassification of the woodland category.

(0.45-1.04) Pg C using the original land use categories (Figure 4.4; 0.76 [0.36-1.16] Pg C using harmonised categories). The soil carbon pool was estimated to have not changed considerably, and not be significantly different from zero, showing a committed uptake of 0.18 (-0.55 to 0.19) Pg C using original categories, and 0.05 (0.01 to 0.11) Pg C using harmonised categories.

The impact of legal protection of land (Chapter 3) is reflected in estimated carbon fluxes. Between 1949 and 2000, protected areas are estimated to have a net carbon uptake of 4.77 (3.84-5.70) Mg C ha^{-1} as forest expands, while there is an estimated net carbon release of 11.89 (7.21-16.57) Mg C ha^{-1} from unprotected areas as forest and savanna are converted to croplands.

4.7 Discussion

4.7.1 Seven-Stage Survey Method

Climate change mitigation schemes such as REDD+ need reliable, low-cost and repeatable estimates of carbon storage, ideally based on existing data. My results suggest that the easiest and most commonly used approach of using global carbon storage values (Tier 1) can potentially result in large errors (generally, underestimation of carbon stocks by 26-78% in my study area). This poor performance is aggravated by the fact that uncertainty is seldom quantified for such values. The method I presented is cost and time efficient, while compliant with Tier 2 standards. Using it I estimate the ALC storage for the study area in the year 2000 is 1.58 (1.56-1.60) Pg C for the original land cover categories, considerably greater than most previous estimates which have a mean of 0.85 Pg C (Table 4.1) (Baccini et al., 2008, Hurtt et al., 2006). My study is in close agreement with the previous result of Ruesch and Gibbs (2008). The recent Baccini et al. (2012) carbon map is the only study to give a higher estimation than mine (Table 4.1). It is perhaps unsurprising that my estimates are close to those of Baccini et al. (2012), given that Tanzania was one of the multiple locations used to develop their regression models.

Here, I focussed on producing regionally appropriate carbon values for land cover types within my study area, whilst the studies I have compared my results to have attempted to map carbon over much larger scales. Thus, my estimates are regionally appropriate and error-bounded, fulfilling Tier 2 approach criteria. Hence, the possible underestimation of some previous models in comparison to this study may indicate that eastern Tanzania has higher carbon storage than generally thought. However, when carbon values for land cover categories in this study are compared to similar land cover types elsewhere, the values appear to be in broad agreement (Table 4.3, App. 3.4) (Lal, 2005, Prentice, 2001, Ruesch and Gibbs, 2008). The carbon values used by both Hurtt et al. (2006) and Baccini et al. (2008) are substantially lower for comparable land cover categories than those in this study and Ruesch and Gibbs (2008), suggesting that these two approximations of carbon storage may be systematically underestimated (Mitchard et al., 2011). Given the policy relevance of the carbon content of tropical vegetation, notably via REDD+, the possibility of such methodological errors should be an area of urgent further investigation. Further differences arise due to the higher resolution of this study (allowing for the identification of smaller fragments of forest, for example) which may have led to the substantial differences in the estimates of carbon storage within the highly heterogeneous landscape of my study area (Table 4.1). It should be noted that my study contains data from both pristine and disturbed habitats; however there is a bias towards undisturbed habitats. Although the landscape is known to include significant habitat degradation, preliminary investigations to produce a ‘Tier 3’ regression model (i.e. explicitly accounting for disturbance and climatic variation) using the same data still give landscape carbon storage estimates higher than most previous studies (see Chapter 5). To act as a sensitivity analysis, if the lower 95% CI limit for each land cover category was used, indicating that every location showed disturbance, I would estimate the study area contained 1.06 Pg and 1.20 Pg of ALC, using original and harmonised land cover categories respectively. These values are still substantially greater than those from most previous studies (Table 4.1). It is important that further work investigates the role of disturbance, edaphic and climatic variation as all three are known to affect carbon storage within my study area (Ahrends et al., 2010, Platts et al., 2011). This will be particularly important in estimating future carbon storage as east Africa is predicted to become both warmer and wetter, potentially increasing the landscape carbon storage (Doherty et al., 2009). However, this effect may be negated by the rising human population and associated demand on natural resources (NBS, 2006), which could lead to increased degradation and land cover change from high carbon systems to those with less carbon (for example, from savanna to agriculture [Table 4.3]).

Previous studies have only focussed on aboveground live and belowground live carbon pools (Hurtt et al., 2006, Ruesch and Gibbs, 2008, Baccini et al., 2008, Saatchi et al., 2011) and by selecting the relevant carbon pools I was able to make direct comparisons. My study is unique in providing estimates for all five IPCC carbon pools for eastern Tanzania. My results show that soil carbon makes up almost 60% of the total carbon stored, over double that represented by ALC, and so emphasise the importance of investigating all five IPCC carbon pools.

Typically, land cover types of lower carbon density are less well studied. For instance, research within Tanzania has typically focussed on forests, which hold the most AGB per unit area but, when all carbon pools are considered, permanent swamp - a poorly known land cover type - holds the most carbon per hectare. Furthermore, within my study region, other land cover categories span a greater area than forest. The systems storing the greatest amount of carbon, within my study region, are neither those land cover types that have the largest carbon store per unit area, nor the most extensive, but are those that are reasonably extensive with relatively high carbon storage per unit area. This result indicates that, on a landscape scale, carbon stored in woodland is extremely important. This ecosystem is currently highly utilised by the local population, resulting in rapid degradation (Shirima et al., 2011, Topp-Jørgensen et al., 2005).

4.7.2 Carbon Flux Estimation

Over the 92-year period the general trend was for high carbon-density vegetation to be replaced by vegetation of lower carbon-density (Chapter 3). This trend led to an estimated committed release of 0.94 (0.37-1.50) Pg C from all five carbon pools, driven by the rapidly growing human population and associated demand for agricultural land. These estimated fluxes are higher than previous comparable estimates over the same area and time-span (Hurtt et al., 2006). Hurtt et al. (2006) present two carbon model outputs (HYDE and HYDE-SAGE, depending on data used for cropland area). The HYDE-SAGE model, which uses cropland data of higher spatial resolution, also suggests that the watershed of the EAM was a substantial carbon source over the twentieth century (Figure 4.4). However, both the magnitude of the carbon storage and flux are underestimated. The HYDE model suggests that the study area has been a carbon sink, which is highly unlikely. Such global databases are less accurate in the tropics due to a lack of data and low resolution when compared to regional studies. Caution must be used before models like HYDE are used to provide LCC feedbacks in earth system models.

The impact of legal protection on LCC and carbon flux is perhaps surprising: protected status in forest reserves is mostly administrative, without patrols or guards, and so these areas are often referred to as ‘paper parks’ (Wyman and Stein, 2010, Lung and Schaab, 2010, Hayes, 2006). Yet, recovery of savanna and forests within the current protected area network meant that, between 1949 and 2000, protected areas showed an estimated committed net uptake of 4.77 (3.84-5.70) Mg C ha^{-1} (0.093 [0.075-0.111] Mg C ha yr^{-1}), while areas lacking legal protection were a carbon source during the same period (11.89 [7.21-16.57] Mg C ha^{-1}). This observation is supported in the literature (Scharlemann et al., 2010) despite the very weak protection such status is thought to afford. Intriguingly, this result indicates that with appropriate incentives, schemes such as REDD+ may lead to altered management regimes and dramatically reduced carbon losses from landscapes.

4.7.3 Study Limitations

4.7.3.1 Seven-Stage Survey Method

Overall, while there are high uncertainties in 1 ha pixel-size estimates, there are narrow confidence intervals around my landscape estimates. This is typical of studies where estimates of error are provided (see Saatchi et al. (2011) for an example) and is a result of both the large study area and the small pixel size. When averaged across a large number of pixels, random pixel error is mostly negated as underestimates in one part of the landscape are counterbalanced by overestimates in other parts. These estimates, however, may give a false sense of confidence if sources of error were directional, for example if sampling was biased towards undisturbed habitats. Thus, my weighting system has potential to introduce some bias, particularly the regional weightings which are somewhat arbitrary as (1) my four regions are not unambiguously clearly defined units and (2) my square-root of approximate distance weightings are a first-order estimate. However, both on a pixel and a landscape level, sensitivity analyses indicated that unweighted results do not alter my overall conclusions (App. 3.9).

Several land cover categories show a disproportionally high level of error, indicative of both high natural carbon storage heterogeneity and low levels of sampling (Table 4.3, App. 3.4). Indeed, some land cover types within my study are relatively data-poor. However, the dominant land cover types within my study site are better sampled and show smaller errors, thus my conclusions are likely robust to both natural heterogeneity and data scarcity in some land cover types (Table 4.3, App. 3.4, App. 3.8). The high natural variation observed in some well-sampled land cover categories illustrate that look-up table methods (Tiers 1 and 2) are oversimplified and hence disturbance and climate effects on carbon storage should be taken into account where data allow (Gibbs et al., 2007). Litter, CWD, and below ground carbon pools all show similar levels of error to above ground live carbon because they are all derived from the latter pool using published ratios. Within this study, soil carbon appears to have a low uncertainty, despite being known to be extremely heterogeneous (Sierra et al., 2007, Vågen et al., 2005), because of limited data availability. Only 54 soil cores were used to produce the SOTER map for Tanzania (Batjes, 2004, ISRIC, 2010), an average of less than two per land cover category. Hence, much like litter, CWD, and belowground carbon, soil carbon in Tanzania (as elsewhere) requires much further research to improve future carbon estimates.

4.7.3.2 Carbon Flux Estimation

Degradation within land use categories was not accounted for, despite being known to occur, which likely leads to a systematic underestimation of the carbon flux to the atmosphere (Ahrends et al., 2010, Lambin et al., 2003). Annually 0.21% of Africa's forests (0.39±0.19 million ha) is degraded (Lambin et al., 2003), and this may result in an increase in carbon emissions of 25-47% on top of that emitted as a result of deforestation (Asner et al., 2005, Asner et al., 2010). Additionally, several of the land cover terms, for example forest (Putz and Redford, 2010), change in definition over time. Forests were classified as areas of nearing 100% canopy closure in the early half of the century (Engler, 1908-10, Shantz and Marbut, 1923, Gillman, 1949) but much lower canopy covers were included within the forest category of the latest map (Swetnam et al., 2011). Hence, degradation has occurred within each land use category, but also the definitions of categories have changed over time, masking LCC. The scale of underestimations of carbon emissions in this study may have been partially or wholly offset by any CO_2 fertilisation effect, which was also not accounted for, potentially causing all land use categories to store more carbon over time (Norby et al., 2005, Hickler et al., 2008). African forest has shown an increase in carbon storage at a rate of 0.29% per year (Lewis et al., 2009b). Over the 92 year study period, the effective increase in carbon emissions due to degradation (~25%) may be negated by the increase in carbon storage over time (~27%), suggesting the results presented here may be an accurate representation of the carbon flux within the study area.

Soil carbon is the most uncertain of all the carbon pools studied. My data indicate that, for the full 33.9 million ha watershed over the 92-year period, soil carbon did not alter significantly. Soil carbon studies involve a great deal of uncertainty (García-Oliva and Masera, 2004) with LCC showing this pool to be both a source and a sink (Guo and Gifford, 2002, Don et al., 2011). Quantifying and better understanding soil carbon is a critical undertaking to reduce the uncertainty of carbon fluxes associated with LCC (Post and Kwon, 2000).

4.8 Conclusions

I have presented a method of producing error-bounded, carbon values that conforms to IPCC Tier 2 reporting requirements. By coupling land cover classifications with systematic data searches it is possible to produce more regionally appropriate values despite the conditions of sparse local data that exist for most of the tropics. This method yields estimates for all five IPCC carbon pools, at low cost, and in manner which can be continually updated and improved, incorporating new studies and inventory data as and when they become available. Such regional carbon storage estimates have the potential to affect regional conservation and research priorities. Using these estimates, it is evident that historic land cover change resulted in a major committed flux of carbon to the atmosphere of 0.94 (0.37-1.50) Pg (aboveground live, CWD, litter, belowground and soil carbon combined). Displaying uncertainties associated with these values transparently enables identification of critical areas of future research. Additionally, by more explicitly acknowledging natural variation and data scarcity, the method helps ensure that the uncertainties and limitations are conveyed to policy makers.

Chapter 5
Variables Influencing Carbon Storage and Sequestration Within the Eastern Arc Mountains of Tanzania, a Tropical Biodiversity Hotspot

5.1 Abstract

The carbon stored in vegetation varies across tropical landscapes due to a complex mix of climatic and edaphic variables, as well as direct human interventions such as deforestation and forest degradation. Mapping and monitoring this variation is essential if policy developments such as REDD+ (Reducing Emissions from Deforestation and Forest Degradation) are to be known to have succeeded or failed. I produce a Tier 3 map of carbon storage across the watershed of the Tanzanian Eastern Arc Mountains (33.9 million ha) using 1,611 forest inventory plots, and associated climate, soil and disturbance data. As expected, tropical forest stores more carbon per hectare (182 [95% CI: 152-360] Mg C ha^{-1}) than woody savannah (51 [38-165] Mg C ha^{-1}). However woody savannah is the largest aggregate carbon store , with 0.49 [0.47-1.60] Pg C over 9.6 million ha. I estimate that the whole landscape stores 1.32 (0.89-3.16) Pg C, at an average of 38.9 [26.2-93.2] Mg per hectare, similar to my Tier 2 estimates (Chapter 4). The most influential variables on carbon storage in the region are anthropogenic, with the variables with strongest impact being historical logging and local governance regime. Of the non-anthropogenic factors, a negative correlation with air temperature and a positive correlation with water availability dominate. High carbon storage is typically found far from the commercial capital, in locations with a low monthly temperature range, without a strong dry season, and in areas that have not suffered from historical logging and are under local control. The occurrence of fire was shown not to impact the spatial distribution of carbon storage, despite being an influential variable of plot-level wood specific gravity (a key component of carbon storage). Overall, the observed variation in ALC results primarily from differences in tree stand structure (particularly the proportion of larger stems) and in wood specific gravity, although these effects are not additive. As human activity is the most influential variable of carbon storage in the region, the results imply that policy interventions can retain carbon stored in vegetation and successfully slow or reverse carbon emissions. Using a smaller number of

inventory plots with two censuses (n=43) to assess changes in carbon storage, and applying the same mapping procedures, I found that due to recent droughts and disturbance carbon storage in the tree-dominated ecosystems has decreased, though not significantly, at a mean rate of 1.47 (95% CI: increase of 2.13 to decrease of 7.75) Mg C ha^{-1} yr^{-1} (c. 2% of the stocks of carbon per year). I include error maps of carbon storage and sequestration to provide the spatially relevant data on which to base decisions on land-use and protection which could greatly affect carbon storage regionally.

5.2 Introduction

Tropical forests are globally significant ecosystems; accounting for ~50% of global forest area (Malhi and Grace, 2000), storing ~45% of all carbon in terrestrial vegetation (IPCC, 2000), maintaining high biodiversity (Myers et al., 2000), and providing ecosystem services (such as timber, non-timber forest products (Timko et al., 2010), and climate change mitigation (Lewis et al., 2009b, Phillips et al., 1998)). However, within the last few decades, vast areas of tropical forests have been felled or degraded. For example, between 1990 and 1997, 5.8 ± 1.4 million hectares of humid tropical forest were converted each year and an additional 2.3 ± 0.7 million hectares of forest were visibly degraded (Achard et al., 2002). This process increased in the early 2000s, with an estimated 27.2 ± 1.7 million hectares of humid tropical forest (and 20.4 ± 3.2 million hectares of dry tropical forest) deforested between 2000 and 2005 (Hansen et al., 2010). The gradual and sustained reduction in forest quality and quantity has resulted in a substantial emissions of CO_2 (Putz et al., 2008b). Globally, deforestation and forest degradation accounted for 6-20% of anthropogenic GHG emissions in the 1990s and early 2000s (IPCC, 2007, van der Werf et al., 2009, Dixon R. K. et al., 1994). Tropical regions make a substantial contribution to this, emitting 0.69-1.52 Pg C yr^{-1} between 1990 and 1999 (Achard et al., 2002, DeFries et al., 2002, Houghton, 2008) and 0.68-1.47 Pg C yr^{-1} between 2000 and 2005 (Houghton, 2008, van der Werf et al., 2009, Hansen et al., 2008b). These processes also impact the future potential of forests to remove additional carbon from the atmosphere (Chave et al., 2008, Lewis et al., 2009b, Field et al., 1998).

Recently, attempts to mitigate increasing anthropogenic CO_2 emissions through reducing emissions from degradation and deforestation (REDD+; see Chapter 1 for a full description) have been instigated (UNDP, 2009).

The REDD+ programme is aimed at contributing to a reduction in greenhouse emissions whilst providing economic incentives for better management and protection of forests. This policy has been widely acclaimed as it is expected that the financial incentive will be enough to significantly reduce carbon emissions (Strassburg et al., 2009, Kindermann et al., 2008). Key issues for the successful implementation of REDD+ are the accuracy of monitoring systems, preventing leakage and establishing accurate historical baselines (see Chapter 1). Thus, the success of REDD+, in part, rests on robust scientific information on the magnitude and extent of carbon storage in tropical regions and how it changes over time.

The IPPC provide a three Tier system through which carbon stocks and emissions can be reported, each with a different level of methodological complexity and accuracy. Tier 1 is the most basic method, using global default values obtained from the IPCC literature (IPCC, 2006a, IPCC, 2003). The intermediate tier is termed Tier 2 and improves on Tier 1 by using country specific data. Tier 1 and 2 have been fully described and compared in Chapter 2 and Chapter 4, and so will not be described here. Tier 3 is the most rigorous approach, requiring the highest level of effort but returning the lower uncertainties. Tier 3 methods use local forest inventory data, focusing on the direct measurement of trees, repeated over a time series (IPCC, 2006a, IPCC, 2003, GOFC-GOLD, 2010).

The uncertainty surrounding estimates provided decreases progressively from Tier 1 to 3. For example, the relatively coarse Tier 2 approach is estimated to have an uncertainty of approximately ± 50% (GOFC-GOLD, 2010), although this has been reported to be as high as 90% in some locations (Asner et al., 2010). Although Tier 2 methods (Chapter 4) present a substantial advancement on Tier 1 methods, they may also involve large uncertainties. There are two main systematic errors that can increase uncertainties in carbon stock and emission estimates (GOFC-GOLD, 2010). The first, completeness, refers to the number of IPCC carbon pools that are to be included, with studies including all five pools (aboveground live, litter, CWD, belowground and soil carbon) being considered complete. The second source of systematic uncertainty, representativeness, derives from the fact that there is substantial natural variability in the carbon stored across landscapes, even within biomes in one particular country (Asner et al., 2010). Thus, for example, the AGB of a forest within a landscape may differ considerably from global default (Tier 1) values or even from country-specific (Tier 2) values. For example, in the Peruvian Amazon, data from the

Los Amigos Conservation Concession (Winrock International, 2006) was shown not to be representative of the forests nationally. Nearby forests situated to the north and south of this local study are estimated to contain 20-35% less carbon per unit area (Asner et al., 2011), suggesting that Los Amigos Conservation Concession is an area of locally high biomass. Since Tier 3 methods better represent the natural variation observed within and between biomes, the representativeness of the carbon estimates is higher and the uncertainties associated with these methods are lower than those associated with Tier 1 and 2 methodologies (Asner et al., 2011, Cláudia Dias et al., 2009).

Due to the reduced uncertainties involved, Tier 3 is the level to which countries should aspire (Gibbs et al., 2007, IPCC, 2006a). However, Tier 3 methods are more expensive (Pedroni et al., 2009, Hardcastle et al., 2008) and many LEDC lack the capacity to follow such methods (Romijn et al., 2012). In fact, several Annex 1 countries, with vastly more resources at their disposal, struggle to conform to the stringent Tier 3 guidelines (Monni et al., 2007, Ramírez et al., 2008). Whilst, in some cases, the capability to follow Tier 3 guidelines can be rapidly developed, many LEDC lack multi-temporal inventory data and data on historical carbon stock changes which may take several decades to accrue (Burgess et al., 2010, Maniatis et al., 2011). Thus, the methodological choice available to many LEDC is a result of obtaining the uncertainty required whilst keeping costs to a minimum and overcoming any capacity shortfall experienced. Hence, it is expected that REDD+ requirements will allow data provisions from several tiers in a single report. Highly variable and substantial carbon pools should be estimated using Tier 3 methodology (e.g. forest ALC), whilst Tier 1 or Tier 2 methodology may be sufficient for smaller carbon pools (e.g. CWD) or carbon poor land covers (e.g. bareground).

In Tier 3 methods, in order to extrapolate from plot data, it is necessary to develop country-specific regressions with remotely sensed data. The remotely sensed data available have been fully discussed in Chapter 2 (Section 2.5) but will be briefly re-introduced here. Generally, carbon storage is either estimated via indirect relationships through statistical correlation with spectral reflectance or whereby attributes, such as crown height, are used in equations to estimated biomass. Within these two estimation techniques, a variety of remotely sensed data sources are employed for carbon mapping and these can be aggregated into six groups: very high resolution imagery, moderate resolution data, coarse resolution data, RADAR, LiDAR, and ancillary geographic information systems (GIS) data. Very high resolution imagery (<5m resolution; e.g. IKONOS, Quickbird) are used for ground-truthing the interpretations made from lower resolution imagery (Mayaux et al., 2006), especially in countries where sample locations are hard to access. However, very high resolution imagery are rarely used for large areas due to the high financial and labour investment that is required (Mumby et al., 1999). Moderate resolution data (30m resolution; e.g. Landsat) can be purchased, processed and managed at reasonable cost (Hardcastle et al., 2008). In fact, historical Landsat data are available free from NASA (USGS, 2012) but many images in the tropics are of limited use due to cloud coverage or seasonality (Asner, 2001). Coarse resolution data (250-1000m resolution; e.g. SPOT, MODIS) are also available free of charge. The daily temporal resolution provided by these satellites solves the problems of cloud cover and seasonality, but the resolution is too coarse for accurate carbon storage estimation (Muukkonen and Heiskanen, 2007). Until recently, radar data have rarely been used for carbon mapping. However, the use of this technology is being explored. Radar is able to penetrate cloud cover and can collect data in day-time and night-time conditions. Early indications suggest that Radar can be used to measure vegetation height and carbon storage estimated from this (Kellndorfer et al., 2004, Collins et al., 2009), however, this technology is still in development and relatively costly (Hardcastle et al., 2008). LiDAR sensors function on a similar concept to that of radar, measuring vegetation height and so estimating biomass (Omasa et al., 2007, Lefsky et al., 1999). Initial research shows that satellite-based LiDAR measurements can be used to survey carbon storage (Lefsky et al., 2005), however, most studies use LiDAR sensors flown on small aircraft (Asner et al., 2010). This current limitation means that only small areas can be sampled before costs become unreasonable. Finally, GIS-based extrapolation of tree inventory plots using modelled statistical relationships with ancillary data (e.g. temperature data, precipitation data, topography) can be used to estimate carbon storage. This data have three main advantages: 1) it is widely available and often free of charge; 2) it is often of moderate resolution (90m (USGS, 2012)); and 3) correlations identified with these variables may provide indications of those that directly affect carbon storage. Developing an understanding of these influential variables is vital if accurate scenarios of future carbon storage are to be developed. Thus, it is for these three reasons I opt to use GIS-based extrapolation in this chapter.

In Chapter 4, I presented a seven-stage method using which Tier 2 values could be obtained in data-deficient regions. Using this method, I produced a Tier 2 estimate of carbon storage within my study area. These estimates were for all five IPCC carbon pools and were of the completeness desired for REDD+ reporting. However, as described above, the representativeness of the carbon estimates applied to each via the Tier 2 look-up table could be improved, for example by accounting for the effect of disturbance. Here, I correlate the carbon storage estimates from tree inventory plots with data on climatic variables (e.g. temperature, precipitation, and solar radiation), edaphic variables (e.g. soil water holding capacity and soil fertility) and proxy variables for direct human interventions (e.g. governance type, distance from the main demand centres, population pressure, and historical logging), and variables that derive from climate-human interactions (e.g. burnt area index). Using these analyses I develop Tier 3 type regression equations estimating the total ALC stored (and associated uncertainties) across the forested and wooded land covers, an improvement on the previous Tier 2 estimates presented in Chapter 4. Additionally, I investigate the most influential correlates of spatial differences in carbon storage and how these changes result from alterations in the forest structure and function, such as wood specific gravity. Lastly, using a small number of inventory plots with two censuses, and the same mapping procedures, I assess changes in carbon storage over time, providing provisional sequestration estimates for the region.

5.3 Definitions

5.3.1 Population Pressure

Natural resources are subject to pressure from both local populations and distant demand centres, such as cities. In this chapter, I use population variables as an attempt to represent the pressure exerted on a particular point in space by all persons across the landscape. Thus, I define population pressure as the pressure on forest and woodland resources, resulting in degradation, when all persons in the landscape (not just those living locally) have been accounted for. I assume that the pressure on a location i increases linearly according to the number of persons (p) in a remote location (j). I also assume that the weight (w) given to a remote population decreases exponentially with distance (d). Hence, population pressure can be represented mathematically as:

$$pressure_i = \sum_{j=1}^{N} p_j . w_{ij} \qquad \text{where} \qquad w_{ij} = \exp(-\left(\frac{d_{ij}}{\sigma}\right)^2)$$

and N is the number of locations of interest (Platts, 2012).

These variables were calculated by VtA using a 1km^2 population density grid based on LandScan (2008) (LandScan, 2008), correcting for ward-level census counts and protected area data (Platts et al., 2011). To aid computational efficiency, the 1km^2 population grid was resampled to a 25km^2 resolution, meaning ‘local’ populations are defined as those within the same 25km^2 grid cell as the forest and/or woodland. Population pressure was calculated at this coarser scale using a range of plausible sigma values (σ = 5, 15, 25, 50) to allow a variety of spatial scales of distant pressure, before being bilinearly interpolated back to a 1km^2 resolution (Platts, 2012). The natural logarithm of the population pressure grid was used for linear regressions as it better conformed to a normal distribution.

5.3.2 Soil fertility

Some studies have suggested aboveground carbon storage is correlated with soil nutrient availability, reporting both positive (de Castilho et al., 2006, Paoli et al., 2008, Slik et al., 2010) and negative (Quesada et al., 2009b, van Schaik and Mirmanto, 1985) correlations with soil fertility (see Section 2.3.2). In this chapter, I seek to determine the whether soil fertility is an influential correlate of aboveground carbon storage in eastern Tanzanian forests and woodlands. The spatial variation of edaphic variables is poorly understood in this region due to data deficiencies (further discussed in Section 5.7.3). However, it is possible to use existing data from the SOTER database (Batjes, 2004) to provide a first order estimate of edaphic variation. Whilst the SOTER database provides useful estimates of soil nitrogen and carbon content, as an indication of overall soil fertility, only effective cation exchange capacity (eCEC*)* is provided (ISRIC, 2010). eCEC is a crude measure of soil fertility because it would show higher values in areas high in potassium and phosphorus, nutrients positively correlated with growth (Malhi et al., 2004, Paoli et al., 2008, Quesada et al., 2009b), but also in areas of high aluminium content, which is toxic to many plants (Matsumoto, 2000). In this chapter, soil fertility is calculated as:

$$\left(\frac{(100 - A)}{100}\right) * eCEC$$

where A is the aluminium saturation.

This partially negates the effect of aluminium levels in the overall measure of soil fertility, so that high values should be indicative of high potential growth rates. Thus, I define soil fertility as the eCEC of the soil, once the presence of aluminium ions has been controlled for.

5.4 Study Area

The study area is the watershed of the Eastern Arc Mountains (EAM) in Tanzania, covering 33.9 million hectares. A full description of the study area is given on pages 33-44 and the location is given in Fig. 1.4.

5.5 Methods

5.5.1 Data

5.5.1.1 Valuing the Arc Data

Written memoranda of understanding, outlining the investigations to be undertaken and the data sharing procedure were constructed with local and international agencies working within the EAM. From this, a total of 2,462 tree inventory plots were obtained. The numerous data sources were created using a variety of methods from a host of organisations and individuals. These will now be described.

The majority of plots (2,302) were collated by Dr Antje Ahrends as part of the York Institute for Tropical Ecosystems (KITE) database. This dataset has been fully described in Section 4.5.3 In addition to the KITE database, VtA was able to obtain data from six other sources, namely Prof Pantaleon Munishi (100 plots), Deo Shirima (4 plots), Mr Elmer Topp-Jorgenson (7 plots), Dr Gerry Hertel (33 plots) and Dr Jack Isango (16 plots). Those plots from Prof Munishi, Mr Topp-Jorgenson and Dr Isango were established at random locations but measured using the Frontier Tanzania protocol (e.g. (Frontier-Tanzania, 2005); Section 4.5.3). The methodology of Dr Hertel and Mr Shirima differed from that of Frontier Tanzania only in that they used circular plots of 7.32m radius and square 100m by 100m plots respectively established at randomly chosen locations (Shirima et al., 2011).

Once the tree inventory data had been collated, a quality control and standardisation protocol was applied. This consists of two main steps: (1) Metadata quality control; and (2) Measurement bias detection.

Firstly, all plots lacking a recorded spatial location and a fixed area were discarded (770 plots). Plots where one or more diameter at breast height (DBH) data were known to be missing were also excluded (7 plots). Furthermore, plots smaller than 0.025ha (16 plots) were deemed to produce unreliable carbon estimates and so also removed from the dataset.

Secondly, to assess the potential impact of measurement bias, i.e. not measuring over buttresses and so overestimating biomass (Phillips et al., 2002), the remaining plots were grouped by the lead field researcher. Size frequency distributions, using 10cm size classes, were created for each of these groups. Forest size frequency distributions are suggested to conform to the -2 power law based on metabolic scaling (Enquist and Niklas, 2001). It has been argued that this rule is not globally applicable (Li et al., 2005), however, many studies accept this observation but highlight a tendency for the metabolic scaling model to over-predicted large stems (Enquist et al., 2009). Additionally, whilst this law holds for large datasets, there is substantial variation at a plot level. This variation could be helpful in indicating potential biases in the data. For example, groups of plots showing a higher proportion of big trees than expected may indicate that the field team had a majestic forest bias. Hence, those researchers whose data significantly differed from this law, showing higher proportions of big trees, were discarded (1 researcher, 100 Plots).

5.5.1.2 Data Collected for this Thesis

The collaborative data described above was supplemented by the addition of 20 new 100m by 100m plots and 22 smaller plots (20m by 200m) using Frontier Tanzania measurement techniques (Frontier-Tanzania, 2005). The one hectare plots were established by Dr Marshall in the Udzungwa and Usamabara mountains to best capture the geographical range of the EAM (Figure 2.4). In 2007 and 2008, these plots were placed using randomised co-ordinates stratified by elevation in predominantly closed-canopy forest (Marshall et al., 2012b). Internationally accepted protocol was followed for the method of plot data collection (Kuebler, 2003). The DHB of stems ≥10cm were measured in 20 x 20m subplots. Smaller stems were not sampled as they typically only hold ~5% of biomass in mature African tropical forests (Lewis et al., 2009b, Chave et al., 2008). Stem heights were recorded using a clinometer or laser rangefinder (see Section 4.5.3.3) across a range of size classes (10-19, 20-29, 30-39, 40-49, ≥50 cm DBH), with at least 10 randomly selected heights being recorded for each size class. A sub-sample of the measurements between the clinometer and laser range finder have been shown to be highly correlated (Pearson $r^2 = 0.977$) (Marshall et al., 2012b). Trees were identified, with the aid of local botanists, following taxonomy of the Africa Plant Phylogeny Group (Angiosperm Phylogeny Group, 2003), with voucher specimens collected for verification at the Royal Botanic Gardens (Kew, London) if there was ambiguity.

In 2010, using the same methods, I recensused the one hectare plots, having previously established 22 smaller sample plots in 2009. The 22 smaller plots were established, using the same methods, in randomly chosen locations on the EAM, stratified by temperature and precipitation measures (Phillips et al., 2009a). I analysed the existing plot network and observed that the total dataset was relatively data poor at temperature and precipitation extremes. Specifically, I established more plots at locations experiencing mean annual temperatures of over 22°C but with mean annual precipitation levels of either below 1000mm (7 plots) or above 1600mm (7 plots). In addition, I established eight plots in forested areas with a mean annual temperature of less than 16°C. The plots I sampled for this thesis were also subjected to the quality control and standardisation protocol described above. No plots were discarded, producing the final plot network which contained 1611 plots, with a mean plot size of 0.088 (median = 0.10, mode = 0.10) hectares.

For plots with multiple census data available, further quality control is possible. Building on standard measurement error detection protocols developed elsewhere (Lewis et al., 2009b, Phillips et al., 2009b), it is possible to detect anomalies between remeasurements. Existing protocols treat as measurement error trees which appear to shrink more than 5mm in any measurement interval, or which are recorded as gaining in diameter faster than 40mm yr^{-1} (Lewis et al., 2009b, Phillips et al., 2009b). I selected all tree inventory plots with multiple censuses (60 plots and 9,090 trees in total). Most plots (41 out of 43) only had two censuses and so trees that were recruited or died between censuses were omitted, ensuring the growth rate of all trees remaining (8,475) could be calculated. With only two censuses, when an error is identified, it is difficult to know if the erroneous value is in the first or last census. I assumed that the original measurement was always the correct value. If the difference in final and initial DBH was less than -5mm then the final census DBH was replaced by the initial census DBH. Thus assuming that no growth occurred over this period and the ‘shrinking’ tree is due to error. This assumption was required for 314 trees (3.5% of all remeasured trees). Trees where the growth rate was over 40mm per year were also considered likely to be due to measurement error. To provide a realistic replacement estimate of growth rate, the average growth rate per year for the respective plot and size class (separated into 10-20, 20-40 and >40cm) was multiplied by the number of years between the censuses and this value was added to the initial census DBH giving a corrected final DBH. 43 trees (0.47% of all recensused trees) required this assumption.

5.5.2 Methods

5.5.2.1 Plot-Based Method

Using the quality-controlled dataset of 1,611 tree inventory plots (median 0.1ha, mean 0.1ha, mode 0.1ha [43 plots with multiple censuses; median 0.1ha, mean 0.5ha, mode 1.0ha]) I calculated plot-level stand structure indices and aboveground carbon storage per unit area. I obtained the exponent and intercept of the population size-frequency distribution using the power law fit for each plot using the log-log transformation method. Whereby, for each plot, I created 10cm bin size-frequency distributions based on diameter at breast height (DBH), and a linear model of the logarithm of the frequency against the logarithm of the size class was fitted. Whilst not as accurate as the maximum likelihood estimation method, my simpler method is more stable for many of my plots, providing both the intercept and slope indicators of population structure, given that these variables need not be highly correlated (Goldstein et al., 2004).

The quality controlled dataset contained 16,534 tree height measurements with concomitant diameter values. Trees with heights in excess of 80m (29 trees) were assumed to be erroneous and removed from the dataset because they were significant outliers within both this and previous data sets (Lovett, 1993b). Using these data I created DBH-height relationships using the equation forms shown in Table 5.1. In addition, I recognised that previous regional studies have identified that tree height varies significantly with altitude (Marshall et al., 2012a, Lovett, 1993b). Since mean annual temperature (MAT; obtained from the WorldClim data source (Hijmans et al., 2005)) is a strong correlate of altitude, as well as dominating the primary axis of the principal components (PC) describing the environmental heterogeneity spanned by the plot network (see PC1 in App. 4.1), I also incorporated MAT into the equation forms as a linear fixed effect. Each plot was included as a random effect, accounting for the non-independence of errors and the best fit model was chosen using the *Akaike Information Criterion (AIC)*.

In addition, I estimated plot biomass using moist forest tree allometry (Chave et al., 2005) based on measurements of diameter at breast height (DBH) from my tree inventory plots, WSG (as described above) and height data (derived using the best fit DBH-height equation form [Equation 5.1], if not measured in the tree inventory plots). Moist forest tree allometry was used in this study as, although all plots are classified as 'dry' when using precipitation categories (Chave et al., 2005), the overwhelming majority are from the EAM and coastal forest (~92% of my collaborative dataset) and are considered as 'moist forests' by most authors (Lovett, 1993b, Lovett, 1990). This is perhaps because the east African precipitation follows a bimodal regime (Mutai et al., 1998) and thus is not well described using precipitation categories. The basal area and forest structure of the EAM and coastal forest area more similar to the moist forests used in the Chave *et al.* dataset than to the dry forests (Marshall et al., 2012a). Additionally, EAM forest is more similar in species composition to moist Guineo-Congolian forests than to the dry forest miombo of east Africa, despite the close spatial proximity of the later (Lovett, 1993b). The dry forest data used to create the allometric equations in Chave *et al*. (2005) include no data from Africa (Chave et al., 2005) and thus may not be applicable to dry forest on this continent, specifically the woodlands of my dataset (~5% of my collaborative dataset).

In order to investigate the effect of tree height on biomass estimates, allometric equations for AGB were applied that both include and exclude height data for each plot (Chave et al., 2005). Since the precipitation classification of the EAM forest is ambiguous, this procedure was applied to standard allometric equations for both tropical moist and tropical dry forest (Chave et al., 2005). Using both moist forest and dry forest allometric equations that include height, WSG and DBH (Chave et al., 2005), the mean biomass for forested areas of my study area was 314.2 (300.6-327.6) Mg ha^{-1} and 280.2 (269.0-291.2) Mg ha^{-1} respectively (App. 4.2). Whilst both estimates are not vastly different, carbon estimated via the moist forest biomass equation was significantly greater than carbon estimated from the dry forest biomass equation (average difference = 34.0 [31.3-36.7] Mg ha^{-1}) p-value <0.001). Excluding height from the allometric equations greatly exacerbates the difference between them, providing biomass estimates of 495.6 (475.8-515.2) Mg ha^{-1} and 262.4 (253.4-271.6) Mg ha^{-1} using the moist forest equation and dry forest equation respectively. This is because

Table 5.1 DBH-height equation forms tested. *H* is height, *D* is DBH and *a, b* and *c* are constant coefficients to be estimated (Banin, 2010, Banin et al., 2012). Equation forms that failed to stabilise are indicated by n/a.

Equation name	Form	Parameter interpretation	Model statistics without temperature	Model statistics including temperature	References
Power	$H = aD^b$	No biological interpretation	AIC = 104035.3 R^2 = 0.61 P-value < 0.001	AIC = 103710.1 R^2 = 0.62 P-value < 0.001	(Huxley, 1932, Enquist, 2002)
Two parameter exponential	$H = a(1 - e^{-bD})$	a = maximum height b = rate parameter	a = 34.3 AIC = 103722.0 R^2 = 0.61 P-value < 0.001	a = -2.8 + 1.5 * MAT AIC =103436.4 R^2 = 0.62 P-value < 0.001	(Meyer, 1940)
Three parameter exponential	$H = a - b.e^{-cD}$	a = maximum height b = height range c = rate parameter	n/a	a = -8.2 + 1.5 * MAT AIC =104463.0 R^2 = 0.64 P-value < 0.001	(Fang and Bailey, 1998, Pinheiro and Bates, 1994)
Gompertz	$H = ae^{-be^{-cD}}$	a = maximum height b = no biological interpretation (reflects choice of zero D) c = rate parameter Inflection at D/e	n/a	a = 1.0 + 1.2 * MAT AIC =102935.1 R^2 = 0.65 P-value < 0.001	(Winsor, 1932, Richards, 1959)
Logistic	$H = a/(1 + be^{-cD})$	a = maximum height b = no biological interpretation (reflects choice of zero D) c = rate parameter Inflection at D/2	a = 27.7 AIC =103491.7 R^2 = 0.65 P-value < 0.001	a = -20.0 + 2.2 * MAT AIC =103058.0 R^2 = 0.65 P-value < 0.001	(Winsor, 1932, Richards, 1959)
Weibull	$H = a(1 - e^{-bD^c})$	a = maximum height b = rate parameter c = shape parameter	n/a	n/a	(Yang et al., 1978, Bailey, 1980)

including height in the model significantly reduces the carbon estimate of the plots when utilising moist forest equations (average decrease = 181.4 [174.0-188.8] Mg ha^{-1}, p-value < 0.001), but significantly increases carbon estimated for dry forest equations (average increase = 17.7 [14.5-20.8] Mg ha^{-1}, p-value <0.001). If height is excluded from the allometric equations then the moist forest equation provides biomass estimates significantly higher than those produced by the dry forest equation (average decrease = 233.1 [222.1-244.0] Mg ha^{-1}, p-value < 0.001). These preliminary findings support previous understanding that including stem height is more important than selecting the correct precipitation category when predicting plot biomass (Chave et al., 2005), justifying my sole use of the moist forest equation, particularly considering the small sample size (none from Africa) used to develop the ‘dry forest’ equation.

I obtained wood specific gravity (WSG) data via the phylogenetic information provided by my tree inventory plots. I used a global wood density database, to extract species average WSG (Zanne et al., 2009). This procedure provided over 32,000 trees with WSG data. When this was not possible the appropriate genus average (~14,000 trees), family average (~9,500 trees), plot average (~4,500 trees) and dataset average (~80 trees) were applied (Baker et al., 2004b). Including WSG as an additional parameter in allometric equations reduces the biomass estimation error (Djomo et al., 2010, Chave et al., 2005, Marshall et al., 2012a). Finally, carbon was assumed to be 50% of biomass (Lewis et al., 2009b). Hence, for all plots stand-level data was obtained on aboveground carbon storage, WSG, height, and population structure.

For a smaller number of plots, multiple measurements were available over time (n = 43; mean plot size = 0.5 ha; mean measurement period = 3.9 years). I calculated changes in carbon storage rates arithmetically by dividing the difference in carbon storage estimates between censuses by the number of years separating them. Thus, obtaining plot-level data representing the aboveground carbon flux over time, a result of the net effect of growth, recruitment and mortality.

5.5.2.2 Regression Model

For each geo-referenced plot location I obtained data on influential variables, falling into five broad categories; anthropogenic, climatic, geographic, edaphic, and pyrologic (App. 1.1). Anthropogenic data, further divided into six subcategories, were obtained from numerous sources: (1)

population pressure variables (n=14 related variables) were obtained from (Platts, 2012); (2) Dar es Salaam related variables (n=3; e.g. distance to Dar es Salaam), (3) market town related variables (n=3; e.g. distance to market towns), and (4) infrastructure related variables (n=2; e.g. distance to roads) were derived from available topographic maps; (5) historical logging (n=1) from Valuing the Arc (Swetnam, 2011); and (6) governance (n=1) from the World Database on Protected Areas (IUCN and UNEP-WCMC, 2010). Climate data were divided into three subcategories (precipitation [n=2; maximum mean cumulative water deficit and mean number of dry months annually], temperature [n=4; mean annual temperature, mean annual minimum monthly temperature, mean annual monthly maximum temperature, and mean annual monthly temperature range] and wind [n=1] related variables) and were derived from the Tropical Rainfall Measuring Mission (Zomer et al., 2008, TRMM, 2010), WorldClim (Hijmans et al., 2005, Jarvis et al., 2008), and United States National Aeronautics and Space Administration Surface meteorology and Solar Energy (NASA and SEE, 2009) datasets. Similarly, geographic data were divided into two categories (aspect [n=1] and solar [n=1] related variables) derived from Shuttle Radar Topography Mission (Jarvis et al., 2008) and National Renewable Energy Laboratory (Perez et al., 2002, NREL, 2010) datasets. Furthermore, I extracted edaphic data (n=6) from the International Soil Reference and Information Centre database (Batjes, 2004, ISRIC, 2010) and fire-related variables (n=5) derived from MODIS images (Roy et al., 2005).

I then correlated the influential variables with carbon storage, and its components: WSG, the intercept of the power law relationship, the gradient of the power law relationship, using general linear models. No transformations were required to ensure a normal distribution when correlating either WSG, the intercept of the power law relationship or the gradient of the power law relationship with the individual influential variables. However, carbon storage estimates required a square root transformation to ensure a normal distribution within the general linear models. In all models, plots were weighted by the square root of their area (see Section 4.5.1). Landscape scale spatial autocorrelation was accounted for by including spatial terms in the model (App. 1.1) (Dormann et al., 2007). The numerous possible interactions were excluded from the models, as these were found to add very little explanatory power to the models, only increasing R-squared values by ~0.001 with the addition of each interaction term. All analysis were performed using R 2.12.1 (R Development Core Team, 2010) and mapped in ArcGIS v9.3.1 (ESRI, 1999-2009).

There were fewer degrees of freedom available to investigate the influential variables of carbon sequestration (n=43). Therefore, covariation of principal components (PC) with carbon sequestration was assessed instead of the individual influential variables. Carbon sequestration estimates required a cube-root transformation to ensure a normal distribution within the general linear models. This enabled the effect of multiple variables to be examined even with this limited dataset. PC analysis of the variables was performed on the scaled data using the prcomp package (Venables and Ripley, 2002). The first five PC were selected as these explained >90% of the cumulative variance of the individual influential variables. All other aspects of the model (weighting, spatial autocorrelation) were performed identically to the models for carbon storage and its components.

The most appropriate model was chosen using forward-backwards and backwards-forwards stepwise selection (Platts et al., 2008). Forward-backwards models are more useful for inferring causal relationships (Platts et al., 2008) and so will be preferentially used to infer the influential variables of carbon storage and sequestration. However, averaging forward–backwards and backward–forwards predictions outperforms conventional selection procedures (Platts et al., 2008) and so both methods will be used when estimating the spatial distributions within the study area. Akaike information criterion (AIC) was used to reduce/expand the models, with variable selection occurring when the variable reduced the mean squared error (MSE) under cross validation. Unlike model selection using R^2, which neglects the principles of parsimony, AIC considers both model fit and complexity, resulting in better predictions and allowing inferences to be made from multiple models (Johnson and Omland, 2004). Model selection continued until the addition/removal of further variables able to reduce cross validation MSE no longer increased AIC, thereby producing the best-fit model with the lowest prediction error (Platts et al., 2008). Ten-fold cross validation (CV) was performed as this process provides the advantage of model validation whilst retaining the use of the full dataset (Varma and Simon, 2006). In ten-fold CV, the dataset is randomly divided into ten subsamples and the model is derived from nine of these subsamples, retaining one for testing prediction error. This process is repeated ten times, using each subsample as validation data once. The validation results are then averaged to produce a final estimate of prediction error.

Within each subcategory, some of the influential variables were highly correlated (App. 4.3) and this may confound the stepwise procedure as each variable does not carry enough distinct information (Chong and Jun, 2005). For example, all temperature related variables (App. 4.3) were correlated (R-squared > 0.6). However, it is unclear which correlated best fit the variables of interest, e.g. carbon storage and sequestration. Many studies include mean annual temperature in biomass models (Raich et al., 2006, Asner et al., 2009a), but theory suggests that it may be the temperature range driving this relationship as photosynthesis correlates with maximum temperatures, but respiration with minimum temperatures (Lloyd and Farquhar, 2008, Clark et al., 2003, Graham et al., 2003). I found that, if I removed correlated influential variables prior to model selection, the final models were artefacts of the variables I had selected. For example, if I included mean annual temperature in the model, but not temperature range, then the significant correlations between mean annual temperature and ALC storage were found. However, these correlations were insignificant if temperature range was added to the model, with the newly added variable showing a significant effect instead. In short, the resultant models were automatically biased towards *a priori* expectations. To avoid this bias, I devised a procedure by which the influential variables included in model selection were selected by their ability to explain variation within the data of interest (e.g. carbon storage). All influential variables were included in model selection (described above). Once this had run to completion the model was assessed. The subcategory with the largest number of correlated variables within the model was selected and all but the most influential, significant variable were removed. For example, if all four temperature-related variables were included in the initial model and this was the largest group of variables then this group would be selected. If mean annual temperature was the most influential and significant temperature-related variable, then all other temperature-related variables would be excluded in the next round of model selection. Thus, stepwise model selection was then repeated excluding these selected correlated variables. This process was repeated until no highly correlated variables remained within the model produced.

Since only landscape-scale variation was accounted for by the spatial terms already included in the model (App. 1.1), it is necessary to investigate the effect of local-scale (<10 km^2) spatial autocorrelation (Dormann et al., 2007). Firstly, the separate forward-backwards and backward-forwards models, containing no highly correlated variables (produced above), were preliminarily mapped. Secondly, the sum of the model estimates within 1, 3, 5, 7 and 10km^2 of the each pixel was extracted, and then included as additional variables (representing local spatial autocorrelation terms) into the stepwise model selection process, which was re-run a final time (Maggini et al., 2006). In all cases, local spatial autocorrelation terms were rejected as they did not reduce cross validated MSE.

Since it was not necessary to include local spatial autocorrelation terms in the models, the preliminary maps produced above could be regarded as final spatial representations of the ten best fit models, two (forward-backwards and backward-forwards) for each variable of interest; WSG, the intercept of the power law relationship, the gradient of the power law relationship, carbon storage and carbon sequestration. Each pair of maps was then combined into a single, final weighted mean estimate. The ratio of the relevant cross validated MSE of the forward-backwards and backward-forwards models was used to create the weighted mean, with the model showing lowest error receiving the highest weighting (Platts et al., 2008). Thus, I ultimately produced five maps (from ten best fit models); one each for WSG, the intercept of the power law relationship, the gradient of the power law relationship, carbon storage and carbon sequestration.

It was recognised that the carbon storage estimates were derived from data representing trees with a DBH greater than 10cm only. As in Chapter 4, Regionally appropriate ratios were used to estimate the unmeasured component of ALC storage (App. 3.3) and this was summed together with my modelled carbon storage estimate, providing an estimate of total ALC storage.

Although the five maps produced covered the entire study area, I was wary that extrapolation beyond the limits of my dataset could result in large errors. Thus, I limited the models to localities where all the associate variables were within the range of that shown in my dataset, thus only interpolating within my regression models for tree-dominated land cover categories. For any pixels outside the data range, look-up table methods were used in preference to the regression model estimates. Thus, for every land cover in my study area containing trees (open woodland; closed woodland; forest mosaic; lowland forest; sub-montane forest; montane forest; and upper montane forest (Swetnam et al., 2011)) that fell within the limits of my dataset, the estimate of carbon storage derived from the regression equations was used. For all other land covers, and for those areas containing trees that fell outside the limits of my dataset, land cover based look-up table values from Chapter 4 were used to estimate ALC storage (App. 3.4). Estimates of WSG and population structure were only made for wooded land covers, with estimates for areas inside the range of my dataset being derived from the relevant regression equations and estimates for other areas coming from land cover based look-up table values derived from the median value of my WSG and population structure data (weighted by the square root of plot size and derived via sampling with replacement 10,000 times) for each land cover type (App. 4.4). For carbon sequestration, again, estimates were only made for wooded land covers and, for those areas inside the range of my dataset, estimates derived from the regression equations were used. However, unlike carbon storage, WSG and population structure, for those areas outside the range of my dataset, a land cover based look-up table was not used as several land covers were poorly represented due to the small sample size available (n=43). Instead, for pixels outside the range of the regression-derived carbon sequestration model, the median value of data from my recensused plots (again weighted by the square root of plot size and derived via sampling with replacement 10,000 times) was utilised.

For every 1ha pixel of each map derived from regression equations, I produced 95% confidence intervals (CI). If the pixel estimate was derived from the general linear models, then the pixel 95% CI was calculated by adding and subtracting the square root of the cross validation MSE. For all other pixels (those derived via the look-up table method), the look up table 95% CI were used. The pixel 95% CI describe, for every pixel, the range I would expect each of my estimates to lie within. However, as I am interested in estimating carbon storage and sequestration on a landscape scale, as well as pixel by pixel, indications of uncertainty are also required at landscape-scale. Simply summing the pixel 95% CI to derive 95% CI of the overall landscape-scale estimates would indicate a systematic, rather than random, bias across the study area and so better represent the range of landscape estimates rather than its 95% CI. Thus, to derive 95% CI for the map as a whole, I randomly allocated each pixel an estimate within the range dictated by its 95% pixel CI, and summed these values across the entire landscape. This process was performed 10,000 times and the median estimates and map 95% CI for aboveground carbon storage and sequestration in the study area were obtained. This therefore provides 10,000 estimates of the map-scale carbon storage, of which the 250th and 9,750th values provide the 95% confidence intervals for map-scale estimates.

Taking the final model of carbon storage estimates, I investigated how the components of carbon storage (population structure, WSG and tree height) interacted to ultimately produce the ecosystem service of carbon storage. I obtained estimates of maximum canopy height from the best fit DBH-height equation developed above, and combined this spatially with my regression model derived estimates of WSG, the intercept of the power law relationship and the gradient of the power law relationship. I then correlated these against my estimates of carbon storage, allowing all possible interactions, and selected the best-fit model (via AIC) using both forwards and backwards stepwise regression.

5.6 Results

5.6.1 Carbon Stocks Using the Plot-Based Method

I estimate that 1.32 (0.89-3.16) Pg C was stored in the aboveground live vegetation in the year 2000 in the study region (Figure 5.1; Table 5.2). Woodland and bushland contributed most to the amount of stored ALC in the study region. Specifically, open woodland stores the most ALC (0.49 [0.47-1.60] Pg C over 9.6 million ha); followed by bushland (0.29 [0.15-0.51] Pg C over 5.0 million ha) and closed woodland (0.18 [0.13-0.61] Pg C over 1.8 million ha).

Best estimate values from my methodology, extracted via land cover class, are given in Table 5.3. Sub-montane forest (189 [95-588] Mg ha^{-1}) was the ecosystem that contained the most ALC per unit area, with other forest types, namely lowland (182 [152-360] Mg ha^{-1}), upper montane (166 [69-533] Mg ha^{-1}), montane (130 [62-702] Mg ha^{-1}), and forest mosaic (121 [55-485] Mg ha^{-1}), following this. In general, woodlands held less ALC than forests, with closed woodland storing 100 (70-331) Mg ha^{-1} and open woodland storing 51 (38-165) Mg ha^{-1} (Table 5.3).

My sequestration model suggests that the landscape is losing biomass carbon (mean net flux to atmosphere of 1.47 [-2.13 to 7.75] Mg C ha^{-1} yr^{-1}). However, there is high uncertainty on a pixel by pixel basis. Of the 12.3 million ha of tree dominated land cover in my study area, only 1.4% (0.17 million ha) shows a carbon decrease over the entire 95% CI range and only 0.8% (0.10 million ha) shows a definite carbon increase (Figure 5.2). The locations with net carbon uptake outside 95% CI's are situated on the Udzungwa mountains, while the locations with net reductions in carbon storage are mainly in the Pare and Usambara mountains.

Table 5.2 Aboveground live carbon stored within the study area for the year 2000, estimated by this and previous studies.

Study	Aboveground live carbon, Pg (95% CI range)	Methodology	Resolution (m^2)	Disturbance included?	Tanzanian on-the-ground data?
Present study – Tier 3	1.32 (0.89-3.16)	Regression equations derived using remotely sensed influential variables.	100	Anthropogenic variables represent human disturbance. Natural disturbance variables also included.	Yes
Chapter 4 Original – Tier 2	1.58 (1.56-1.60)	Land cover based look-up table.	100	Only where land cover types are identified as disturbed (e.g. cropland mosaics).	Yes
Chapter 4 Harmonised – Tier 2	1.64 (1.52-1.76)	Land cover based look-up table.	100	Only where land cover types are identified as disturbed (e.g. cropland mosaics).	Yes
Baccini *et al.* (2012) (2012) – Tier 1	2.03	Derived from MODIS and GLAS LiDAR data.	500	Partially includes disturbance through impacts on canopy heights.	Yes
Saatchi *et al.* (2011) (2011) – Tier 1	0.83	Derived from MODIS, SRTM, QSCAT and GLAS LiDAR.	1000	Partially includes disturbance through impacts on canopy heights.	No
Hurtt *et al.* (2006) (2006) HYDE-SAGE – Tier 1	0.63	Modelled from the Miami LU ecosystem model with cropland data from the Centre for Sustainability and the Global Environment.	~110,000	Contains simple submodels of natural plant mortality, disturbance from fire, and organic matter decomposition, as well as wood harvesting.	No
Hurtt *et al.* (2006) (2006) HYDE – Tier 1	0.41	Modelled from the Miami LU ecosystem model.	~110,000	Contains simple submodels of natural plant mortality, disturbance from fire, and organic matter decomposition, as well as wood harvesting.	No
Baccini *et al.* (2008) (2008) – Tier 1	0.34	Derived from MODIS and GLAS LiDAR data.	1000	Partially includes disturbance through impacts on canopy heights.	No

5.6.2 Links between Carbon Stock and Influential Variables

The influential variables of carbon storage and sequestration may be inferred from the correlations shown in the regression models. Forward-backwards selection results are presented in the following paragraphs (with influential variables separated into positive and negative correlations but presented in order of influence) as these best indicate causal relationships (Platts et al., 2008). In general, backward-forwards models were in close agreement with forward-backwards models (Table 5.4-5.8).

Carbon storage (adjusted R-squared [Adj R-sq] = 0.18) is correlated positively with the natural logarithm of the population pressure with decay constant of 12.5km (p-value < 0.001), the distance to roads (p-value <

0.010), and the cost distance to Dar es Salaam (p-value < 0.010). Negative correlations were found with the mean annual monthly temperature range (p-value < 0.001), the total available water capacity of the soil (p-value < 0.001), and the mean number of dry months annually (p-value < 0.050). Carbon storage was lower in areas where historical logging was present (p-value < 0.010), and higher in areas under the control of local communities (p-value < 0.010). Thus, carbon storage is high far from the commercial capital, in areas with a low monthly temperature range, without a dry season, that have not suffered from historical logging and are under local control (Figure 5.3; Table 5.4). Curiously, high population pressures also correspond with high carbon storage. The latter correlation emphasises caution; my results are not proof of causation, for example, it is a reasonable hypothesis that people preferentially inhabit areas where tall forest occurs (perhaps as forest resources are desirable, or there is a better climate for crop growth), rather than the presence of people per se directly increasing carbon storage.

Turning to carbon sequestration, the forward-backwards and backward-forwards stepwise selection settled on the same final model (Adj R-sq = 0.41). The associated variables formed five PCA axes (Table 5.9), of which three correlated with the rate of carbon sequestration (again presented in order of influence). Carbon sequestration was negatively correlated with the soil fertility axis (PC5; p-value < 0.050), warmer temperatures and longer dry seasons (PC3; p-value < 0.050), and the negatively anthropogenic disturbance axis (PC1; p-value < 0.010). Thus, carbon sequestration was highest in infertile areas with little or no drought and little anthropogenic disturbance (Table 5.5).

WSG (Adj R-sq = 0.28) was correlated positively, in order of influence, with the annual mean burned area probability (p-value < 0.001), the pH of the soil (p-value < 0.001), the mean annual monthly temperature range (p-value < 0.001), the natural logarithm of the cost distance to roads (p-value < 0.001), and mean annual global horizontal solar radiation (p-value < 0.001). Negative correlations were found with the natural logarithm of the cost distance to Dar es Salaam (p-value < 0.001), the total available water capacity of the soil (p-value < 0.001), and the wind speed (p-value < 0.050). Thus, WSG is higher in burnt areas near the commercial capital, showing extremes of temperature but little available water (Figure 5.4; Figure 5.5; Table 5.6).

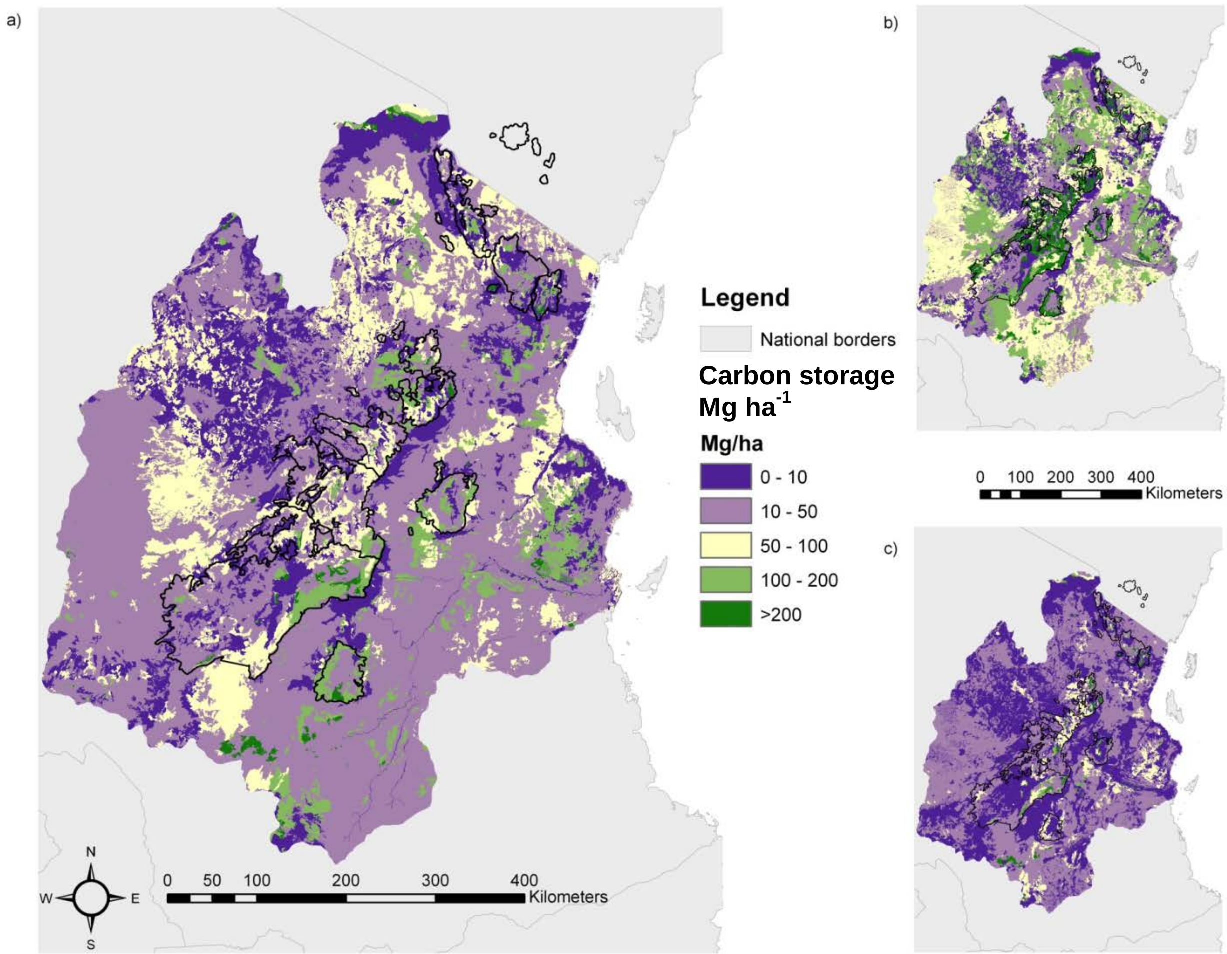


Figure 5.1 Aboveground live carbon storage in the study area (a), with upper (b) and lower (c) pixel based 95% CI. See text for details on methods.

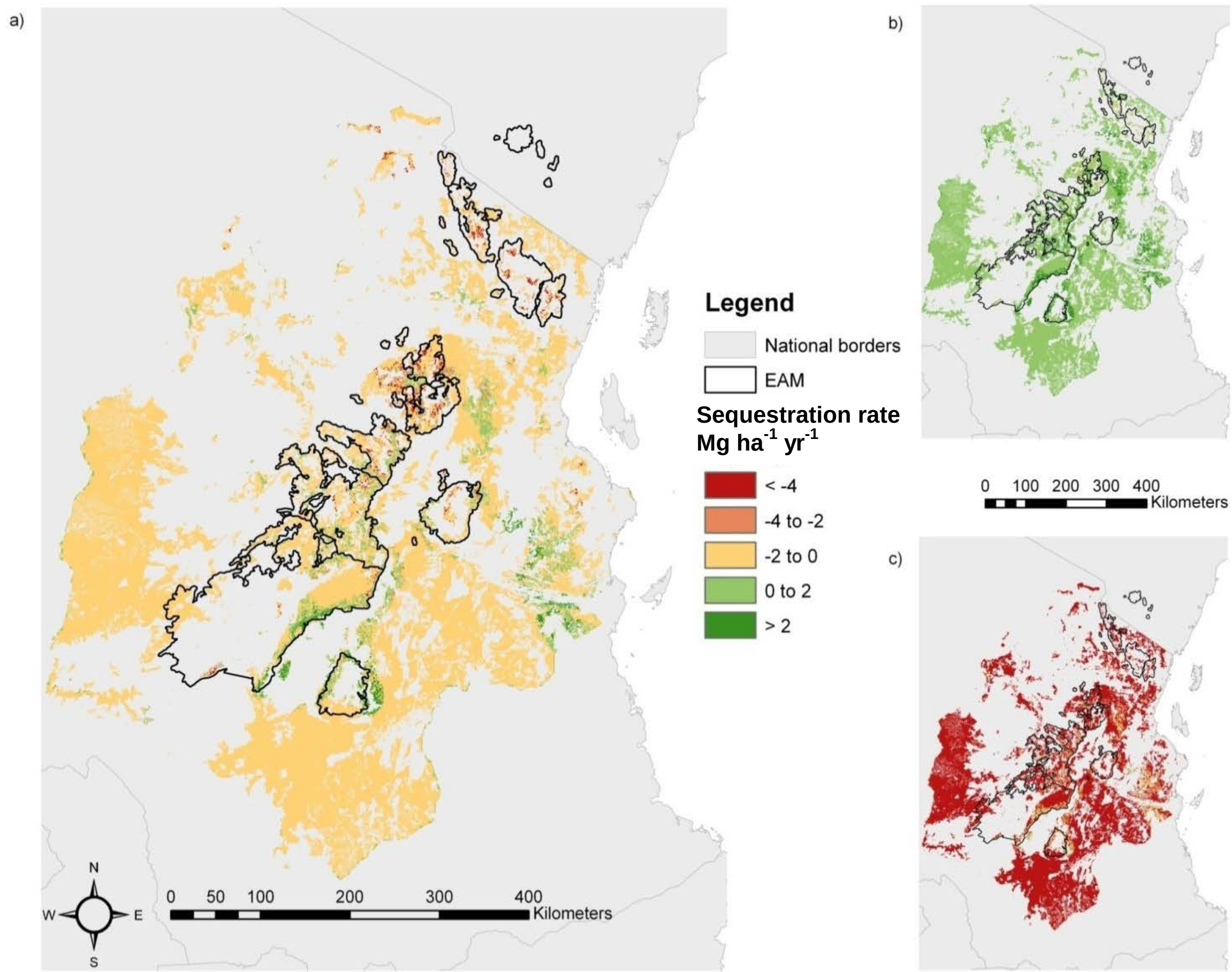


Figure 5.2 Aboveground live carbon sequestration in tree-dominated land cover categories within the study area (a), with upper (b) and lower (c) pixel based 95% CI. See text for details on methods.

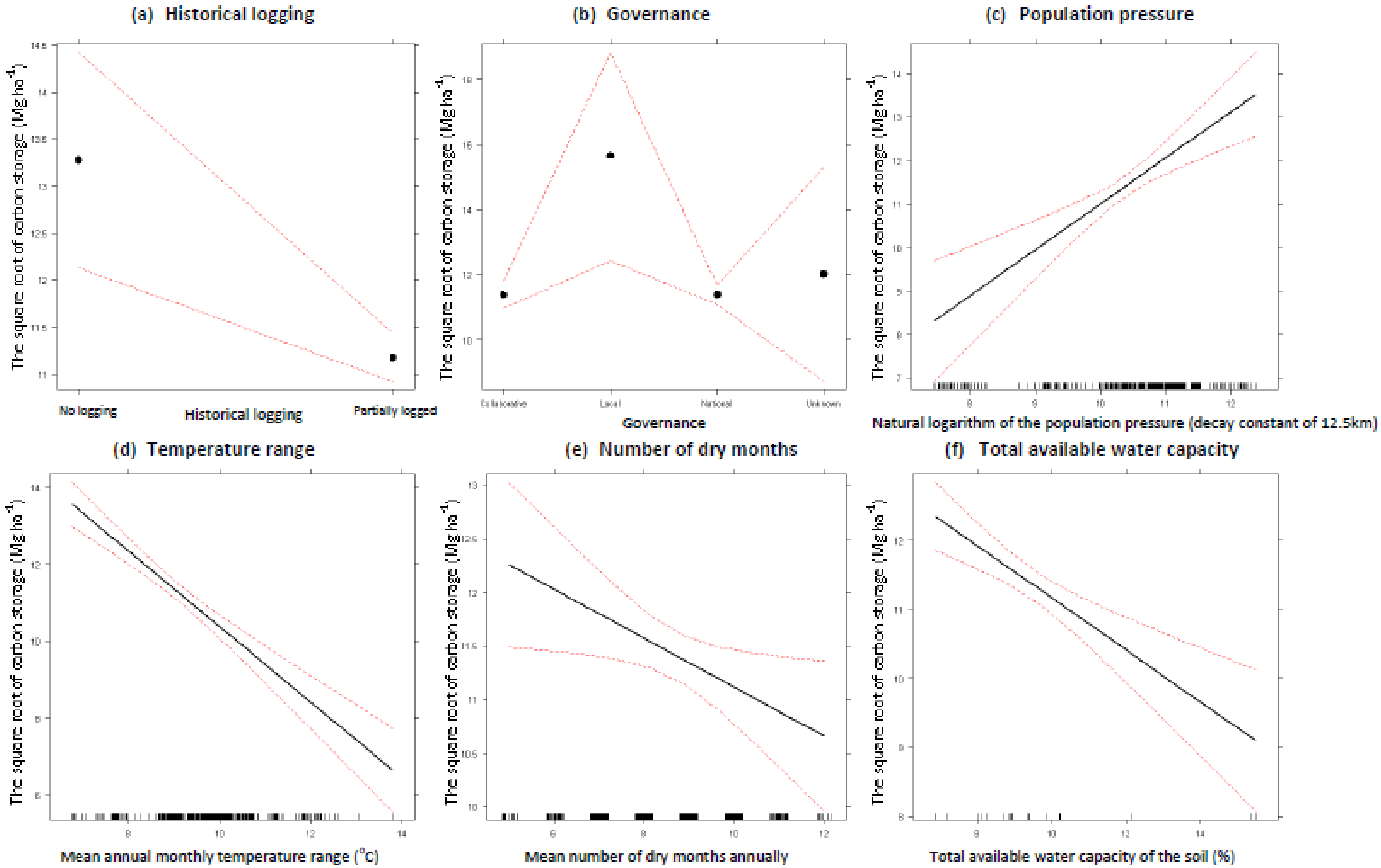


Figure 5.3 The effect of most influential, significant anthropogenic (a, b, and c), climatic (d and e) and edaphic (f) variables of aboveground live carbon storage. Dashed red lines indicate 95% CI.

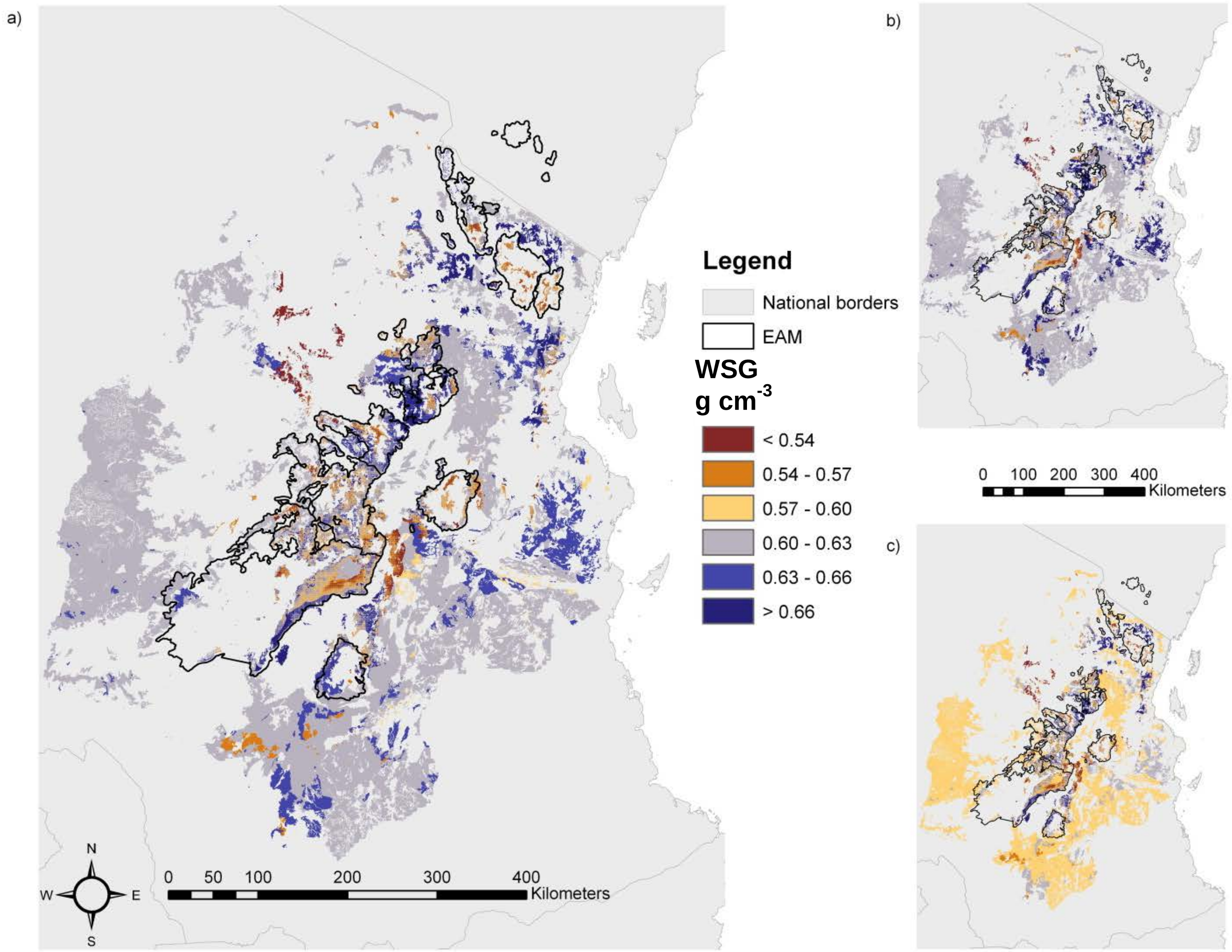


Figure 5.4 The spatial variation of WSG in tree-dominated land cover categories within the study area (a), with upper (b) and lower (c) pixel based 95% CI. See text for details on methods.

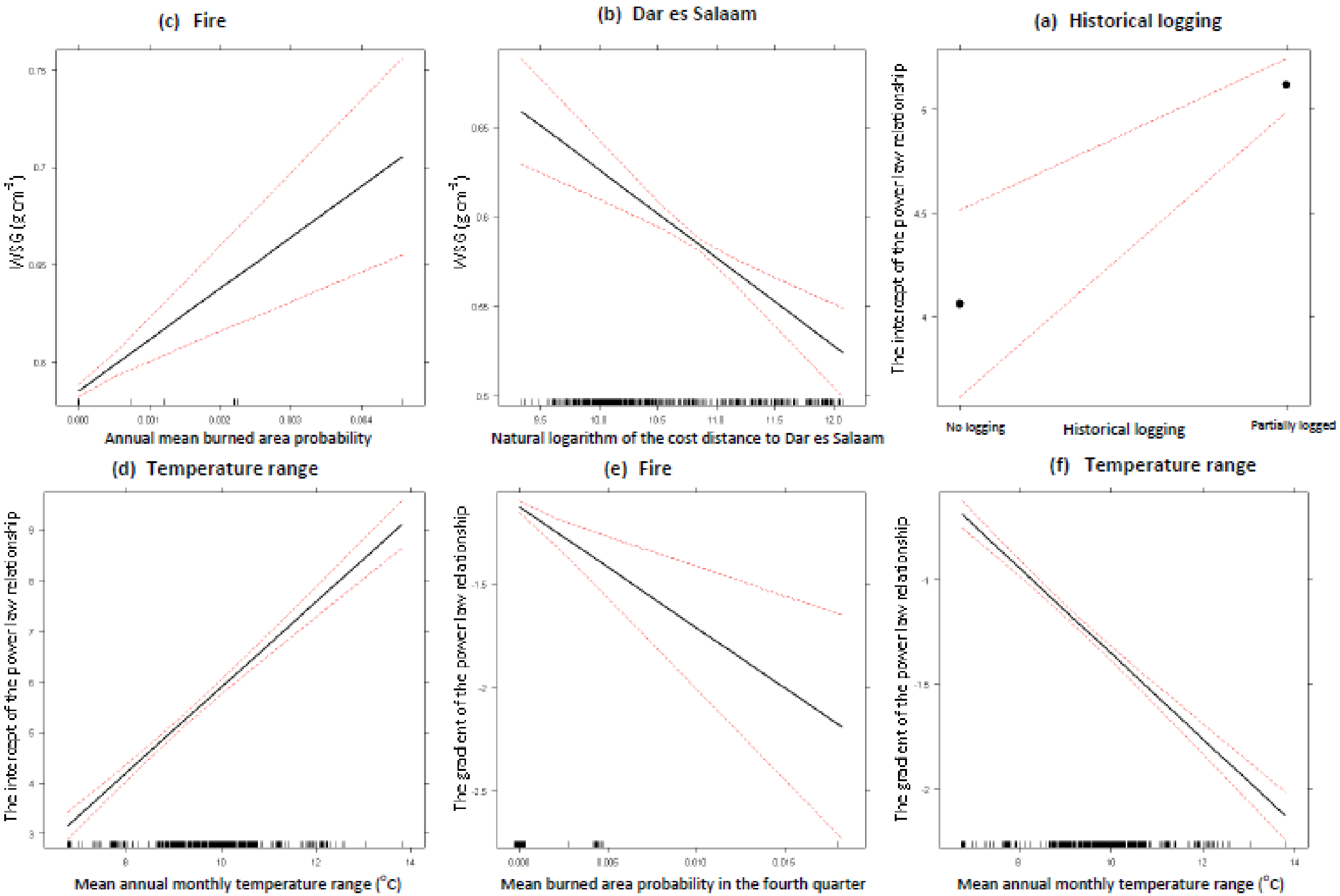


Figure 5.5 The most influential, significant influential variables on WSG (a and b), the intercept of the power law relationship (c and d), and the gradient of the power law relationship (e and f). Dashed red lines indicate 95% CI.

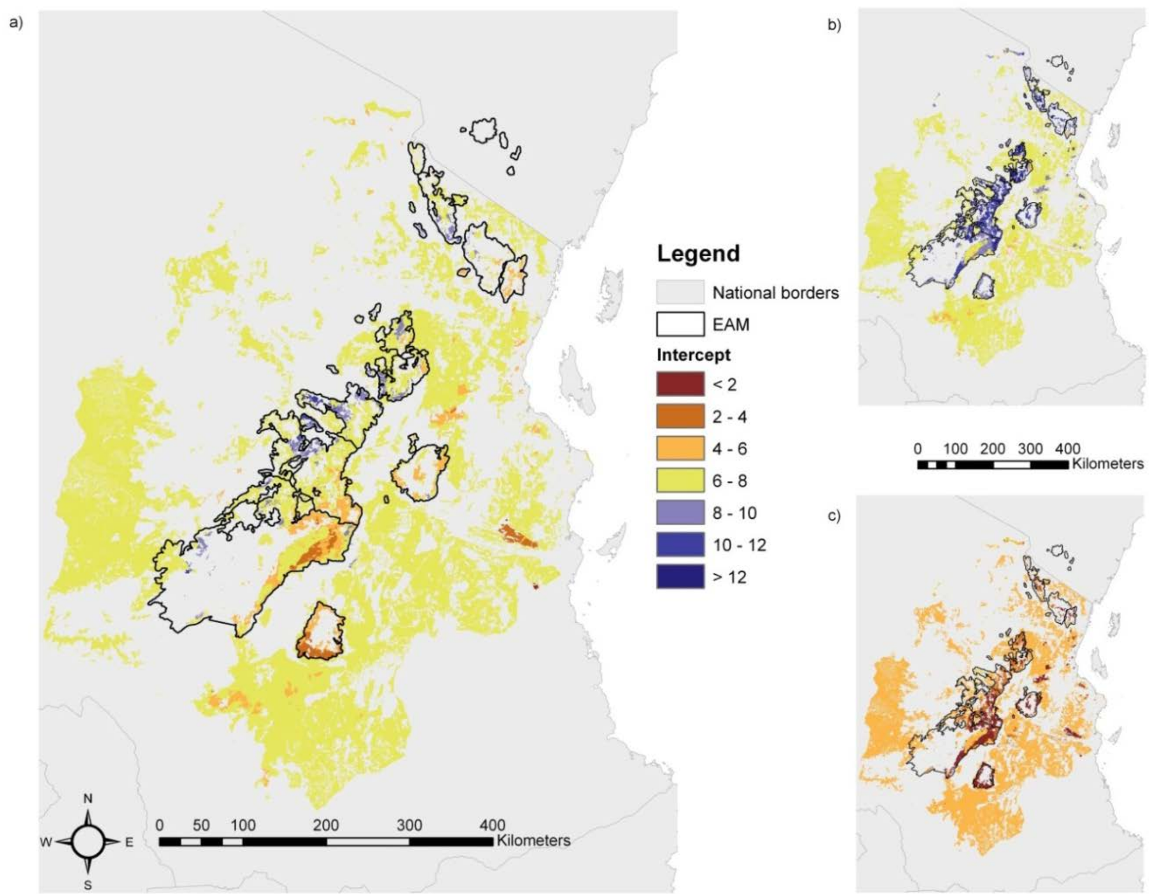


Figure 5.6 The spatial variation in the intercept of the power law relationship (a proxy measure for potential stem density) in tree dominated land cover categories within the study area (a), with upper (b) and lower (c) pixel based 95% CI. See text for details on methods.

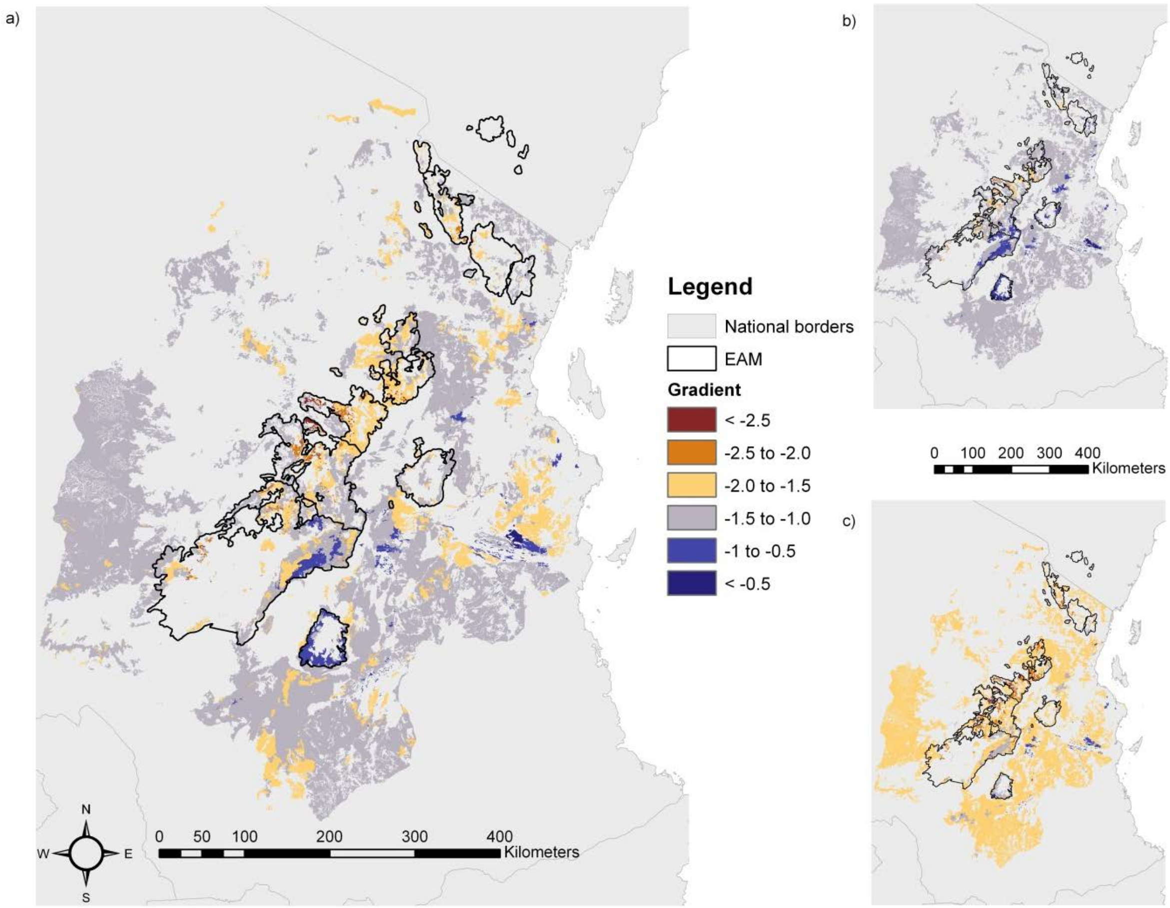


Figure 5.7 The spatial variation in the gradient of the power law relationship (a proxy measure for the proportion of larger stems) in tree-dominated land cover categories within the study area (a), with upper (b) and lower (c) pixel based 95% CI. See text for details on methods.

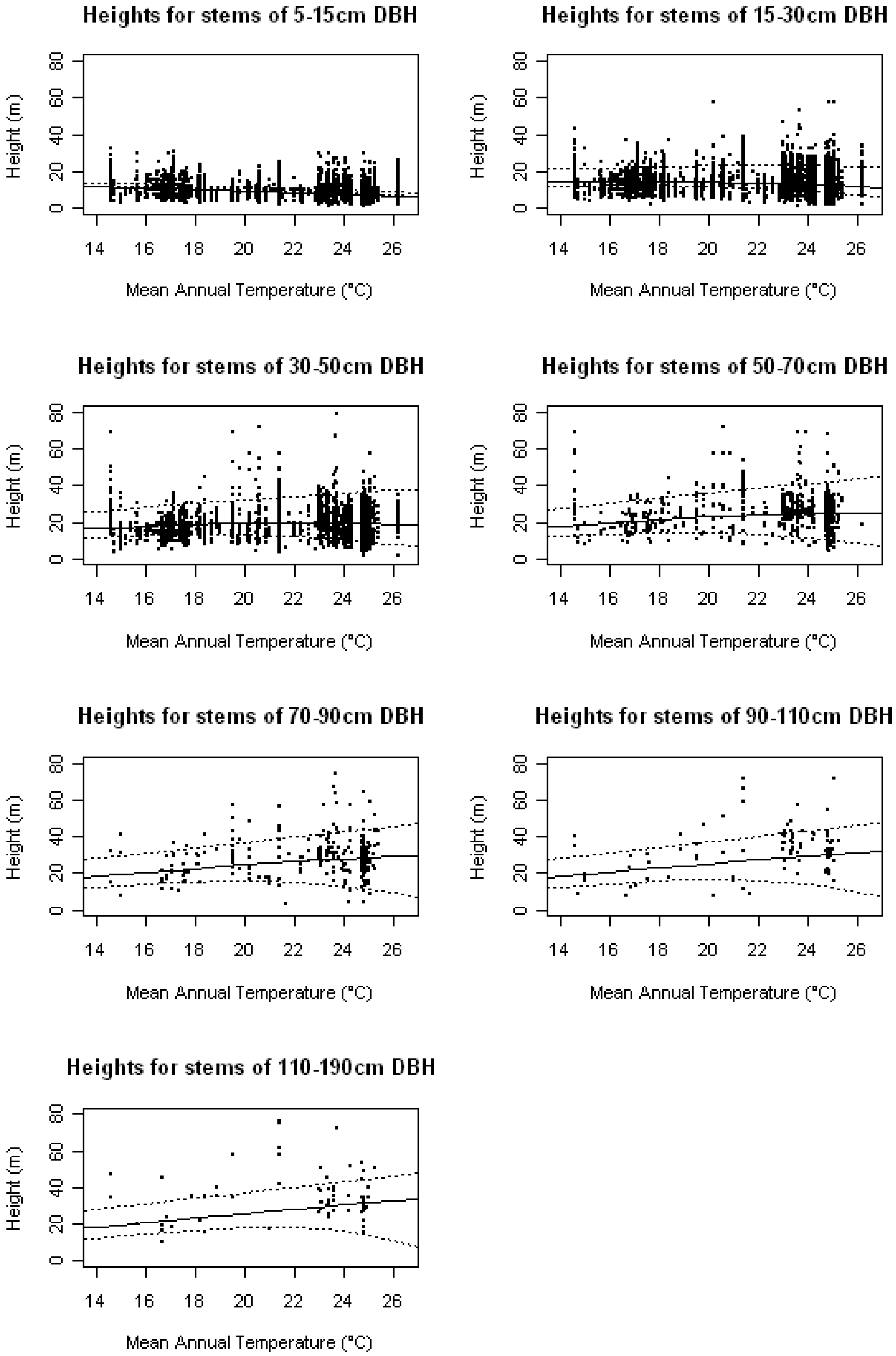


Figure 5.8 The effect of MAT on tree height for a range of DBH. The data (points) correspond to DBH ranges whereas the Gompertz model fits (solid lines) illustrate the relationship for mid-point of this range only. Dotted lines represent the 95CI of the model fits.

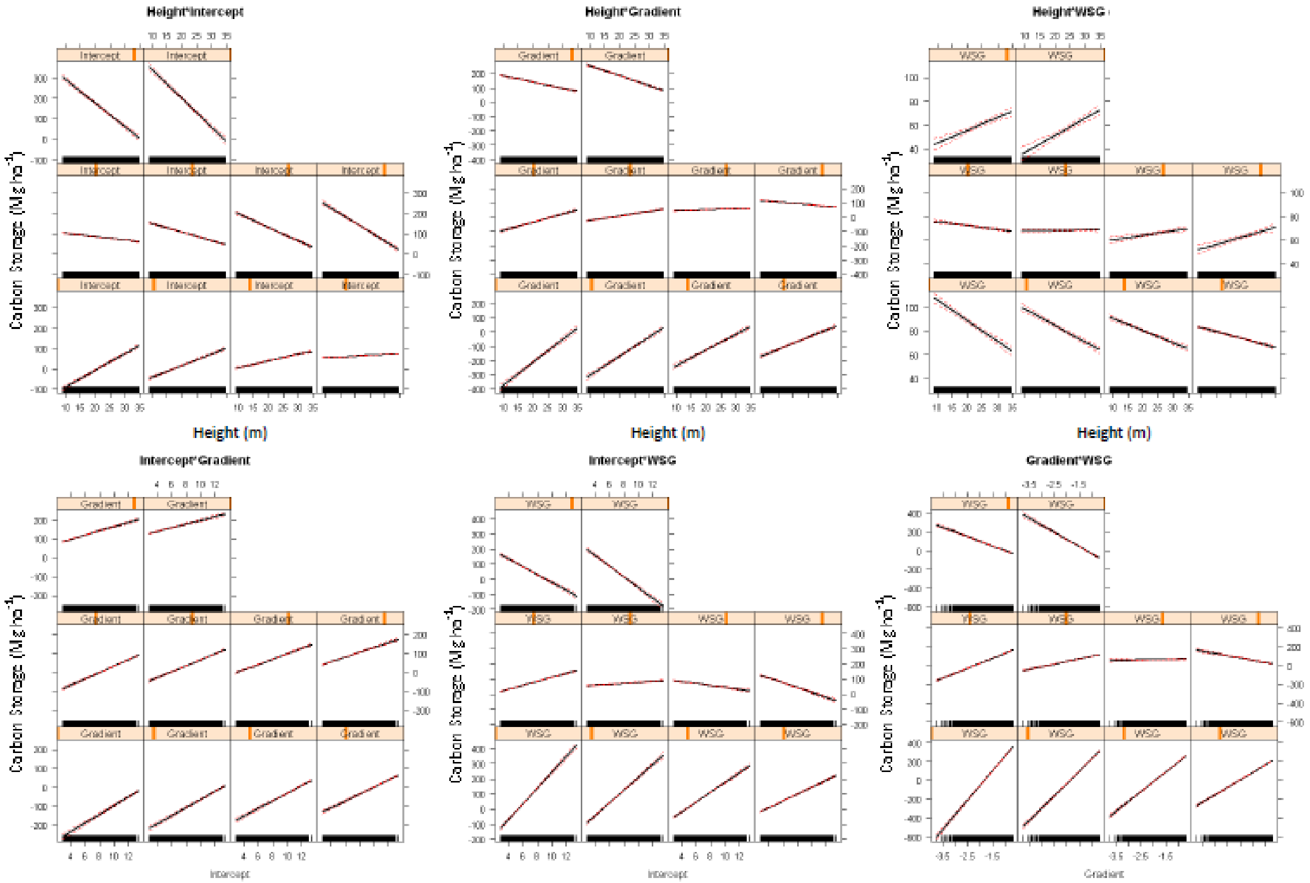


Figure 5.9 The 2nd order interactions relating my carbon storage derivatives (wood specific gravity, maximum canopy height, the intercept of the power law relationship, and the gradient of the power law relationship [shown here as WSG, height, intercept, and gradient respectively]) to aboveground live carbon storage. Dashed red lines indicate 95% CI.

The intercept of the power law relationship (Adj R-sq = 0.30) was correlated positively, in order of influence, with the mean annual monthly temperature range (p-value < 0.001), the natural logarithm of the population pressure with decay constant of 12.5km (p-value < 0.001), the total available water capacity of the soil (p-value < 0.001), the mean annual global horizontal solar radiation (p-value < 0.001), and the cost distance to Dar es Salaam (p-value < 0.001). A negative correlation was found with the natural logarithm of the cost distance to roads (p-value < 0.001). Thus, the density of smaller stems increases in accessible areas with a high population pressure and large temperature fluctuations (Figure 5.5; Figure 5.6; Table 5.7).

Correlations identified for the gradient of the power law relationship were broadly the inverse of those identified for the intercept. The gradient of the power law relationship (Adj R-sq = 0.26) was correlated positively, in order of influence, with the natural logarithm of the cost distance to roads (p-value < 0.001). Negative correlations were found with the mean burned area probability in the fourth quarter (p-value < 0.001), the natural logarithm of the population pressure with decay constant of 20.8km (p-value < 0.001), the mean annual monthly temperature range (p-value < 0.001), the total available water capacity of the soil (p-value < 0.001), the mean annual global horizontal solar radiation (p-value < 0.001), and the cost distance to Dar es Salaam (p-value < 0.001). Thus, the proportion of large stems was greater in inaccessible areas experiencing few disturbances from fire, people, or large temperature fluctuations (Figure 5.5; Figure 5.7; Table 5.8).

The best fit DBH-height equation was the Gompertz, determined by choosing the fit with the lowest AIC value (p-value < 0.001; Equation 5.1; Table 5.1). There was a significant positive correlation between maximum canopy height and MAT using the Gompertz (p-value < 0.001; Equation 5.2) and all other equation forms (Table 5.1).

Equation 5.1

$$\mathbf{Height} = (\mathbf{0.980726296} + \mathbf{1.236525192} * \mathbf{MAT}) * \mathbf{e}^{(-(-0.974598751 + 0.126698008 * \mathrm{MAT}) * e^{(-(0.068341379 - 0.001264387 * \mathrm{MAT}) * \mathrm{DBH})})}$$

Equation 5.2

$$\mathbf{Maximum\ height} = \mathbf{0.980726296} + \mathbf{1.236525192} * \mathbf{MAT}$$

Within my data, height-MAT relationships differ amongst tree size classes (Figure 5.8). At lower mean annual temperatures the smallest size classes reach a peak in height, with height decreasing at higher temperatures. Larger size classes peak in height at higher temperatures, with trees >40 cm apparently reaching their height maxima at higher air temperatures than found today. Specifically, stems with a 10cm DBH are estimated to obtain maximum height of 11.5 m (95% CI: 8.3-14.3) in temperatures of 12.0 °C (9.8-16.2), while stems of 40cm DBH may not reach their maximum of 19.7 m (9.7-41.3) until temperatures of 22.1 °C (18.5-38.0). Size classes between 10 and 40cm DBH show intermediate maxima (Figure 5.8; Table 5.10). This implies that, initially, stem height increases with temperature (or variables correlated with temperature, although I find that windspeed, soil fertility and soil water availability are poorly correlated with temperature [App. 4.1]). This result is expected under the cohesion-tension theory, whereby negative pressure gradients and surface tension provide the forces necessary to lift water against gravity (Tyree and Zimmermann, 1983), provided that water is not limiting (Koch et al., 2004). However, nutrient and water limitation could indirectly be driving the maxima across all DBH ranges, with small stems being outcompeted by larger stems and therefore reaching maxima at lower temperatures (King et al., 2005, Cairns et al., 1997, Poorter et al., 2008, Poorter et al., 2006) (Figure 5.8; Table 5.10).

The final Tier 3 carbon storage estimates were positively correlated with both size-frequency distribution estimates (both intercept and gradient [p-values < 0.001]), and negatively correlated with WSG estimates (p- value < 0.001) and maximum height estimates (p-value < 0.001). All possible interactions were investigated and were significant (Adj R-sq = 0.35; p-values < 0.001), however, the majority of the explanatory power lay within the second order interactions (Adj R-sq = 0.33; p-values < 0.001; Table 5.11). Broadly, WSG and the proportion of larger stems had largest influence over the carbon storage estimate. Considering only second order interactions, in areas of low potential stem density, carbon storage is positively correlated with maximum canopy height (Figure 5.9). However, the opposite correlation is observed in areas of higher stem density. Although similar interactions are observed between both size-frequency distribution estimates (gradient and intercept), the interaction between WSG and maximum canopy height is inverse, with carbon storage only showing positive correlations with maximum canopy height in areas of high WSG. Both size-frequency distribution estimates also interacted similarly with

Table 5.3 The mean (and 95% CI) estimates of forest characteristics investigated in this study (carbon storage, carbon sequestration, WSG, the intercept from the power law relationship and the gradient from the power law relationship) separated by land cover category.

Land cover category (Swetnam et al., 2011)	Carbon storage (Mg ha^{-1})	Carbon sequestration (Mg ha^{-1} yr^{-1})	WSG (g cm^{-3})	The intercept from the power law relationship	The gradient from the power law relationship
Lowland Forest (<1000m)	182 (152 to 360)	-0.91 (-7.08 to 4.29)	0.60 (0.59 to 0.60)	6.01 (2.94 to 5.17)	-0.93 (-1.04 to -0.82)
Sub-montane forest (1000-1500m)	189 (95 to 588)	-2.02 (-11.06 to 1.29)	0.58 (0.57 to 0.58)	5.95 (3.68 to 8.23)	-1.31 (-1.48 to -1.14)
Montane Forest (1500-2000m)	130 (62 to 702)	-2.03 (-11.85 to 1.07)	0.60 (0.59 to 0.60)	6.95 (3.51 to 10.39)	-1.57 (-1.82 to -1.32)
Upper-montane forest (>2000m)	166 (69 to 533)	-2.08 (-10.49 to 1.23)	0.60 (0.58 to 0.60)	7.03 (4.60 to 9.45)	-1.61 (-1.93 to -1.26)
Forest mosaic	121 (55 to 485)	-1.18 (-6.69 to 2.92)	0.56 (0.56 to 0.56)	9.22 (6.98 to 11.46)	-1.90 (-1.99 to -1.81)
Closed Woodland	100 (70 to 331)	-1.24 (-7.91 to 2.63)	0.64 (06.2 to 0.65)	6.67 (4.95 to 8.60)	-1.55 (-1.85 to -1.30)
Open Woodland	51 (38 to 165)	-1.49 (-7.53 to 2.05)	0.61 (0.59 to 0.62)	6.38 (4.88 to 7.82)	-1.45 (-1.70 to -1.19)

Table 5.4 The coefficients and associated p-values of the variables correlated with aboveground carbon storage using both forward-backwards and backward-forwards selection procedures.

Variable	Group	Forward-backwards		Backward-forwards	
		Coefficient	p-value	Coefficient	p-value
(Intercept)	n/a	-1.21E+03	3.14E-03	-2.80E+00	7.55E-01
Natural logarithm of the population pressure with decay constant of 12.5km	Anthropogenic	1.06E+00	1.06E-05	1.42E+00	2.27E-06
Natural logarithm of the population pressure with decay constant of 16.7km	Anthropogenic	n/a	n/a	1.42E+00	2.27E-06
Distance to roads	Anthropogenic	1.15E-04	1.09E-03	1.78E-04	1.30E-05
Historical logging – Partially logged	Anthropogenic	-2.10E+00	1.09E-03	-3.83E+00	4.97E-07
Cost distance to Dar es Salaam	Anthropogenic	3.41E-05	2.00E-03	2.58E+00	5.46E-03
Natural logarithm of the cost distance to market towns	Anthropogenic	-6.05E-01	5.24E-02	-9.85E-01	1.89E-02
Governance - local	Anthropogenic	4.24E+00	9.29E-03	n/a	n/a
Governance - national	Anthropogenic	-7.95E-03	9.78E-01	n/a	n/a
Governance - unknown	Anthropogenic	6.26E-01	7.10E-01	n/a	n/a
Mean annual monthly temperature range	Climatic	-9.79E-01	2.00E-16	-1.15E+00	1.98E-13
Mean annual minimum monthly temperature	Climatic	n/a	n/a	1.09E+00	3.07E-16
Mean annual maximum monthly temperature	Climatic	n/a	n/a	-1.15E+00	1.98E-13
Mean number of dry months annually	Climatic	-2.28E-01	2.57E-02	-3.09E-01	5.58E-03
Total available water capacity of the soil	Edaphic	-3.75E-01	1.16E-05	-8.59E-01	3.05E-05
Total nitrogen content of the soil	Edaphic	n/a	n/a	-4.13E-01	2.50E-03
Total carbon content of the soil	Edaphic	n/a	n/a	6.18E+00	1.15E-03
pH of the soil	Edaphic	n/a	n/a	1.73E+00	2.96E-02
Spatial autocorrelation term 5	Spatial	6.45E+01	3.15E-03	6.60E+00	1.18E-01
Spatial autocorrelation term 7	Spatial	-8.48E-01	3.57E-03	-1.71E-01	1.45E-01
Spatial autocorrelation term 4	Spatial	n/a	n/a	6.60E+00	1.18E-01
Spatial autocorrelation term 3	Spatial	n/a	n/a	-1.71E-01	1.45E-01

Table 5.5 The coefficients and associated p-values of the variables correlated with aboveground carbon sequestration.

Variable	Coefficient	p-value
(Intercept)	3.22E-02	8.90E-01
PC1	-1.12E-01	5.88E-03
PC3	-2.55E-01	1.01E-02
PC5	-4.12E-01	1.17E-02

Table 5.6 The coefficients and associated p-values of the variables correlated with WSG using both forward-backwards and backward-forwards selection procedures.

Variable	Group	Forward-backwards		Backward-forwards	
		Coefficient	p-value	Coefficient	p-value
(Intercept)	n/a	-1.98E+02	2.14E-05	-1.59E+02	6.20E-04
Natural logarithm of the population pressure with decay constant of 16.7km	Anthropogenic	-7.33E-03	9.78E-02	n/a	n/a
Natural logarithm of the population pressure with decay constant of 12.5km	Anthropogenic	n/a	n/a	-1.33E-02	5.20E-03
Natural logarithm of the cost distance to roads	Anthropogenic	1.89E-02	9.40E-11	n/a	n/a
Distance to roads	Anthropogenic	n/a	n/a	2.69E-06	6.13E-05
Natural logarithm of the cost distance to Dar es Salaam	Anthropogenic	-4.91E-02	9.90E-07	n/a	n/a
Cost distance to Dar es Salaam	Anthropogenic	n/a	n/a	-1.50E-06	2.00E-16
Natural logarithm of the cost distance to market towns	Anthropogenic	n/a	n/a	2.24E-02	9.99E-07
Governance - local	Anthropogenic	3.83E-03	8.71E-01	n/a	n/a
Governance - national	Anthropogenic	-7.71E-03	6.46E-02	n/a	n/a
Governance - unknown	Anthropogenic	3.93E-02	1.17E-01	n/a	n/a
Mean annual monthly temperature range	Climatic	2.90E-02	2.00E-16	n/a	n/a

Mean annual maximum monthly temperature	Climatic	n/a	n/a	2.62E-02	2.00E-16
Mean annual minimum monthly temperature	Climatic	n/a	n/a	-2.53E-02	2.00E-16
Wind speed	Climatic	-3.70E-05	2.04E-02	-4.98E-05	7.84E-04
Mean number of dry months annually	Climatic	n/a	n/a	3.71E-03	2.51E-02
pH of the soil	Edaphic	9.68E-02	2.00E-16	8.63E-02	1.27E-12
Total available water capacity of the soil	Edaphic	-1.22E-02	3.90E-09	-7.01E-03	4.59E-02
Total nitrogen content of the soil	Edaphic	n/a	n/a	7.14E-03	1.31E-02
Total carbon content of the soil	Edaphic	n/a	n/a	5.59E-02	8.35E-02
Percentage sand content of the soil	Edaphic	n/a	n/a	3.99E-03	2.02E-03
Annual mean burned area probability	Fire	2.63E+01	3.80E-06	2.09E+01	2.62E-04
Mean annual global horizontal solar radiation	Geographic	7.47E-05	3.40E-04	7.93E-05	1.32E-04
Spatial autocorrelation term 4	Spatial	-4.88E+00	3.20E-04	-1.16E+01	1.28E-03
Spatial autocorrelation term 6	Spatial	1.04E-01	5.83E-08	8.83E-02	2.92E-06
Spatial autocorrelation term 8	Spatial	1.27E-01	1.34E-04	n/a	n/a
Spatial autocorrelation term 5	Spatial	9.83E+00	1.61E-05	n/a	n/a
Spatial autocorrelation term 2	Spatial	-1.18E-01	1.46E-05	7.70E+00	5.15E-04
Spatial autocorrelation term 1	Spatial	n/a	n/a	-7.79E+00	5.14E-04
Spatial autocorrelation term 3	Spatial	n/a	n/a	7.89E+00	5.27E-04

Table 5.7 The coefficients and associated p-values of the variables correlated with the intercept of the power law relationship using both forward-backwards and backward-forwards selection procedures.

Variable	Group	Forward-backwards		Backward-forwards	
		Coefficient	p-value	Coefficient	p-value
(Intercept)	n/a	-2.95E+01	1.89E-11	-5.37E+02	9.92E-08
Natural logarithm of the cost distance to roads	Anthropogenic	-5.29E-01	9.09E-10	-3.09E-01	1.05E-04
Historical logging – Partially logged	Anthropogenic	1.06E+00	1.68E-05	1.67E+00	2.18E-09
Natural logarithm of the population pressure with decay constant of 12.5km	Anthropogenic	8.45E-01	1.23E-12	4.98E-01	1.06E-05
Cost distance to Dar es Salaam	Anthropogenic	1.40E-05	3.47E-06	n/a	n/a
Mean annual monthly temperature range	Climatic	8.46E-01	2.00E-16	9.52E-01	2.00E-16
Total available water capacity of the soil	Edaphic	2.72E-01	3.82E-10	2.47E-01	1.22E-07
Mean burned area probability in the fourth quarter	Fire	n/a	n/a	2.05E+02	1.27E-03
Mean annual global horizontal solar radiation	Geographic	3.64E-03	9.90E-08	3.76E-03	4.37E-07
Spatial autocorrelation term 1	Spatial	n/a	n/a	-3.35E+01	4.45E-07
Spatial autocorrelation term 2	Spatial	n/a	n/a	3.30E+01	4.45E-07
Spatial autocorrelation term 3	Spatial	n/a	n/a	3.29E+01	4.48E-07
Spatial autocorrelation term 6	Spatial	n/a	n/a	1.24E+00	1.93E-06

Table 5.8 The coefficients and associated p-values of the variables correlated with the gradient of the power law relationship using both forward-backwards and backward-forwards selection procedures.

Variable	Group	Forward-backwards		Backward-forwards	
		Coefficient	p-value	Coefficient	p-value
(Intercept)	n/a	7.74E+00	1.05E-10	9.21E+01	1.53E-04
Natural logarithm of the cost distance to roads	Anthropogenic	1.22E-01	1.12E-08	6.05E-02	1.15E-03
Historical logging	Anthropogenic	-1.01E-01	9.71E-02	-2.95E-01	8.78E-06
Natural logarithm of the population pressure with decay constant of 20.8km	Anthropogenic	-2.50E-01	6.99E-10	-1.75E-01	2.91E-05
Cost distance to Dar es Salaam	Anthropogenic	-3.76E-06	1.62E-06	n/a	n/a
Mean annual monthly temperature range	Climatic	-2.05E-01	2.00E-16	-2.38E-01	2.00E-16
Total available water capacity of the soil	Edaphic	-5.40E-02	1.24E-07	-4.16E-02	2.10E-04
Mean burned area probability in the fourth quarter	Fire	-5.81E+01	1.23E-04	-5.62E+01	2.51E-04
Mean annual global horizontal solar radiation	Geographic	-8.68E-04	4.20E-07	-1.05E-03	2.47E-08
Spatial autocorrelation term 1	Spatial	n/a	n/a	5.42E+00	7.01E-04
Spatial autocorrelation term 2	Spatial	n/a	n/a	-5.35E+00	6.99E-04
Spatial autocorrelation term 3	Spatial	n/a	n/a	-5.32E+00	7.03E-04
Spatial autocorrelation term 6	Spatial	n/a	n/a	-2.08E-01	9.66E-04

Table 5.9 The PC axes derived from the candidate variables (App. 1.1). Axes shown in this study to significantly affect carbon sequestration are indicated by an asterisk.

Variable	PC1 Coefficient*	PC2 Coefficient	PC3 Coefficient*	PC4 Coefficient	PC5 Coefficient*
Population pressure with decay constant of 41.6km	0.18	-0.08	-0.03	-0.12	0
Population pressure with decay constant of 20.8km	0.19	-0.02	0.02	-0.04	0.01
Population pressure with decay constant of 16.7km	0.19	-0.02	0.02	-0.02	0.01
Population pressure with decay constant of 12.5km	0.19	-0.01	0.02	-0.01	-0.01
Population pressure with decay constant of 8.6km	0.19	-0.02	0	-0.01	-0.05
Population pressure with decay constant of 4.2km	0.18	-0.06	-0.03	-0.05	-0.09
Population pressure with decay constant of 1.7km	0.17	-0.08	-0.07	-0.08	-0.07
Natural logarithm of the population pressure with decay constant of 41.6km	0.18	-0.06	-0.01	-0.16	-0.03
Natural logarithm of the population pressure with decay constant of 20.8km	0.18	0.08	0.08	-0.04	-0.02
Natural logarithm of the population pressure with decay constant of 16.7km	0.18	0.09	0.09	-0.02	-0.03
Natural logarithm of the population pressure with decay constant of 12.5km	0.18	0.11	0.09	-0.01	-0.05
Natural logarithm of the population pressure with decay constant of 8.6km	0.18	0.1	0.07	0	-0.08
Natural logarithm of the population pressure with decay constant of 4.2km	0.18	0.05	-0.02	0.01	-0.17
Natural logarithm of the population pressure with decay constant of 1.7km	0.12	-0.04	-0.22	-0.05	-0.26
Cost distance to Dar es Salaam	-0.17	0.01	0.22	-0.08	-0.01
Cost distance to market towns	-0.12	-0.14	0.3	0.06	0.04
Distance to roads	-0.1	-0.22	0.09	-0.08	-0.24
Distance to Dar es Salaam	-0.16	0.04	-0.03	-0.32	-0.1
Distance to market towns	-0.13	-0.21	-0.09	0.02	0
Natural logarithm of the cost distance to Dar es Salaam	-0.17	0.02	0.19	-0.05	-0.03
Natural logarithm of the cost distance to market towns	-0.11	-0.15	0.3	0.08	-0.02
Natural logarithm of the cost distance to roads	-0.09	-0.23	0.15	-0.04	-0.22
Mean annual temperature	-0.08	0.17	-0.32	0.1	-0.17
Mean annual maximum monthly temperature	-0.1	0.14	-0.3	0.06	-0.15
Mean annual minimum monthly temperature	-0.06	0.19	-0.31	0.12	-0.18
Mean annual monthly temperature range	-0.07	-0.22	0.14	-0.19	0.19
Mean maximum cumulative water deficit	-0.1	-0.15	-0.21	-0.14	0.06

Mean number of dry months annually	-0.03	-0.25	-0.18	-0.05	0.03
Wind speed	0.16	-0.14	-0.04	0.12	0.11
Total nitrogen content of the soil	-0.02	-0.17	-0.03	-0.11	-0.53
Total carbon content of the soil	0.01	-0.23	0.15	0.31	-0.13
Percentage sand content of the soil	-0.06	0.17	-0.12	-0.23	0.43
Total available water capacity of the soil	0.01	0.18	0.21	0.41	0.03
pH of the soil	0	0.23	0.17	0.28	-0.19
Soil fertility	0	-0.29	-0.04	-0.05	0.02
Mean burned area probability in the fourth quarter	-0.12	-0.2	-0.15	0.17	0.07
Mean burned area probability in the third quarter	-0.12	-0.2	-0.15	0.17	0.07
Annual mean burned area probability	-0.12	-0.2	-0.15	0.17	0.07
Aspect	0.03	0.14	0.06	-0.24	0.1
Mean annual global horizontal solar radiation	-0.11	0	-0.17	0.31	0.17
Spatial autocorrelation term 1	0.18	-0.08	-0.03	0.08	0.08
Spatial autocorrelation term 2	0.19	-0.04	-0.01	0.13	0.08
Spatial autocorrelation term 3	0.17	-0.14	-0.05	0.02	0.06
Spatial autocorrelation term 4	0.17	-0.13	-0.05	0.04	0.07
Spatial autocorrelation term 5	0.18	-0.06	-0.01	0.12	0.08
Spatial autocorrelation term 6	-0.17	0.14	0.04	-0.07	-0.07
Spatial autocorrelation term 7	0.18	-0.06	-0.01	0.12	0.08
Spatial autocorrelation term 8	0.17	-0.14	-0.05	0.02	0.06

Table 5.10 The maxima associated with the Gompertz model fits for a range of DBH measurements.

DBH (cm)	Estimate maximum height (m)	MAT where maximum height occurs (^oC)
10	11.5 (8.3-14.3)	12.0
20	13.9 (8.8-20.9)	16.2
40	19.7 (9.7-41.3)	22.1
60	29.0 (10.6-62.9)	26.2
80	29.7 (11.4-81.5)	29.3
100	33.6 (12.1-96.7)	31.8
150	40.5 (13.5-123.5)	36.1
200	45.1 (14.5-140.4)	39.0

Table 5.11 The coefficients and associated p-values of the correlations between the derivatives of carbon storage (the intercept of the power law relationship, the gradient of the power law relationship, WSG and maximum canopy height [shown here are intercept, gradient, WSG and height respectively]) and the carbon storage estimates made in this study.

Variable	4th order interactions		2nd order interactions	
	Coefficient	p-value	Coefficient	p-value
(Intercept)	2.77E+03	2.00E-16	5.08E+02	2.00E-16
height	-8.61E+01	2.00E-16	-2.71E+00	3.99E-07
intercept	2.79E+02	2.00E-16	1.93E+02	2.00E-16
gradient	3.97E+03	2.00E-16	1.04E+03	2.00E-16
WSG	-4.25E+03	2.00E-16	-5.95E+02	2.00E-16
height:intercept	-9.12E+00	5.61E-12	-2.10E+00	2.00E-16
height:gradient	-1.32E+02	2.00E-16	-7.53E+00	2.00E-16
height:WSG	1.42E+02	2.00E-16	8.23E+00	2.00E-16
intercept:gradient	-1.64E+02	2.00E-16	-4.33E+00	2.00E-16
intercept:WSG	-3.59E+02	6.84E-12	-2.27E+02	2.00E-16
gradient:WSG	-5.87E+03	2.00E-16	-1.20E+03	2.00E-16
height:intercept:gradient	5.90E+00	2.00E-16	n/a	n/a
height:intercept:WSG	1.09E+01	5.36E-07	n/a	n/a
height:gradient:WSG	1.98E+02	2.00E-16	n/a	n/a
intercept:gradient:WSG	2.55E+02	2.00E-16	n/a	n/a
height:intercept:gradient:WSG	-9.38E+00	2.00E-16	n/a	n/a

WSG, with both showing positive correlations with carbon storage in areas of low WSG, but negative correlations in areas of high WSG (Figure 5.9).

Furthermore, the carbon sequestration regression values were positively correlated with carbon storage estimates (p-value < 0.001), indicating that areas storing the most carbon are also those that are increasing in stock at the fastest rate.

5.7 Discussion

5.7.1 Tier 3 Correlation-based Method vs. Tier 2 Seven-Stage Survey Method

Comparing the estimates of carbon storage over the 33.9 million hectares from this study to other published values shows that my estimate of aboveground carbon storage is larger than most, although closer to the most recently produced estimate (Table 5.2). The values produced in this chapter are also in close agreement with those produced in Chapter 4. The underestimation of the amount of carbon stored in the EAM region in global analyses is suspected to be the result of their poor resolution and/or application of data from other regions which may differ systematically compared to East African forests, woodlands and savannahs (see Chapter 4). When divided by land cover category, my locally derived carbon estimates are comparable to those presented in other published studies, often containing little or no data from East Africa (Baccini et al., 2008, Baccini et al., 2012, Saatchi et al., 2011, Ruesch and Gibbs, 2008, Hurtt et al., 2006). Differences may arise because many previous studies mapped carbon storage at lower resolutions (Baccini et al., 2008, Baccini et al., 2012, Saatchi et al., 2011, Ruesch and Gibbs, 2008, Hurtt et al., 2006). In homogenous landscapes, these scale effects are unlikely to cause a dramatic difference in carbon estimates. However, in heterogeneous landscapes, such as East Africa, the forests are highly fragmented and thus the effect of scale is likely to be substantial. Forest fragments, typically of high carbon storage, may be omitted at lower resolutions, being ‘replaced’ by more dominant, but low carbon, land cover categories (e.g. open woodland), hence resulting in an underestimation of regional carbon storage.

My study is directly comparable to Chapter 4, as both investigations use the same spatial resolution, as well as overlapping data collected from the study area. However, the Tier 2 study solely uses a look-up table method and the oversimplification of this method is emphasised by comparing the respective carbon storage estimates across the EAM range (App. 4.5). In general, the carbon storage estimates produced here are lower than (although not statistically different from) the Tier 2 estimates due to the fact that I account for anthropogenic and natural disturbance, known to reduce carbon storage estimates (Chazdon, 2003, Omeja et al., 2012, Blanc et al., 2009, Ahrends et al., 2010). The systematic bias across all wooded land covers of the look-up table estimates used in Chapter 4 indicates that disturbed habitats were under-sampled. It must be noted that, the landscape-scale confidence intervals surrounding my Tier 3 estimates are considerably wider than those around the Tier 2 estimates. Confidence intervals derived from look-up table values may show a systematic bias. The ranges provided are an artefact of the study area, the number of land cover categories and the resolution as, when summed across a large number of pixels, pixel error is mostly negated as underestimates in one part of the landscape are counterbalanced by overestimates in other parts (Chapter 4). The 95% CI developed from regression equations are effectively based on numerous continuous variables, containing the uncertainty relating to anthropogenic, climatic and edaphic variables, and hence have many thousands of possible combinations, severely limiting the ability of the ‘law of averages’ to act. Hence, the 95% CI presented in this chapter may better reflect that of the actual landscape, containing more variables that make-up the complex landscape heterogeneity (i.e. improved representativeness), and the look-up table 95% CI presented in Chapter 4 may be an underestimate.

5.7.2 Links Between Carbon Stock and Influential Variables

The results presented here indicate that ALC storage in tree dominated ecosystems is correlated with anthropogenic, climatic and edaphic variables. Direct anthropogenic factors are most strongly correlated with carbon storage. Within my study area, people are clustered around high carbon areas (Figure 5.3). Rather than arising because people in some way enhance carbon storage (which seems implausible - see below), I suggest this clustering could be due to these areas having favourable climatic conditions for plant (and thus crop) growth. Additionally, the incidence of malaria is lower at high elevations (Balls et al., 2004), making these locations more habitable for human populations. Thus there is a peak in population density near the base of high-carbon montane forests (Platts et al., 2011). Hence, when observed at one point in time, there is frequently a positive correlation between human population density and carbon storage, yet, when followed over time, degradation at the local level caused by the population is evident. This can be seen both in Chapter 3 and in published studies (Ahrends et al., 2010, Bayon et al., 2012). For example, areas near Dar es Salaam are known to have lower biomass due to the local demand of low grade timber by the city, as well as international demand for high grade timber via the city's port (Ahrends et al., 2010). Similarly, I also show a decrease in carbon storage in accessible areas near to the commercial capital and after logging. This emphasises the connections between the rural and urban landscape and how the sphere of urban influence is driving change in rural ecosystems. The decrease in carbon storage as a result of logging (51-77% of the ALC is retained) is of similar magnitude to other reported estimates (Putz et al., 2012). I observe a comparable decrease due to differing governance. Land under national control holds between 40% and 65% of the ALC stored in areas under the control of the local population. This result may indicate that participatory and community led forestry is successful in my study area (Topp-Jørgensen et al., 2005, Burgess et al., 2010). However, it is not possible to prove causation within the framework of this study. Community led forestry activities are located in the south-east of my study area within an area of naturally high carbon storage, whereas land under national control covers a vast area, including the dry, carbon-poor east. Hence, my finding that carbon storage is higher in areas under local control may be a result of natural processes rather than differences in land management. Further studies, monitoring the change in carbon storage over time under the two different governance regimes would enable the effect of land management to be determined. My preliminary results show that the change in carbon over time is not statistically different under either governance regime (p-value > 0.05).

The overall effects on carbon storage are a result of many changes in forest characteristics. Both WSG and the proportion of larger stems decrease with increasing anthropogenic disturbance, however, stem density increases. Anthropogenic disturbance, for example logging, is often a commercial activity and results in the preferential removal of the largest, most valuable stems (Ahrends et al., 2010). The more open canopy, following stem removal, would result in increased recruitment from young trees (Silva et al., 1995), leading to the high numbers of small stems observed. My results highlight how influential the negative effect of people on tropical forest carbon storage can be. This assertion is supported using data from across the tropics (Chhatre and Agrawal, 2009, Chhatre and Agrawal, 2008, Mbwambo et al., 2012). The significant impact of anthropogenic activities on carbon storage, implies that REDD+ could, at the local scale, have significant positive impacts on carbon storage. However, careful policy designs to limit leakage of deforestation and encourage the involvement of the local population are needed to ensure REDD+ schemes achieve their carbon storage and sequestration aims (Fisher et al., 2011).

After anthropogenic effects, climatic variables are the next most influential correlate of carbon storage. The effect of climate on tropical forest biomass is quite well documented but also highly contentious (Larjavaara and Muller-Landau, 2012, Clark et al., 2003, Slik et al., 2010). My results clearly demonstrate that the temperature range (the difference between mean monthly maximum and minimum temperatures), and not the mean annual temperature, is key to understanding carbon storage in the tropical forests of the EAM. However, my results appear to conflict with expectations from theory (Larjavaara and Muller-Landau, 2012). Respiration is known to be correlated with high night-time temperatures (Clark et al., 2010), while high day-time temperatures may result from high insolation, leading to increased photosynthesis, provided that water is not limiting (Graham et al., 2003). However, my findings indicate that carbon storage actually *decreases* as temperature range widens, i.e. with higher monthly maxima and lower monthly minima temperatures. As the temperature range increase, both the potential stem density (indicated by the intercept of the power law relationship) and WSG increase and so the reduction of carbon storage is driven by the decreasing proportion of larger stems. A possible explanation for these results can be found in niche theory, with each species having a unique 'goldilocks zone' in which it functions most efficiently (Silvertown, 2004). Typically, large-stemmed species are specialists, growing slowly in a specific niche over a long period of time (Rüger et al., 2011, Baltzer et al., 2005). Thus, if environments are more constant (with a lower temperature range) then, under niche theory, each locality will be occupied by species specifically adapted to function best at that temperature, thus resulting in many large stems and high biomass (Herwitz, 1993, Way and Oren, 2010). Areas experiencing high temperature variation may be occupied with generalist species, having to tolerate a variety of temperatures, and resulting in lower productivity. In addition, extreme climate variations are known to increase mortality (Phillips et al., 2009b) increasing dynamism, reducing the residence time of carbon and potentially killing large stemmed species before they grow to their full capacity, preventing the accumulation of high biomass levels.

Precipitation is also known to be an important variable influencing carbon storage (Stegen et al., 2011). My best fit model suggests that increased dry season length reduces carbon storage, whereas drought intensity does not have a significant affect. In times of water scarcity, plants close stomata to reduce water loss through transpiration, leading to a reduction in carbon assimilation (Meir and Grace, 2005). Interestingly, precipitation-based variables were not found to significantly correlate with any of the components of carbon storage and so the mechanism driving this correlation is unclear. Previously studies investigating the derivatives of carbon storage have produced conflicting results (Bunker et al., 2005, Wiemann and Williamson, 2002, ter Steege and Hammond, 2001).

Within the next century, the region is predicted to become both warmer and wetter, having a similar length dry season but experiencing increased seasonality, with higher probabilities of intense drought and flooding (Doherty et al., 2009, Sitch et al., 2008). Thus, my results support the anticipated 'greening' expected as a result of the general trend shown in future climate scenarios (i.e. high temperatures and levels of precipitation may lead to increased carbon storage) (Doherty et al., 2009). However, caution should be applied as more intense droughts and/or floods may hinder growth. Specifically, the water limitation experienced in times of drought may complicate the predicted increase in growth as a result of the increasing temperature, despite the mediating action of increasing CO_2 concentrations on plant water use efficiency.

Soil water availability is also known to effect plant growth and carbon storage (Baker et al., 2003). However, this effect can be complex, with both too little water (droughts) and too much water (floods) known to reduce carbon storage (Asner and Alencar, 2010, Phillips et al., 2009b, Kozlowski, 2002). I find carbon storage decreases with an increase in soil water availability, driven by a reduction in WSG and the proportion of large stems, although somewhat buffered by an increasing density of smaller stems. My result may be considered counter-intuitive, with water scarcity known to lead to a reduction in carbon assimilation (Meir and Grace, 2005). However, droughtedness has already been accounted for in my model and thus, the observed effect of soil water availability may be structural rather than hydrological. More saturated soils, may be unable to provide large stems with enough structural support to remain upright, particularly in montane areas (such as the EAM) where slopes may be extremely steep. Thus, larger stems may not be present in saturated soils, leading to low levels of carbon storage. In addition, drier, sandier soils appear to filter species towards those with higher WSG (Phillips et al., 2009b, Slik et al., 2010).

I find no effect of soil fertility on tropical forest biomass. Previous studies have shown that more fertile soils have the potential to support higher levels of growth, but that these are often also more dynamic and so likely to have higher mortality (Paoli et al., 2008). However, regional studies have produced conflicting results, finding positive, negative and no correlations between soil fertility and AGB (DeWalt and Chave, 2004, Laurance et al., 1999, van Schaik and Mirmanto, 1985, Quesada et al., 2009b, Quesada et al., 2012). The most recent, in-depth studies by Quesada *et al* (2009, 2012) support my result. They found that Amazon forest biomass was not significantly correlated with soil conditions once corrections for spatial autocorrelation were applied, perhaps because aboveground biomass does not seem to be directly influenced by edaphic conditions unless conditions are particularly extreme (Quesada et al., 2009b, Quesada et al., 2012). The debate surrounding the effect of soil properties on the components of carbon storage is as equally contentious to that surrounding AGB. For example, in the Amazon, WSG has been found to have negative correlations with soil fertility (Quesada et al., 2009b, Muller-Landau, 2004, Quesada et al., 2012), but, similar to results presented here, no correlations have also been reported (ter Steege and Hammond, 2001, Woodcock, 2000). In general, edaphic characteristics in the tropics are relatively understudied and involve large uncertainties, perhaps hindering our understanding of any mechanisms involved (García-Oliva and Masera, 2004, Phillips et al., 2010, Quesada et al., 2009b). The lack of accurate, high resolution soil data was a key limitation of my study (and many other studies). This emphasises the need for tropical forest research and REDD + projects, both regional and global, to include soil in their investigations.

Although additional variables, such as solar radiation and fire, were not found to affect carbon storage estimates, I demonstrate significant correlations with its components. Forests experiencing lower light levels show a lower potential stem density, but a higher proportion of larger trees. Larger trees are usually taller (Feldpausch et al., 2011) and so would dominate in regions receiving less solar radiation, intercepting the little light available and decreasing the number of smaller stems present in the understory (King et al., 2005). The reduced number of small stems in forests experiencing low light levels may be countered by the increased proportion of large stems, leaving overall carbon storage values unaffected. Fire, on the other hand, is negatively correlated with the proportion of big trees, but this affect may be countered by an increase in WSG, again resulting in no overall effect on carbon storage. Stems of high WSG are able to provide equal strength to lower WSG stems, at a reduced DBH. Thus, high WSG stems show a reduced surface area and lower costs of bark construction and maintenance. These costs are particularly important in fire-prone habitats, where thick bark is needed for protection (Larjavaara and Muller-Landau, 2010). Hence, smaller, high WSG stems are increasingly selected for as the probability of fire occurrence increases.

Thus, the variables correlating with aboveground carbon storage and its components are numerous (spanning anthropogenic, climatic and edaphic variables) and complex. But, how do the components interact to contribute to carbon storage? I find that all components correlate with carbon storage, although WSG and the proportion of large stems dominate. In addition, I find that there are complex interactions between all components. For example, the proportion of large stems and the potential stem density do not combine additively with maximum canopy height to contribute to aboveground carbon storage. In areas of low potential stem density and areas with a low proportion of large stems, carbon storage is positively correlated with maximum canopy height. However, this correlation is reversed in areas of high potential stem density and also areas with a high proportion of large stems. This change in correlation may be due to maximum canopy heights not being attained in areas of high potential stem density or areas with a high proportion of large stems. Up to 25% of species examined in Bolivian forest fail to show asymptotic DBH-height relationships (Poorter et al., 2006). Furthermore, the maximum height may not be realised as mechanical damage and/or death can prevent this (West et al., 1999, Banin et al., 2012). Thus, competition amongst stems in areas of high stem density and areas with a high proportion of large stems may prevent stems reaching the predicted maximum canopy height, and so altering the positive correlation between maximum canopy height and carbon storage that may be expected.

In Amazonia, WSG has been proposed to drive landscape-scale variations in aboveground biomass (Baker et al., 2004b). In my study, while highly influential, WSG does not combine additively with other components to impact on carbon storage. In areas of low WSG, as expected, the potential stem density (intercept of the size-frequency power law relationship) and the proportion of large stems (gradient of the same relationship) correlate positively with carbon storage. However, the low WSG provides less structural support for a given diameter than in higher WSG areas (Larjavaara and Muller-Landau, 2010), this may result in stems not obtaining maximum canopy height. Indeed, I find stem height to be disproportionately below maximum canopy height in low WSG areas (p-value < 0.01). In high WSG areas, the dense wood provides stems with more structural support, allowing them to attain maximum canopy height. Thus, I observe the expected positive correlation between carbon storage and maximum canopy height, which dominates variation in carbon storage in these areas, decoupling the previous size-frequency component effects.

Like carbon storage and its components, carbon sequestration is also correlated with anthropogenic, climatic and edaphic variables. I estimate that some localities (for example the Udzungwa Mountains National Park) are a carbon sink of comparable per-area magnitude to that observed over recent decades in pristine African forest (Figure 5.3) (Lewis et al., 2009b). However, many areas of forest and woodland within the study area experience a high level of degradation and disturbance, and are a carbon source. Here, I have shown that anthropogenic disturbance is a key determinant of the trend in carbon storage over time in eastern Tanzania. Although, due to the small number of resampled plots available (n=43), I am not able to separate the individual variables of changing carbon storage over time. Important locations of high carbon losses are the Pare and Usambara mountains (App. 4.5), which historically have seen the highest rates of degradation and disturbance (Chapter 3). As such, the study area as a whole is a potential carbon source. The national population of Tanzania is increasing (NBS, 2006) and this will increase the pressure on the tree dominated ecosystems and could result in the study area becoming a significant source of carbon in the future.

The effect of increase in anthropogenic pressures could be compounded by potential decrease in carbon storage as a result of increasing temperatures (Clark et al., 2003, Raich et al., 2006) and changes in soil nutrients, also shown here (although the limitations of my soil data have been previously discussed above). However, these future effects could be complicated by increasing levels of atmospheric CO_2, varying effectiveness of legally protected areas and shifting consumption patterns, none of which are within the scope of this investigation.

5.7.3 Study Limitations

Despite stringent quality control and standardisation protocols, there are limitations to my dataset. The mean plot size used in this study is small for a tropical tree-dominated vegetation study, at 0.09ha. Biomass estimates resulting from small plots are known to suffer from a left-hand skew, leading to high uncertainties (Chave et al., 2003). However, as the number of plots increases, the confidence also increases (Chave et al., 2003). Thus, results obtained from my extensive network of small plots are likely to be robust, covering a sampled area of >160 ha, although caution is still recommended. Secondly, the plots have been measured in different regions by different field teams and using different plot designs. This could be a further source of error if methods were not fully comparable; however, all plots from field teams whose data showed measurement bias were removed. Thirdly, height was not recorded for every stem, only ~34% of sampled stems had height measurements. For stems lacking height data, a value was derived from the DBH using the best fit DBH-height equation available for the region (Equation 5.1). Finally, my biomass estimates utilise pantropical allometric equations (Chave et al., 2005). However, no data used to derive these relationships was from Africa or from montane environments (Chave et al., 2005). By utilising the combination of DBH, height and wood specific gravity data, I have minimised this source of error as much as possible (Chave et al., 2005, Djomo et al., 2010). However, these errors may mean that the data used to calculate the regression models used in this investigation may not be a true representation of carbon storage, and its components, on-the-ground. Ideally, an extensive plot network, developed using global standard protocols containing multiple censuses over time would be available. However, such a network has not yet been developed across the EAM.

In all my models there is a large amount of unexplained variation. The R-squared values for my regression models vary between 0.18 and 0.41. Hence, at least 60% of the variation in carbon storage and its components are unexplained by my regression models. This is likely to be due to three main reasons. Firstly, although I used the highest resolution datasets that are freely available, several of the associated variables are of relatively poor resolution or are very sparsely located across the EAM (including; wind, light and soil variables [App. 1.1]). This is particularly important here as my plot network comprised of many small plots (median, mean and mode are all 0.1ha). Small plots contain a higher level of variation than larger plots, and this is likely to be unexplained in statistical models if datasets describing heterogeneity are not available on the same scale. Secondly, forest characteristics in the present are the result of growth, recruitment and mortality over many years. It is difficult to obtain data on historical variables and yet these could have had a significant impact on present day carbon storage and other forest characteristics. I included the extent of historical logging and this was retained as an important variable in 75% of the final models, being the most influential correlate of carbon storage (Table 5.4-5.8). Thirdly, present day information is also lacking, for example datasets describing physical soil properties in the study area are unavailable. The lack of data (albeit completely lacking or at courser-scale resolution) may mean that the correlations identified from the regression equations produced here are inappropriate. Furthermore, the unexplained variation resulting from these data inadequacies is problematic when investigating how the components of carbon storage combine to produce observed carbon storage. As such, these results should be regarded as a first order estimate. In the future, higher resolution and historical datasets may enable further correlations to be observed when producing models estimating carbon storage, as well as each of the component variables. By reducing the level of unexplained variation in these models, more accurate assessments of how the components of carbon storage interact could be made.

The limited number of multiple censuses available (n=43 plots with >1 census) within my study area gives rise to uncertainty in my estimated sequestration rates. Calculating carbon sequestration requires multiple census tree inventory data, which are rare across the EAM. I have collated the most extensive network of recensused tree inventory plots within my study area to date. However, during the time period covered by my censuses, climatic conditions tended to be drier than over recent decades (Giannini et al., 2008). As such, mortality during this period may have been higher than usual background rates. By contrast, sampling done over shorter time periods may result in overestimation of rates of carbon sequestration as rare stochastic mortality events may not be sampled (Lewis et al., 2004b, Fisher et al., 2008). However, there is debate surrounding the importance of these rare disturbance events (Lloyd et al., 2009). During the sampling period, mortality events were recorded (for example, by both windstorms and felling) but 79% of my plots had a census history of <5 years, with only one plot exceeding 10 years, and so my estimates of carbon sequestration rates may be inflated, indicating that the study area maybe a larger carbon source than presented here. Whilst I examined numerous candidate variables (App. 1.1), due to my limited dataset, I was only able to examine PC axes (Table 5.9). Numerous potential influential variables of changing carbon storage have been identified in tropical tree communities (Lewis et al., 2004a, Lewis et al., 2009a). Further work is needed to expand the existing multiple census inventory plot networks (Lewis et al., 2009b, Phillips et al., 2009b) in order to shed further light on the relative importance of these influential variables. The production of datasets able to separate the multiple variables that correlate with changes in carbon storage would lead to an increased ability to anticipate any future changes, perhaps resulting from population increases, climate change and/or changes in nutrient deposition.

5.8 Conclusions

My results show that the amount of carbon stored in forests across 33.9 million ha of the Eastern Arc Mountains of Tanzania is considerable: 1.32 (0.89-3.16) Pg. This is smaller, although not significantly, than my previous Tier 2 estimates, likely due to the inclusion of the effects of disturbance. Within the tree-dominated land covers, historical logging and governance regime are the most influential direct anthropogenic factors, while the mean number of dry months is the most influential environmental factor, with an order of magnitude less impact. I show that WSG, size-frequency distribution variables and height variables are all important in determining carbon storage, although these effects are not additive. My preliminary estimates indicate that, between 2004 and 2008, tree dominated communities across the study areas showed no significant change, in contrast with previous results from pristine African forest, showing how direct human impacts can override the carbon sink in these systems. The carbon maps and statistical relationships documented can assist policy-makers in designing policies to maintain and enhance carbon storage for climate mitigation and other ecosystem services.

Chapter 6
Research Synthesis

6.1 Thesis Summary

In Chapter 1 and 2, I reviewed the current literature surrounding the estimation of land cover change and carbon storage. Throughout the tropics, these subject areas have a long history of research as scientists, conservationists and policy makers have sought to further the understanding of these changes and the impact of these changes on ecosystems and local populations. I described six main research aims through which my thesis could further the scientific understanding of land cover change and issues surrounding carbon storage. These are:

1. To increase the current LCC data available from satellites by complementing this dataset with historical maps and, using both datasets, to estimate the historical rate of tree cover change, identifying the possible pathways of any observed forest transition (Chapter 3).
2. To improve on contemporary carbon stock estimates (currently using Tier 1 methods) by producing a Tier 2 carbon storage map for the EAM region that is of a high enough spatial and temporal resolution to be of use to policy-makers (Chapter 4).
3. To determine how carbon stocks have altered over the twentieth century across the Eastern Arc Mountains drainage basin as a result of land cover change, providing a long-term baseline of carbon emissions as a result of LCC (Chapter 4).
4. To discover which anthropogenic, edaphic and climatic variables are correlated with the present day distribution of carbon storage and sequestration in the EAM and to produce Tier 3 carbon stock estimates for forests and woodlands, identifying the most influential variables (Chapter 5).

In Chapter 3 I investigated land cover change within the study area across the twentieth century. By geo-referencing and digitising historical land cover maps dated between 1891 and 2008, I quantified the change in land cover over this period. I showed that, between 1908 and 2000, 2.79 million ha of forest and 2.91 million ha of savanna were lost, driven by a five-fold increase in crop area. I suggest that both the EAM watershed and the EAM themselves show a forest transition between 1960 and 1990. It is likely that this transition predominantly occurred as a result of a doubling in the extent of protected areas, termed the state forest policy pathway. Using linear and non-linear regressions, I provide first-order estimates of a long-term baseline deforestation rate for the EAM (Figure 3.11). My results emphasise the potential future importance of reducing land cover change via policy through the successful implementation of protected areas. Thus, both Aim 1 is addressed in Chapter 3.

In Chapter 4, I presented a new methodology to enable regionally appropriate carbon estimates to be obtained for data-deficient areas. In these areas default global carbon storage values and relationships are often used, termed ‘Tier 1 type’ analyses by the Intergovernmental Panel on Climate Change (IPCC). Such estimates may be provide biased results if regional carbon storage average values for local land cover types differ from global average. In addition, uncertainty assessments are rarely provided. My method, compatible with IPCC Tier 2 standards, (i) enables existing inventory data and published literature to be combined in a manner that can be easily updated, (ii) incorporates the most recent studies to ensure that estimates are as temporally accurate as possible, (iii) estimates carbon storage values and associated 95% confidence intervals (CI) for all five IPCC carbon pools (ALC, litter, CWD, belowground live carbon and soil carbon), and (iv) uses weightings to ensure the final values are regionally appropriate. Using this method to estimate carbon storage within my study area (33.9 million hectares of the Tanzania Eastern Arc Mountains (EAM) and associated drainage basins), I show that it is possible to produce Tier 2 estimates in data-deficient regions, an improvement on the Tier 1 estimates previously relied upon in these regions (see Table 2.4 for tier definitions). Additionally, I demonstrate how estimates of uncertainty can be produced. This allows targeted assignment of limited funds to collect missing data that will have the greatest impact on reducing carbon storage estimate uncertainty.

Through combining the above Tier 2 carbon estimates, and associated uncertainty, with land cover maps, I produced spatially explicit estimates of ALC, revealing that my study area stored 1.58 (95% CI: 1.56-1.60) Pg of ALC in the year 2000 (Figure 4.2; Table 4.1). Furthermore, through the use of published ratios, I provided preliminary estimates of the spatial distribution of the other four IPCC carbon pools (litter, CWD, belowground live and soil carbon pools; Table 4.1; App. 3.3; App. 3.4) for which fewer data are often available. Surprisingly, the soil carbon pool exceeded that of ALC and so was the largest carbon store in the region (3.74 [3.43-4.05] Pg). Additionally, by applying the carbon estimates developed in this chapter to the historical land cover maps presented in Chapter 3, I provided estimates of the carbon emission associated with the land cover change that occurred over the mapped period, concluding that, over the twentieth century, my study area committed to released 0.75 (0.45-1.04) Pg of ALC into the atmosphere (Figure 4.4, Table 4.2). These emission estimates are a significant advance on previously modelled estimates for the region (Houghton, 2003, Hurtt et al., 2006) because the land cover data I used was at higher resolution, by three orders of magnitude, and I relied on observational data (via maps) rather than model simulations. Thus, in Chapter 4, Aims 2 and 3 has been addressed.

In Chapter 5, I investigated the influential natural and anthropogenic variables of ALC storage and refined the regional carbon storage estimate provided in Chapter 4 (Table 5.2, Figure 5.1). Look-up table approaches, such as those presented in Chapter 4, are highly simplified and may not provide robust estimates when applied to heterogeneous landscapes. They often do not adequately represent the impacts of human disturbance, which is frequently one of the most important variables in carbon estimates across landscapes. If the plot data underlying look-up tables tended to avoid highly disturbed areas carbon storage estimates may be overestimated (and the converse is also true). Thus, I revised my estimates using regression models developed from correlations between ground-based plot data (1,611 tree inventory plots) and spatially explicit climate, soil and disturbance proxy data, accounting for the effect of natural and anthropogenic disturbance. I reported that the most influential determinants of present day carbon storage, by an order of magnitude, are of anthropogenic origin (the degree of historical logging and the nature of the local governance regime) as opposed to those variations caused by climate, soil or fire. Specifically, land under national control contained 40-65% of the carbon stored in areas under local control, whilst those areas that had previously experienced some logging held 51-77% of the ALC stored in undisturbed areas (Table 5.4). Hence, I expect future changes in carbon storage to be predominantly driven by changes in land management and logging regimes.

Additionally, using the plot inventory data, I developed a diameter-height relationship to reduce uncertainty in my plot-based carbon estimates

(Equation 5.1; Table 5.1; Figure 5.8). Furthermore, I investigated the candidate variables of the components of carbon storage (population structure and WSG) and also how the components combine to result in the ecosystem service of carbon storage. Anthropogenic variables, particularly population pressure, were an order of magnitude more influential in determining all of the component distributions than edaphic or climatic variables. I also concluded that ALC storage is predominantly driven by a positive correlation with the proportion of larger stems and a negative correlation with wood specific gravity, however, the components do not combine additively (Figure 5.9; Table 5.10). Thus, the final aim of my thesis (Aim 4) was addressed in Chapter 5.

6.2 Study Limitations

Whilst this thesis has addressed a number of the scientific aspects of the requirements of REDD+, the study was limited by the availability of data related to the questions I answer. This data-deficiency is evident in Chapters 3, 4 and 5 and will be discussed further here.

I made a concerted effort to collect as many historical maps of land cover as possible. However, if more maps were available then this could greatly reduce the uncertainties identified in Chapter 3. For example, additional maps between 1891 and 2000 would have greatly assisted conforming or rejecting my tentative conclusion that the EAM watershed passed through a forest transition between 1960 and 1990. By contrast, I was able to convincingly demonstrate a forest transition on the EAM, where I had at least nine maps. If more historical land cover maps were available then the harmonisation procedure used in this thesis to allow for comparison between maps may result in narrower categories. This would be beneficial as it would reduce the potential for change within land cover categories (as narrow harmonised land cover categories allow for little degradation before a change in land cover would be reported) but would be highly dependent on the vegetation classification system used in the additional maps. Future studies would benefit from the inclusion of further historical land cover maps if they are available. For example, inclusion of the Millington et al. (1989) data showing land cover in 1984 may help better describe the forest transition in my study area, since this is near the time period where I suggest that the transition occurred. However, despite extensive efforts, I could not obtain access to this data.

My carbon storage maps show a bias towards forested land as tree inventory data from forest cover types were disproportionately abundant in the underlying dataset. However, woodland was shown to be a more important carbon store on a landscape scale because, although woodlands store less carbon per unit area, they are much more extensive. In addition, the difference between the landscape estimates of carbon storage in Chapters 4 and 5 indicates that disturbed areas are also under-sampled. This data deficiency may increase uncertainty in non-forest and disturbed land covers. Future regional inventory programmes would benefit from focussing on non-forest land cover types, particularly on woodland and bushland. This process has already begun under a new WWF-REDD+ project, which focusses on better sampling the data-deficient land cover types identified in this thesis (Burgess et al., in press).

In addition, most regional estimates of carbon storage report only the ALC pool. I show that soil carbon makes up about 59% of the total carbon stored and over double that represented by ALC. However, litter, CWD, belowground and soil carbon pools are understudied and this results in high uncertainty in landscape carbon estimates for these pools. Having identified the data-deficiencies within these carbon pools, I produced a standard operating procedure (Willcock, 2011) detailing the plot establishment protocol to be utilised in the new WWF-REDD+ project, aimed at reducing the uncertainty in carbon estimation in this region (Burgess et al., in press). The plot establishment protocol that I established involves direct measurement of wood specific gravity (through the collection of tree cores) as well as the collection of litter and CWD, and the sampling of soil carbon down to a depth of 1m (Burgess et al., in press). These methods are all derived from established protocols (RAINFOR, 2008) and the data obtained may allow for more accurate mapping of regional carbon storage using the methods provided in Chapter 4 and Chapter 5.

As well as investigating the current levels of carbon stored in all carbon pools, the rate of decrease of carbon storage within these pools following disturbance (e.g. land cover conversion) should also be quantified. For example, using historical maps from Chapter 3, I was able to map changes in all IPCC carbon pools over the twentieth century. However, whilst carbon emissions as a result of land cover change occur over a relatively short time-frame for aboveground carbon pools (aboveground live, litter and CWD), the release of carbon from belowground stores (belowground live and soil) may be much slower. As a result of this, I was only able to estimate the committed carbon emission resulting from land cover change, rather than providing estimates of how emissions varied temporally. Monitoring carbon emissions from all carbon pools that occur as a result of land cover change conversion, for example via flux towers, could provide the half-life of carbon in each pool under differing environmental conditions. This would enable far more detailed accounting of the carbon flux associated with land cover change conversions.

The large amount of unexplained variation in my Tier 3-type regression models used to estimate contemporary spatial patterns of carbon storage and its components is likely due to the relatively coarse resolution of candidate variable datasets, as well as the unavailability of historical datasets. In order to better describe the variation observed in my 1,611 tree inventory plot network, these data-deficiencies need to be addressed. Using historical maps and expert local knowledge, it was possible to provide preliminary estimates of areas where logging had occurred in the past (Swetnam, 2011). However, land cover maps only identify logging activities if they result in a change in land cover type. More selective logging activities (within land cover types) may not be detected using these methods, but could still cause substantial degradation (Asner et al., 2005). Recently, I discovered historical archives within Tanzania containing the licences issued for logging activities during the colonial era. Through the information provided in these archives it may be possible to more accurately represent past logging activities, as they may provide better indications of the degradation within land cover types that has occurred over time. Including this extra information as an additional candidate variable may account for some variation that is currently unexplained in my Tier 3-type regression models.

Other soil characteristics, as well as soil carbon, are also poorly understood across the region. Few data on physical soil properties are available for my study area, and the data on soil chemical characteristics are also extremely limited. Soil is well-known to be extremely heterogeneous, showing large variations in its properties over relatively small areas (Quesada et al., 2009a, Quesada et al., 2009b). I would anticipate that once the spatial variation in soil characteristics had been accurately mapped, correlations with ALC storage would be stronger than those found in this thesis, reducing the amounts of unexplained variation. I am unaware of any current projects operating in the region that are creating such a dataset, despite the benefit it may provide local livelihoods through targeted agricultural land management techniques.

I chose not to investigate the variables of carbon storage within litter, CWD, belowground and soil carbon pools, as, these were calculated from aboveground live carbon values, thus, any patterns identified would mostly reflect the aboveground live carbon trends. The current sampling occurring under the WWF-REDD+ project (previously described) may enable the development of a dataset large enough to begin preliminary analyses into these carbon pools. The techniques used in Chapter 5 could be similarly used for the remaining carbon pools, once the data becomes available.

Calculating carbon sequestration requires multiple census tree inventory data, which are rare in Tanzania. Therefore only very preliminary estimates were produced (a mean carbon decrease of 1.47 [95% CI: increase of 2.13 to decrease of 7.75] Mg C ha^{-1} yr^{-1}), from 43 multiple census plots. Further work is needed to expand the existing multiple census inventory plot network in order to reveal the relative importance of anthropogenic, climatic and edaphic candidate variables affecting this process. The new WWF-REDD+ project plans to re-census all 43 multiple census plots used in this thesis over the next 5 years (Burgess et al., in press). In addition, the Tanzanian government has instigated the National Forest Resources Monitoring and Assessment (NAFORMA) project to establish over 32,000 circular plots (radius = 15m), of which 25% will be made up of permanent sample plots (Tomppo et al., 2010b). Once these datasets have become established, the techniques used in this thesis could be followed, producing a more accurate estimation of changing carbon storage over time within the study area.

6.3 Applications to REDD+ Monitoring

This thesis provides high resolution, spatially-explicit carbon storage maps for eastern Tanzania. These maps can assist policy-makers and civil society to make more informed decisions regarding land-use and protection. Given the large role of humans in determining carbon storage in the landscape such decisions have the potential to dramatically affect landscape carbon storage across the EAM region. The carbon maps, associated uncertainty and statistical relationships documented here can assist in designing policies and management plans to maintain and enhance carbon storage for climate mitigation. In the remainder of this sub-section, I describe the several ways in which the work presented in my thesis can, and is, influencing policy decisions.

Using the method presented in Chapter 4, many countries currently relying on Tier 1 techniques to provide national carbon estimates are capable of producing regionally appropriate Tier 2 estimates with associated uncertainty estimates for relatively little financial investment. These results are already being utilised by Tanzanian government officials. For example, at United Nations meeting on Sustainable Development, known as the Rio+20 Conference in Rio, Brazil, earlier this year, Hon. Terezya Huvisa, (the Minister of State in the Vice President's Office for Environment, Tanzania) presented the Tier 2 estimates of carbon storage within my study area from Chapter 4 in a speech outlining the preparations Tanzania has made in order to benefit from any future REDD+ systems as they are developed. At a previous meeting, in the United Nations Convention on Climate Change, in Copenhagen in 2010, provisional Tier 2 results from my carbon research were also presented by Tanzania officials.

Key issues for the successful implementation of REDD+ include the accuracy of the monitoring systems, detecting and preventing so-called leakage (reducing deforestation in one place, only to see it displaced to somewhere outside the REDD+ project area) and establishing accurate historical baselines (see Chapter 2 and Chapter 3). Here, I have provided improved estimates of current carbon stocks as well as historical baselines. The method presented in Chapter 4 helped to identify data-deficient areas in which future sampling would reduce bias and uncertainty. Through collaboration with local NGOs and government officials, sampling of these data-deficient areas (for example, woodland land cover types; and litter, CWD, belowground live carbon and soil carbon pools) has already begun. Thus, the accuracy of monitoring systems has already begun to increase.

Additionally, the results presented in Chapter 4 were used to demonstrate a method by which carbon could be valued in a manner that would prevent leakage. This work was a result of collaboration under the Valuing the Arc project (see Sections 1.7 and 6.5). We deduced that, to increase the welfare of the increasing population within my study area, future charcoal and food provision would have to increase over time (Fisher et al., 2011). By estimating the regional profit resulting from conversion of other land cover types to those supporting agriculture and charcoal production, we demonstrated that the level of payments to secure emissions reductions varies spatially. Given this, we simulated a scheme that provides the required reduction in fuel-wood demand, through the provision of fuel efficient stoves, and increase in food security, through the use of fertilisers. We determined that a doubling of crop yields would cost only ~US$12.30 per Mg CO_2 (median value; including all stove-efficiency and forest-monitoring costs; interquartile range: US$8.70–US$18.10 per Mg CO_2), well below the European Union's Emission Trading Scheme price point for CO_2 (currently ~US$24 per Mg CO_2) (Fisher et al., 2011). By meeting the demand for charcoal and food provision on existing land, the threat of leakage through the conversion of remaining natural resources is lessened.

Furthermore, by demonstrating the existence and usefulness of historical land cover maps, I provide regional data on historical rates of land cover change and associated carbon emissions (Chapter 3). These data allow the Tanzanian government to better assess which of the possible mechanisms (described in Table 1.6) used to calculate REDD+ baselines would most benefit the welfare of its populous by best balancing the trade-off of emissions reductions against economic and social development. Additionally, correlations between carbon storage and candidate variables identified in Chapter 5 provide indications of the variables affecting current distributions of carbon storage. These indications may help predict the future variables of carbon storage, allowing policies to be developed to counter negative effects, for example subsidising the direct initial cost to consumers of purchasing fuel efficient stoves. As previously described, land under national control contains 40-65% the carbon stored in areas under local control, whilst previously logged areas hold 51-77% of the ALC stored in undisturbed areas. Thus, in order to maximise carbon storage in the region, policy makers should minimise logging activities whilst simultaneously encouraging local community involvement in forest management. Tanzania has a long history of participatory and community led forestry (Topp-Jørgensen et al., 2005, Burgess et al., 2010) and the association of high levels of carbon storage with increased levels of community control may show policy makers that such strategies are effective and should be continued. However, the success of these projects should be continually monitored enabling communities to share knowledge of more successful practices, whilst ensuring those communities given new opportunities to manage natural resources are as successful as those currently involved in the practice.

I have shown protected areas to be effective in encouraging forest transition, transforming net deforestation patterns to those of forest establishment. This impact is perhaps surprising as protected status in forest reserves is mostly administrative, without patrols or guards (Lung and Schaab, 2010, Wyman and Stein, 2010, Hayes, 2006). It is likely that, although ‘paper parks’ may not completely prevent land cover conversion by local people, the protected status is enough to afford the land protection from large-scale commercial businesses, such as large and foreign-owned logging companies, which compete for government tenders in order to exploit natural resources. For example, much of the unprotected land in Udzungwa Mountains has been sold to the Kilombero Valley Teak Company and Illovu Sugar Limited and converted to teak and sugar plantations respectively, whilst the protected areas (Udzungwa Mountains National Park and the Selous Game Reserve) have been spared (KVTC, 2012, Harrison, 2006).

Whilst the success of current legally protected areas is applauded, it must still be noted that, as a whole, the EAM are estimated to be a net source of carbon (mean emissions of 1.2 Mg ha^{-1} yr^{-1}, ranging from 0.2 Mg ha^{-1} yr^{-1} at Mahenge to 3.6 Mg ha^{-1} yr^{-1} in the West Usambara mountains; App. 4.5). However, some specific localities (for example the Udzungwa Mountains National Park, the only Tanzanian national park containing a substantial portion of forest) are a carbon sink, suggesting management practices occurring in these localities should be investigated and perhaps initiated elsewhere, as well as encouraging the future creation of further national parks aimed at preserving tropical forests. I also show anthropogenic activities to be the most influential variables of present day carbon storage. Thus, with appropriate incentives, schemes such as REDD+ may lead to altered management regimes and dramatically reduced carbon losses from landscapes.

6.4 Recommendations for Future Research

Through addressing my research aims, I identified several ways in which future research could improve current understanding of carbon storage in tropical landscapes. I have previously discussed research addressing the data-deficiencies identified in Section 6.2, so only remaining lines of future investigate will be identified in this section.

I showed a substantial loss of forest cover, driven by a dramatic increase in cropland area, resulting in a large estimated committed emission of carbon through mapping land cover change over the course of the 20^{th} century. It is often reported that historical land cover data, beyond that obtained via remote sensing satellites, is often unavailable in the tropics (Lambin, 1997) and this lack of data hinders efforts to estimate historical baseline rates of carbon emissions as a result of land cover change (Pages 22-25). However, data were available for my study area and my preliminary investigations indicate that this is also likely to be the case for many other tropical regions (Kuchler, 1970). Although it would require significant investment, the digitisation of historical maps depicting tropical land cover would be worthwhile for three main reasons. Firstly, the data obtained could be used to evaluate global products of gridded historical land cover change and carbon emissions (for example (Hurtt et al., 2006, Houghton et al., 1999)). Secondly, the maps would provide good validation data for dynamic global vegetation models, enabling the better prediction of how anthropogenic activities and climate change may affect future distributions of biomass. Thirdly, the historical emissions data obtained could be correlated with national development indicators (e.g. Gross Domestic Product) to obtain ‘real-world’ baseline emissions targets that would not penalise development in high resource, low income countries (see Section 2.8 for further details).

In Chapter 4, I produce a seven-stage method by which Tier 2-type carbon values can be produced for data-deficient regions. It may not be likely that governments have the resources (both in time and computing power) to carry out the complex data searches and weighting calculations as I have indicated. It may be more practical to refine the Tier 1 values that are already globally accepted. Currently, Tier 1 values show some differences between continents (Ruesch and Gibbs, 2008) but these could be made more elaborate using my seven-stage method at a sub-continental scale. For example, global institutions (such as the IPCC or FAO) could perform the extensive data searches and weighting calculations for East Africa, reducing the uncertainty of Tier 1 estimates for Tanzania, Kenya, Uganda, Rwanda and Burundi. If this strategy was followed across the globe, Tier 1 carbon estimation could be much improved by making such estimates regional.

The production of regionally appropriate carbon maps (previously unavailable for most carbon pools), associated uncertainties and statistical relationships documented can assist policy-makers in designing policies to maintain and enhance carbon storage for climate mitigation (see Section 6.3). Previously, when estimates of carbon storage are provided, they are rarely associated with any indications of uncertainty. Overall, there is high uncertainty in pixel estimates, but look-up table methods show narrow confidence intervals around landscape estimates. This is predominantly an artefact of the size of the study area, number of land cover classifications and the pixel size, as the uncertainty resulting from the heterogeneity of environmental and anthropogenic variables are neglected. The uncertainties produced from regression equations, which better describe the impact of environmental heterogeneity on carbon storage estimates, may therefore be better representations of true uncertainty. Whilst these uncertainty estimates are available for ALC storage estimates for tree-dominated land cover types (see Chapter 5), uncertainty estimates for the remaining IPCC carbon pools (litter, CWD, belowground live carbon and soil carbon) could be improved. In Chapter 4, I provided the first regional estimates of all IPCC carbon pools for my study area. However, the estimates for litter, CWD and belowground live carbon (and their associated uncertainties) are derived from ALC estimates using published ratios. These ratios could be substantially improved in two main ways. Firstly, the published ratios available were not developed within my study area. The direct measurement of these carbon pools in association with tree inventory plots being carried out as part of the new WWF-REDD+ project (described above) will enable regionally appropriate ratios to be produced. Secondly, there is likely to be uncertainty associated with these ratios and so the uncertainties provided in Chapter 4 for litter, CWD, belowground live carbon and soil carbon pools may be underestimates. Again, further characterisation of these relationships will better enable this uncertainty to be estimated and incorporated into future investigations.

It is important to note that the correlations identified in this thesis do not necessarily prove causation. In order to unambiguously identify the true drivers of carbon storage and sequestration, it is necessary to carry out factorial experiments on mature stands of tropical forest. The challenges surrounding the feasibility of such experiments should not prevent this vital research from being undertaken. Whilst these studies could be as a result of scientific manipulation (for examples see (Brando et al., 2008, Iversen et al., 2012)), the Mufindi District of the Tanzanian Eastern Arc Mountains (EAM) provides an opportunity for a ‘natural experiment’. In the past, this area was in close proximity to the Kihansi Falls, and, as a result of the high pressure spray emitted from the waterfall, had a super-saturated environment (Lovett et al., 1997). During this period, plot censuses were performed alongside detailed climatic surveys. In 1995, construction of a dam to provide the region with hydro-electric power began (Marwa and Kimaro, 2005). After completion, in the year 2000, the local climate changed substantially, with the air becoming significantly drier (Msyani et al., 2009). If future plot censuses were again accompanied by climatic surveys, the direct effect of this moisture reduction on tree growth, recruitment, mortality and the resultant change in carbon storage could be identified.

Finally, significant technological advances may be possible through critically examining the methodology used to sample plot-based carbon storage. These advances may help to reduce some of the data-deficiencies identified in Section 6.2. One area of investigation that is as of yet unexplored is the use of handheld near-infrared spectroscopy to aid the measurement of litter, CWD and soil carbon in the field. Laboratory based measurements have shown very strong correlations between the spectra of field samples of both wood and soil and their carbon content (Gong and Zhang, 2008, Ludwig et al., 2002, Kelley et al., 2004, Jones et al., 2005, Tsuchikawa, 2007). Further investigation of these relationships in field conditions may enable regional correlations between the spectra of live wood, litter, dead wood and soil and their respective carbon contents to be developed. Once these *in situ* correlations have been established, the sampling time required to measure all carbon pools of future inventory plots may be reduced, as recording NIR spectra is a quick procedure (often taking less than 10 seconds per sample). As such, future studies could benefit from obtaining data on all IPCC carbon pools for a relatively small increase in labour time or costs.

6.5 Recommendations for Integrated Monitoring of Carbon Cycling and Other Ecosystem Services

This thesis forms the basis of the carbon-related services (including timber provision, carbon storage and carbon sequestration) investigated as part of the Valuing the Arc (VtA) project (Section 1.7). Other project partners focused on hydrological-related services (including the provision of water for drinking, irrigation and hydroelectric power generation), and biodiversity-related services (including tourism, the existence value of biodiversity and the sustainable harvesting of non-timber forest products). Thus, in combination with the work of other scientists involved in the project, broad conclusions of the use of payments for ecosystem services (PES) to provide conservation incentives can be made.

Preliminary results suggest that retaining EAM habitats is a net benefit to society as a whole. However, the opportunity costs paid by the local populations are far greater than the benefits they currently receive. This highlights the importance of examining the distribution of costs as well as benefits when investigating PES, and of using payments captured to meet (or lower) local opportunity costs (Fisher et al., 2011). In particular, the high value of carbon storage (derived from the results presented in this thesis) suggests that the previous focus in the EAM on timber and water provision for PES schemes may have been suboptimal, provided REDD+ payment mechanisms can be established. Moreover, payments for the full-suite of services these ecosystems provide could substantially improve local well-being. Similarly, most attention has been focused on the high-biodiversity forests, whereas most service values and conservation costs (in financial terms) are associated with the more extensive, more threatened woodlands. Thus, I suggest there should be a broadening of conservation efforts to encompass woodland areas, ensuring ecosystem service provision continues into the future.

Future work for VtA includes using policy relevant scenarios to explore future distribution of ecosystem service provision and the associated opportunity costs. VtA generated regional scenarios using local stakeholders and experts to define how land cover types may change over time (Swetnam et al., 2011). By formalising these as spatially-explicit rules, VtA created future land cover maps under two different scenarios, based on either a suite of policies emphasising sustainable development principles, or the continuation of current management practices, i.e. largely maximising immediate revenue (Swetnam et al., 2011). By applying the Tier 2 carbon estimates produced in Chapter 2 to these maps, we estimated that, between 2000 and 2025, only ~4% of carbon stocks would be lost if sustainable development approaches were adopted, compared to the ~41% carbon stock reduction expected under the business as usual scenario (Swetnam et al., 2011). Whilst these results highlight the possible impact of following the development of sustainable practices pathway, further scenarios are being developed to better examine specific policy interventions, such as the implementation of REDD+. The impact of these scenarios on hydrological-related and biodiversity-related services remains to be investigated.

There is future opportunity to compare VtA estimates of ecosystem service provision with those provided for a much lower investment. For example, InVEST is a freely available online resource which can map the value of ecosystem services with minimal data inputs (see http://www.naturalcapitalproject.org/InVEST.html for more details). InVEST generally provides Tier 1 estimates of ecosystem services, such as carbon storage, and so comparison with the results presented in my thesis could highlight the differences in the uncertainty of Tier 1, Tier 2 and Tier 3 based estimates and enables the cost-efficiency of each tier to be investigated. Since research and conservation budgets are limited, there is a trade-off between the accuracy of ecosystem service valuations and their cost. Hence, this research would enable the most efficient use of limited conservation and research funds, and could help ensure that transaction costs for carbon payments are as low as possible given the required level of certainty. These investigations are already underway, with preliminary collaborations occurring between Integrated Valuation of Environmental Services and Trade-offs (InVEST; a global project tool providing Tier 1 ecosystem services valuations) (McKenzie et al., 2012) and VtA, whilst comparisons with the more data-intensive, Tier 3 Artificial Intelligence for Ecosystem Services (ARIES) tool are also possible (Villa et al., 2009).

Finally, through the mapping and valuation of multiple ecosystem services, future studies could investigate potential trade-offs and any interactions that occur between them. These trade-offs could occur in both space and time (Rodríguez et al., 2006). For example, the management of a forest for carbon storage may affect water quality downstream or alter the value of the land for recreation. In the Nilgiri Plateau, India, *Ecalyptus globulus* plantations provide valuable non-timber forest products (e.g. paper pulp), but have reduced water yield from downstream catchments by up to 23% (Samraj et al., 1988). VtA could investigate how these trade-offs may affect the EAM spatially, by investigating correlations between the mapped services, as well as temporally, using the regionally appropriate scenarios (described above).

6.6 Final Summary

In this thesis, I have attempted to better understand the variables influencing land cover change and changes in carbon storage across the Eastern Arc Mountains region of Tanzania. Through regression equations, I have demonstrated that both carbon storage and sequestration within this landscape are most impacted by anthropogenic activities. For example, logged forest shows a reduction in carbon storage of 51-77% when compared to undisturbed areas. By creating maps of contemporary carbon storage I estimate that 1.32 (95% CI: 0.89-3.16) Pg of ALC is stored in the EAM. This provides a spatially explicit dataset with which to provide information into the policy decision process on land-use and protection in eastern Tanzania. I show that using historical land cover maps can enable baseline rates of land cover change and carbon emissions to be estimated. For the 33.9 million ha of my EAM study region I estimate that a total of 0.75 (0.45-1.04) Pg of ALC has been emitted or is committed to being emitted as a direct result of land cover change over the 92 year period between 1908 and 2000. Finally, the negative correlation observed between carbon storage and many anthropogenic activities, combined with the suggested ability of protected areas to encourage forest transition, indicate that, with appropriate incentives, schemes such as REDD+ that lead to altered management regimes have the potential to dramatically reduced carbon losses from tropical landscapes. Importantly, the findings of this thesis have already begun to impact REDD+ policies in Tanzania and may, in turn, help to realise substantial emission reductions as other developing nations look to learn from the experiences of this REDD+ focal country.

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