The potential of REDD+ as a conservation opportunity for the Angolan Scarp Forests: Lessons from the unique Kumbira forest

Ana Catarina Mendes Leite
Mestrado em Biodiversidade, Genética e Evolução
Departamento de Biologia
2015

Orientador
António Monteiro, Post-Doctoral Researcher, Centro de Investigação em Biodiversidade e Recursos Genéticos (CIBIO)

Co-Orientador
Martim Melo, Post-Doctoral Researcher, Centro de Investigação em Biodiversidade e Recursos Genéticos (CIBIO)

U. PORTO

FACULDADE DE CIÊNCIAS
UNIVERSIDADE DO PORTO

Todas as correções determinadas
pelo júri, e só essas, foram efetuadas.

O Presidente do Júri,

Porto, ______/______/_________

“To understand our world, we must use a revolving globe and look at the earth from various vantage points. If we do so, we will see that the Atlantic is but a bridge linking the colorful, tropical Afro-Latin American world, whose strong ethnic and cultural bonds have been preserved to this day. For a Cuban who arrives in Angola, neither the climate, nor the landscape, nor the food are strange. For a Brazilian, even the language is the same.”

Ryszard Kapuściński
In “*Another Day of Life - Angola 1975*”

Agradecimentos

Em primeiro lugar, e como não poderia deixar de ser, agradeço ao meu orientador Doutor António Monteiro por entusiasticamente ter envergado neste projeto e por ter contribuído para o meu enriquecimento académico ao partilhar comigo todo o conhecimento que poderia pedir.

Ao meu co-orientador, Doutor Martim Melo, por ter-me proporcionado a melhor experiência ao permitir que realizasse este trabalho de campo e descobrisse a minha paixão na ciência.

Um agradecimento especial à Aimy Cáceres, pelo exemplo. Obrigado por me ensinares que tal como na vida, também na Conservação o importante é nunca baixar os braços. Gracias!

To Michael Mills, for the amazing help in the fieldwork (and for teach me how to drive a 4x4 in the rainforest).

À Doutora Fernanda Lages, pelo apoio imprescindível. Ao Hugo, ao Congolé, aos Kundas, e a todas pessoas em Angola que diretamente ou indiretamente contribuíram para o sucesso do trabalho de campo.

À Ju e ao Paulo, por estarem sempre prontos a ajudar.

Aos meus colegas de Mestrado, por perceberem. Obrigada à mesa, em especial à Catarina pela motivação, à Sarinha e à Filipa pela boa-disposição.

Aos meus queridos Sapos, os primeiros a fazerem parte desta caminhada.

Às princesas do 304, obrigada pela convivência, pelo carinho, pela constante presença e pela amizade.

À Vera, a de todas as horas.

A todos os familiares e amigos que todos os dias me fazem sentir especial e nunca duvidam das minhas capacidades mesmo quando eu já pouca confiança deposito nelas.

À melhor mãe do Mundo, a minha.

O trabalho em Angola foi realizado no âmbito do laboratório geminado CIBIO-InBIO - Museu de Zoologia e Herbário do Lubango (ISCED-Huíla).

Sumário

As florestas tropicais são uma componente significativa do balanço global de carbono. As altas taxas de desflorestação que têm lugar nos trópicos contribuem com cerca de 6-17% das emissões globais de CO_2 causadas pelo Homem, e estão intrinsecamente relacionadas com a perda da biodiversidade e outros serviços dos ecossistemas. Daí que o mecanismo para a redução de emissões devido à desflorestação e degradação (REDD+) em países com mais área ocupada por floresta, usualmente países em desenvolvimento, seja uma das estratégias mais importantes a serem discutidas no combate às alterações climáticas. Alguns autores defendem uma abordagem mais inclusiva para o REDD+, sugerindo que este mecanismo deve ter em conta outros benefícios para além da redução de emissões de carbono. Estes benefícios deverão incluir a conservação da biodiversidade e o desenvolvimento das condições de vida das comunidades rurais. Para além disso, os incentivos para reduzir as emissões de carbono deverão ser transversais a todos os países em desenvolvimento que apresentem áreas de florestas, incluindo aqueles que mostram áreas não tão significativas e baixas taxas de desflorestação. Além de uma abordagem nacional, o REDD+ deverá também considerar projetos em escalas inferiores que apresentem potencial de redução de emissões. De forma a assegurar a integridade e credibilidade das estratégias REDD+ são necessárias estimativas de biomassa e carbono consistentes para as florestas tropicais, principalmente em África onde ainda pouca informação existe.

Através de dados recolhidos no campo e técnicas de deteção remota avaliamos o potencial do REDD+ na Escarpa Angolana, um habitat não prioritário para os exercícios REDD+, usando a floresta de Kumbira como referência. Depois de conduzirmos inventários florestais, estimamos para Kumbira um valor médio de 89.4 Mg de carbono acima do solo por hectare. Com o objetivo de determinar o carbono emitido devido à perda de floresta, uma classificação supervisionada (Maximum Likelihood) foi aplicada para três imagens de LANDSAT respetivas aos anos de 1991, 2001 e 2014. Para a classe 'Floresta' conseguiu-se obter uma precisão média de 98.06% através deste método de classificação. Depois de um período florestal estável, que coincidiu com o ultimo terço da guerra civil em Angola, a taxa de desflorestação foi calculada em 4.04% para os últimos 13 anos. Isto significa uma perda de 41% da área de floresta desde 2001 e uma emissão bruta de 492833.6 Mg*C*. Os fatores relacionados com a perda de floresta para o período 2001-2014 foram também examinados usando um modelo de relação logística. Com uma razão de

possibilidades de 0.803, a ‘distância aos trilhos’ mostrou ser a variável mais importante no processo de desflorestação. A avaliação do potencial de um projeto REDD+ foi feita em comparação com um ponto de referência que estabelece o nível de emissões que resultam de uma estratégia *business-as-usual* (BAU) quando nenhuma intervenção é realizada. As nossas projeções indicam que de acordo com um cenário BAU a floresta de Kumbira poderá emitir cerca de 296377.7 Mg*C* até 2027, quase 33000 MgC por ano. Se a desflorestação for imediatamente e completamente interrompida a emissão de cerca de 714203.2 Mg*C* poderá ser evitada. Um cenário mais realista, envolvendo a delimitação de uma área protegida correspondente a 50% do total da atual floresta, poderá salvar 1568 ha de floresta até 2027 e metade das emissões brutas de carbono em comparação com o cenário BAU.

Embora uma análise nacional do carbono sequestrado pelas florestas de Angola sugira um potencial reduzido para a aplicação de uma estratégia REDD+, estes resultados realçam também o facto de o país ter áreas florestais de grande valor para a biodiversidade que estão severamente ameaçadas. Estas áreas oferecem um potencial significativo de redução de emissões de carbono através da redução da desflorestação e do enriquecimento dos stocks de carbono, assim como a provisão de importantes co-benefícios. Assumindo que as restantes florestas da escarpa seguem a tendência de Kumbira este potencial é ainda mais relevante. Apesar da necessidade de estudos adicionais, a adoção de uma estratégia de conservação é urgente. Consideramos que os resultados obtidos neste estudo apresentam argumentos sólidos para a inclusão da floresta de Kumbira no mercado voluntário de carbono. Não existem expectativas quanto a uma futura integração da Escarpa Angolana num projeto certificado pelo REDD+ mas neste trabalho fomos capazes de realçar a importância de considerar uma abordagem mais alargada em relação aos critérios de seleção que compõem a certificação de um projeto desta natureza.

Palavras-chave

REDD+; Escarpa Angolana; Kumbira; stocks de carbono; deteção remota; desflorestação; emissões de carbono; conservação.

Summary

Tropical forests are an important component of the global carbon balance due their high levels of carbon content. The deforestation rates that take place in the tropics contribute with 6–17% of global anthropogenic CO_2 emissions to the atmosphere, and are also linked with the loss of biodiversity and other environmental services. Therefore, reducing carbon emissions from deforestation and degradation (REDD+) in forest-rich developing countries is of central importance in efforts to combat climate change. Some authors defend a broadened approach for REDD+, suggesting that this mechanism should bring additional benefits for biodiversity and rural communities and incentivise emissions reduction in all developing forested countries, including those with low forest cover and low deforestation rates, and at sub-national and project scales. To ensure the integrity and credibility of REDD+ strategies, reliable estimates of biomass and carbon pools in tropical forests are urgent, especially in Africa where there still exists a serious lack of data.

Using field data and remote sensing techniques we investigated the potential of REDD+ for the forest of the Angolan Escarpment, a unique habitat easily overlooked in large-scale REDD+ prioritisation exercises. Kumbira forest was used as case study. After forest inventory measurements, we found an average value of 89.4 Mg of aboveground carbon stocks *per* hectare for Kumbira. In order to determine the carbon emissions from forest change a supervised Maximum Likelihood classification for three LANDSAT images from 1991, 2001 and 2014 was performed, achieving an average producer's accuracy of 98.06% for the class 'Forest'. After a forest stability period, which coincided with the last third of the civil war conflict in Angola, the change detection revealed a deforestation rate of 4.04% across the entire study site for the last 13 years. This means a loss of 41% of forest area since 2001 and gross carbon emissions of 492833.6 Mg*C*. The factors related with the forest loss process for the period 2001-2014 were also examined using a GIS-based logistic regression model. The 'distance to trails' was found to be the best single predictor for forest loss with an odds ratio of 0.803. The potential of a REDD+ project was evaluated in comparison with a baseline scenario that establishes the level of business-as-usual (BAU) emissions when no project implemented. The carbon emitted under BAU in Kumbira forest was projected to be 296377.7 Mg*C* until 2027, almost 33000 MgC *per* year. If deforestation could be stopped immediately and completely about 714203.2 Mg*C* emissions could be avoided. A more realistic scenario involving the delimitation of a protected area covering 50% of the total actual forest would save almost 1658 ha of forest by 2027 and half of the gross carbon emissions compared with the BAU scenario.

These results suggest that although a national analysis of forest carbon in Angola would identify little REDD+ potential, the country has forest areas that are threatened conservation hotspots. These forests offer significant potential for reducing emissions by reducing deforestation and enhancing carbon stocks as well as provide valuable co-benefits. Assuming that the remaining forests of the Scarp follow the trends of Kumbira this potential is even greater. Further research is needed, but considering the urgency of conservation action for the Scarp forests, we consider that our results provide sufficient evidence to call for the integration of Kumbira forest in the voluntary carbon market. We do not have expectations regarding the integration of the Angolan Escarpment in a certified REDD+ project in the near future. Nevertheless, this work has highlighted the importance of using a more inclusive approach in the REDD+ framework regarding site selection criteria, so that small forests of high conservation significance can be quickly included.

Key-words

REDD+; Angolan Escarpment; Kumbira; carbon stocks; remote-sensing; deforestation; carbon emissions; conservation.

Index

List of Figures

List of Tables

List of Abbreviations

AFOLU - Agriculture, Forestry and Other Land Uses

AGB - Aboveground Biomass

AGC - Aboveground Carbon

AUC - Area Under Curve

BAU - Business-As-Usual

CBFP - Congo Basin Forest Partnership

CDM - Clean Development Mechanism

COP - Conference of Parties

DBH - Diameter at Breast Height

DEM - Digital Elevation Model

DN - Digital Numbers

DOS - Dark-Object Subtraction

FAO - Food and Agriculture Organization of the United Nations

FRA - Forest Resources Assessment

GHG - Greenhouse Gases

GLCF - Global Land Cover Facility

GLM - Generalized Linear Model

HFLD - High Forest Low Deforestation

IPCC - Intergovernmental Panel on Climate Change

LRM - Logistic Regression Model

LSU - Linear Spectral Unmixing

MLA - Maximum Likelihood Algorithm

MRV - Monitoring, Reporting and Verification

NDBR - Normalized Difference Blue Red ratio

PCA - Principal Component Analysis

PIFs - Pseudo Invariant Features

REDD+ - Reduce Emissions from Deforestation and forest Degradation

REL - Reference Emission Level

ROC - Relative Operating Characteristic

RRN - Relative Radiometric Normalization

TOA - Top-of-atmosphere

UNFCCC - United Nations Framework Convention on Climate Change

USGS - United States Geological Survey

VCM - Voluntary Carbon Market

VER - Verified Emissions Reductions

VIFs - Variance Inflation Factors

1. Introduction

Human well-being is strongly dependent of the tropical forests ecosystems. According to the 2010 Global Forest Resources Assessment (FRA) report published by the Food and Agriculture Organization of the United Nations (FAO), forests and other wooded land represents 31% of the total land area, of which 40% are open and closed forests at tropical and subtropical latitudes, with the two largest tropical blocks being located along the Amazon and Congo Basins (FAO, 2010). Rainforests support the direct livelihood of 1.6 billion people (FAO, 2010) - about 25% of the world's population - by providing food, medicinal products, fibre, non-timber forest products and full-filling cultural and recreational functions (Nasi *et al*., 2011). At the global scale, rainforests are remarkable reservoirs of biodiversity being the terrestrial biome that shows highest levels of biological diversity from gene to habitat level (Shvidenko *et al*., 2005). They also contribute to maintain the balance in numerous natural processes, supporting the nutrient cycle and soil formation, being fundamental regulators of the hydrological cycle and an important carbon sink in the global carbon cycle (Malhi *et al*., 2008).

The spatial and temporal variation of carbon stocks (Asner *et al*., 2010) and their changes in the different reservoirs forms, such as living vegetation including aboveground and belowground biomass components, soils, woody debris and wood products, are in charge of the net flux of carbon between the land and atmosphere (Houghton, 2005). When these reservoirs are either immediately damaged or slowly decay by natural or anthropogenic causes, carbon dioxide is released into the atmosphere contributing to the increase of greenhouse gases (GHG) concentration and consequently to the rise of the global average temperature. If the expected increase of 2º C in global average temperature is confirmed (Allen *et al*., 2009; Matthews *et al*., 2009; Meinshausen *et al*., 2009) there is the risk that tropical forests lose their ability to store carbon (Brienen *et al*., 2015) or even turn from a carbon sink into a carbon source, thus amplifying climate change and potentiate the negative impacts on ecosystems (Fischlin *et al*., 2007). Tropical regions show the highest mean of annual biomass increment among the different biomes of the world (Clark and Clark, 2000; Malhi *et al*., 1999), with tropical woody vegetation accounting for the largest pool of aboveground carbon stocks (AGC) in the terrestrial biosphere (Pan *et al*., 2011). Although soils hold more carbon than that stored aboveground in forest vegetation (Davidson and Janssens, 2006), aboveground biomass (AGB) is more easily mobilized by disturbance processes such as forest clearing and degradation (Houghton, 2007). This turns the high levels of deforestation rates that take place in tropics one of the most alarming sources of anthropogenic GHG emissions and the major concern of the conservation policies that intend to mitigate CO_2 emissions by tackling the multiple driving forces of forest change (Busch and Engelmann, 2015). Proximate causes of tropical deforestation include the expansion of agriculture and infrastructure, and the extraction of forest products, namely timber (Geist and Lambin, 2002). These activities have a direct impact in the tropical physical environment, inducing a long-term reduction of tree canopy cover. The ultimate causes are demographic and economics, with a rapid population growth in tropical areas coupled with the rise and rapid growth of industries that depend on the removal of the forest – such as the soy and palm oil industries. Also, corruption and lawlessness leads to an increase of CO_2 emissions by allowing, for example, illegal logging (Geist and Lambin, 2002).

Recent findings estimated the total amount of carbon held in tropical woody vegetation to be 228.7 petagrams (Pg – 1 Pg = 1 x 10^{15} g); the total net and gross carbon emissions from tropical deforestation and land-cover change were estimated at 1.0 Pg C yr^{-1} and 2.2 Pg C yr^{-1} during the period 2000-2010, respectively (Baccini *et al.*, 2009). Other studies for the 2000s estimate a net source of 1.3 Pg C yr^{-1} and a gross tropical deforestation emission of 2.9 Pg C yr^{-1} that was partially compensated by a carbon sink in tropical forest regrowth of 1.6 Pg C yr^{-1} (Pan *et al.*, 2011). Harris *et al.* (2012) provides a lower estimate for the gross carbon emissions for the period 2000-2005 (0.81 Pg C yr^{-1}), arguing that the quantification of net emissions based on assumptions about the fate of converted lands produces unreliable estimates.

Different assumptions, data and methodologies for estimating deforestation rates and carbon stored in aboveground biomass over tropical regions often introduces large uncertainties into estimates of CO_2 emissions (Houghton *et al.*, 2000; Houghton, 2005; Grassi *et al.*, 2013; Mitchard *et al.*, 2013; Pelletier *et al.*, 2013; Lusiana *et al.*, 2014; Chen *et al.*, 2015). Despite all methodological improvements in recent years (DeFries *et al*., 2007; Goetz *et al*., 2009; Asner *et al*., 2010; Saatchi *et al*., 2011; Baccini et al., 2012; Vaglio Laurin *et al*., 2014), it is still not possible to obtain direct measurements of carbon stocks at a national or sub-national level. The combination of remote-sensing and ground-based measurements are the best actual methodology available to estimate past changes in forest cover and CO_2 emissions (Gibbs *et al.*, 2007). This approach relies on high-resolution satellite imagery and on national estimates of AGC derived from ground-based forest inventories. This can hinder the inference of reliable estimates as satellite imagery does not always have the required resolution and many countries do not have or only have outdated forest inventories (Baccini *et al.*, 2012).

Potential inaccurate estimates and weak country governance contribute significantly to the failure of the implementation of policy mechanisms that attempt to protect existing forests in order to limit the increase of GHG emissions. Such mechanisms fall under the umbrella of **R**educe **E**missions from **D**eforestation and **F**orest **D**egradation (REDD+), a program created by the United Nations Framework Convention on Climate Change (UNFCCC). The REDD+ goal is to facilitate the reduction of emissions by providing financial incentives to forest-rich developing countries, in order to voluntarily reduce national deforestation rates.

1.1 The development and monitoring of REDD+

The Kyoto Protocol created a Clean Development Mechanism (CDM) to assist industrial countries (listed in Annex I) in achieving compliance with their objective of reducing GHG emissions below the levels of 1990. CDM allows trading carbon credits from renewable energy, afforestation (planting forest in areas where there was previously no forest vegetation for at least 50 years) and reforestation (planting forest in areas that were deforested before 1990) projects, but does not provide incentives for reducing emissions from deforestation (UNFCCC, 2003). In 2005, at the 11º Session of the Conference of Parties (COP-11) to the United Framework Convention on Climate Change (UNFCCC) in Montreal, Papua New Guinea and Costa Rica proposed a separate approach for "*reducing emissions from deforestation in developing countries*" (RED) at a national level (UNFCCC, 2005). They were supported by several other Parties under the UNFCCC, starting the process of considering reducing emissions from deforestation. The concept has expanded since then to include "*forest degradation*" (REDD) (UNFCCC, 2008) and, *"the role of conservation, sustainable management of forests, and enhancement of forest carbon stocks in developing countries"* (UNFCCC, 2009a, p. 3). This program is now known as REDD+ (or REDD-plus).

Attempts to recognize REDD+ in CDM proposals have systematically failed due to concerns related to environmental and market risks. These include the 'leakage effect' and the 'non-permanence problem'. The former occurs when a reduction of deforestation in a target area increases the process of deforestation in other regions or countries, bringing up the problem of at what scale—national, sub-national, or project—should forest conservation actions be eligible. The latter highlights the risk that any reductions in emissions gained from current efforts to halt deforestation may be lost in the future due to natural or anthropogenic disturbances. The unpredictable fluctuation of markets and the potential flood of carbon markets caused by large amounts of cheap carbon credits can also prevent real reductions from occurring and undermine strategies for reducing emissions from the use of fossil fuels, representing a huge financial risk. The recognized volatility of carbon investments (Phelps *et al*., 2011; Sandker *et al*., 2010) and the uncertainties regarding the monitoring of deforestation and degradation (Plugge and Köhl, 2012) were the main reasons why negotiations over the integration of land use, land-use change and forestry (LULUCF) activities in the CDM have failed and why the European Union does not allow forestry credits into the Emissions Trading System, the largest compliance carbon market at the moment. Forest projects only represent a small fraction of the transactions of verified emissions reductions (VER) on the voluntary carbon market (VCM) (Hamrick and Goldstein, 2015). The VCM is currently the only global market for trading REDD+ credits and it is supported by socially responsible individuals, corporation and cities, but even those are aware of the risks associated with the carbon marketplace. Because emissions reductions will culminate in financial compensations, high quality monitoring systems are needed to set reliable baselines over which reductions will be certified. Almost all baselines submitted use historical reference trends (DeFries *et al*., 2007; Olander *et al*., 2008; Stickler *et al*., 2009; Asner *et al*., 2010). This issue is politically sensitive with some countries Parties of the UNFCCC which argue that the technical capacity and resources available for each country to monitor REDD+ have to be taken into account (UNFCCC, 2009b). In order to allow a broad participation of countries with different capacities and to achieve complete, accurate and comparable emissions estimates, the Intergovernmental Panel on Climate Change (IPCC) guidelines for reporting emissions from Agriculture, Forestry and Other Land Uses (AFOLU) provides three different methodological standards (Tiers 1, 2 and 3) according to the level of detail for the reporting of emissions (Paustian *et al*., 2006). However, each step in the estimation of forest changes and related emissions is a source of errors and they still need to be addressed by the research community.

These technical issues were debated during the 19th Conference of the Parties (COP-19), which produced the 'Warsaw Framework for REDD+' that provides guidance for the full implementation of REDD+ (UNFCCC, 2013). REDD+ will be implemented in a three-phased approach, as agreed in the COP-16 in Cancun (UNFCCC, 2010). The initial phase focuses on Readiness, including the adoption of national REDD+ strategies, the development of climate-effective, cost-efficient and equity reference emission levels (RELs), the design of Monitoring, Reporting and Verification (MRV) systems and the dialogue with indigenous people and local communities to ensure social safeguards. In phase 2, REDD+ demonstration activities are implemented and MRV's improved, while phase 3 relates to the performance of result-based actions. Therefore, countries that intend to participate in REDD+ have to demonstrate robust MRV's systems for the accounting of emissions from deforestation and forest degradation and thus ensure the integrity and credibility of REDD+ mechanisms. A transparent and accountable forest monitoring system reflects a good forest governance, a critical factor for investors' choice. Investors may prefer projects in countries with stronger governance capabilities over countries with high carbon values but with limited governance capabilities (Phelps *et al*., 2010). A stronger governance capability accounts for a large inclusiveness of civil society and fair tenure laws, which significantly decrease costs and/or risks of REDD+ opportunities. Despite some difficulties in addressing governance issues (Davis *et al*., 2008; Romijn *et al*., 2012), currently forty-seven developing countries signed a Participation Agreement to participate in the Readiness Fund, a donor-led public finance, and were selected to receive the support of the World Bank's Forest Carbon Partnership Facility. Additionally, 62 partner countries of high carbon value are being supported by the United Nations to implement national REDD+ strategies (UN-REDD Programme).

Beyond the scientific and financial challenges, equitable and sustainable management of forests are dependent of non-carbon benefits and non-markets mechanisms. REDD+ strategies must take into account other relevant international conventions and agreements such as the UN Declaration on the Rights of Indigenous Peoples and the Convention on Biological Diversity. Otherwise there is the risk that some REDD+ actions affect negatively the rights and livelihoods of forest-dependent people and indigenous communities (Lyster, 2011) and cause direct harms in biodiversity and ecosystems services. A report presented at COP-15 provided recommendations on how REDD+ could generate biodiversity co-benefits (SCBD, 2009), such as the prioritization of REDD+ actions in areas not only of high forest biodiversity but also of high endemism. To avoid the investors' preference for low-cost emissions mitigation over co-benefits, the capitalization of opportunities created by REDD+ to enhance biodiversity conservation was also suggested. Thomas *et al*. (2013) compared three conservation strategies and found that a carbon-biodiversity strategy could simultaneously protect 90% of carbon stocks (relatively to a carbon-only conservation strategy) and > 90% of the biodiversity (relatively to a biodiversity-only strategy) in America and Great Britain. Busch *et al*. (2011) confirmed that greater financing combined with REL's and a broad participation offer the greatest benefits for biodiversity conservation. However, these recommendations were not incorporated in the negotiations of the following COPs and there is still no clear definition inside the World Bank and the UNFCCC about the extent of REDD+ in yielding co-benefits.

Although a clear set of criteria is still lacking, a REDD+ country is generally selected by its ability to be climate-effective in reducing CO_2 emissions, and so countries with high remaining forest, such as the Democratic Republic of Congo but especially Brazil and Indonesia due their current high deforestation rates, are at the core of REDD+ priorities. These countries account for the larger values of tropical carbon stocks (Baccini *et al*., 2012), offering the possibility of high-return REDD+ actions, but they also entail high-risks associated with governance and social impact. A REDD+ planning that includes several factors, such as quality of forest governance, biodiversity conservation and local rights would provide lower-risk and low-return at short-time scales but costly non-carbon benefits (Stickler *et al*., 2009; Campbell *et al*., 2009; Phelps *et al*., 2010; Bush *et al*., 2011). Therefore, countries with low forest cover and low deforestation rates that are not typically considered as carbon hotspots, and sub-national projects that are often overlooked by the site selection criteria have gained increasing attention in the REDD+ discussions (Pedroni *et al*., 2009; Strassburg *et al*., 2009).

1.2 The Central Africa rainforests

Rainforests in Africa are divided into three main ecological zones: Guineo-Congolian (in West and Central Africa), East Malagasy (Madagascar) and Afromontane (Central and Eastern Africa). They cover only 13% of the continent (Mayaux *et al*., 2004) but store more than 90% of the carbon amongst Africa's terrestrial ecosystems (Saatchi *et al*., 2011; Bacinni *et al*., 2012). The Guineo-Congolian ecoregion covering the majority of the Central African countries, the so-called 'Congo Basin countries', holds the most significant block of African tropical rainforest and the second largest worldwide after the Amazon. Several species, namely the last intact natural communities of large vertebrates on earth, depend on the resource pool and the refuge that the Congo Basin forests offer. This ecoregion further includes exceptional centres of endemism, like the coastal part (South Cameroon, Equatorial Guinea and Gabon) and the Gulf of Guinea islands (Olson and Dinerstein, 1998; Olson *et al*., 2001). Finally, these forests support the direct livelihood of millions of rural people and people living in urban centres in the vicinity of the forests (Nasi *et al*., 2011).

The Congo Basin has experienced low deforestation rates over the years, and for this reason it has been classified as "High Forest, Low Deforestation" (HFLD) region.

HFLD countries are not immediate targets for the REDD+ program because their contribution to reduce CO_2 emissions owing to deforestation is limited. In opposition to the trends showed by the tropical forests of South America and South-East Asia (Hansen *et al*., 2010), the deforestation in Central Africa has slowed down post-2000 (but remains higher in West Africa and Madagascar), which is most likely explained by the lower population pressure in areas with more than 20% of forest cover (Mayaux *et al*., 2013), the extraction of oil and minerals and the growth of importation of foodstuffs (Rudel, 2013), together with an absence of a significant local market for wood products and poor transportation infrastructure (Duveiller *et al*., 2008). However, there is an increased pressure on forest resources in coastal Central Africa which is expected to spread over all Congo Basin countries, as the human population dependent on subsistence agriculture continues to increase (Fisher, 2010). Especially in Central Africa, most of the tropical forests are in societies with armed conflicts or in post-conflict areas that usually stimulate human migration inside core forests (Draulans and van Krunkelsven, 2002) and where little political attention is given to environmental problems (Conca and Wallace, 2009). Additional political unrest and corruption often impels unregulated resource exploitation, including timber extraction. Despite being a key part of export incomes, illegal timber extraction means quick money for locals. The construction of logging roads and other infrastructure to support logger companies amplifies the negative impacts of this activity by increasing forest degradation and biodiversity loss (Laporte *et al*., 2007, Clark *et al*., 2009). However, Mayaux *et al*. (2013) show that deforestation in Central Africa does not vary as a function of the area occupied by logging concessions, and this can be due the recent efforts to improve forest management across the Congo Basin. Compared to the Amazonia and South-East Asia, little and accurate information exists about the current state of the Congo Basin forests, limiting the design of efficient forest management policies. Nevertheless, one can highlight the Congo Basin Forest Partnership (CBFP), established in 2002 and based on principles of representativeness, species viability and ecosystem sustainability, integrity and resilience (Duveiller *et al*., 2008). Beyond forest conservation, CBFP has gained recognition as an ‘environmental peacemaking’ strategy due its capacity to prevent social conflicts by promoting economic development, alleviate poverty and improve governance.

1.2.1 The Angolan Scarp forests

Located on the south-western coast of Africa in the confluence of six major biomes (Huntley, 1974), Angola is an incredibly biologically diverse country. The climate ranges from tropical wet/humid in the north and north-west – where we can find Congolian forest-savanna mosaics – , to extremely arid environments in the south-west occupied by the Kaokoveld desert and the Namibian dry savanna woodlands (Rodrigues *et al*., 2015). A north-south Escarpment runs parallel to the coast separating the arid littoral plains from the miombo woodlands of the inland plateau where the highest mountain rises to 2620 m above sea level (Rodrigues *et al*., 2015). Despite its great biological interest resulting from the combination of such specific biophysical factors, Angola remains one of the least studied countries in Africa. Field biodiversity research was limited during the war of independence (1961-1974) and almost non-existent during the subsequent civil war (1975-2002). The succession of armed conflicts over almost 40 years left a devastating impact on Angolan ecosystems, mainly due the uncontrolled poaching of large mammals that have been reduced to the threshold of extinction (Huntley and Matos, 1992), with little still known about their current status (Pitra *et al*., 2006; Chase and Griffin, 2011). Recent years have seen a renewed interest in the biodiversity of the country (Figueiredo *et al*., 2009; Mills, 2010; Mills *et al.,* 2011, 2013; Cáceres *et al*., 2014; Romeiras *et al*., 2014; Rodrigues *et al*., 2015). However, they are still scarce considering the urgency for information in a period when Angola experiences rapid economic and human population growth, and a post-war return of populations to farming, all factors increasing the pressure on the forest resources due to wood extraction for charcoal and firewood and the expansion of slash-and-burn agriculture (USAID, 2008).

One of the most biologically interesting and threatened regions in Angola are the forests occurring along the west-facing escarpment (hereafter, the ‘Scarp’). In the north a discontinuous series of moister vegetation-types from the Guinea-Congo forest have continuity along the Scarp supporting rainforest at higher altitude, in the east we find the miombo woodlands, and in the south the influence of the arid deserts of Namibe. The Scarp Forests, mostly concentrated in the Central Scarp, have affinities with the three adjoining biomes but at the same time act as a barrier between them (Dean, 2001). This has resulted in a high diversity of vegetation types and significant levels of endemism. They are a truly evolutionary hotspot for birds (Hall, 1960), the most well-documented species group (Dean, 2001; Ryan *et al*., 2004; Sekercioglu and Riley, 2005; Mills, 2010; Cáceres *et al*., 2014), containing most of the endemic species and subspecies of Angola, together with near-endemics and isolated populations of species occurring elsewhere (Hall, 1960). These forests represent the main habitat of the Western Angola Endemic Bird Area (Stattersfield *et al*., 1998), the only endemic bird area of the country. They have been considered one of the most important areas for bird conservation in Africa (Collar and Stuart, 1988) and a priority for global conservation (Dean, 2001; BirdLife International, 2015). The Angolan Scarp was considered by Myers *et al*. (2000) to integrate the list of the world's biodiversity hotspots but lack of data at the time prevented this. None of the unique forests of the Scarp are within the protected areas network (Huntley, 1974), and due to the climatic and edaphic conditions they face huge human pressures.

The Central Scarp forests are being damaged since the settlements by the Portugueses, up to 1974. At this time it is believed that 95% of the forest was converted into coffee plantations, although large-canopy trees were mostly left intact to provide shade (Hawkins, 1993). The replacement of the undergrowth vegetation with coffee trees has resulted in homogenous and even-age monospecific forests (Dean, 2001). With the falling of coffee prices worldwide in the mid-1970's and the upheaval of the civil war (Hawkins, 1993) many of the coffee plantations were abandoned and some native vegetation recovered. Once the stability returned to Angola in the mid-2000s', agricultural activities increased in the Scarp, mainly for self-subsistence as people returned to the rural areas and more recently for timber extraction. Slash-and-burn agriculture has become very common replacing shade coffee plantations (Mills, 2010; Ryan *et al*., 2004). Charcoal production, illegal logging and bushmeat are all serious, but yet to quantify, threats to this unique habitat.

1.2.1.1 Study area

Slash-and-burn activities, illegal logging and the hunting of birds and mammals such as primates have been observed in Kumbira Forest, the largest forest remnant and one that holds more populations of the endemic bird species of the Central Scarp forests. Kumbira Forest is located in the western Angolan province of Cuanza Sul, municipality of Conda (Fig. 1.1). The exact limits of the forest are difficult to define because there is a gradient between forest and other dense habitats of the Scarp. For the field survey, was defined the northern limit of the forest as Fazenda Fefe (11.14°S 14.29°E) and the southern limit as 11.23°S. For the following analyzes the study area was extended to comprise all forest between the Njelo Mountain range. Within the study area, the elevation varies from 250 m in the western margins to 1160 m at the closest forest limit on the slopes of Njelo Mountain. Influenced by the climate and the terrain features, the habitat varies from tall and very moist forests to drier, stunted and very densely tangled forests at the bottom of the valley (Mills, 2010). The native vegetation is semi-deciduous moist forest with Congo Basin affinities, which has been mostly replaced with shade coffee plantations (where *Inga vera* is a dominant shade tree), as well as scrubby grassland and secondary growth with wild coffee plants in the understory.

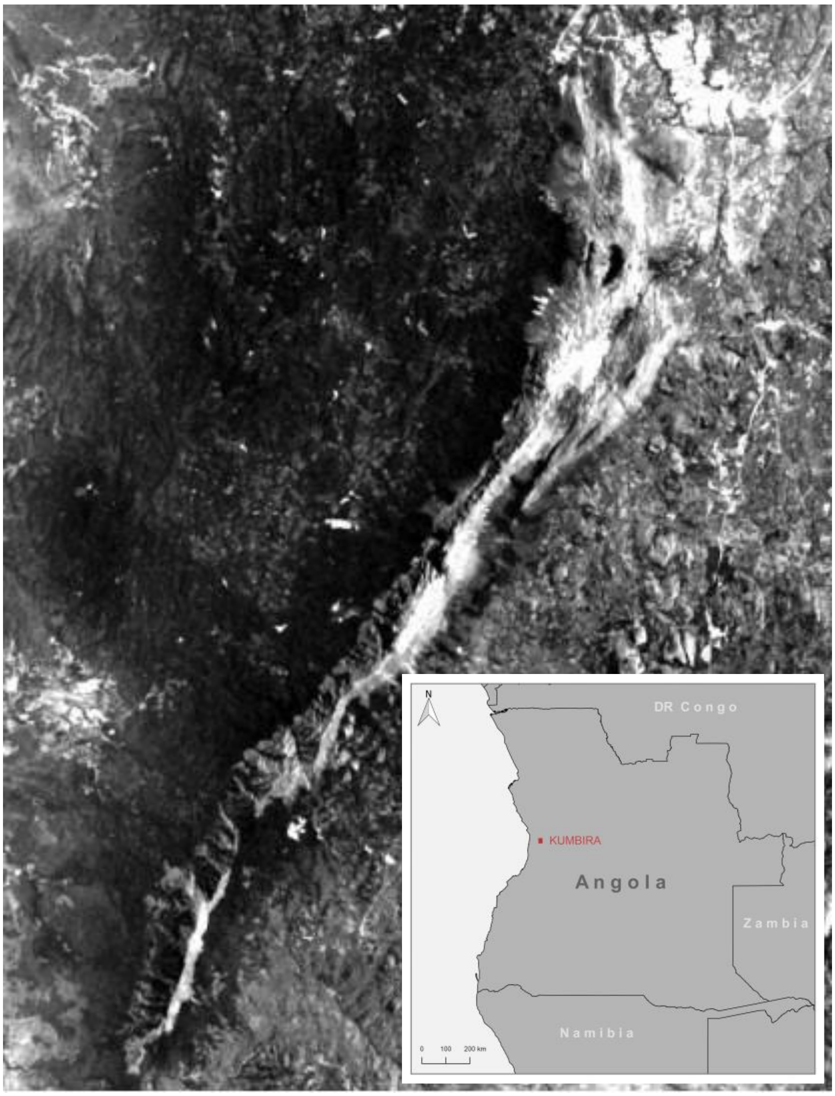


Fig. 1.1 – Study site, Kumbira forest. The inset image shows the location of Kumbira in Angola.

1.3 Objectives

The aim of this study is to address the potential of REDD+ as a conservation opportunity for the Angolan Scarp Forests, using the Kumbira forest as a case study. This potential was assessed by quantifying the carbon emissions from forest change over a period of 23 years using LANDSAT images from 1991, 2001 and 2014 for Kumbira. We hypothesize that the study site suffered a severe reduction in forest cover since the end of Angolan civil war (2002), with the return of the farming communities to the area, and we recognize REDD+ as a possible conversation strategy to halt this reduction.

Specifically, the objectives of this work were to:

(1) Estimate aboveground carbon stocks in Kumbira forest;
(2) Assess forest change since 1991 and deforestation rates for Kumbira forest using LANDSAT images;
(3) Identify the variables that determine forest cover change in Kumbira using logistic regression models.
(4) Quantify carbon emissions from forest change in Kumbira;
(5) Assess the potential of REDD+ for reducing emissions from deforestation in Kumbira using future scenarios.

Although Angola is currently not a target country for REDD+, we expected to provide insights about the impacts of a possible adoption of this mechanism and reinforce the need of a broadened approach at project-level for REDD+ planning.

2. Material and methods

2.1 Sampling design and in-field allometric forest data collection

A field campaign was conducted in the Kumbira forest during June 2014. Forest inventory measurements were performed to obtain quantifications of aboveground biomass (AGB) that could greatly improve the accuracy of carbon stocks estimates (Gibbs *et al.*, 2007) on aboveground live tree carbon (AGC).

Field data campaign was split in two stages: sampling design with site selection and in-field survey. In the first stage, in order to improve field data collection, sampling areas has been selected using a LANDSAT satellite scene for March 2014 (see Table 2.1) and the Normalized Difference Blue Red ratio (NDBR; Sharma *et al*., 2013; Vaz *et al.*, 2014). The near temporal window of LANDSAT image respect to field survey allowed us a good representation of expectable conditions for June 2014. NDBR (see eq.1) is sensitive to forest canopy characteristics, namely vertical structure, enhancing of canopy shadow linked with the heterogeneity of canopy height. NDBR varies between -1 to 1, achieving values lower than 0 in case of absence of canopy. Therefore, as a preliminary effort to enclose as much as possible the heterogeneity of forest canopy during field survey, three thresholds were applied to NDBR, assuming that would split the region of Kumbira according to three levels of canopy shadow representing different forest structures. It was assumed that areas with greater NDBR values have denser and complex canopies. According that, using stratified random sampling, 54 points separated by a minimum of 200 meters were selected, 16 with lower shadow representing homogeneous canopy (NDBR > 0 and < 0.025516), 22 with medium shadow representing intermediate heterogeneity in canopy structure (NDBR ≥ 0.025516 and < 0.059152) and 16 with higher shadow representing expectable higher heterogeneity in canopy structure and height (NDBR ≥ 0.059152). In order to minimize any influence of edge effects on forest biomass and dynamics, all points were established taking into consideration a buffer of 50 m around previously established trails, considering the poor accessibility in some regions of our study area and the limited time for data collection. All sampling plots, taken with a GPS (Garmin GPSMAP 62s), as well as NDBR thresholds are represented in Fig. 2.1.

$$\text{eq. 1)}\quad NDBR = \frac{Blue\text{-}Red}{Blue+Red}$$

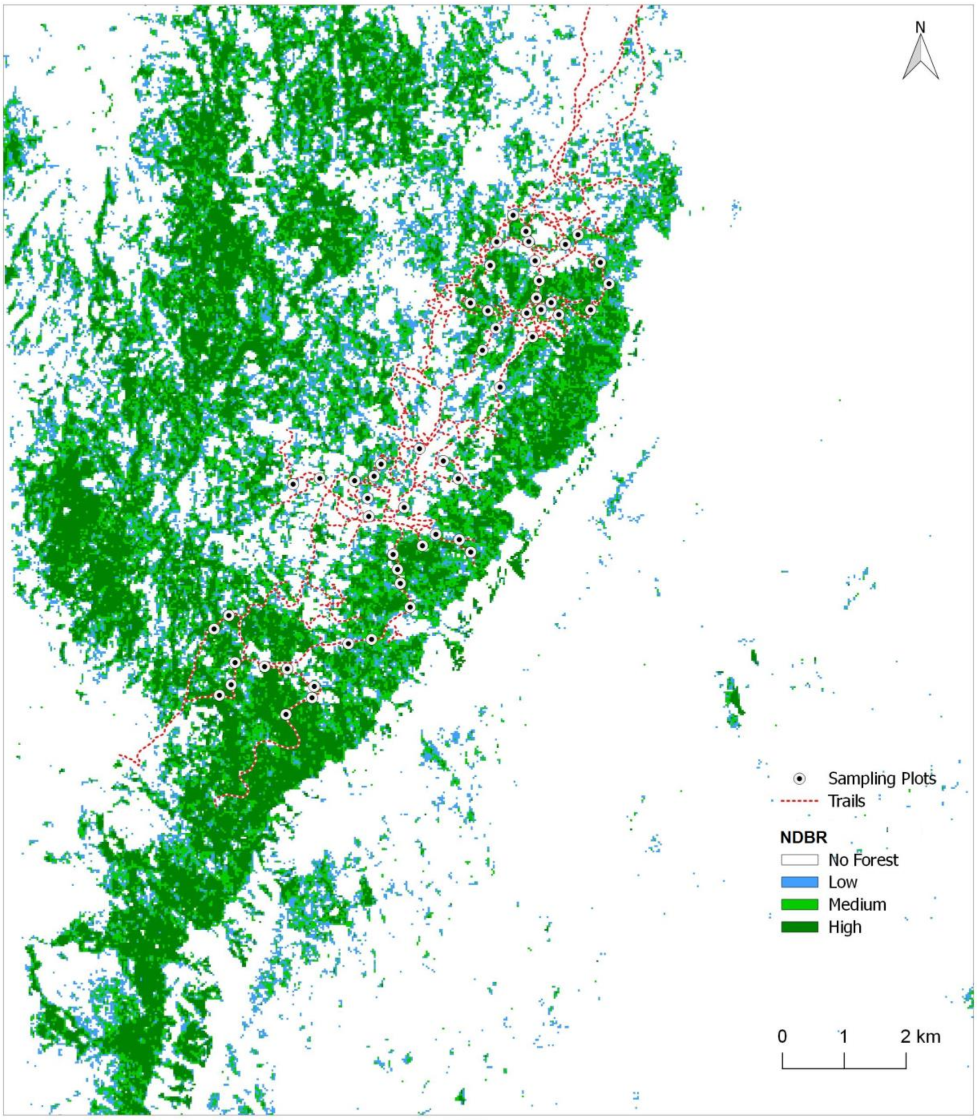


Fig. 2.1 – Sampling design. The colors show the three forest sampling regions identified by the NDBR spectral index. Each dot represents the location of the 54 sampling plots where measurements took place and the dashed lines indicate the previously established trails.

During second stage or in-field survey, the forest inventories were conducted using a square plot of 10 m x 10 m around each point and three variables were considered: diameter at breast height (DBH), canopy height and canopy cover (Fig. 2.2). The DBH was estimated for all trees in each plot with a measuring tape or a calliper at 1.30 m height from the ground, the international recognized standard height at which tree diameter is measured. Tree height was measured with a clinometer or a Nikon 550 Laser rangefinder according to the visibility of the canopy (Dallimer *et al*., 2009). Usually, 'trees' are considered to be all woody plants with a DBH ≥ 10 cm. In our case all trees with a DBH ≥ 5 cm were measured, since a considerable number of plots were dominated by regeneration of young trees with high canopy cover but low DBH. Lianas were excluded, since they generally represent a small fraction of total forest biomass (Nascimento and Laurance, 2002). Unfortunately, we were not able to obtain an identification of tree at species and genus level due to absence of floristic literature to Kumbira flora, but also by difficulties and uncertainty of local expertize to proceed with the identification. Contacts with several experts, including a botanist from the Royal Botanic Gardens (Kew), who visited the area at the same time, did not produce significant identifications. This is a lack of this study, but symbolize how much understudied is Kumbira flora and the opportunities existing for further in-field research. Canopy cover was estimated by taking photographs with a Nikon D70S, posteriorly processed and classified using color transformation from RGB to HSV to enhance canopy gaps on value band. ENVI-IDL version 4.7 software program (Exelis Visual Information Solutions, Boulder, Colorado) was used during these operations.

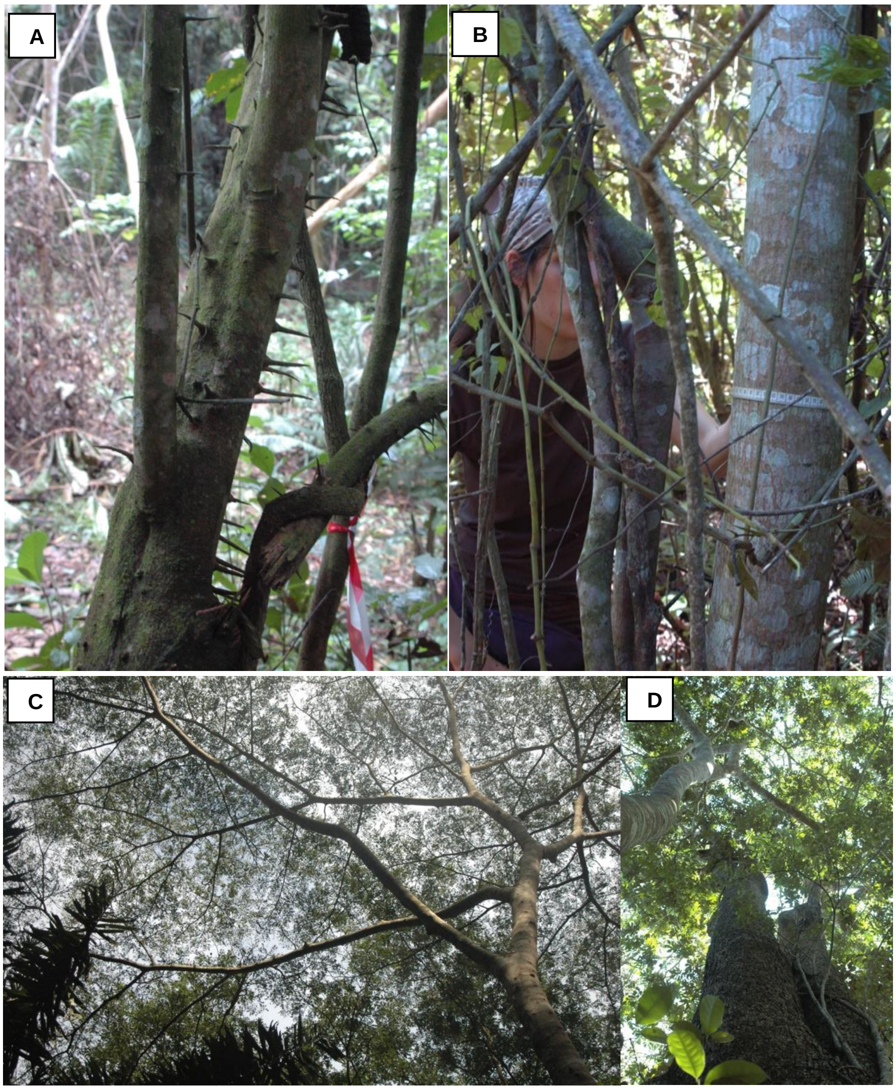


Fig. 2.2 – In-field allometric forest data collection. (A) Marking the plot, (B) measurement of the DBH, (C) canopy cover and height and (D) tree height.

2.2 Estimation of aboveground carbon stocks

We focused our estimates of carbon stocks on AGB, since this commonly represents the main carbon pool in tropical forests ecosystems and the most susceptible to deforestation and degradation (Houghton, 2007). Moreover, it can be estimated using cost-effective protocols (Berenguer *et al.*, 2015) unlike other carbon components (understory vegetation, belowground biomass or dead mass of litter).

The AGB of each individual tree was calculated using a pantropical allometric equation (Chave *et al.*, 2005). Pan-tropical models are described as the best models to estimate forest biomass and preferred over local allometric models (Gibbs *et al.*, 2007). Chave *et al.* (2014) developed generalized allometric equations for the pan-tropics based on 4004 harvested trees at 58 sites across a wide range of forest types. These equations relate the AGB of individual trees and some measured parameters like DBH, total height and wood density. Thus, in this study AGB for each tree was calculated using the allometric equation 2 following Chave *et al.* (2014):

$$\text{eq. 2)}\quad AGB_{est} = 0.0673 \times (\rho D^2 H)^{0.976}$$

where D is the DBH in cm, H is the height in m and ρ is the wood density in g cm^{-3}. Since sampled trees were not identified at species level, instead of specific-species wood density values, a constant wood density (ρ) of 0.59 g cm^{-3} was applied. This value was reported by Henry *et al* (2010) as the overall average wood density in Ghana tropical rainforest and in line with current average values reported for trees in Africa (Brown, 1997). Biomass estimates were converted to carbon values using the carbon fraction of AGB for tropical and subtropical regions of 0.47 tonne C (tonne d.m.$^{-1}$) reported by the IPCC (Paustin *et al*., 2006)

A Kruskal-Wallis test was used to analyze differences in AGB between the three categories identified by NDBR indice.

2.3 Long-term forest cover estimation and forest change analysis

Three LANDSAT scenes (7-June-1991, 30-September-2001 and 2-March-2014) were considered to quantify and characterize trends in forest cover across the study area between 1991 and 2014 (Table 2.1). This allowed us to infer and comprehend forest cover properties in different socio-political contexts of Angola, respectively during (1991), at the end (2001) and after (2014) of civil conflict. The scenes were obtained from the United States Geological Survey (USGS) and Global Land Cover Facility

(GLCF) databases, and orthorectified to the UTM-WGS84 Zone 33 South. Three steps were established to allow multi-temporal forest cover estimation and change analysis: imagery pre-processing, forest cover mapping and accuracy assessment, and image differencing.

Concerning to imagery pre-processing, the late scene (2014) was used as the reference image. The digital numbers (DN) recorded by the sensors were converted to TOA spectral reflectance and atmospherically corrected using the dark-object subtraction (DOS) (Chavez, 1996) to reduce any influence of haze and atmospheric particles (Fig. 2.3) In order to perform multi-temporal analysis with satellite data, radiometric normalization of scenes is necessary. This allows comparison between scenes captured in different periods reducing the noise associated to sensor used and atmospheric conditions present during capture. Here, a relative radiometric normalization (RRN) was implemented using the Pseudo Invariant Features method (PIFs) assuming the late scene (2014) as the reference image and earlier scenes were normalized respect to that. PIFs targets were manually identified choosing locations with no vegetation mainly along flat landscape units and present in all scenes. Once the targets were isolated, linear regression equations were developed to relate the earlier to the reference scene band by band (Schott *et al*., 1988; Salvaggio, 1993). Normalization was therefore performed including landscape elements with invariant reflectivity nearly constant over time (Hajj *et al*., 2008).

Table 2.1 – **Satellite data.** Satellite images used to analyze trends in forest cover across Kumbira forest.

Sensor	Pixel Size	Acquisition date	Source
LANDSAT 5TM	30 *m* (visible, NIR, SWIR) 120 *m* (thermal)	07-06-1991	GLCF
LANDSAT 7ETM+	30 *m* (visible, NIR, SWIR), 60 *m* (thermal) 15 *m* (panchromatic)	30-09-2001	USGS
LANDSAT 8 OLI-*TIRS*	OLI Multispectral bands (visible, NIR, SWIR): 30 *m* OLI panchromatic band: 15 *m* TIRS Thermal bands: 100 *m* [a]	02-03-2014	USGS

[a] resampled to 30 meters to match multispectral bands

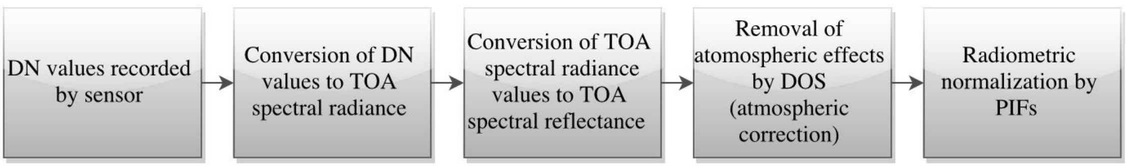


Fig. 2.3 – Process of radiometric correction. Raw data recorded by sensors are converted into TOA spectral reflectance and atmospherically corrected. A correct radiometric normalization between both images is fundamental for change detection.

Regarding to forest cover estimation, mapping considered two classes: ‘forest’ and ‘non-forest’. Here, we adopted the ‘forest’ definition followed by FAO, which considers tree crowns covering more than 10% of the ground and a minimum height of 5 meters (FAO, 2001), and thus can include forests with human intervention such as shade coffee plantations. Two classification methods were used, namely Linear Spectral Unmixing with Principal Component Analysis for endmember collection and Maximum Likelihood, except for the earlier images (1991 and 2001). Classification of earlier images was only performed with latest method. This was due to the absence of panchromatic band in LANDSAT 5 TM as well as our willing to enjoy the possibility to refine resolution and improve classification for 2014 by using adequately the panchromatic band. Besides that, a preliminary stage of exploratory analysis shown that Maximum Likelihood Algorithm (MLA) performed better and was decided to used it as the baseline classification technique for the multi-temporal analysis. Therefore, multi-temporal forest cover comparison was based on the forest mask resulting from latest classification method. Classification procedure, respective training and validation strategies, are described individually hereafter.

For 2014 two forest masks with 15 and 30 m resolution were obtained. The finest mask was obtained by fusing the high-resolution panchromatic image (band 8 of LANDSAT 8 OLI-*TIRS*) with the lower resolution multispectral image trough Principal Component Analysis (PCA) spectral sharpening technique (Chavez, 1989; Shetigarra, 1989; Shah *et al*., 2008; Vrabel *et al*., 1996; Yang *et al*., 2012). After that, was combined a PCA for forest endmembers collection (Smith *et al*., 1985) by selecting the centre of the scatter plot of the 1st and 2nd principal components (Fig. 2.4), and Linear Spectral Unmixing (LSU) to determine the relative abundance of the selected endmembers within the volume of each pixel (Settle and Drake, 1993). The coarsest forest mask was achieved by a supervised MLA classification (Jensen, 2005). MLA calculates the probability that a given pixel belongs to a specific class. To perform this classification, a total of 61 sites (at least 4x4 pixels) were used as training data. Sites were randomly visually selected across the satellite scene using very high resolution imagery from Google Earth and field knowledge from in-field campaign as ancillary data.

To map forest cover in 1991 and 2001, as described ahead it was also considered the Maximum Likelihood Algorithm (MLA) and using 54 and 64 training sites, respectively. These sites were also visually identified and selection was made in areas where the presence of forest was clear. Visual identifications in the satellite images are a potential source of errors, but such risk is higher when a larger set of land cover classes are considered and images enclosed in period of large cover transitions. In our case, accuracy of our selected training samples was highly supported by the stability of forest during civil war conflict.

Classification accuracy of forest cover was verified through confusion-matrix (Pontius *et al*., 2004) and Cohen's Kappa coefficient (*k)* (Congalton, 1991). This reflects the difference between actual agreement and the agreement expected by chance. The accuracy was expressed as the overall percentage of correctly classified pixels. Therefore, for 2014 were considered a total of 78 validation sites, 51 resulting from in-field data collection and representing 'forest' class and 27 representing 'non-forest' class. Three in-field validation plots were excluded since they did not present the required forest cover or height reported by FAO. Accuracy of 1991 and 2001 forest masks was estimated using 45 (20 for 'forest' class and 25 for 'non-forest' class) and 46 (26 for 'forest' class and 20 for 'non-forest' class) validation samples, respectively. Validation samples were also visually estimated. All training and validation samples were subject to Jeffries-Matusita distance test (Trigg and Flasse, 2001), which estimate class separability across band pairs to 'forest' and 'non-forest' classes. All samples presented values greater than 1.9, confirming their spectral separability or that classes are well separated (Richards and Jia, 1999).

To determine forest loss over time and identify stable and non-stable forest cover that suffered change due to anthropogenic influence was applied a post-classification change detection within classified forest cover mask (Lu *et al*., 2004; Alphan *et al*., 2009). Forest loss for each period (1991-2001 and 2001-2014) was obtained by establishing the image differencing between later image and earlier image. Stable forest refers to the forest area present in the three times, while unstable refers to those areas that have change by regeneration or deforestation. The annual rate of deforestation was calculated using the Puyravaud (2003) equation 3:

$$\text{eq. 3)}\quad r = \frac{1}{t_1 - t_2} ln \frac{A_2}{A_1}$$

where r is the deforestation rate in % of lost per year, and A_1 and A_2 are the forest cover at time t_1 and t_2, respectively.

With these methods the detection and quantification of forest degradation and regrowth was not possible. All the operations were executed in ENVI-IDL 4.7.

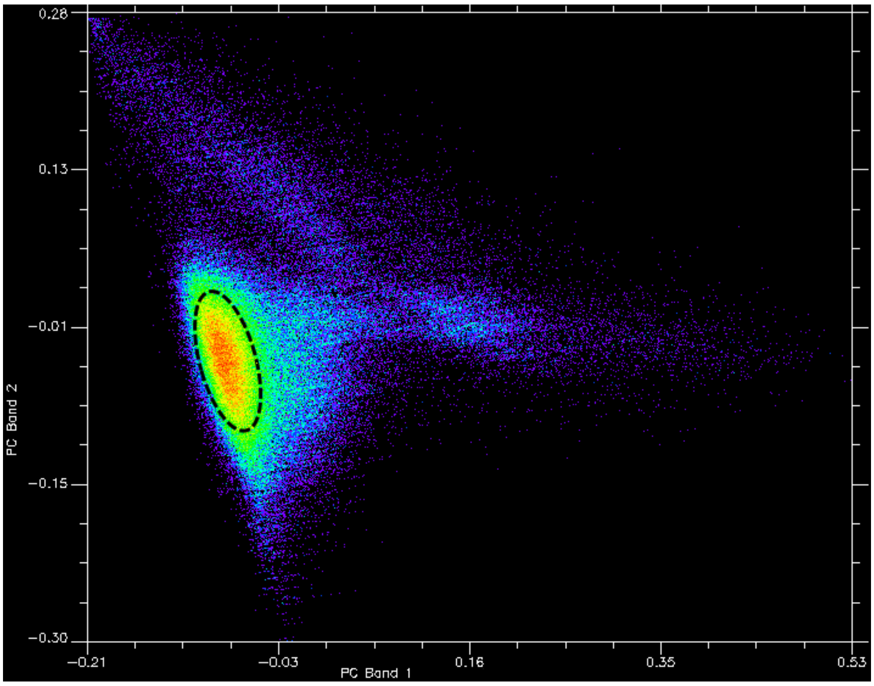


Fig. 2.4 – **Forest endmembers collection**. By selecting the centre of the two main PCs from a PCA scatter plot, forest class can be isolated from the other land cover components.

2.4 Modelling forest loss using spatial explicative factors

2.4.1 Variable selection and model setup

Deforestation can be more or less severe according to the influence of spatial environmental factors and their interactions at different spatial and temporal scales (Kumar *et al*., 2014). Regression type models and models based on spatial transition allow the assessment of the relative significance of spatial explicative factors in specific contexts of forest conversion. A GIS-based Logistic Regression Model (LRM) was used to assess the ultimate causes of forest change in Kumbira during the period of 2001-2014. When the dependent variable is binary, which is the case, the LRM is an effective technique to analyse land cover conversions (Kumar *et al*., 2014; Luo and Wei, 2009; Rutherford *et al*., 2007). The dependent variable was the 'forest cover change' layer that took place between 2001 and 2014. The layer was obtained with a post-classification comparison on a pixel-by-pixel basis using a change detection matrix between the two independent classified images (Fig. 2.5). The result forest cover change map is a binary layer (1 *versus* 0), where "1" indicate the category that had remained the same ('no change') and "0" the category that had changed ('forest change') (Shalaby and Tateishi, 2007). Since Kumbira was under a typical context of a civil war until 2002, changes between 1991 and 2001 were not considered for the modelling analysis.

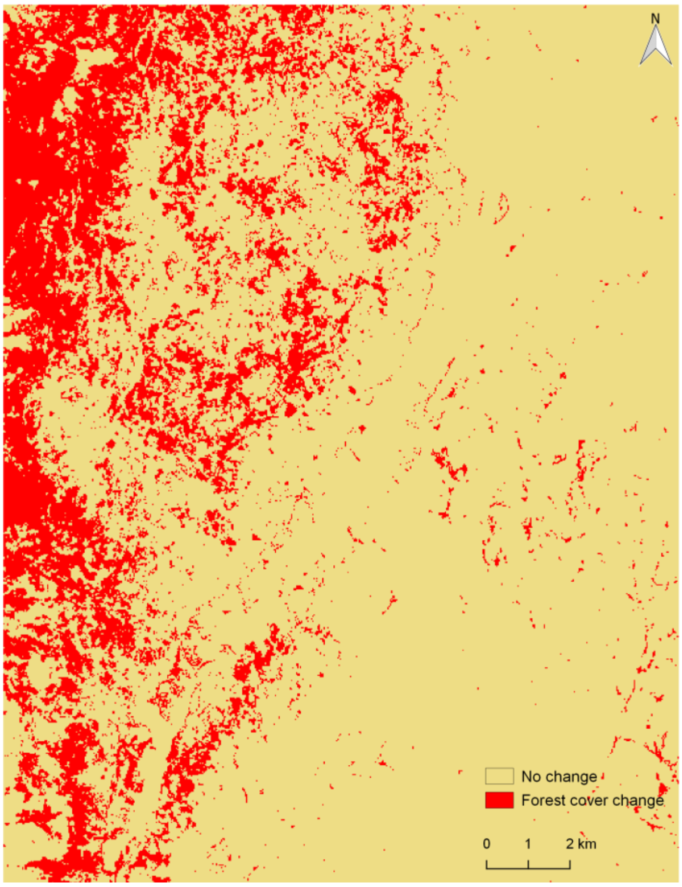


Fig. 2.5 – **Dependent variable.** 'Forest cover change' during 2001-2014 used for LRM.

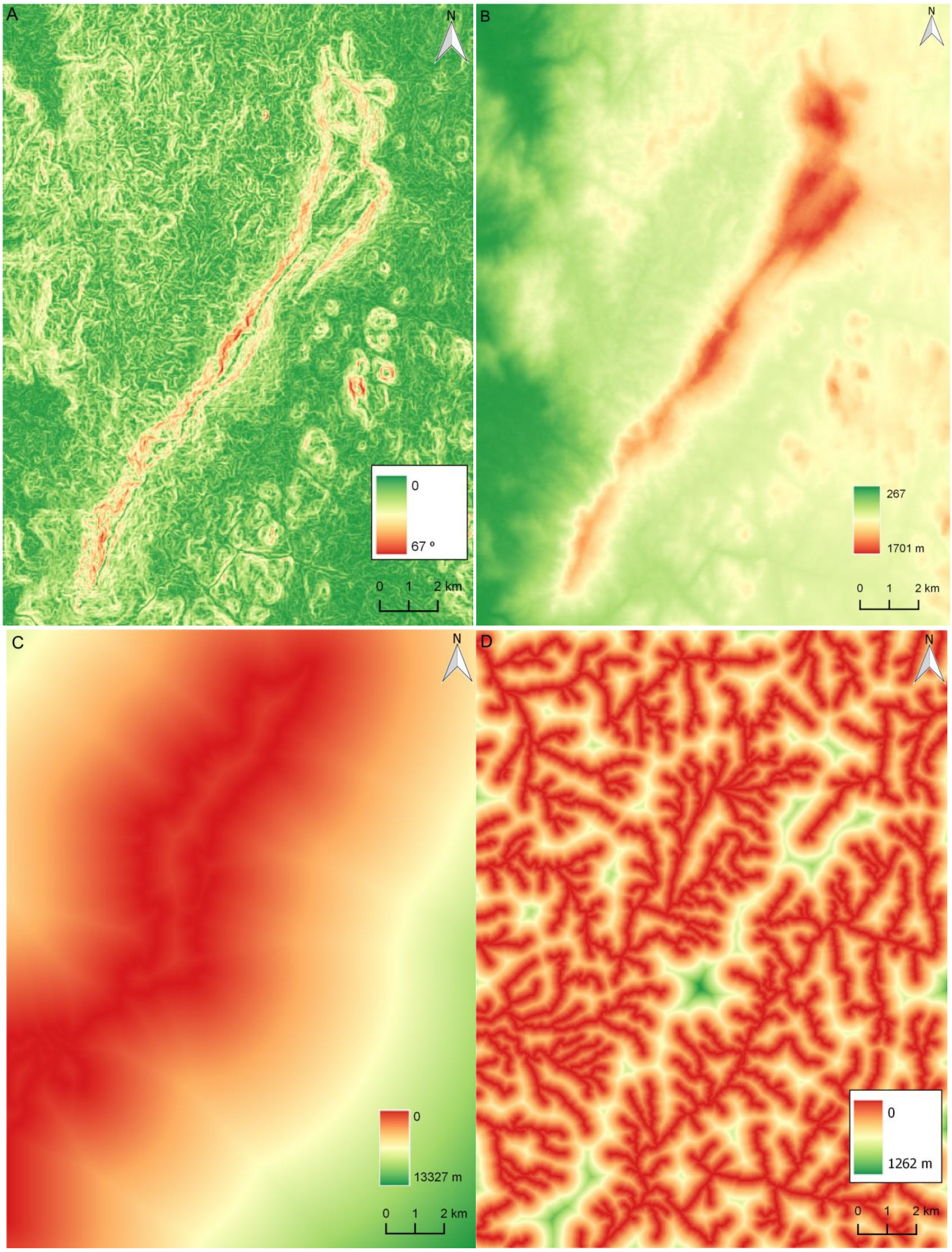
Based on the literature, eight explanatory variables (Fig. 2.6), grouped in three thematic fields, were selected as potential driving forces of forest change (Table 2.2): topography ('slope', 'elevation' and 'aspect'), neighbourhood ('distance to trails', 'distance to streams', 'density of settlements' and 'density of bare land') and spectral related ('NDBR index') (Geist and Lambin, 2002; Mahapatr and Kant, 2005; Echeverria *et al*., 2008; Müller *et al*., 2011; Arekhi S, 2011; Vieilledent *et al*., 2013; Mayaux *et al*., 2013; Kumar *et al*., 2014).

The NASA STRM Digital Elevation Model (DEM; 30 m resolution) was used to generate the topography variables: slope, elevation and aspect maps. These variables served as a proxy for the effect of landscape shape and exposure on forest loss (Geist and Lambin, 2002). The circular variable aspect (º) was transformed to cosine aspect and sine aspect to be represented as a continuous variable with output values respect to North and East (Piedallu and Gégout, 2008). Northness varies from -1 (south-facing) to 1 (north-facing), and eastness from -1 (west-facing) to 1 (east-facing).

Neighbourhood variables were estimated using trails, DEM and satellite-derived information. In specific, major trails and trails networks were manually digitized with very high resolution imagery data for 2010 in Google Earth (2015). Next, data was imported in QGIS 2.6.1 (QGIS Development Team, 2014) converted to raster format and applied a proximity operator to estimate ‘distance to trails’. Ideally, should be used images from ~2001 to depict this variable, but most close available image for the study area with appropriate resolution refers to 2010. We assume that this may carry limitations in the interpretation of the variable, but we decided to risk since data for forest conservation in Angolan Scarp forest is urgently necessary and missing. In addition, we observe that is unlikely that deforestation occurred much before 2010 (as proved by an additional MLA forest cover mask performed for the year of 2010 not present in this thesis; Cáceres *et al*., in prep) due to civil conflict.

Hydrologic features were extracted from DEM after removing pits by filling depressions. Pits are artificial depressions that usually result from the pre-processing operations that can create discontinuities in drainage patterns (Grimaldi *et al*., 2007). Pit filling method increases the elevation of the pits until they drain out (Jenson and Domingue, 1988). Once we had hydrologically corrected the DEM, the Catchment area (Parallel) module of QGIS 2.6.1 (QGIS Development Team, 2014) was executed using the D8 algorithm and set a channel initiation threshold greater than 10000000 using the Channel Network algorithm. Once again the Proximity operator was applied in order to obtain the ‘distance to streams’ variable. Settlements were also manually identified in Google Earth in 2010, imported in QGIS (QGIS Development Team, 2014) and convert from KML to a vector layer. Settlements do not change easily as trails do, so the outlined in 2010 image is not a major limitation. The ‘density of settlements’ was then obtained using the Heatmap tool, where was settled a radius of 1000 m around the center of each of the identified settlements. All distance explanatory variables were transformed to the natural log (ln) and evaluated the effect of accessibility and the influence of water resources on forest loss (Geist and Lambin, 2002). The ‘density of settlements’ evaluated the influence of settlements structure in the surrounding vegetation (Monteiro *et al*., 2011). To estimate the ‘density of bare land’ (e.g., bare soil, rock, dirt, etc.) the satellite-derived Normalized Differenced Vegetation Index (NDVI) was estimate for the LANDSAT scene of 2001 (Rouse *et al*., 1973; Glenn *et al*,. 2008) and a threshold of 0.5 applied, with values below this threshold identifying bare land features. This variable measured the effect of bare land structure on forest loss (Monteiro *et al*., 2011). The spectral related variable ‘NDBR’ evaluated the effect of vegetation density in forest loss and it was calculated as described in section 2.1 for the LANDSAT scene of 2001.

All data layers were in grid format (30 m spatial resolution)


A
N
0
67 º
0 1 2 km
B
N
267
1701 m
0 1 2 km
C
N
0
13327 m
0 1 2 km
D
N
0
1262 m
0 1 2 km

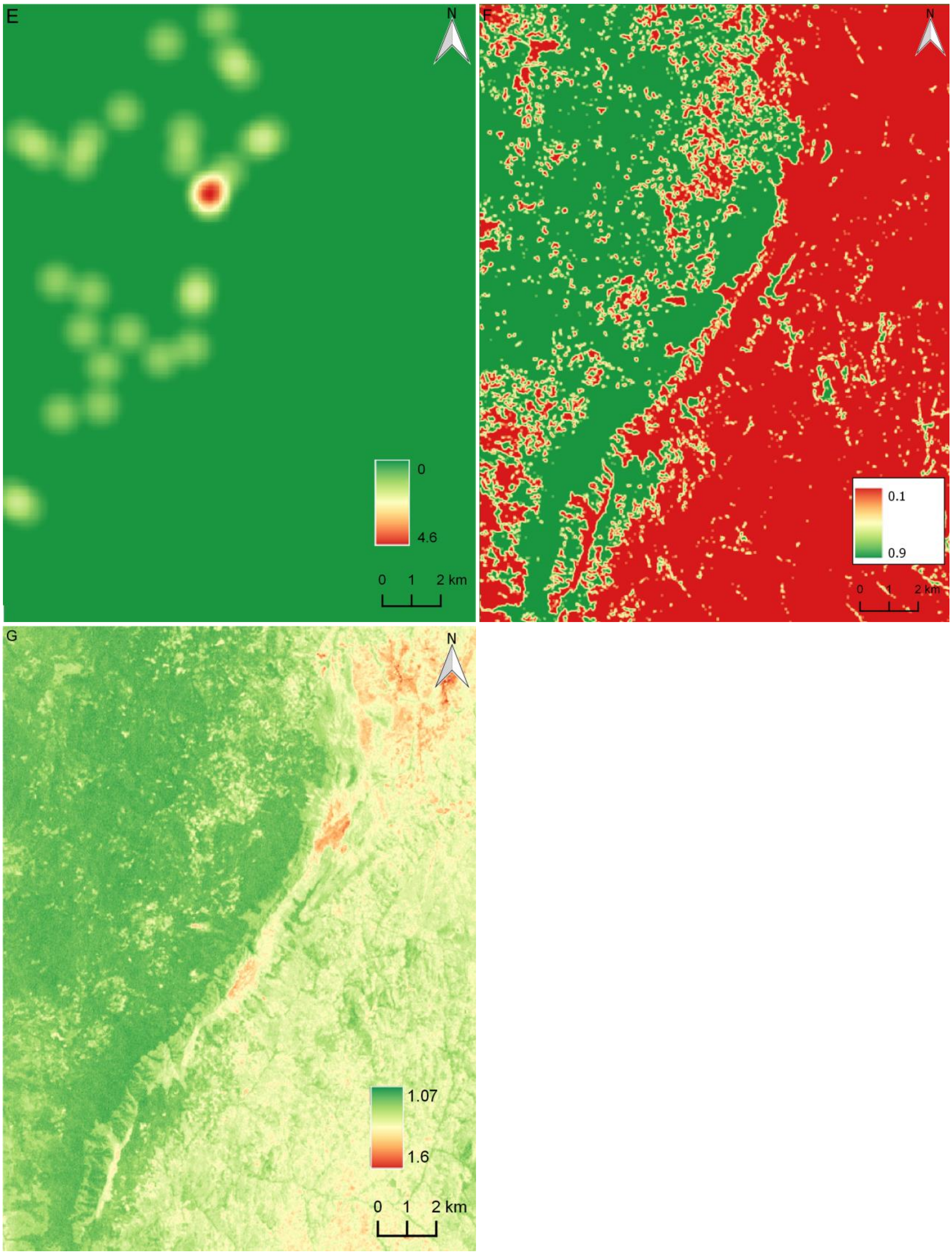


Fig. 2. 6 – Explanatory variables used for LRM and SBA. (A) Slope, (B) elevation, (C) distance to roads, (D) distance to streams, (E) density of settlements, (F) density of bare land and (G) NDBR index. Since aspect was transformed to cosine aspect and sine aspect is not represented here.

2.4.2 Logistic Regression model run and validation

For the logistic regression analysis, 500 pixel observations were selected through stratified random sampling from the dependent data layer ('forest cover change'), with equal sampling to 1 (change) and 0 (no change) observations. For each independent variable, observations were obtained through spatial overlay using ENVI-IDL 4.7 (Fig. 2.7). The set of independent variables was tested for multicollinearity by examining correlation structure between explanatory variables using the Pearson's rank correlation coefficient, since high collinearity violates the assumption of independence between data points (Graham, 2003; Legendre, 1993). Pairs of variables with magnitudes > 0.5 (Booth *et al.*, 1994) and VIF ≥ 2 (Zuur *et al*., 2010) indicate high collinearity. For this analysis, the 'car' package of R version 3.1.1 (R Core Team, 2014) was used. Then, the change/no change dataset was split into a training dataset using 75% of the 500 observations, and a test dataset using the remaining 25% (Papeş *et al*., 2012; Vieilledent *et al*., 2013). The training dataset was used for model calibration purposes and the test dataset to validate the best fitted model. In logistic regression, the probability of forest change is described as a function (equation 4) of the explanatory variables:

$$\text{eq. 4)}\ \ p=\mathrm{E(Y)}\frac{e^{\beta_0+\beta_1X_1+\beta_2X_2+\beta_3X_3+\beta_4X_4}}{1+e^{\beta_0+\beta_1X_1+\beta_2X_2+\beta_3X_3+\beta_4X_4}}$$

where p is the probability of forest change, E(Y) is the expected value of the dependent variable Y, β_0 is a constant to be estimated, β_i is the coefficient to be estimated for each explanatory variable X_i. This function is logistic transformed into a linear function (equation 5) and the dependent variable of regression is bounded between 0 and 1:

$$\text{eq. 5)}\ \ \mathrm{logit}(p)=\ln\left(\frac{p}{1-p}\right)=\beta_0+\beta_1X_1+\beta_2X_2+\beta_3X_3+\beta_4X_4$$

Initially, we assessed the extent of any remaining collinearity by fitting a preliminary generalized linear model (GLM) (Guisan *et al*., 1998) with the training dataset and all variables and looking at the variance inflation factors (VIFs) of the resulting model (Rhodes *et al*., 2009). By suggestion of Zuur *et al.* (2010), explanatory variables with VIFs above 2 were dropped from the dataset, which in our case excluded from analysis the variables 'density of bare land' and 'NDBR index'. Like multicollinearity, spatial autocorrelation between observations may be a problem. Spatial autocorrelation in the preliminary GLM was assessed with a spline correlogram of the Pearson residuals (Bjørnstad and Falck, 2001) using 'ncf' package of R 3.1.1 (R Core Team, 2014). These correlograms use a spline function and produce graphical representations of the spatial correlation between locations of the observations at a range of lag distances (Zuur *et al*., 2009). In this case the maximum lag distance was 10 km.

In addition to the modeling task, spatial bivariate analysis was performed in order to describe the relationship between forest loss and the variation of each explanatory variable (exception for density variables) not excluded from the multicollinearity analysis (Table 2.2).

Table 2.2 – List of variables included in the spatial bivariate analysis and GIS-based logistic regression model.

Variable description	Unit	Proxy for	Source[a]	Task level[b]
Topography related				
Slope	º	Landscape shape	DEM	SBA/GIS-LRM
Aspect[c]	º	Exposure	DEM	SBA/GIS-LRM
Elevation	m	Landscape shape	DEM	SBA/GIS-LRM
Neighbourhood related				
Distance to trails	m	Accessibility	GE-10	SBA/GIS-LRM
Distance to streams	m	Accessibility/Water resources	DEM	SBA/GIS-LRM
Density of settlements	nº/1000 m	Settlements structure	GE-10	GIS-LRM
Density of bare land	index	Bare land structure	7ETM01	GIS-LRM
Spectral related				
NDBR	index	Vegetation density	7ETM01	GIS-LRM

[a] DEM (digital elevation model); GE-10(Google Earth image 2010); 7ETM01 (LANDSAT 7ETM+ 2001).
[b] Analysis where the variable was included: SBA (spatial bivariate analysis); GIS-LRM (GIS-based logistic regression model)
[c] Variable represented by cosine aspect and sine aspect in the GIS-LRM.

Once a suitable set of independent variables were identified, they were grouped in six explanatory sets with different combinations. The set-1 included all the topography and neighbourhood related variables, the set-2 only the two distance variables, the set-3 was formed by all the neighbourhood related variables, set-4 included the distance and all the topographic variables, set-5 only the topographic and set-7 the topographic and the 'density of settlements' variables. Also, was constructed a 'null' model that includes no explanatory variables as a check of our assumption of the importance of the selected variables. To find the set producing the best model and that would be used to make predictions, each model was fitted to the training data and ranked by their AIC values using equation 6:

$$\text{eq. 6)}\quad AIC = -2L + 2K$$

where L is the maximum log-likelihood of the model and K is the number of parameters in the model (Akaike, 1973). The chosen model is the one with low values of AIC. Also, we calculated the relative probability of each model being the best model by calculating their Akaike weights, w_i (equation 7):

$$\text{eq. 7)}\quad w_i = \frac{\exp\left(-\frac{1}{2}\Delta i\right)}{\sum_{j=1}^{R} \exp\left(-\frac{1}{2}\Delta j\right)}$$

where Δi is the difference between the AIC for model I and the model with the lowest AIC and the sum is over all the alternative models in the set $j = 1,...,R$. AIC and w_i were calculated with the 'MuMIn' package in R 3.1.1 (R Core Team, 2014).

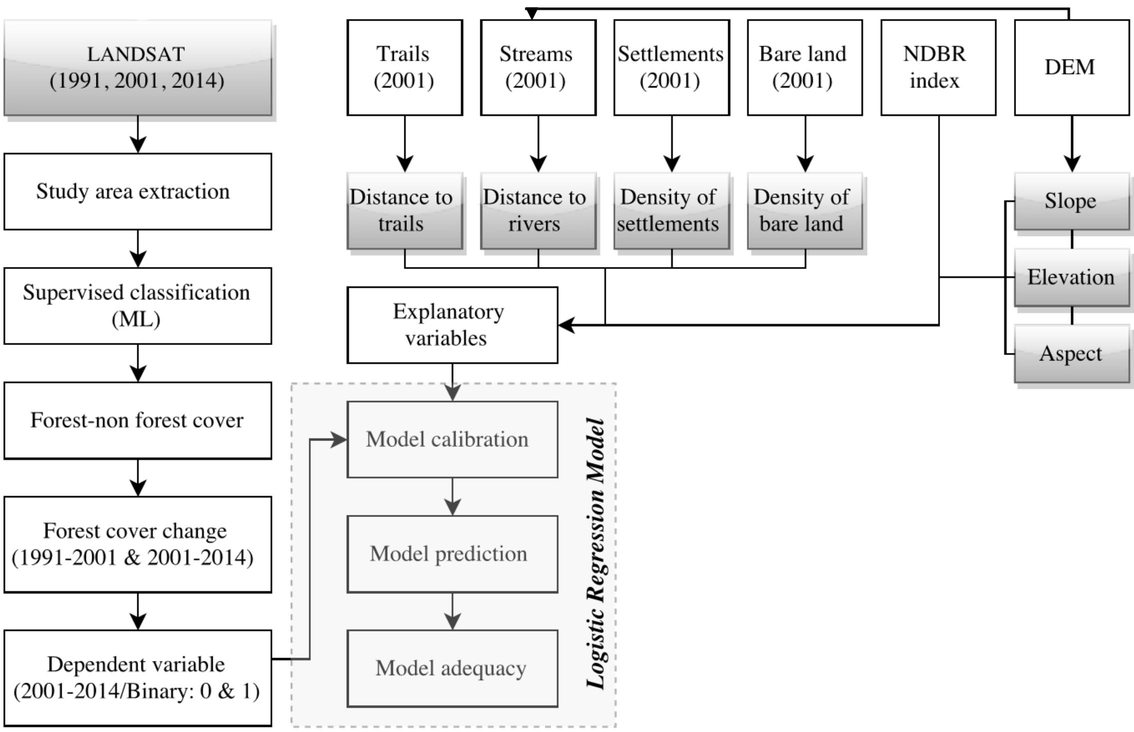


Fig. 2.7 – Overview of the LRM process. GIS and remote sensing data are used to produce the binary dependent variable 'forest cover change' and the eight explanatory variables to be included in the GLMs. DEM – Digital Elevation Model; ML – Maximum Likelihood.

Predictions on the test dataset were done in order to assess the quality of the selected model, which were then validated using the Relative Operating Characteristic/Area Under Curve (ROC/AUC) (Pontius and Schneider, 2001) using the 'pROC' package in R 3.1.1. ROC compared the probability for forest loss against the forest loss layer resulting in a curve of true positive fraction vs. false positive fraction with values ranging between 0.5 (completely random) and 1(perfect fit) (Monteiro *et al.*, 2011; Kumar *et al.*, 2014). Also, other model statistics like pseudo R^2 (1 − (ln L (L = Likelihood)) for the best fitting model / ln L0 for the null hypothesis) were calculated using the ‘rms’ package in R 3.1.1.

2.5 Quantification of carbon emissions from forest change

The mean carbon content obtained after conversion of AGB into AGC in 49 plots surveyed during field work at Kumbira was used as reference to quantify the carbon emissions associated to forest change.

The change in the carbon content was determined from the change in the area of the two classes (‘forest’ and ‘non-forest’) derived from the change detection analysis across forest classifications with satellite data. The carbon emissions were estimated by multiplying the area of the ‘forest’ converted to ‘non-forest’ by the average carbon content. Only gross carbon emissions caused by deforestation were recorded. In future work, we aim to improve our carbon estimates and better understand the forest dynamics by developing methodologies to assess both forest regrowth and degradation in Kumbira forest.

2.6 Evaluation of REDD+: scenarios development

To evaluate the potential of REDD+ as incentive for reducing forest loss, three scenarios for a 13-year period were projected: 1) business-as-usual scenario (BAU); 2) full-conservation (FC); and 3) give-and-take (GAT). The BAU scenario implies no REDD+ intervention and incorporates forest loss following the linear trend and rate of deforestation measured during the historical reference period (2001-2014). In the FC model, the allocation of REDD+ payments would be used by the government to monitor and enforce the total protection of the current forest area. All land owners and farmers with forest are directly payed with REDD+ incentives and they opt to maintain forest instead to cut or convert tor farming uses. This scenario represents the maximum potential of reducing emissions from deforestation. In the GAT scenario, REDD+ payments would be used to ensure the protection of a delimited area corresponding to 50% of the current forest. Land owners and farmers opt to receive incentive to preserve this forest land and all farming activities would restricted to the remaining area by allowing deforestation at the current rate.

3. Results

3.1 Aboveground carbon stocks

A total of 496 trees were recorded across all 49 survey plots considered for the quantification of carbon stocks. Medium shadow plots show the highest mean values of AGB and DBH, 225.2 Mg ha^{-1} (s.d. = 366.3) and 17.1 cm (s.d = 14.1), respectively and a mean tree height of 9.2 m (s.d. = 4.2). Low shadow plots presents the lowest mean values of AGB, DBH and tree height, 84 Mg ha^{-1} (s.d. = 196.9), 13.6 cm (s.d. = 8) and 9.2 m (s.d. = 3.9), respectively. The highest mean tree height value belongs to the high shadow plots (9.5 m, s.d. = 3). This class also presents a mean DBH of 14.8 cm (s.d. = 7.7) and mean AGB of 149.3 Mg ha^{-1} (s.d. = 143.3). However, the AGB estimates for the three spectral categories calculated by NDBR were not significantly different (Kruskall Wallis test, p = 0.4731). The AGC in the 49 plots ranged from 0.7 to 737.1 Mg ha^{-1}, with a mean of 89.4 Mg ha^{-1} (s.d. = 126.4).

The relationship between DBH and tree height as well as the distribution of AGB and AGC estimates are provided in Fig. 3.1 and 3.2, respectively. The AGB and AGC estimates and the number of trees measured for each plot are shown in Appendix I – Ib.

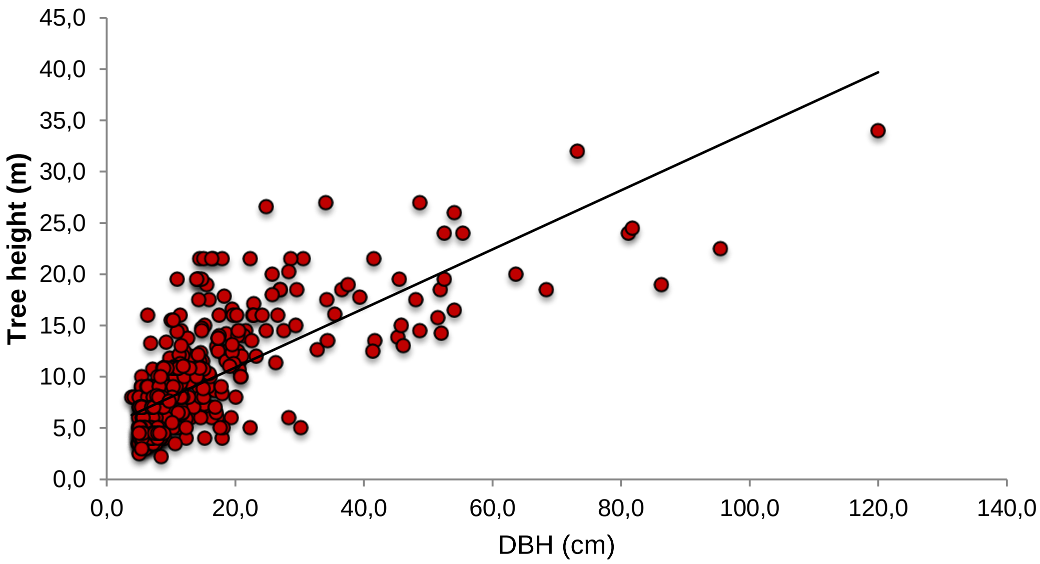


Fig. 3.1 – **Relation between DBH and tree height.** A stratified random sampling was used for the selection of 49 plots, where 496 trees (DBH ≥ 5 cm) were tree height measured using either a clinometer or a laser range finder

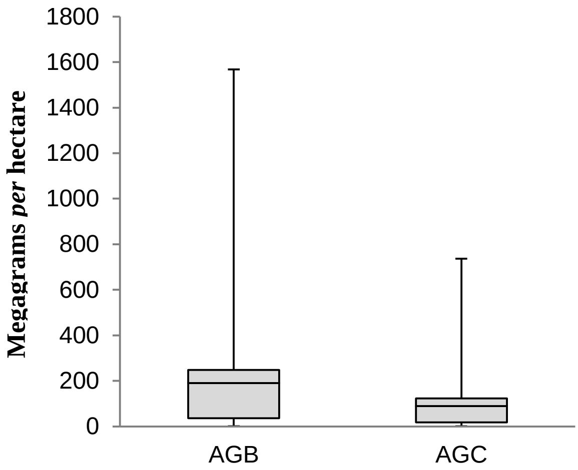


Fig. 3.2 – Aboveground biomass and carbon (Mg ha^{-1}) for forest plots. Box plots show 25% quartile, median and 75% quartile of the distributions (horizontal lines); vertical lines extend a further 1.5 times the interquartile (25–75%) range; vertical lines extend a further 1.5 times the interquartile (25–75%) range.

3.2 Forest classification and change detection

The overall accuracy of the forest/non-forest classification indicated that accurate forest masks were obtained for the years 1991, 2001 and 2014. Accuracies ranged from 95.13% for 2014 to 98.2% for 1991, with Kappa (*k*) coefficients varying from 0.82 to 0.97, respectively. For 2014, MLA performed better than the Linear Spectral Unmixing with Principal Component Analysis for endmember collection method (PCA + LSU; Fig. 3.3 and Table 3.1), supporting the decision of chosen this method for the multi-temporal forest classification (Table 3.2 and Fig. 3.4). The producer's accuracy or the fraction of correctly classified pixels with regard to all pixels of that ground-truth class was high to all classifications, with values ranging from 96.08% (2014) to 100% (2001) for the 'forest' class and from 95.24% (2001) to 100% (2014) for the 'non forest' class (Table 3.2). The user's accuracy or the fraction of correctly classified pixels with regard to all pixels classified in a given class in the classified image were also very good, with values varying from 96.4% (2001) to 100% (2014) for the 'forest' class and from 93.85% (2014) to 100% (2001) for the 'non-forest' class (Table 3.2).

Table 3.3 summarizes the forest cover changes occurred in Kumbira during the period 1991-2014. Results indicated that the greatest change took place in post-conflict society between 2001 and 2014 where 40,8% of forest was lost in only 13 years, at a deforestation rate of 4.04% year^{-1}. Both Table 3.3 and Fig. 3.5 illustrate the accentuated decrease of forest in this period. In 2001, almost 39.3% (13501.53 ha) of the study area was forest, while in 2014 only 23.3% (7988.85 ha) remained forest. For the early period (1991-2001), which coincided with the last third of the civil war conflict in Angola, the forest cover remained constant over the 10 years and may even have increased by about 35 ha.

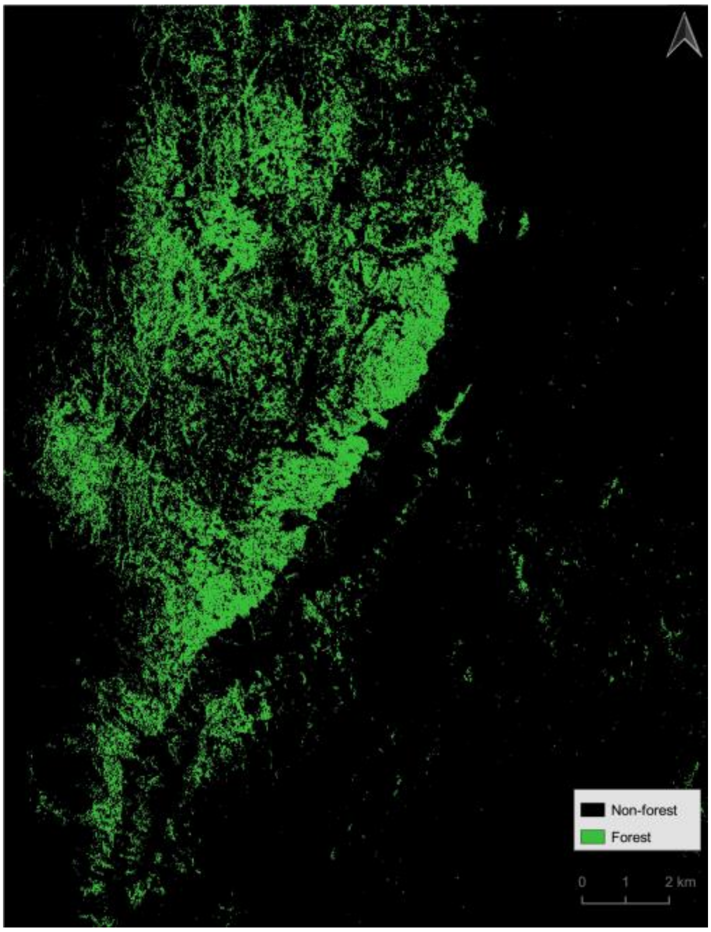


Fig. 3.3 – Forest cover during 2014 extracted by the combination method. The forest mask was obtained by the fusion of the high-resolution panchromatic band to the low-resolution multispectral image. A PCA was used for the forest endmembers collection and LSU to determine the relative abundance of forest in each pixel.

Table 3.1 – Confusion matrix for the classification of the forest cover map using the PCA + LSU method, LANDSAT 2014.

<table>
<tr><th rowspan="3">Year</th><th colspan="4">Error matrix</th><th rowspan="3">Accuracy</th></tr>
<tr><th rowspan="2">Class</th><th colspan="3">Reference data</th></tr>
<tr><th>Forest</th><th>Non-forest</th><th>Total</th></tr>
<tr><td rowspan="3">2014</td><td>Forest</td><td>190</td><td>0</td><td>190</td><td rowspan="3">Overall = 95.13%
Producer’s (%):
Forest = 93.13, Non-forest = 100
Omission error (%):
Forest = 0.14, Non-forest = 1
User’s (%):
Forest = 100, Non-forest = 85.71
Comission error (%):
Forest = 0, Non-forest = 0.14
k = 0.8162</td></tr>
<tr><td>Non-forest</td><td>14</td><td>84</td><td>98</td></tr>
<tr><td>Total</td><td>204</td><td>84</td><td>288</td></tr>
</table>

Table 3.2 – Confusion matrix for the classification of the forest cover map using the MLA method, LANDSAT 1991, 2001 and 2014.

Year	Error matrix				Accuracy
	Class	Reference data			
		Forest	**Non-forest**	Total	
1991	**Forest**	155	3	158	**Overall** = 98.2143% **Producer's** (%): Forest = 100, Non-forest = 95.24 **Omission error** (%): Forest = 1.9, Non-forest = 1.69 **User's** (%): Forest = 98.1, Non-forest = 98.31 **Comission error** (%): Forest = 1.9, Non-forest = 0 ***k*** = 0.9673
	Non-forest	3	175	178	
	Total	158	178	336	
2001	**Forest**	107	4	111	**Overall** = 97.9% **Producer's** (%): Forest = 98.1, Non-forest = 98.31 **Omission error** (%): Forest = 0, Non-forest = 4.73 **User's** (%): Forest = 96.4 Non-forest = 100 **Comission error** (%): Forest = 3.6, Non-forest = 1.69 ***k*** = 0.9573
	Non-forest	0	80	80	
	Total	107	84	191	
2014	**Forest**	196	0	196	**Overall** = 97.546 % **Producer's** (%): Forest = 96.08, Non-forest = 100 **Omission error** (%): Forest = 3.92, Non-forest = 0 **User's** (%): Forest = 100, Non-forest = 93.85 **Comission error** (%): Forest = 0, Non-forest = 6.15 ***k*** = 0.9483
	Non-forest	8	122	130	
	Total	204	122	326	

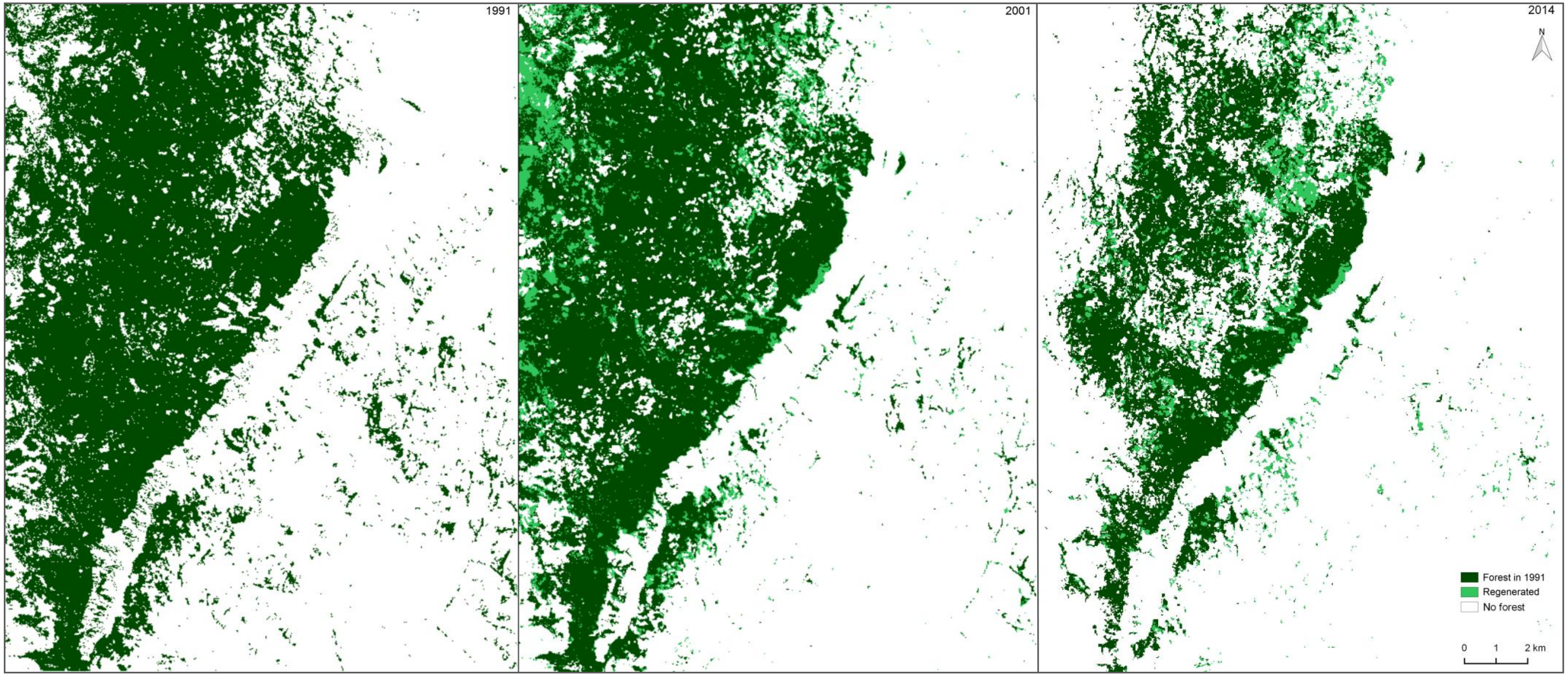


Fig. 3.4 – Forest classification for LANDSAT scenes (1991, 2001, 2014) obtained by MLA classifier. Dark green is the forest that has been maintained since 1991. Light green is the potential regenerated forest. However, due the 10 years intervals, it is probable that many areas classified as ′forest since 1991′ may also be regenerated area

Table 3.3 – Forest cover changes and deforestation rates for the 1991-2001 and 2001-2014 periods.

Year	Class	Area (ha)	Area (%)	Deforestation rate *r* Puyravaud (% yr^{-1})
1991	Forest	13466.52	39.2	
	Non-forest	20893.68	60.8	
2001	Forest	13501.53	39.3	
	Non-forest	20858.67	60.7	
2014	Forest	7988.85	23.3	
	Non-forest	26371.35	76.7	
Change 1991-2001	Forest	35.01	0.26	
Change 2001-2014	Forest	-5512.68	-40,8	4.04

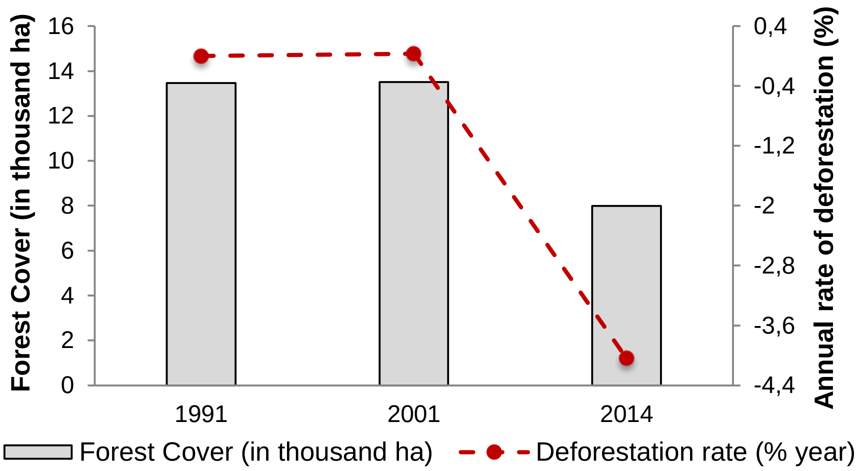


Fig. 3.5 – Forest cover for the years 1991, 2001 and 2014 and deforestation rates. Forest cover remained constant between 1991 and 2001 (war period) and was followed by a dramatic reduction for the period 2001-2014.

3.3 Identification of the significant drivers for forest loss

3.3.1 Correlation and multicollinearity among the spatial explicative factors

Pearson's correlations and VIF values identified that 'density of bare land' and 'NDBR' variables were highly correlated (r= 0.86; VIF= 2.8039 and 2.8918) and were excluded (Zuur *et al.*, 2010) from the candidate models (see Fig. 3.6 and Table 3.4). This is understandable, since in bare ground NDBR values are supposed to be lower. Moreover, correlogram showed that (Fig. 3.7) that spatial autocorrelation between observations was not observed, and modelling task can proceed without any previous treatment.

Table 3. 6 – Variance inflation factors for each explanatory variable. Variables with VIFs above 2 were excluded from the dataset (Density of bare land and NDBR index).

Slope	Cosine aspect	Sine aspect	Elevation	Distance to trails	Distance to streams	Density of settlements	Density of bare land	NDBR
1.1528	1.0293	1.0268	1.1429	1.1464	1.0755	1.1490	2.8039	2.8918

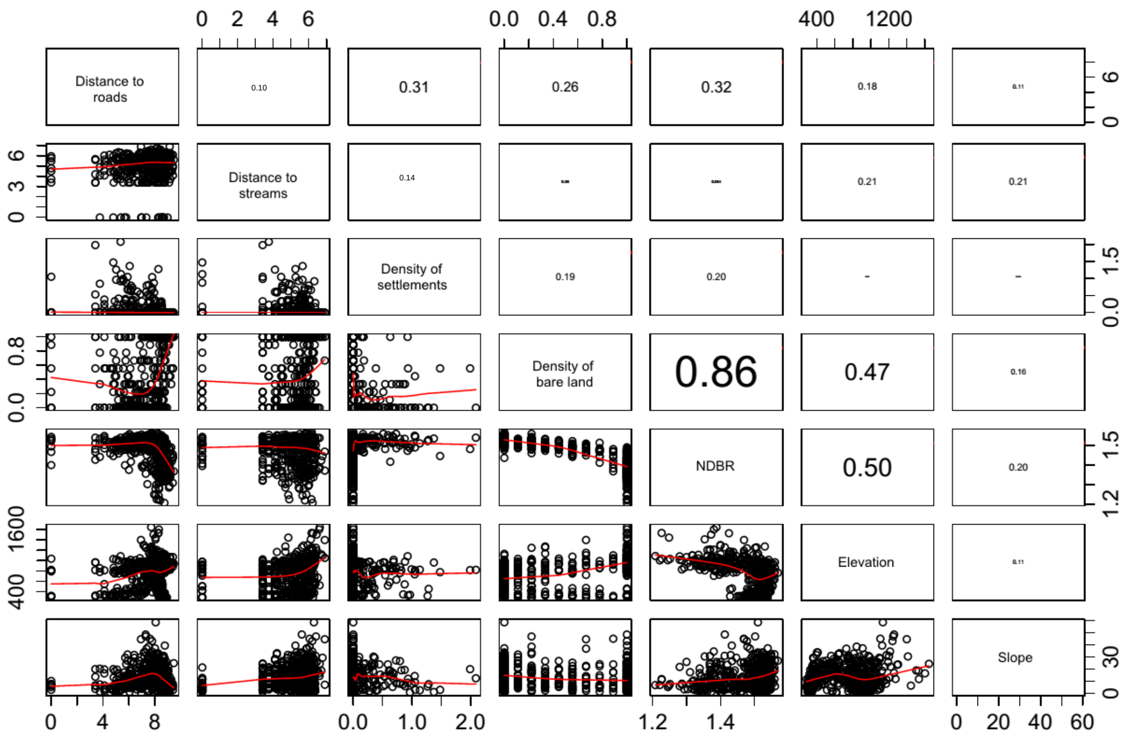


Fig. 3.6 – Pairplot of the explanatory variables and Pearson's correlation coefficients. Coefficient values greater than 0.5 indicate high collinearity ('density of bare land' vs 'NDBR'). The circular variable aspect is not represented but did not show any signal of collinearity with the remaining variables.

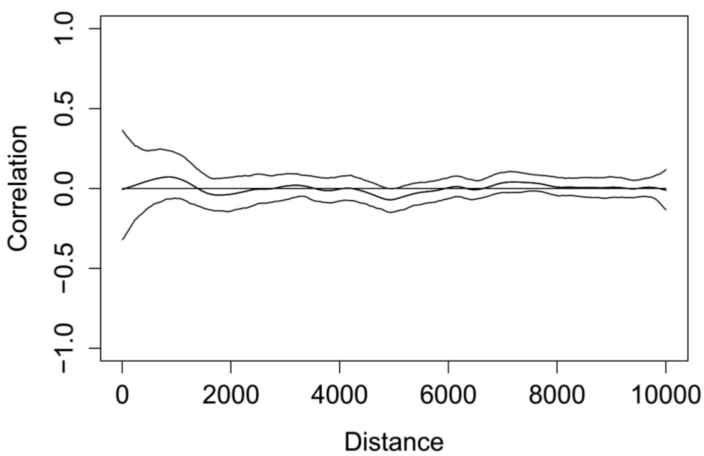
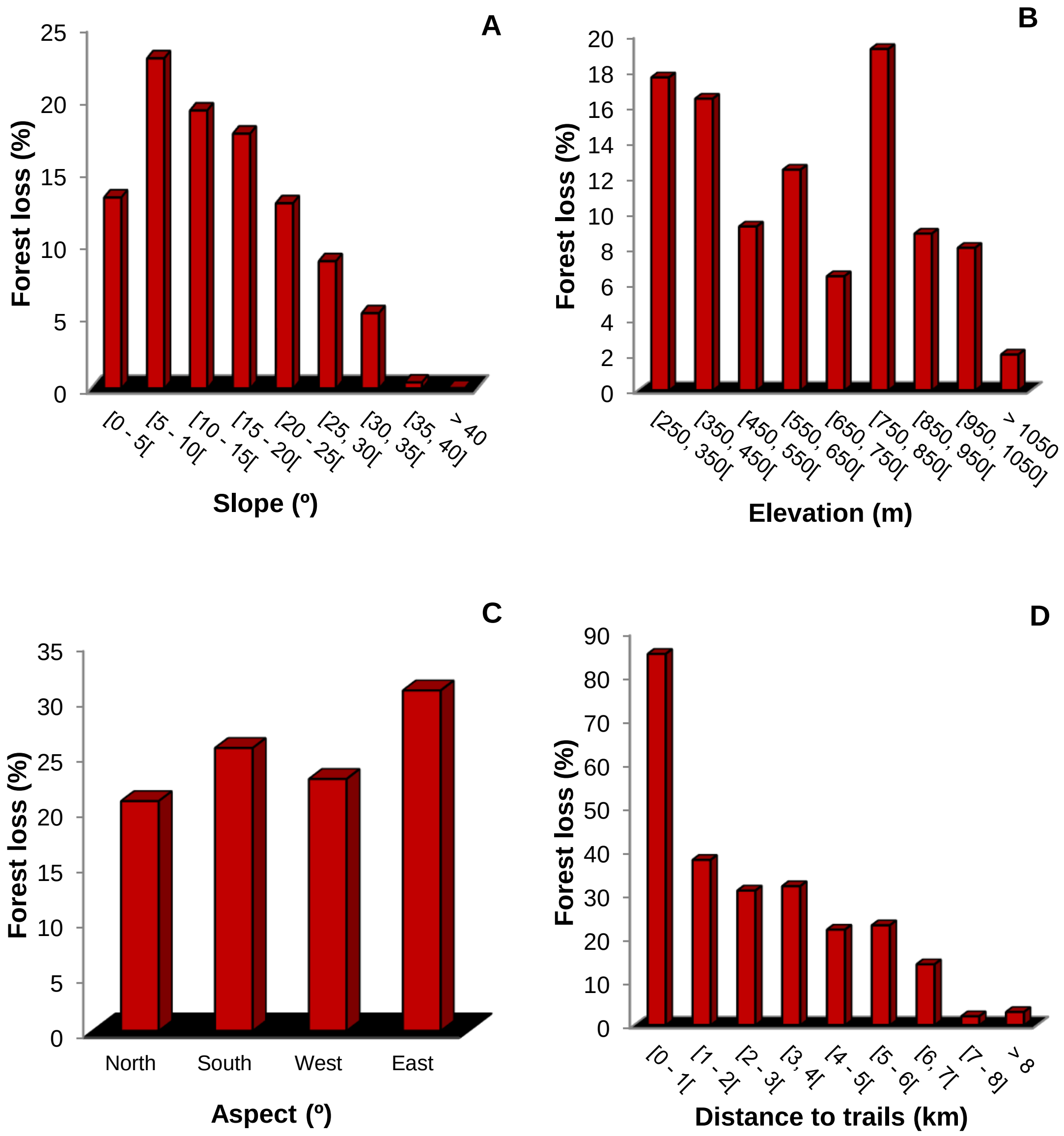


Fig. 3.7 – Correlogram to evaluate spatial autocorrelation between observations. Spline correlogram of the Pearson residuals, with 95% confidence intervals, including all the explanatory variables, and fitted to the training data.

Spatial bivariate analysis was used for the selection of the explanatory variables to be included in the forest loss model. Fig. 3.8 shows the relationship between the dependent variable and each explanatory variable. Maximum forest loss has occurred at mid slopes (≥ 5 and < 10; 22.8%) (Fig. 3.8A), occurrences of forest change within lower slopes (> 5) were noticed to be distinct, indicating a non-linear relationship between forest loss and slope. A non-linear relationship was also observed between forest loss and 'elevation', with maximum forest loss occurring between 750 and 850 m of altitude (19.2%) (Fig. 3.8B) and mainly exposed to East (30.8%) or South (25.6%) (Fig. 3.8C). Similar pattern is observed for 'distance to streams', with forest loss occurring preferentially between 65 and 130 m (Fig. 3.8E). Also, forest loss has taken place near the trails, mainly within 1 km of distance (34%) (Fig. 3.8D).



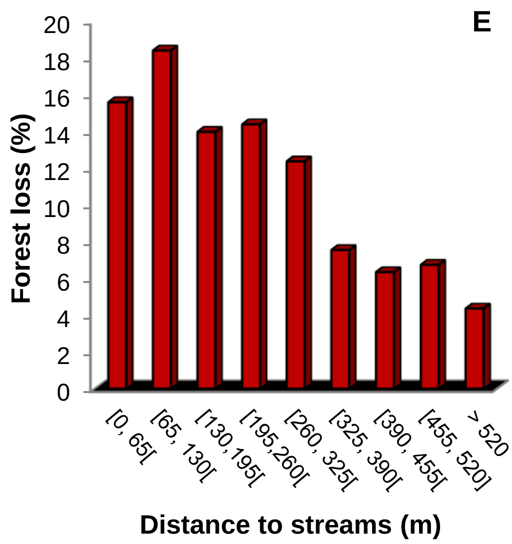


Fig. 3.8 – Variation of the areas of forest loss according to the explanatory variables. (A) Slope, (B) elevation, (C) aspect, (D) distance to trails and (E) distance to rivers.

3.3.2 Drivers of forest cover change in Kumbira forest

In the LRM analysis, six explanatory sets of variables were compared. Table 3.5 summarizes the results obtained for all sets. Results evidenced low model uncertainty, with the Akaike weights confirming that two models (set-4 ad set-1) are much more likely to be the best model than the other models. The explanatory set-4, including all topography-related and the two distance variables, was found to be the best combination for prediction with an AIC of 406.85. However, this model is only 1.5 times more likely than the next best model, which also includes ‘density of settlements’ (evidence ratio=0.576/0.390), but it is 23 times more likely than the third model. This strongly suggests that topography together with distance variables are important determinants of forest loss in Kumbira. This is further supported by the comparison of the AICs of the models containing only the topography or the distance variables (415.25 and 503.48, respectively) relatively to the null models AIC of 521.4. The pseudo R^2 of the best model was 0.278, which according to Hensher and Johnson (1982) is considered as extremely good fit. The ROC/AUC graph generated between training data and the test data used to evaluate the quality of the selected model is shown in Fig. 3.9. The area under ROC curve is 0.78 which gives an accuracy of 78% for the predicted forest loss.

Hence, the regression equation (8) of the best-fitted explanatory set-4 is given below:

eq. 8) $\text{logit}(p)=4.719+0.036(SP)-0.005(ELE)-1.405(cASC)-0.015(sASC)-2.079(DT)+0.100(DS)$

where 4.719 is the intercept and the remaining values are the regression coefficients for slope (SP), elevation (ELE), cosine aspect (cASC), sine aspect (sASC), distance to trails (DT) and distance to streams (DS).

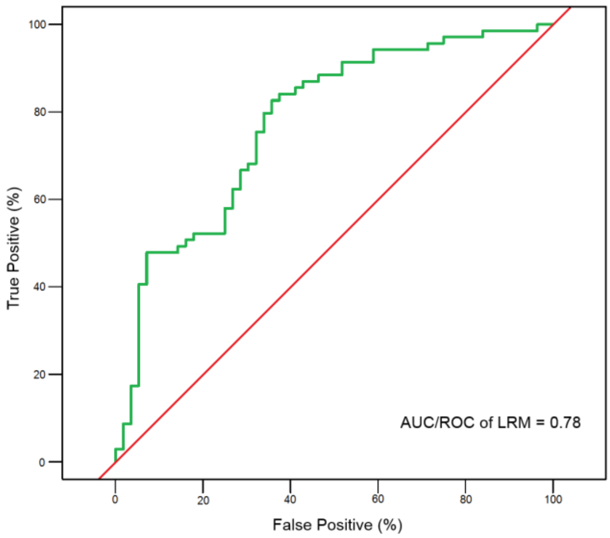


Fig. 3.9 – Validation of LRM prediction (AUC/ROC) of best-fitted model.

The relative contribution of the explanatory variables was evaluated using the corresponding odds ratio (hereafter, 'OR') in the LRM (Table 3.5). An OR tells us the factor by which the odds of forest loss *versus* no forest loss change when the continuous variable is increased by one unit. Specifically, the distance variables seem to be more important than the topographical ones. 'Slope', 'elevation' and 'sine aspect' show OR values of roughly 1. There is an increase of 4% ($1 - e^{\beta}$) in forest loss for one-unit increase in slope and a decrease of 0.4% for one-unit increase in elevation. The results of 'cosine aspect' supports the southerness of forest loss (OR = 0.894) as observed in the SBA, but suggest a western trend (OR = 0.980). However, 'sine aspect' together with 'elevation' are the variables that less predicted forest change. And among the distance variables, 'distance to trails' was the best single predictor for forest change with an OR of 0.803. This means that the odds of forest loss decreases by a factor of 0.803 (almost 20%) for one-unit increase in the distance to trails. For 'distance to streams' was obtained an OR of 1.115. The variable 'density of settlements' is not included in top ranked model but given that this model is not obviously the best when compared with the second ranked model (set-1), a sensible approach is to acknowledge for the influence of 'density of settlements'. In this case, a strong impact of this variable (OR = 1.432) was observed, with the second model assigning high values of forest loss in areas where settlements are denser.

Table 3.5 – Regression equation coefficients, AICs, *w*, and model rankings for all the explanatory sets of GIS-based logistic regression models. Set-4 was confirmed as the best predictor set to explain forest loss in Kumbira. GLM - Generalized logistic model; AIC - Akaike's information criteria; *w* - Akaike weights.

Rank	Explanatory set	LRM	Slope	Elevation	Cosine aspect	Sine aspect	Distance to trails	Distance to streams	Density of settlements	(Intercept)	AIC	*w*
			✓	✓	✓	✓	✓	✓				
1	set-4	Coefficient (β)	0.036	-0.005	-0.145	-0.015	-0.279	0.100		4.719	406.82	0.576
		Standard error	0.014	0	0.177	0.176	0.086	0.096		0.823		
		Odds ratio (e^{β})	1.040	0.996	0.894	0.980	0.803	1.115				
			✓	✓	✓	✓	✓	✓	✓			
2	set-1	Coefficient (β)	0.037	-0.005	-0.151	0.002	-0.247	0.114	0.606	4.368	407.51	0.390
		Standard error	0.014	0	0.177	0.177	0.090	0.097	0.541	0.869		
		Odds ratio (e^{β})	1.041	0.996	0.886	0.995	0.819	1.128	1.432			
			✓	✓	✓	✓			✓			
3	set-5	Coefficient (β)	0.035	-0.005	-0.146	0.017			0.981	3.083	413.2	0.025
		Standard error	0.013	0	0.174	0.174			0.510	0.458		
		Odds ratio (e^{β})	1.040	0.996	0.893	1.004			1.907			
			✓	✓	✓	✓						
4	set-6	Coefficient (β)	0.033	-0.005	-0.128	-0.007				3.215	415.25	0.009
		Standard error	0.013	0	0.172	0.173				0.459		
		Odds ratio (e^{β})	1.038	0.996	0.914	0.976						
							✓	✓				
5	set-2	Coefficient (β)					0.083	-0.071		2.828	503.48	0
		Standard error					0.079	0.083		0.709		
		Odds ratio (e^{β})					0.779	1.029				
							✓	✓	✓			
6	set-3	Coefficient (β)					-0.308	-0.068	0.287	2.688	505.17	0
		Standard error					0.082	0.084	0.524	0.750		
		Odds ratio (e^{β})					0.779	1.029	1.004			
7	null	Coefficient (β)								-0.069	521.41	0
		Standard error								0.103		

3.4 Emissions from forest change

Because Kumbira forest area was stable between 1991 and 2001, only gross carbon emissions from forest change that occurred in the period 2001-2014 were recorded. During these 13 years, forest change lead to gross carbon emissions of 492833.6 Mg*C*, this corresponds to annual gross carbon emissions of around 37910.6 Mg*C* (Table 3.6).

Table 3.6 – Gross carbon emissions from forest change for 2001-2014.

Years	Change	Area (ha)	Carbon emissions	
			Annual (Mg yr^{-1})	Total (Mg)
2001-2014	Forest to non-forest	- 5512.68	37910.6	492833.6

3.5 Feasibility of REDD+ as forest conservation strategy

As expected, assuming the same trend in deforestation under the BAU scenario, forest cover will be significantly reduced in 13 years (the same range of the reference period 2001-2014). Forest area will decrease by 41.5% and will contribute with 296377.7 Mg*C* of gross carbon emissions to the atmosphere (Table 3.7 and Fig. 3.10). The total amount of gross carbon emissions that will be emitted if the forest disappears completely is around 714203.2 Mg*C.* This value represents the maximum potential of carbon emissions that can be saved by the immediate stop of deforestation under the FC scenario. The GAT scenario, involving the delimitation of a protected area covering 50% of the total actual forest will save almost 1658 ha of forest by 2027 compared with BAU scenario and half of gross carbon emissions, with emissions totalling 148188.2 Mg*C*.

As mentioned before, change detection allowed the quantification of deforestation but it was not possible to detect and quantify forest degradation and regrowth, whereby carbon gained by the natural reforestation and additional losses due to degradation were not taken into account.

Table 3.7 – Predicted forest cover, forest change and gross carbon emissions for the next 13 years (2014-2027) under two different deforestation scenarios. Business-as-usual (BAU) and give-and-take (GAT) are defined in section 2.6.

Scenario	Predicted forest cover in 2027 (ha)	Forest change from 2014-2027 (ha)	Total gross carbon emissions (Mg*C*)	Annual gross carbon emissions (Mg*C*/yr)
BAU	4673.66	3315.19	296377.7	22798.3
GAT	6331.26	1657.59	148188.2	11399.1

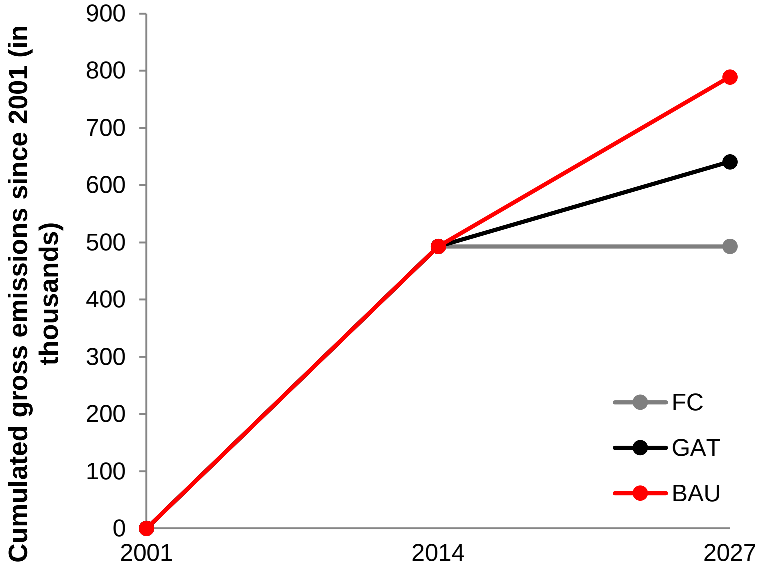


Fig. 3.10 – Cumulative gross carbon emissions from forest cover change under three different deforestation scenarios. Business-as-usual (BAU), give-and-take (GAT) and full-conservation (FC) are defined in section 2.6.

4. Discussion

Within the United Nations Framework Convention on Climate Change (UNFCCC) it is explored how mechanisms for reducing emissions from deforestation and forest degradation and promote sustainable management of forests as well as biodiversity conservation (REDD+) can be included in a post-Kyoto agreement for reducing global greenhouse gas emissions. Despite some uncertainties still remaining, REDD+ projects are being implemented across most of the tropical countries that show high forest cover and high deforestation rates. However, small-scale projects in low forest countries have also potential to provide significant carbon emissions reductions and valuable co-benefits.

The potential of REDD+ was investigated for one of the most emblematic forests of the Angolan Central Escarpment using satellite data for the analysis of the historical changes in the forest cover from 1991 to 2014. The results confirm a high historical deforestation rate of 4.04%, taking place predominantly in the proximity of trails. If current deforestation rates continue, the forest is likely to emit 296377.7 Mg*C* until 2027 and the exceptional biological diversity of the Kumbira will be seriously compromised. These trends are likely to be transversal to the remaining Scarp forests. A forest-management conservation strategy under REDD+ involving rural-communities could help to prevent this scenario and even enhance carbon stocks in the area.

In the following sections the results and the methodologies used are discussed in more detail.

4.1 Forest classification

The assessment of the historic forest cover change is a key requirement for the estimation of carbon emissions from forest loss over time. This trend was analysed based on a thematic land cover classification of LANDSAT scenes from 1991, 2001 and 2014 using MLA classifier and one additional method for 2014 scene where after the fusion of the high-resolution panchromatic band, two different techniques were combined (forest endmembers collection by Principal Component Analysis, and Linear Spectral Unmixing). However, we are aware that each step in the classification process involved uncertainties that will affect the accuracy of the classification and consequently the end result of the change detection.

In the first place, high quality of historical remote sensing data is required to achieve reliable estimates of CO_2 emissions. This is particularly difficult for tropical ecosystems because their complex structures, such as dense canopy closure, often tend to saturate the signals from remote-sensing instruments resulting in the underestimation of carbon stocks. Moreover, cloud cover is frequent in the tropics and this generally limits the performance of technologies that rely on optical remote-sensing data. The three LANDSAT images used in this study are some of the few cloud free images available for the study site. A new, promising, technology called Light Detection and Ranging (LiDAR) uses light in form of a pulsed laser and measures the signal return time to directly estimate the distances to the Earth's surface (Meyer *et al*., 2013). This remote-sensing technique has the ability to penetrate clouds and usually produces more accurate estimates of forest biomass than optical (Gonzalez *et al*., 2010) and radar satellite sensors (Asner *et al*., 2012), without saturation problems (Santos *et al*., 2003). But not only it is highly costly, as there are no historical data available, thus limiting the analysis of past trends in forest distribution.

To obtain accurate estimations of carbon stocks a detailed classification is needed because different land cover characteristics store different levels of carbon. However, there is a trade-off between the number of land cover classes and the overall accuracy of a classification. In traditional per-pixel spectral-based classification methods, which is the case of this study, increasing the number of classes usually increases the class confusion within alike vegetation classes due the similarity of spectral signal (Lu *et al*., 2010). Considering the complexity of our study region, where forest patches merge into other dense vegetation classes associated with the escarpment, and the shadow problem due the influence of a mountain region, only 'Forest' and 'No forest' classes were defined. Even knowing that the 'Forest' class contains a large variability habitats with tree cover, we wanted to ensure that the validation and training data were correctly assigned to the corresponding land cover class. The use of only two major classes can explain the high overall accuracy of the all classifications performed.

The sampling of the ground-truth data in the field used as validation data for the classification of the LANDSAT scene from 2014 helped to gain knowledge on the characteristics of the land cover, being of greater importance for the visual sampling of the land cover classes within the LANDSAT satellite images. The poorer performance of the combination method for the classification of LANDSAT scene from 2014 in comparison with the MLA method is likely explained by the lack of field based information in training data, since the collection of forest endmembers was only based in the classes' spectral features. As depicted in the PCA from Figure 2.4, vegetated areas have spectral signatures that are easily distinguishable from bare land for instance. However the identification of 'Forest' is not precise because other potential vegetated habitats that do not qualify as 'Forest' show similar spectral signals. The class 'Forest' achieves the lower average omission error across all scenes with the MLA classifier, indicating that we can use this classification method to accurately estimate the deforestation rate and the resulting emissions. Nevertheless, contrary to the expected, the LANDSAT scenes from 1991 and 2001 were those that achieved the highest accuracies for 'Forest' class. Both the training and validation data was visually collected within the LANDSAT satellite images of 1991 and 2001 and would be expect lower accuracies considering the lack of in-field data for the historic forest cover. Ground-truth data was collected around each of the 54 plots pre-selected in the LANDSAT scene from 2014 after applying the NDBR index and dividing the region into three sampling categories according to the level of canopy shadow, a proxy for the complexity of the forest structure. It turns out that poor accessibility, limited time for data collection and scarce human resources have forced the establishment of plots in the proximity of the defined buffer of 50 m around the pre-know trails. This, together with a coarse LANDSAT pixel resolution of 30 m and limited number of ground-truth samples, made the sampling very homogeneous as can be observed in the Figure 3.1 where most of the trees sampled are below the 15 m in height and 20 cm in DBH. Consequently, 50% of the AGB and AGC estimates are concentrated in a small range (Fig. 3.2). In this study 'Forest' class includes forest with human interventions and a homogeneous ground-truth data may have undermined the classification.

The absence of a clear definition of forest degradation makes its mapping challenging. While deforestation corresponds to a permanent conversion of land use (Margono *et al*., 2012), forest degradation is related with a progressive forest fragmentation that alters the canopy cover and overall forest structure along a vegetation gradient, reducing carbon content, biodiversity, ecological integrity and the ability to provide ecosystem services (Sasaki and Putz, 2009; Zhuravleva *et al*., 2013). Therefore, a thematic land cover classification with discrete classes based in a parameter such as tree cover is not sufficient for analysing and quantifying forest degradation. Also, the regrowth of secondary vegetation creates a dense cover that can be confused with stable forest but that could still be in a degraded state. In Figure 3.4 it is possible to observe some potential regenerated areas. However due to the 10 years intervals, it is probable that many areas classified as 'forest since 1991' may also be regenerated areas. The Intact Forest Landscape (IFL) method is a novel approach for mapping and monitoring the extent of forest degradation (Potapov *et al*., 2008), which determines the boundaries of large intact forest areas and uses these boundaries as a baseline for monitoring forest degradation (Zhuravleva *et al*., 2013).

The IFL method should be used in future work, when carbon quantification will be extended to all forests of the Angolan Scarp region, since IFL requires a minimum area of 50 thousand ha.

4.2 Forest change

The forest area in Kumbira remained constant during the early period (1991-2001) analysed, which corresponds to the last 10 years of civil conflict in the country. Contrary to the pattern observed in the remaining countries of Central Africa that have lived armed conflicts (Draulans and van Krunkelsven, 2002), during its 27 years of civil war Angola experienced a large depopulation of rural regions (USAID, 2008). This allowed the vegetation to recover in areas that were once cultivated, mainly with coffee plantations. With the onset of peace most people settled back in the rural areas and pressures in the forest resources have increased. From 2001 to 2014 the forest cover in Kumbira experienced a loss of 41%. This dramatic decline over the past decade suggests that deforestation in Kumbira is mostly driven by the increase in the demand for land in order to grow food, cash crops and infrastructures as result of population growth, which is also seen in other central African nations (Mayaux *et al*., 2013). The estimated loss corresponds to an annual deforestation rate of 4.04%, which is much higher than the 0.21% national deforestation rate presented by the FAO for the 2000-2010 period (FAO, 2010). This highlights the need of including project-level strategies in the scope of the REDD+ mechanism, since an exclusive focus at the national and regional levels can obscure realities on the ground (Phelps *et al*., 2010).

4.2.1 Drivers of forest change

Our analysis of forest loss drivers for a 13 years' period are in concordance with previous research on land cover change, showing that roads promote deforestation (Soares-Filho, *et al*., 2006; Gaveau *et al*., 2009; Margono *et al*., 2012; Zhuravleva *et al*., 2013; Gaveau *et al*., 2014). The trails identified in this study are used either for illegal logging or to reach terrains for agriculture expansion. The former is a plausible approach since forest canopy gaps were observed in Kumbira in the vicinity of the trails. 'Slope' and 'elevation variables have not produced an extensive impact in forest loss when compared with 'distance to trails' but we have to be aware that no single cause ever operates alone, especially when discussing driving forces of land cover change (Geist and Lambin, 2002). Although the higher soil fertility in rainforests is located on lower slopes and valley bottoms (Porder *et al*., 2005), these areas are not usually used for farming due their dense vegetation. Consequently, the forest loss in Kumbira is mostly concentrated at mid and moderate steep slopes as observed in the field. At these slopes, forest is more open and plantations are less vulnerable to the rainy season, which also explains the increase of deforestation with the distance to streams. The sudden increase of forest loss between the 750 and 840 m of elevation is most likely explained by the establishment of the settlements at this altitudes and a contiguous cultivation that follow the road network linking the different villages – a pattern already present during the colonial period (Mayaux *et al*., 2013). However, there exists possibly important geophysical and socioeconomic factors influencing spatial deforestation patterns that we failed to include in the model due to the unavailability of suitable data. For example, distance to forest edges, post-war land tenure challenges (Foley, 2007) that we suspect to be of great importance in the study area, travel time to urban areas and the actual population density (Geist and Lambin, 2002; Gaveau *et al*., 2009; Mayaux *et al*., 2013; Kumar *et al*., 2014).

The overall explanatory power of our GIS-based logistic regression model is in line with similar studies applying logistic regression to characterize forest cover dynamics, but despite having a good discrimination ability (Pearce and Ferrier, 2000) the accuracy of the prediction (78%) was lower than the reported ones (85 - 96%) (Gaveau *et al*., 2009; Müller *et al*., 2011; Vieilledent *et al*., 2013; Kumar *et al.,* 2014). These studies fit the models to the forest change data from an early period and then compare model predictions to forest change data from a later period, ensuring the independency of the data set. However, in our case we adopted a cross-validation approach by splitting the forest change data from one period (2001-2014) into a training dataset to calibrate the model and a test dataset to validate it, which could have introduced some bias in the measurement of predictive performance (Pearce and Ferrier, 2000).

4.2.2 CO_2 emissions from forest change

The average abovegound biomass (AGB) of 190.1 Mg ha^{-1} estimated in Kumbira forest is not within the range (216 - 429 Mg ha-1) of AGB found in the most recent studies conducted in tropical forests of Central Africa (Nasi *et al*., 2009; Djomo *et al*., 2011; Lewis *et al*., 2013). The divergence between these values and our results is most likely due the differences in the methodologies adopted for AGB estimation. Firstly, we recognized that the small size of our plots may have underestimated stem density and biomass. According to Chave *et al.* (2004) the size of one quarter of a hectare should be the minimal size for biomass estimations. Within the 49 plots sampled, AGB ranged from 1.44 to 1568.18 Mg ha^{-1}. This wide variation should be lower with the increase of the plot size and the number of trees sampled (Keller *et al*., 2001). To estimate AGB all studies integrated the parameters diameter, height and wood density in the allometric equations. In our case we do not include specific values of wood density since the identification of tree species was not possible. Ignoring the variation of wood density among species can result in poorer model performance and introduce bias in the overall estimates of AGB (Baker *et al*., 2004; Muller-Landau, 2004; Henry *et al*., 2010; Fayolle *et al*., 2013; Chave *et al*., 2014). However, some researchers argue that there is little evidence of species-specific allometric relationships (Gibbs *et al*., 2007; Malhi, 2006). Stegen *et al.* (2009) showed that there is no general relationship between forest biomass and wood density.

Unlike the other studies that sampled trees with more than 10 cm, in this study was used a minimum DBH of 5 cm, but Berenguer *et al.* (2015) concluded that the sampling of the stems with ≥ 20 cm of DBH without taxonomic identification can identify with confidence areas that are relatively carbon-rich or carbon-poor, plus being more cheaper than sampling and identifying all the stems with ≥ 10 cm of DBH. This may constitute an effective sampling method for countries like Angola that are lacking in reliable assessments of forest carbon stocks. The NDBR index was used by Sharma *et al.* (2013) and Sofia *et al.* (2014) to extract the canopy shadow fraction since this is related with canopy biological and structural features. However, the AGB calculated for the three categories generated by NDBR index was not significantly different. This is most likely due the reasons already mentioned: sampling plots had to be located close to the trails or in the borders of the delimited NDBR categories, which in addition with a coarse LANDSAT resolution generated a very homogenous sample. Additionally, the performance of NDBR may have been influenced by atmospheric scattering (even after correction) due to the intensity of cloud cover in tropical forest regions (Sharma *et al*., 2013).

As consequence of the AGB estimates, the AGC values found in Kumbira (84.2 Mg ha^{-1}) are also lower than those reported in other studies (Nasi *et al*., 2009; Djomo *et al*., 2011; Lewis *et al*., 2013). From 2001 to 2014 the total gross carbon emissions were estimated to be 492833.6 Mg ha^{-1} and the annual gross carbon emissions from an area of around 13500 ha amounted to 37910.6 Mg $ha^{-1.}$ Large carbon emissions occur when old-growth forests are degraded to give way for plantations. These plantations may not lead to a reduction in forest area but to a change in biomass that ends up decreasing the carbon stocks. We have therefore to take into account that not considering degradation and other components of biomass beyond the AGB is likely to underestimate total emissions (Houghton, 2007). Carbon gains from forest regeneration and/or tree plantations together with carbon losses from deforestation are included in the ‘net deforestation’ estimation. Yet, net carbon emissions targets have may easily lead to perverse outcomes by “*equate the value of protecting native forests with that of planting new ones*” to achieve an erroneously “*zero deforestation*” certification (Brown and Zarin, 2013, p. 805).

REDD+ projects aim to halt the dynamics of deforestation and/or degradation in a given area by generating tradable carbon credits in exchange of a verified emission reduction. Both the environmental and financial potential of a REDD+ project are evaluated in comparison with a baseline scenario that establishes the level of *business-as-usual* (BAU) emissions without the project. The BAU in Kumbira forest was extrapolated from the historical deforestation between 2001 and 2014. The total amount of carbon that would be emitted under the BAU scenario was estimated as the carbon in aboveground related to the loss of 41, 5% of the actual forest. This was projected to be 296377.7 Mg*C* until 2027, almost 33000 MgC *per* year. It must be highlighted that these values are almost certainly underestimated. They should be greater if we had modeled the effect of the likely expansion of the road network, the most important driver of forest loss assessed in this study, and the growth of croplands plantations, which we believe is one of the most important underlying causes of deforestation in the area.

4.3 Outlook on possible strategies for REDD+

The premise behind the REDD+ initiative is apparently simple and straightforward, but turning it into actions is a very complex process. Any REDD+ proposal seeks to reduce emissions (effectiveness) at a minimum cost (efficiency), while also contributing to sustainable development (equity and co-benefits) (Angelsen *et al*., 2008). However, each project needs to be adapted to specific issues as comprehensive as the features of forest dynamics and the governance context of the country. The ideal conditions are hard to find and even those may not be attractive from a financial point of view.

Projects at the national scale have the potential to be more climate-effective, since they cover a significant carbon pool and address indirect drivers that come into play at much larger scales, such as those related with demographic, political and economic factors. Also, constraints related to additionality (emissions reductions would not have taken place without the generation of carbon value), non-permanence and leakage are less likely. The matter of transferring emissions elsewhere is particularly difficult to handle in small-scale projects, since the opportunity costs to displace the deforestation are expected to be smaller than the adoption of alternative resources. According to some methodologies and standards like the Voluntary Carbon Standard, the definition of a reference zone that covers both the project perimeter and the leakage area is essential. Brown *et al*. (2007) suggests for projects covering more than 100000 ha that the reference zone should be 5 to 7 times larger than the project zone, and 20 to 40 times larger for projects covering less than 100000 ha. However, there are no guarantees that national scale projects will be more cost-effective in the long-term than a medium or a small-scale project. The larger the area, the higher the costs of reducing deforestation and of monitoring the implementation of the project. Also, there is evidence that small-scale projects are more flexible by facilitating tight management in specific contexts (Corbera, 2005). This attracts private stakeholders that can invest in countries that are not institutionally ready to implement a national approach (Angelsen *et al*., 2008).

Angola is a LFLD country (low forest cover at low deforestation rates), which means that it is not an immediate priority for a national REDD+ implementation. However, taking Kumbira forest as a reference, we conclude that the forests of the Angolan Scarp, and specifically those located in the Central Scarp, show potential to be included in a future REDD+ project on the voluntary market. The overall potential of emissions reduction by avoiding immediately and completely the deforestation in Kumbira is 714203.2 Mg*C*, but we believe that this value should be higher as discussed in section 4.2. Moreover, if we had extended our analysis to all forests of the Scarp we would probably find higher values of AGC in the forests located in the north of the Scarp due their stronger affinities with the vegetation-types from the Guinea-Congo forest. We hypothesized a REDD+ scenario (GAT), where 50% of the actual forest area of Kumbira would be protected. This area should be located in sectors that remained forest since 1991 in order to increase the likelihood of conservation tracts of native forest and also where the probability of forest loss is smaller, namely away from trails. A REDD+ activity must be targeted to the agents and drivers of deforestation, otherwise it is likely to be ineffective. Also, the habitat requirements of the forest-dependent species must be evaluated and integrated in order to avoid strategies with limited conservation success (Gaveau *et al*., 2009). In the Angolan Scarp, this is particularly important for the communities of the endemic bird species. Protected areas have been proven to be an efficient mitigation strategy in reducing deforestation and degradation (Gaveau *et al*., 2009; Zhuravleva *et al*., 2016; Ernst *et al*., 2013; Barber *et al*., 2014). This scenario is likely to avoid 148189. Mg*C* of gross carbon emissions and save almost 1658 ha of forest by 2027 in comparison with a BAU scenario where no action is taken. However, we recognize that the payments used to compensate rural communities for their opportunity costs in not clearing protected forests may not be enough to prevent the leakage effect, which is accentuated by the threat of illegal logging. An alternative income for rural communities could be the provision of additional payments for the improvement of agricultural techniques in the non-protected area. For example, turning traditional land use schemes into shade and regulated coffee plantations, as a result of replanting degraded and abandoned plantations from the colonial period. Beyond the enhancement of carbon stocks, this promotes the decentralization and community-based forest management, which has often been called into question according to the actual requirements of REDD+ (Phelps *et al.*, 2010).

It is important to bear in mind that Voluntary Carbon Markets have limited capacities for generating tradable carbon credits in comparison with the compliance markets. Only if the forestry sector is integrated into compliance markets together with afforestation/reforestation under the Clean Development Mechanism will attract significant financial flows from the reduction of deforestation (Calmer *et al*., 2010). Currently, REDD+ is not able to compete with highly profitable human activities, such as oil palm agriculture (Butler *et al*., 2009). Therefore, good forest governance is vital for guaranteeing a sustainable use and protection of forest ecosystems. Angola often receives weak overall governance scores, with ongoing corruption and lack of transparency. According to the Ibrahim Index of African Governance (IIAG, 2014), governance has improved significantly since 2000 but effective environmental governance policy is still missing (USAID, 2008).

5. Conclusion

Angola is emerging from a longstanding war, where its economy and infrastructures were seriously damaged. Rehabilitating the country and stimulating the economic growth are the priorities of the Angolan government. Angola is now one of the world's fastest growing-economies, mostly driven by the exploitation of its vast reserves of oil and diamonds. However, all of this is taking place in the absence of an institutional and regulatory framework to ensure that the environmental impact of economic activities are incorporated into development planning. Furthermore, the profits of the export of non-renewable resources are mostly canalized by the government and cannot meet the needs of the larger percentage of the Angolan population. Faced with reduced livelihood options, people naturally look to the exploitation of Angola's vegetation and wildlife. Due their exceptional resources, tropical forests are particularly vulnerable to human pressures.

The unique forests of the Angolan Scarp are a hotspot of diversity with high levels of endemism. They are also one of the most threatened habitats of Angola. This was clearly demonstrated in this study from the first ever estimate of rates of deforestation for the Scarp forests. We found a deforestation rate of 4.04% per year in the last 13 years in Kumbira, one of the most representative forests of the Angolan Scarp. Although these forests are of global conservation significance they are not represented in Angola's protected areas system. If the same deforestation trend continues Kumbira forest is likely to be completely lost within two decades.

Due the urgency of the adoption of conservation measures we evaluated the potential of a REDD+ strategy for Kumbira forest. This forest stores 89.4 Mg of carbon *per* hectare, a value close to the actual range of those reported by other tropical forests studies. Under a REDD+ scenario, where 50% of the actual forest will be protected, 213168.3 Mg of gross carbon emissions will be avoid by 2027. If forest degradation will be monitored it is likely that the potential for REDD+ will be even greater. A scenario that promotes the improvement of carbon stocks in degraded lands by involving rural communities is strongly recommended and would consequently increase the potential of carbon emissions reduction.

Despite the apparent potential of a REED+ strategy for the Scarp, additional research is still needed. First, there is the need to increase the number of sample plots in order to obtain a carbon quantification for a bigger area of the Scarp. This is also valid for the quantification of forest degradation, which is lacking due the insufficient ground-truth data and the limits of differentiating the stages of forest degradation with multispectral satellite data. The stratification between forest categories and the identification of trees species must be achieved in future works too. Finally, it should be address the influence of economic and social variables in forest loss and integrate them in the baseline scenario together with those reported in this study. That way, we will be able to estimate a more realistic BAU scenario and obtain a better evaluation of the REDD+ potential. The methodologies concerns are just one of the problems that REDD+ still needs to address, especially when dealing with tradable credits. Failing to acknowledge the limitations of REDD+ project could even promote the loss of areas that are rich in carbon and biodiversity, apart from impairing the livelihoods of forest-dependent communities. Currently, analyses to assess the spatial congruence between carbon stocks and the diversity and endemism of forest-restricted birds are being made. This will allow to identify the priority zones for conservation.

The REDD+ mechanism is heavily reliant on global and national systematic approaches and we are aware that it will be difficult to adapt it to help protect smaller forest areas. However, under the likely assumption that the remaining forests of the Scarp follow the trends of Kumbira, we consider that this region has the potential to integrate voluntary schemes. Voluntary schemes are usually more flexible and incorporate the additional co-benefits for biodiversity conservation. Also, this work has highlighted the importance of an expanded selection criteria for identifying REDD+ projects, by allowing the inclusion of small forests of high conservation significance and valuable carbon stocks.

6. References

Akaike H (1973). Information theory and an extension of the maximum likelihood principle. In: Petrov BN, Csáki F (eds), *Second International Symposium on Information Theory*, Akadémiai Kiadó, Budapest, pp 267-281.

Allen MR, Frame DJ, Huntingford C, Jones CD, Lowe J, Meinshausen M, Meinshausen N (2009). Warming caused by cumulative carbon emissions towards the trillionth tonne. *Nature*, **458**, 1163–1166.

Alphan H, Doygun H, Unlukaplan YI (2009). Post-classification comparison of land cover using multitemporal Landsat and ASTER imagery: The case of Kahramanmaraş, Turkey. *Environmental Monitoring and Assessment*, 151, 327–336.

Angelsen A, Streck C, Peskett L, Brown J, Luttrell C (2008).) *Moving Ahead with REDD: issues, options and implications.* Center for International Forestry Research (CIFOR), Bogor, Indonesia, pp 35-39.

Asner GP, Powell GVN, Mascaro J, Knapp DE, Clark JK, Jacobson J, Kennedy-Bowdoin T, Balaji A, Paez-Acosta G, Victoria E, Secada L, Valqui M, Hughes FR (2010). High-resolution forest carbon stocks and emissions in the Amazon. *Proceedings of the National Academy of Sciences of the United States of America*, **107**, 16738-16742.

Asner GP, Mascaro J, Muller-Landau HC, Vieilledent G, Vaudry R, Rasamoelina M, Hall JS, van Breugel M (2012). A universal airborne LiDAR approach for tropical forest carbon mapping. *Oecologia*, **168**, 1147–1160.

Arekhi S (2011). Modeling spatial pattern of deforestation using GIS and logistic regression: A case study of northern Ilam forests, Ilam province, Iran. *African Journal of Biotechnology*, **10**, 16236–16249.

Baccini A, Goetz SJ, Walker WS, Laporte NT, Sun M, Sulla-Menashe D, Hackler J, Beck PSA, Dubayah R, Friedl MA, Samanta S, Houghton RA (2012). Estimated carbon dioxide emissions from tropical deforestation improved by carbon-density maps. *Nature Climate Change*, **3**, 182–185.

Baker T, Phillips O, Malhi Y, Almeida S, Arroyo L, Di Fiore A, Erwin T, Killeen TJ, Laurence SG, Laurance WF, *et al*. (2004). Variation in wood density determines spatial patterns in Amazonian forest biomass. *Global Change Biology*, **10**, 545–562.

Barber CP, Cochrane MA, Souza C, Verissimo A (2012). Dynamic performance assessment of protected areas. *Biological Conservation*. 2012, **149**, 6–14.

Berenguer E, Gardner TA, Ferreira J, Aragão LEOC, Camargo PB, Cerri CE, Durigan M, Oliveira Junior RC, Vieira ICG, Barlow J (2015). Developing cost-effective field assessments of carbon stocks in human-modified tropical forests. *PLoS ONE*, **10**, e0133139.

BirdLife Internation (2015). Endemic Bird Areas factsheet: Western Angola. http://www.birdlife.org/datazone/ebafactsheet.php?id=85 [accessed 5 August 2015]

Bjørnstad ON, Falck W (2001). Spatial covariance functions: estimation and testing. *Environmental Ecological Statistics*, **8**, 53–70.

Booth GD, Niccolucci MJ, Schuster EG (1994). Identifying proxy sets in multiple linear regression: an aid to better coefficient interpretation. United States Department of Agriculture, Forest Service, Ogden, USA.

Brienen RJW, Phillips OL, Feldpausch TR, Gloor E, Baker T, Llyod J, Lopes-Gozales G, Monteagudo-Mendoza A, Malhi Y, Lewis S, *et al*. (2015). Long-term decline of the Amazon carbon sink. *Nature*, **519**, 344–348.

Brown S (1997). Estimating biomass and biomass change of tropical forests: a primer. *FAO Forestry Paper*, Nº 134, Rome.

Brown S, Hall M, Andrasko K, Ruiz F, Marzolis W, Guerrero G, Masera O, Dushku A, Dejong B, Cornell J (2007). Baselines for land-use change in the tropics: application to avoided deforestation projects. *Mitigation and Adaptation Strategies for Global Change*, **12**, 1001-1026.

Brown S, Zarin D (2013). What zero deforestation mean? *Environmental Science*, **342**, 805–807.

Busch J, Godoy F, Turner WR, Harvey, C (2011). Biodiversity co-benefits of reducing emissions from deforestation under alternative reference levels and levels of finance. *Conservation Letters*, **4**, 101–115.

Busch J, Engelmann J (2015). The Future of Forests: Emissions from Tropical Deforestation with and without a Carbon Price, 2016–2050. *CGD Working Paper 411*. Washington, DC: Center for Global Development.

Butler RA, Koh LP, Ghazoul J (2009). REDD in the red: palm oil could undermine carbon payment schemes. *Conservation Letters*, **2**, 67-73.

Calmel M, Martinet A, Grondard N, Dufour T, Rageade M, Feryé-Devin A (2010). *REDD+ at project scale: Evaluation and Development Guide*. ONF International (ONFI), pp 215

Campbell A (2009). Beyond Copenhagen: REDD-plus, agriculture, adaptation strategies and poverty. *Global Environmental Change*, **19**, 397–399.

Chave J, Condit, R, Aguilar S, Hernandez A, Lao S, Perez R, (2004). Error propagation and scaling for tropical forest biomass estimates. *Philosophical transactions of the Royal Society B*, **359**, 409–420.

Chave J, Andalo C, Brown S, Cairns M a., Chambers JQ, Eamus D, Fölster H, Fromard, Higuchi N, Kira T, Lescure JP, Nelson BW, Ogawa H, Puig H, Riéra B, Yamakura T (2005). Tree allometry and improved estimation of carbon stocks and balance in tropical forests. *Oecologia*, **145**, 87–99.

Chave J, Réjou-Méchain M, Búrquez A, Chidumayo E, Colgan MS, Delitti WBC, Duque A, Eid T, Fearnside PM, Goodman RC, *et al*. (2014). Improved allometric models to estimate the aboveground biomass of tropical trees. *Global Change Biology*, **20**, 3177–3190.

Chavez PS (1996). Image-Based Atmospheric Corrections - Revisited and Improved. *Photogrammetric Engineering and Remote Sensing*, **62**, 1025–1036.

Chavez PS, Kwarteng AY (1989). Extracting spectral contrast in Landsat Thematic Mapper image data using selective principal component analysis. *Photogrammetric Engineering and Remote Sensing*, **55**, 339-348.

Chen Q, Vaglio Laurin G, Valentini R (2015). Uncertainty of remotely sensed aboveground biomass over an African tropical forest: Propagating errors from trees to plots to pixels. *Remote Sensing of Environment*, **160**, 134–143.

Clark DB, Clark D a. (2000). Landscape-scale variation in forest structure and biomass in a tropical rain forest. *Forest Ecology and Management*, **137**, 185–198.

Clark CJ, Poulsen JR, Malonga R, Elkan PW Jr (2009). Logging concessions can extend the conservation estate for Central African tropical forests. *Conservation Biology*, **23**, 1281–93.

Collar NJ and Stuart SN (1988). Key Forests for Threatened Birds in Africa. ICBP Monograph No.3. International Council for Bird Preservation, Cambridge, UK

Conca K, Wallace J (2009). Environment and peacebuilding in war-torn societies: Lessons from the UN Environment Programme's experience with post-conflict assessment. *Global Governance*, **15**, 485–504.

Congalton RG (1991). A review of assessing the accuracy of classifications of remotely sensed data. *Remote Sensing of Environment*, **37**, 35-46.

Corbera E (2005). Bringing development into carbon forestry markets: Challenges and outcomes of small-scale carbon forestry activities in Mexico. In: Murdiyarso D, Herawati H (eds), *Carbon Forestry: Who will benefit?* CIFOR, Bogor, Indonesia, pp 42-56.

Dallimer MT, King T, Atkinson RJ (2009). Pervasive threats within a protected area: conserving the endemic birds of Sao Tome, West Africa. *Animal Conservation*, **12**, 209-219.

Davidson E a, Janssens I a (2006). Temperature sensitivity of soil carbon decomposition and feedbacks to climate change. *Nature*, **440**, 165–173.

Davis C, Daviet F, Nakhooda S, Thuault A (2009). A review of 25 readiness plan idea notes from the World Bank Forest Carbon Partnership Facility. WRI Working paper, World Resources Institute, Washington, DC.

Dean WRJ (2001). Angola. In: Fishpool LDC, Evans MI (eds), *Important Birds Areas in Africa and Associated Islands: Priority Sites for Conservation,* Pisces Publications, Newbury, UK, and BirdLife International, Cambridge, UK, pp 71–91.

DeFries R, Achard F, Brown S, Herold M, Murdiyarso D, Schlamadinger B, de Souza C (2007). Earth observations for estimating greenhouse gas emissions from deforestation in developing countries. *Environmental Science and Policy*, **10**, 385–394.

Djomo AN, Knohl A and Gravenhorst G (2011). Estimations of total ecosystem carbon pools distribution and carbon biomass current annual increment of a moist tropical forest. *Forest Ecology and Management*, **261**, 1448–1459.

Draulans D, van Krunkelsven E (2002). The impact of war on forest areas in the Democratic Republic of Congo. *Oryx*, **36**, 35–40.

Duveiller G, Defourny P, Desclée B, Mayaux P (2008). Deforestation in Central Africa: Estimates at regional, national and landscape levels by advanced processing of systematically-distributed Landsat extracts. *Remote Sensing of Environment*, **112**, 1969–1981.

Echeverria C, Coomes D a., Hall M, Newton, AC (2008). Spatially explicit models to analyze forest loss and fragmentation between 1976 and 2020 in southern Chile. *Ecological Modelling*, **212**, 439–449.

Ernst C, Mayaux P, Musampa C, Verhegghen A, Bodart C, Defourny P (2013). National forest cover change in Congo Basin: deforestation, reforestation and regeneration for the years 1990, 2000 and 2005. *Global Change Biology*, 19, 1173–1187.

FAO (2001). *Global forest resources assessment 2000*: *Main report*. FAO Forestry Paper, Nº 140, Rome, pp 324.

FAO (2010). *Global forest resources assessment 2010*: *Main report*. FAO Forestry Paper, Nº 163, Rome, pp 12-15.

Fayolle A, Doucet JL, Gillet JF, Bourland N, Lejeune P (2013). Tree allometry in Central Africa: Testing the validity of pantropical multi-species allometric equations for estimating biomass and carbon stocks. *Forest Ecology and Management*, **305**, 29–37.

Figueiredo E, Smith GF, César J (2009). The flora of Angola: First record of diversity and endemism. *Taxon*, **58**, 233–236.

Fischlin A, Midgley GF, Price JT, Leemans R, Gopal B., Turley C, Rounsevell MDA, Dube OP, Tarazona J, Velichko AA (2007). Ecosystems, their Properties, Goods, and Services. In: Parry ML, Canziani OF, Palutikof JP, van der Linden PJ, Hanson, CE (eds) *Climate Change 2007: Impacts, Adaptation and Vulnerability*. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge, pp 211–272.

Fisher B (2010). African exception to drivers of deforestation. *Nature Geosciences*, **3**, 375–376.

Foley C (2007). Land Rights in Angola: Poverty and Plenty. *HPG Working Paper*, November, ODI, London.

Gaveau D, Wich S, Epting J, Juhn D, Kanninen M, Leader-Williams N (2009). The future of forests and orangutans (Pongo abelii) in Sumatra: predicting impacts of oil palm plantations, road construction, and mechanisms for reducing carbon emissions from deforestation. *Environmental Research Letters*, **4**, 034013.

Gaveau D, Sloan S, Molidena E, Yaen H, Sheil D, Abram NK, Ancrenaz M, Nasi R, Quinones M, Wielaard N, Meijaard E (2014). Four Decades of Forest Persistence, Clearance and Logging on Borneo. *PLoS ONE*, **9**, e101654.

Geist HJ, Lambin EF (2002). Proximate Causes and Underlying Driving Forces of Tropical Deforestation. *Bioscience*, **52**, 143-150.

Chase MJ, Griffin CR (2011). Elephants of south-east Angola in war and peace: their decline, re-colonization and recent status. *African Journal of Ecology*, **49**, 353–361.

Gibbs HK, Brown S, Niles, JO, Foley, J a. (2007). Monitoring and estimating tropical forest carbon stocks: making REDD a reality. *Environmental Research Letters*, **3**, 045023.

Glenn E, Huete A, Nagler P, Nelson S (2008). Relationship between remotely-sensed vegetation indices, canopy attributes and plant physiological processes: What vegetation indices can and cannot tell us about the landscape. *Sensors*, **8**, 2136–2160.

Goetz SJ, Baccini A, Laporte NT, Johns T, Walker W, Kellndorfer J, Houghton R a, Sun M (2009). Mapping and monitoring carbon stocks with satellite observations: a comparison of methods. *Carbon Balance and Management*, **4**:2.

Gonzalez P, Asner PG, Battles JJ, Lefsky a. L, Waring MK, Palace M (2010). Forest carbon densities and uncertainties from Lidar, QuickBird, and field measurements in California. *Remote Sensing of Environment*, **114**, 1561–1575.

Graham MH (2009). Statistical confronting multicollinearity in ecological. *Ecology*, **84**, 2809–2815.

Grassi G, Federici S, Achard F (2013). Implementing conservativeness in REDD+ is realistic and useful to address the most uncertain estimates. *Climate Change*, **119**, 269–275.

Grimaldi S, Nardi F, Bras RL, Grimaldi S, Nardi F, Benedetto F Di, Istanbulluoglu E, Bras RL (2007). A physically-based method for removing pits in digital elevation models. *Advances in Water Resouces*, **30**, 2151-2158.

Guisan A, Theurillat JP, Kienast F (1998). Predicting the potential distribution of plant species in an alpine environment. *Journal of Vegetation Science*, **9**, 65-74.

Hajj M El, Lafrance B, Hagolle O, Dedieu G, Rumeau M (2008). Relative radiometric normalization and atmospheric correction of a SPOT 5 time series. *Sensors*, **8**, 2774-2791.

Hall BP (1960). The faunistic importance of the scarp of Angola. *Ibis*, **102**, 420–442.

Hamrick K, Goldstein A (2015). Ahead of the curve: State of the Voluntary Carbon Markets 2015. Ecosystem Marketplace and Forest Trend, Finance, Washington, DC.

Hansen MC, Stehman SV, Potapov, PV (2010). Quantification of global gross forest cover loss*. Proceedinf of the National Academy of Sciences of the United States of America*, **107**, 8650–8655.

Harris NL, Brown S, Hagen SC, Saatchi SS, Petrova S, Salas W, Hansen MC, Potapov P, Lotsch a (2012). Baseline Map of Carbon Emissions from Deforestation in Tropical Regions. *Science*, **336**, 1573–1576.

Hawkins F (1993). An integrated biodiversity conservation project under development: the ICBP Angola scarp project. In: Wilson R (eds), *Proceedings of the 8th Pan-African Ornithological Congress*. Annales Musée Royal de l'Afrique Centrale (Zoologie), Tervuren, Belgium, pp 279–284.

Henry M, Besnard a., Asante W a., Eshun J, Adu-Bredu S, Valentini R, Bernoux M, Saint-André L (2010). Wood density, phytomass variations within and among trees, and allometric equations in a tropical rainforest of Africa. *Forest Ecology and Management*, **260**, 1375–1388.

Hensher DA, Johnson LW (1981). Applied discrete-choice modelling. London: Croom Helm.

Houghton R a (2005). Aboveground forest biomass and the global carbon balance. *Global Change Biology*, **11**, 945–958.

Houghton R a (2007). Balancing the Global Carbon Budget. *Annual Review of Earth and Planetary Sciences*, **35**, 313–347.

Houghton R a, Skole DL, Nobre C a, Hackler JL, Lawrence KT, Chomentowski WH (2000). Annual fluxes of carbon from deforestation and regrowth in the Brazilian Amazon. *Nature*, **403**, 301–304.

Huntley BJ (1974). Ecosystem conservation priorities in Angola. Ecologist's Report Nº 28. Servicos de Veterinaria, Luanda, Angola.

Huntley BJ, Matos GC (1992). Biodiversity: Angolan environmental status quo assessment report. IUCN Regional Office for Southern Africa, Harare, Zimababwe.

Ibrahim Index of African Governance (2014). Available at: www.moibrahimfoundation.org/ (Accessed 10 September 2015).

Jenson SK, Domingue JO (1988). Extracting Topographic Structure from Digital Elevation Data for Geographic Information System Analysis. *Photogrammetric Engineering and Remote Sensing*, **54**, 1593-1600.

Jensen JR (2005) *Introductory Digital Image Processing: A Remote Sensing Perspective*. Prentice Hall, Upper Saddle River, pp 526.

Keller M, Palace M, Hurtt G (2001). Biomass estimation in Tapajos National Forest Brazil examination of sampling and allometric uncertainties. *Forest Ecology and Management,* **154**, 371–382.

Kumar R, Nandy S, Agarwal R, Kushwaha SPS (2014). Forest cover dynamics analysis and prediction modeling using logistic regression model. *Ecological Indicators*, **45**, 444–455.

Laporte NT, Stabach JA, Grosch R, Lin TS, Goetz SJ (2007). Expansion of industrial logging in Central Africa. *Science*, **316**, 1451.

Legendre P (1993). Spatial autocorrelation: trouble or new paradigm? *Ecology*, **74**, 1659-1673.

Lewis SL, Sonké B, Sunderland T, Begne SK, Lopez-Gozanlez G, van der Heijden GMF, Phillips OL, Affum-Baffoe K, Baker T, Banin L, *et al.* (2013). Above-ground biomass and structure of 260 African tropical forests. *Philosophical transactions of the Royal Society B*, **368**, 20120295.

Lusiana B, van Noordwijk M, Johana F, Galudra G, Suyanto S, Cadisch G (2014). Implications of uncertainty and scale in carbon emission estimates on locally appropriate designs to reduce emissions from deforestation and degradation (REDD+). *Mitigation and Adaptation Strategies for Global Change*, **19**, 757–772.

Lu D, Mausel P, Brondízio E, Moran E (2003). Change detection techniques. *International Journal of Remote Sensing*, **25**, 2365–2407.

Lu D, Hetrick S, Moran E (2010) Land cover classification in a complex urban-rural landscape with Quickbird imagery. *Photogrammetric Engineering and Remote Sensing*, ***76***, 1159–1168.

Luo J, Wei YHD (2009). Modeling spatial variations of urban growth patterns in Chinese cities: The case of Nanjing. *Landscape and Urban Planning*, **91**, 51–64.

Lyster R (2011). REDD+, transparency, participation and resource rights: the role of law. *Environmental Science and Policy*, **14**, 118–123.

Mahapatr K, Kant S (2005). Tropical deforestation: A multinomial logistic model and some country-specific policy prescriptions. *Forest Policy and Economics*, **7**, 1–24.

Malhi Y, Baldocchi DD, Jarvis PG (1999). The carbon balance of tropical, temperate and boreal forests. *Plant, Cell and Environment*, **22**, 715–740.

Malhi Y, Wood D, Baker TR, Wright J, Phillips O, Cochranek T, Meir P, Chave J, Almeida S, Arroyo L, Higuchi N, *et al*. (2006). The regional variation of aboveground live biomass in old-growth Amazonian forests. *Global Change Ecology*, **44**, 1–32.

Malhi Y, Roberts T, Betts R a (2008). The past, present and future of Africa's rainforests. *Philosophical transactions of the Royal Society B,* **363**, 20120293.

Margono BA, Turubanova S, Zhuravleva I, Potapov P, Tyukavina A, Baccini A, Goetz S, Hansen MC (2012). Mapping and monitoring deforestation and forest degradation in Sumatra (Indonesia) using Landsat time series data sets from 1990 to 2010. *Environmental Research Letters,* **7**, 034010.

Mayaux P, Bartholome E, Fritz S, Belward A (2004). A new land-cover map of Africa for the year 2000. *Journal of Biogeography*, **31**, 861–877.

Mayaux P, Pekel JF, Desclée B, Donnay F, Lupi A, Achard F, Clerici M, Bodart C, Brink A, Nasi R, Belward A (2013). State and evolution of the African rainforests between 1990 and 2010. *Philosophical transactions of the Royal Society B*, **368**, 20120300.

Monteiro AT, Fava F, Hiltbrunner E, Della G, Bocchi S (2011). Assessment of land cover changes and spatial drivers behind loss of permanent meadows in the lowlands of Italian Alps. *Landscape and Urban Planning*, **100**, 287–294.

Matthews H, Gillett NP, Stott P a, Zickfeld K (2009). The proportionality of global warming to cumulative carbon emissions. *Nature*, **459**, 829–832

Meinshausen M, Meinshausen N, Hare W, Raper SCB, Frieler K, Knutti R, Frame DJ, Allen MR (2009). Greenhouse-gas emission targets for limiting global warming to 2 degrees C. *Nature,* **458**, 1158–1162.

Meyer V, Saatchi SS, Chave J, Dalling JW, Bohlman S, Fricker GA, Robinson C, Neumann M, Hubbell S (2013). Detecting tropical forest biomass dynamics from repeated airborne lidar measurements. *Biogeosciences*, **10**, 5421-5438.

Müller R, Müller D, Schierhorn F, Gerold G (2011). Spatiotemporal modeling of the expansion of mechanized agriculture in the Bolivian lowland forests. *Applied Geography*, **31**, 631–640.

Muller-Landau HC (2004). Interspecific and Inter-site Variation in Wood Specific Gravity of Tropical Trees. *Biotropica*, **36**, 20–32.

Mills MSL (2010). Angola's central scarp forests: Patterns of bird diversity and conservation threats. *Biodiversity and Conservation*, 1**9**, 1883–1903.

Mills MSL, Olmos F, Melo M, Dean WRJ (2011). Mount Moco: its importance to the conservation of Swierstra's Francolin *Pternistis swierstrai* and the Afromontane avifauna of Angola. **Bird Conservation International**, *21*, 119-133.

Mills MSL, Melo M, Vaz A (2013). The Namba Mountains: new hope for Afromontane forest birds in Angola. *Bird Conservation International*, 23, 159-167.

Mitchard ET, Saatchi SS, Baccini A, Asner GP, Goetz SJ, Harris NL, Brown S (2013). Uncertainty in the spatial distribution of tropical forest biomass: a comparison of pan-tropical maps. *Carbon Balance and Management*, **8**:10.

Nascimento HEM, Laurance WF (2002). Total aboveground biomass in central Amazonian rainforests: A landscape-scale study. *Forest Ecology and Management*, **168**, 311–321.

Nasi R, Mayaux P, Devers D, Bayol N, Eba'a Atyi R, Mugnier A, Cassagne B, Billand A, Sonwa DJ (2009). A first look at carbon stocks and their variation in Congo Basin forests. In: de Wasseige C, Devers D, de Marcken P, Eba'a Atyi R, Nasi R, Mayaux P (eds), *The Forests of the Congo Basin - State of the Forest 2008*, Publications Office of the European Union, Luxembourg, pp 191-208.

Nasi R, Taber A, van Vliet N (2011). Empty forests, empty stomachs: bushmeat and livelihoods in Congo and Amazon Basins. *International Forestry Review*, **13**, 355-368.

Olander LP, Gibbs HK, Steininger M, Swenson JJ, Murray BC (2008). Reference scenarios for deforestation and forest degradation in support of REDD: a review of data and methods. *Environmental Research Letters*, **3**, 025011.

Olson DM and Dinerstein E (1998). The Global 200: A representation approach to conserving the Earth's most biologically valuable ecoregions. *Conservation Biology*, **12**, 502–515

Olson DM, Dinerstein E, Wikramanayake ED, Burgess ND, George VNP, Underwood EC, D'amico J a, Itoua I, Strand H e, Morrison JC *et al.* (2001). Terrestrial ecoregions of the world: A new map of life on Earth. *BioScience*, **51**, 933–938.

Pan Y, Birdsey RA, Fang J, Houghton R, Kauppi PE, Kurz WA, Phillips OL, Shvidenko A, Lewis SL, Canadell JG, *et al*. (2011). A large and persistent carbon sink in the world's forests. *Science*, **333**, 988-993.

Papeş M, Peterson a.T, Powell GVN (2012). Vegetation dynamics and avian seasonal migration: Clues from remotely sensed vegetation indices and ecological niche modelling. *Journal of Biogeography*, **39**, 652–664.

Paustian K, Ravindranath NH, Van Amstel A (2006) (coordinating lead authors). Volume 4: Agriculture, Forestry and Other Land Use. In: Eggleston H.S, Buendia L, Miwa K, Ngara T, Tanabe K (eds) *2006 IPCC Guidelines for National Greenhouse Gas Inventories*. Prepared by the National Greenhouse Gas Inventories Programm, IGES, Tokyo, Japan.

Pearce J, Ferrier S (2000). Evaluating the predictive performance of habitat models developed using logistic regression. *Ecological Modelling*, **133**, 225–245.

Pedroni L, Dutschke, MCS, Porrura ME, (2009). Creating incentives for avoiding further deforestation: the nested approach. *Climate Policy*, **9**, 207–220.

Pelletier J, Martin D, Potvin C (2013). REDD+ emissions estimation and reporting: dealing with uncertainty. *Environmental Research Letters*, **8**, 034009.

Phelps J*,* Webb EL, Agrawal A (2010). Does REDD+ threaten to recentralize forest governance? *Science,* **328***,* 312–313*.*

Phelps J, Guerrero MC, Dalabajan D. a, Young B, Webb EL (2010). What makes a “REDD” country? *Global Environmental Change*, **20**, 322–332.

Phelps J, Webb EL, Koh LP (2011). Risky business: An uncertain future for biodiversity conservation finance through REDD+. *Conservation Letters*, **4**, 88–94.

Piedallu C, Gégout, JC (2008). Efficient assessment of topographic solar radiation to improve plant distribution models. *Agricultural and Forest Meteorology*, **148**, 1696–1706.

Pitra C, Vaz Pinto P, O’keefe B, Munro S, Van Vuuren B, Robinson T (2006). DNA-led rediscovery of the giant sable antelope in Angola. European *Journal of Wildlife Research,* **52**, 145–152

Plugge D, Köhl M (2012). Estimating carbon emissions from forest degradation: implications of uncertainties and area sizes for a REDD + MRV system. *Canadian Journal of Forest Research,* **42**, 1996–2010.

Pontius RG, Schneider LC (2001). Modeling the spatial pattern of land-use change with GEOMOD2: application and validation for Costa Rica*. Agriculture, Ecosystems and Environment*, **85**, 191–203.

Pontius RG, Shusas E, McEachern M (2004). Detecting important categorical land changes while accounting for persistence. *Agriculture Ecosystems and Environment*, **101**, 251–268.

Porter S, Asner G, Vitousek P (2005). Ground-based and remotely sensed nutrient availability across a tropical landscape. *Proceedins of the National Academy of Sciences of the United States of America,* 102, 10909–10912.

Potapov PV, Yaroshenko A, Turubanova S, Dubinin M, Laestadius L, Thies C, Aksenov D, Egorov A, Yesipova Y, Glushkov I, Karpachevskiy M, Kostikova A, Manisha A, Tsybikova E, Zhuravleva I (2008). Mapping the world’s intact forest landscapes by remote sensing. *Ecology and Society*, **13**, 51.

Puyravaud JP (2003). Standardizing the calculation of the annual rate of deforestation*. Forest Ecology and Management*, **177**, 593–596.

Quantum GIS Development Team (2014). Quantum GIS Geographic Information System. Open Source Geospatial Foundation Project. URL*: http://qgis.osgeo.org.*

R Core Team (2014). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL: *http://www.R-project.org/*

Rhodes JR, McAlpine CA, Zuur AF, Smith GM, Ieno EN (2009). GLMM Applied on the Spatial Distribution of Koalas in a Fragmented Landscape. In: Zuur AF, Ieno EN, Walker NJ, Saveliev AA, Smith GM (eds) *Mixed Effects Models and Extensions in Ecology with R*, Springer Science & Business Media: New York, pp 469–492.

Richards JA, Jia X (1999). Feauture Reduction. In: Richards JA, Jia X (eds) *Remote Sensing Digital Image Analysis*, Springer-Verlag: Berlin, pp 273–276.

Rodrigues P, Figueira R, Vaz Pinto P, Araújo MB, Beja P (2015). A biogeographical regionalization of Angolan mammals. *Mammal Review*, **45**, 103–116.

Romeiras MM, Figueira R, Duarte MC, Beja P, Darbyshire I (2014). Documenting Biogeographical Patterns of African Timber Species Using Herbarium Records: A Conservation Perspective Based on Native Trees from Angola. *PLoS One*, **9**, e103403.

Romijn E, Herold M, Kooistra L, Murdiyarso D, Verchot L (2012). Assessing capacities of non-Annex I countries for national forest monitoring in the context of REDD+. *Environmental Science and Policy*, **19**–**20**, 33–48

Rouse JW, Hass RH, Schell JA, Deering DW (1973). Monitoring vegetation systems in the Great Plains with ETRS. In: *Proceedings of the third ERTS Symposium*, Washington DC, 309–317.

Rudel TK (2013). The national determinants of deforestation in sub-Saharan Africa. *Philosophical Transactions of the Royal Society B*, **368**, 20120405.

Rutherford GN, Guisan a., Zimmermann NE (2007). Evaluating sampling strategies and logistic regression methods for modelling complex land cover changes. *Journal of Applied Ecology*, **44**, 414–424.

Ryan PG, Sinclair I, Cohen C, Mills MSL, Spottiswoode CN, Cassidy R (2004). The conservation status and vocalizations of threatened birds from the scarp forests of the Western Angola Endemic Bird Area. *Bird Conservation International*, **14**, 247–260.

Saatchi SS, Harris NL, Brown S, Lefsky M, Mitchard ETA, Salas W, Zutta BR, Buermann W, Lewis, SL, Hagen S, Petrova S, White L, Silman M, Morel A, (2011). Benchmark map of forest carbon stocks in tropical regions across three continents. *Proceedings of the National Academy of Sciences*, **108**, 9899–9904.

Salvaggio C (1993). Radiometric scene normalization utilizing statistically invariant features. In: Salvaggio C (eds) *Proceedings of the workshop on atmospheric correction of Landsat imagery*, Torrance, California, 155–159.

Sandker M, Nyame SK, Förster J, Collier N, Shepherd G, Yeboah D, Blas DE De, Machwitz M, Vaatainen S, Garedew, E, Etoga G, Ehringhaus C, Anati J, Quarm ODK, Campbell BM (2010). REDD payments as incentive for reducing forest loss. *Conservation Letters*, **3**, 114–121.

Santos JR, Feitas CC, Araujo SL, Dutra VL, Mura CJ, Gama FF, Soler SL, Sant'Anna JSS (2003). Airborne P-band SAR applied to the aboveground biomass studies in the Brazilian tropical rainforest. *Remote Sensing of Environment*, **87**, 482–493.

Sasaki N and Putz FE (2009). Critical need for new definitions of 'forest' and 'forest degradation' in global climate change agreements. *Conservation Letters*, **2**, 226–232.

Schott JR, Salvaggio C, Volchok WJ (1988). Radiometric scene normalization using pseudoinvariant features. *Remote Sensing of Environment*, **26**, 1-16.

Secretariat of the Convention on Biological Diversity (2009). Connecting Biodiversity and Climate Change Mitigation and Adaptation: Report of the Second Ad Hoc Technical Expert Group on Biodiversity and Climate Change. Technical Series Nº. 41, Montreal.

Sekercioglu ÇH, Riley A (2005). A brief survey of the birds in Kumbira Forest, Gabela, Angola. *Ostrich*, **76**, 111–117.

Settle JJ, Drake NA (2007). Linear mixing and the estimation of ground cover proportions. *International Journal of Remote Sensing*, **14**, 1159–1177.

Shah VP, Younan NH, Member S, King RL, Member S (2008). An Efficient Pan-Sharpening Method via a Combined Adaptive PCA Approach and Contourlets. *IEEE Transactions on Geoscience and Remote Sensing*, **46**, 1323–1335.

Shalaby A, Tateishi R (2007). Remote sensing and GIS for mapping and monitoring land cover and land-use changes in the Northwestern coastal zone of Egypt Remote sensing and GIS for mapping and monitoring land cover and land-use changes in the Northwestern coastal zone of Egypt. *Applied Geography*, **27**, 28–41.

Sharma CR, Kajiwara K, Honda Y (2013). Automated extraction of canopy shadow fraction using unmanned helicopter-based color vegetation índices. *Trees*, **27**, 675–684.

Shettigara KV (1989). A Linear Transformation Technique for Spatial Enhancement of Multispectral Images Using a Higher Resolution Data Set. *International Geoscience and Remote Sensing Symposium (IGARS) Digest*, **4**, 2615–2618.

Shvidenko A, Barber CV, Persson R, Gonzalez P, Hassan R, Lakyda ., McCallum I, Nilsson S, Pulhin J, van Rosenburg B, Scholes B, de los Angeles M, Sastry C (2005). Forest and Woodland Systems. In: R. Hassan, R. Scholes, N. Ash (eds). *Ecosystems and Human Well-being: Current State and Trends*, Findings of the Condition and Trends Working Group, Washington DC, Island Press, pp 585–621.

Smith MO, Johnson PE, Adams JN (1985). Quantitative determination of mineral types and abundances from reflectance spectra using principal components analysis. *Journal of Geophysical Research*, **90**, 797–804.

Soares-Filho B S, Nepstad D C, Curran LM, Cerqueira G C, Garcia R A, Ramos C A, Voll E,McDonald A, Lefebvre P, Schlesinger P (2006). Modelling conservation in the Amazon basin. *Nature*, **440**, 520–3.

Sofia A, Marcos B, Gonçalves J, Monteiro AT, Alves P, Civantos E, Lucas R, Mairota P, Garcia-Robles J, Alonso, J, Blonda P, Lomba A, Honrado JP (2014). Can we predict habitat quality from space? A multi-indicator assessment based on an automated knowledge-driven system. *International Journal of Applied Earth Observation and Geoinformation*, **37**, 106-113.

Stattersfield A, Crosby M, Long A, Wege D (1998). Endemic Bird Areas of the World: Priorities for Biodiversity Conservation. BirdLife International, Cambridge, UK.

Stegen JC, Swenson NG, Valencia R, Enquist BJ, Thompson J (2009). Above-ground forest biomass is not consistently related to wood density in tropical forests. *Global Ecology and Biogeography*, **18**, 617–625.

Stickler CM, Nepstad DC, Coe MT, McGrath DG, Rodrigues HO, Walker WS, Soares-Filho BS, Davidson E (2009). The potential ecological costs and cobenefits of REDD: A critical review and case study from the Amazon region. *Global Change Biology*, **15**, 2803–2824.

Strassburg B, Turner RK, Fisher B, Schaeffer R, Lovett A (2009). Reducing emissions from deforestation - the ‘‘combined incentives’’ mechanism and empirical simulations. *Global Environmental Change*, **19**, 265–278

Thomas CD, Anderson BJ, Moilanen A, Eigenbrod F, Heinemeyer A, Quaife T, Roy DB, Gillings S, Armsworth PR, Gaston KJ (2013). Reconciling biodiversity and carbon conservation. *Ecology Letters*, **16**, 39–47.

Trigg S, Flasse S (2001). An evaluation of different bi-spectral spaces for discriminating burned shrub-savannah. *International Journal of Remote Sensing*, **13**, 2641–2647.

UNFCCC (2003). Decision 19/CP.9: Modalities and Procedures for Afforestation and Reforestation Project Activities under the Clean Development Mechanism in the First Commitment Period of the Kyoto Protocol, In: Report of the Conference of the Parties on its Ninth Session, held at Milan on December 2003. Addendum Part Two: Action taken by the Conference of the Parties at its Ninth Session, Bonn, Germany (FCCC/CP/2003/6/Add.2.).

UNFCCC (2005). Reducing Emissions from Deforestation in Developing Countries: approaches to stimulate action. Submission from the Governments of Papua New Guinea and Costa Rica (FCCC/CP/2005/MISC.1). Conference of the Parties, Eleventh Session held in Montreal in November - December 2005.

UNFCCC (2008). Decision 2/CP.13: Reducing emissions from deforestation in developing countries: approaches to stimulate action, In: Report of the Conference of the Parties on its thirteenth session, held in Bali from 3 to 15 December 2007 Addendum Part Two: Action taken by the Conference of the Parties at its thirteenth session, Bonn, Germany (FCCC/SBSTA/2008/MISC.4.).

UNFCCC (2009a). Policy approaches and positive incentives on issues relating to reducing emissions from deforestation and forest degradation in developing countries; and the role of conservation, sustainable management of forests and enhancement of forest carbon stocks in developing countries. Ad Hoc Working Group on Long-Term Cooperative Action Under the Convention (FCCC/AWGLCA/2009/L.7/Add.6) Conference of the Parties Fifteenth Session held in Copenhagen in December 7–18.

UNFCCC (2009b) Decision 4/CP.15. Methodological guidance for activities relating to reducing emissions from deforestation and forest degradation and the role of conservation, sustainable management of forests and enhancement of forest carbon stocks in developing countries, In: Report of the Conference of the Parties on its fifteenth session, held in Copenhagen in December 7–18. Addendum Part Two: Action taken by the Conference of the Parties at its fifteenth session, Bonn, Germany (FCCC/CP/2009/11/Add.1).

UNFCCC (2010). Decision 1/CP.16. The Cancun Agreements: Outcome of the work of the Ad Hoc Working Group on Long-term Cooperative Action under the Convention, In: Report of the Conference of the Parties on its sixteenth session, held in Cancun in November - December 2015. Addendum Part Two: Action taken by the Conference of the Parties at its sixteenth session, Bonn, Germany (FCCC/CP/2010/7/Add.1).

UNFCCC (2013). Report of the Conference of the Parties on its nineteenth session, held in Warsae from November 11-23. Addendum Part Two: Action taken by the Conference of the Parties at its nineteenth session, Bonn, Germany.

USAID (2008). 118/119 Biodiversity and tropical forest assessment for Angola. Biodiversity Analysis and Technical Support (BATS) Program. Washington, DC.

Vaglio Laurin G, Chen Q, Lindsell J a, Coomes D a, Frate FD, Guerriero L, Pirotti F, Valentini R (2014). Above ground biomass estimation in an African tropical forest with lidar and hyperspectral data. *ISPRS Journal of Photogrammetry and Remote Sensing*, **89**, 49–58.

Vieilledent G, Grinand C, Vaudry R (2013). Forecasting deforestation and carbon emissions in tropical developing countries facing demographic expansion: A case study in Madagascar, *Ecology and Evolution*, **3**, 1702–1716.

Vrabel J, Range FB, Ripley C (1996). Multispectral Imagery Band Sharpening Study. *Photogrammetric Engineering and Remote Sensing*, **62**, 1075–1083

Yang S, Wang M, Jiao L (2012). Fusion of multispectral and panchromatic images based on support value transform and adaptive principal component analysis. *Information Fusion*, **13**, 177–184.

Zhuravleva I, Turubanova S, Potapov P, Hansen M, Tyukavina A, Minnemeyer S, Laporte N, Goetz S, Verbelen F, Thies C (2013). Satellite-based primary forest degradation assessment in the Democratic Republic of the Congo, 2000–2010. *Environmental Research Letters*, **8**, 24034.

Zuur AF, Ieno EN, Elphick CS (2010). A protocol for data exploration to avoid common statistical problems. *Methods in Ecology and Evolution*, **1**, 3–14.

R Packages Used

car: Fox J, Weisberg S (2011). An R Companion to Applied Regression, Second Editio n. Thousand Oaks CA: Sage.
URL: http://socserv.socsci.mcmaster.ca/jfox/Books/Companion

MuMIn: Barton K (2015). MuMIn: Multi-Model Inference. R package version 1.13.4.
URL: http://CRAN.R-project.org/package=MuMIn

ncf: Bjornstad ON (2013). Spatial nonparametric covariance functions. R package ver sion 1.1.5.URL: http://CRAN.R-project.org/package=ncf

pROC: Robin X, Turck N, Hainard A, Tiberti N, Lisacek F, Sanchez JC, Müller M (2011). pROC: an open-source package for R and S+ to analyze and compare ROC curve s. BMC *Bioinformatics*, **12**, 77.

rms: Harrell Jr F (2015). Regression Modeling Strategies. R package version 4.3.1.
URL: http://CRAN.R-project.org/package=rms

Google Earth Images

“Kumbira.” 11º02’20.75”S and 14º15’40.46”E. **Google Earth.** December 20, 2003. April 16, 2015.

“Kumbira.” 11º02’20.75”S and 14º15’40.46”E. **Google Earth.** February 27, 2006. April 16, 2015.

“Kumbira.” 11º02’20.75”S and 14º15’40.46”E. **Google Earth.** September 26, 2010. April 16, 2015.

7. Appendix

Appendix I – Field work

Ia. Field data sheet form

VEGETATION DATA SHEET – KUMBIRA 2014

Date					**Point**			**Obs**	
Descrip.									
Photos									

1. CANOPY COVER (Amount of dots/quarter squares NOT COVERED by vegetation) – 5m away from centre
2. CANOPY HEIGHT (Measure in meters taken with the range finder to the canopy) – 5m away from centre

	North	***South***	***West***	***East***
Canopy Cover (# dots)				
Canopy Height (m)				
Photos ID/Hour				

3. BIOMASS (Measure every tree DBH >5cm, inside the 10x10m square plot)

Tree ID	**Species**	**DBH (cm)**	**Clin (% or º) / range finder (m)**	**Photo ID**	**Obs.**

NOTES (Tree density – number of trees, surrounding perturbations – in 1 point, agriculture activity, etc.)

Photos ID:

Ib. Aboveground biomass and carbon for each sampling plot.

ID	Latitude	Longitude	AGB (Mg ha^{-1})	AGC (Mg ha^{-1})	Nº trees (DBH ≥ 5cm)
L23	-11.14	14.30	62.30	29.28	35
L24	-11.15	14.29	323.75	152.62	15
L26	-11.16	14.29	18.91	8.89	8
L28	-11.19	14.28	36.96	17.37	10
L29	-11.18	14.27	83.29	39.15	19
L30	-11.20	14.27	568.34	267.12	6
L37	-11.21	14.26	318.10	149.51	11
L38	-11.18	14.27	15.68	7.37	19
L39	-11.19	14.27	189.56	89.09	8
L42	-11.18	14.26	494.01	232.19	7
L41	-11.15	14.29	2.25	1.06	1
L51	-11.15	14.29	84.69	39.80	6
M11	-11.14	14.29	594.77	279.54	3
M12	-11.15	14.30	101.98	47.93	7
M13	-11.15	14.30	144.65	67.98	8
M14	-11.15	14.29	264.38	124.26	8
M15	-11.16	14.28	23.31	10.95	16
M16	-11.17	14.29	594.86	279.58	17
M17	-11.19	14.27	160.63	75.50	7
M18	-11.19	14.28	35.68	16.77	11
M19	-11.21	14.26	122.67	57.65	2
M20	-11.18	14.27	136.92	64.35	12
M21	-11.21	14.25	10.95	5.15	6
M43	-11.20	14.25	69.34	32.59	7
M44	-11.21	14.25	28.38	13.34	20
M45	-11.20	14.24	1568.18	737.04	4
M46	-11.20	14.26	1.44	0.68	3
M47	-11.20	14.27	61.43	28.87	12
M48	-11.18	14.27	118.33	55.61	10
M49	-11.18	14.26	626.96	294.67	2
M50	-11.15	14.29	10.07	4.73	9
M52	-11.14	14.29	45.72	21.49	25
M54	-11.16	14.28	8.90	4.18	7
H01	-11.21	14.26	137.29	64.53	18
H02	-11.22	14.25	336.69	158.24	7
H03	-11.21	14.25	255.17	119.93	4
H05	-11.19	14.28	15.17	7.13	12
H06	-11.19	14.27	200.52	94.24	5
H07	-11.20	14.27	77.38	36.37	7
H08	-11.19	14.28	297.31	139.74	13
H09	-11.16	14.30	92.84	43.63	11
H04	-11.21	14.25	16.15	7.59	9
H31	-11.15	14.29	177.32	83.34	4
H32	-11.15	14.30	88.86	41.76	6
H33	-11.16	14.29	525.41	246.94	2
H34	-11.16	14.29	22.41	10.53	6
H35	-11.18	14.28	69.88	32.84	32
H36	-11.18	14.27	45.43	21.35	9
H53	-11.15	14.28	31.76	14.93	10