Efficient, innovative, and inclusive options to overcome monitoring challenges in the early phases of REDD+

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Summary

This cumulative thesis is composed of two parts. The first part consists of a general background on tropical forests and deforestation: it introduces us to the state of the art of the REDD+ program and presents the thematic context of the thesis. The second part integrates the articles into the thematic context and describes the concepts of innovation, efficiency, and inclusion in the domain of this thesis. The second part includes a summary and discussions into the thematic context for each article. A short explanation of the personal contribution of the author to the articles is also provided. Finally, the last section of the second part includes the overall conclusions of the thesis. The full versions of the two articles are attached in Annex 1.

The vast contribution of forests to the well-being of all living organisms is widely recognized. For example, people depend on forests for a remarkable variety of goods and services, such as provision of food and water, maintenance of biodiversity, regulation of water flow, air quality and climate. Keeping forests vigorous and healthy is paramount to ensuring long-lasting and stable provision of the goods and services. Climate regulation is one of the most important ecosystem services for its global impact and because climate change is projected to affect, directly and indirectly, all aspects of ecosystem services provision over the next century. Thanks to their capacity to regulate climate, forests represent the cornerstone of any global climate change mitigation strategy. For the first time, in the 1992 Conference of the Parties of the UN Framework Convention on Climate Change (UNFCCC), forests achieved a prominent position in the international negotiations on climate change. Since then, supporting forests and their management has gained increasing broad public attention. A number of measures have been taken to address threats that forests face and to preserve their capacity of regulating global climate.

Reducing Emissions from Deforestation and forest Degradation (REDD) is the major international political achievement to protect tropical forests' carbon stocks. The basic idea of REDD+ is to pay forest owners (either through national government funds or directly) to reduce forest emissions and increase forest carbon sequestration. Such a simple idea is facing a number of challenges. This thesis analyses some of the forest monitoring technical challenges that countries can face, particularly during the early phases of REDD+ projects. The objective of this thesis is to provide a better understanding on approaches that could enable effective planning and implementation of monitoring activities. In doing so, this cumulative thesis focuses on three main concepts related to monitoring, reporting, and verification (MRV) systems: innovation, inclusion, and efficiency. Scientific and technological innovations support MRV systems, providing effective instruments to design and execute REDD+. Inclusion refers to the possibility of tropical countries or provinces to participate in REDD+; in fact, the capacity to implement a reliable MRV system determines the possibility of joining and

executing an effective REDD+ program. Finally, pursuing efficiency is paramount, since most developing countries grapple with a shortage of resources, and the REDD+ mechanism copes even with a critical lack of finance.

The first article presents a model, which using only available and easily accessible data and software, predicts the risk of deforestation. To predict the risk of deforestation, the model uses ten independent variables (called predictors), extracted from remotely sensed data. Environmental, social, demographic, and economic variables were incorporated in the model and used as proxies of deforestation. The model combines a machine learning approach and GIS. The machine learning approach is random forests; it is a decision tree–based method, which combining many classification trees produces a prediction of the variable of interest. We adopted *random forests* due to the strong non-linear relationships between the variables and because it supports evidence-based, data-driven decisions and is therefore often used in decision-making processes. We tested the model using data from Nicaragua. Results show that the accuracy of the model in predicting areas under moderate and high risk of deforestation can be considered satisfactory for some REDD+ purposes, e.g., when identifying potential target areas for REDD+ projects. Furthermore, the adoption of the model may be effective in the first phase of projects: when a country is still developing the capacity to build its own sound and accurate datasets. Therefore, the model is suitable for a stepwise implementation approach of REDD+ projects in regions with limited availability of data, capital, technical infrastructure, or human capacities. Stepwise approaches are needed to overcome existing data and capacity gaps and enable a wider participation to REDD+. Adopting an innovative model can improve efficiency and promote inclusion by exploiting already available data, by applying powerful methods to handle data, and by using open source software.

The second article examines three key factors affecting the generation of forest carbon credits from REDD+. The factors are (i) setting Reference Levels (RLs); (ii) supplying of emission reduction due to REDD+; (iii) uncertainties in forest carbon emissions estimates. This article includes two analyses: a simulation study and a sensitivity analysis . In the simulation study, the interrelationships between the costs of forest carbon monitoring, the associated reliability, and the resulting accountable carbon credits were investigated. We assumed the employment of both Lidar data and passive optical data. Findings of the simulation study highlight that combining statistically rigorous sampling methods with Lidar data can significantly boost the accountable amount of forest carbon credits that can be claimed. In fact, the generation of carbon credits is mainly affected by the uncertainties of the estimate of forest area and carbon stock changes per unit of area. We found that innovative monitoring techniques have a positive effect on the efficiency of MRV systems, and that despite having a larger initial cost, the investment in MRV system, based on Lidar, could be paid-off by the potential result-based payments. Conceiving an MRV system as an investment can encourage the

implementation of well-defined, long-term monitoring strategies. In the sensitivity analysis, the above-mentioned three factors are ranked according to their impact on the generation of carbon credits. Findings show that the amounts of avoided emissions under a REDD+ scheme mainly vary according to the monitoring technique adopted; nevertheless, RLs have a nearly equal influence. The target for reduction of emissions showed a relatively minor impact on the generation of carbon credits, particularly when coupled with low RLs.

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Acronyms

COP	Conference of the Parties
FAO	Food and Agriculture Organization
GHG	Greenhouse gas
GFRA	Global Forest Resources Assessment
IPCC	Intergovernmental Panel on Climate Change
Lidar	Light Detection And Ranging
REDD+	Reducing emissions from deforestation and forest degradation
RL	Reference Level
UNFCCC	United Nations Framework Convention on Climate Change

Part 1. Thematic context

Why do tropical forests matter?

Answering the question “why is the health status of forests so important for the whole planet?” is simple: forests provide a number of vital services to all living organisms. Past human experiences teach that large-scale forest clearance can have irreversible consequences for people and, along with other factors, can drive societies to collapse (Abrams and Rue, 1988; Diamond, 2005). Environmental degradation, as a consequence of deforestation, generates devastating effect on soil erosion and further depletion of soils. Deforestation can influence the survival of societies, especially those that base their economies on agriculture. The importance of forests is associated to the wide set of services that they offer. An exhaustive classification of the forest environmental services is complex. For simplicity and clarity, four categories of services can be described: ecological, economic, socio-cultural, and scenic and landscape (Table 1).

Table 1 Overview of forest services by typology (Source: TEEB).

Provisioning services	Regulating services	Habitat or supporting services	Cultural services
Food	Local climate and air quality	Habitats for species	Recreation and mental and physical health
Water	Carbon sequestration and storage	Maintenance of genetic diversity	Tourism
Raw materials	Moderation of extreme events		Aesthetic appreciation and inspiration for culture, art and design
Medicinal resources	Waste-water treatment		Spiritual experience and sense of place
	Erosion prevention and maintenance of soil fertility		
	Pollination		
	Biological control		

All types of forests can potentially provide the services reported in Table 1. However, tropical forests’ contribution to global climate regulation and to biodiversity richness is far larger than other forest ecosystems. “Certainly the tropics, and particularly tropical moist forests, stand out as highly significant reservoirs of global biodiversity” (Dirzo and Raven, 2003); they contain the majority of the world's biodiversity hotspots and the largest concentration of species densities. Despite covering less than 2% of the planet's surface, they house over 50% of its biodiversity. A number of plant and animal species living in tropical ecosystems are classified as critically endangered by the International Union for the Conservation of Nature and Natural Resources (IUCN). Tropical deforestation and forest degradation represent the greatest threat to biodiversity, with potentially irreversible effects (Vieira et al., 2008). In fact, the cascade effect on human activities can be dramatic when the loss of tropical biodiversity leads to the extinction of living species (Bradshaw et al., 2009).

Another pivotal role of tropical forests —which has brought them to the top of the international agenda on climate change— is the capacity to sequester and stock carbon dioxide: they sequester more carbon at faster rates than temperate and boreal forests (Bonan, 2008). From 1750 to 2011, the human-induced CO_2 emissions to the atmosphere were 555 ± 85 PgC (1 Pg = 10^{15} g). With 180 ± 80 PgC, changes in land use represent the second largest anthropogenic source of CO_2 to the atmosphere —it mainly includes deforestation, though afforestation and reforestation also have a role. The Intergovernmental Panel on Climate Change's (IPCC) fifth assessment report states that it is between 90-100% certainty that "more than half of the observed increase in global mean surface temperature from 1951 to 2010 is due to the observed anthropogenic increase in greenhouse gas (GHG) concentrations" (Intergovernmental Panel on Climate Change, 2014). In fact, one effect of the release of anthropogenic carbon (i.e. the carbon released by human activities) into the atmosphere is the increase of the Earth's temperature. It clearly appears the decisive influence of forests on climate, and why any global climate change agreement has to put them at its core. In fact, without any mitigation efforts, emissions from the forest sector are likely to increase throughout the XXI century (Eliasch, 2008).

Tropical forests' threats: deforestation and degradation drivers

In 1990, forests represented about 31.6% of the global land surface. Twenty-five years later, the Global Forest Resources Assessment (GFRA), issued by the Food and Agriculture Organization (FAO), reported that forests covered 30.6% of the global land surface, which is about 0.6 ha per every person on the planet (Keenan et al., 2015). Overall, considering the global forest area, there was a net decrease of 3% between 1990 and 2015 (Keenan et al., 2015). However, this percentage results from a combination of a loss of natural forests and an increase in planted forests, therefore does not supply information on the actual net loss of natural forests, which is indeed far higher.

The annual rate of net forest loss nearly halved over the 25-year period between 1990 and 2015. At a first glance, one may deduce from these figures that world forests are, despite everything, rather healthy or that, perhaps, the heated international debate on deforestation is overemphasizing the need to protect forests. However, turning the spotlight on the national level, the situation varies dramatically. Before the 1980s, deforestation and other land use changes mainly occurred in mid-northern latitudes; while since the 1980s, the tropics, particularly tropical America and Asia with smaller contributions from tropical Africa, registered alarming deforestation rates (Ciais et al., 2014). Currently, the vast majority of forest area loss occurs in the tropics. In 142 tropical countries, the area of natural forest decreased by 11% between 1990 and 2015 (FAO, 2015). Tropical rainforests experienced the largest share of deforestation: 32% of the global forest loss occurred there, of which nearly half took place in South America (Hansen et al., 2013) (Figure 1). It is estimated that up to 50% of the world's tropical forests have been cleared, representing one of the most significant anthropogenic land use changes in history (Lewis, 2006). A recently published study states that intact forest landscape extent has been reduced by 7.2% from 2000 to 2013, of which 60% occurred in tropical regions (Potapov et al., 2017).

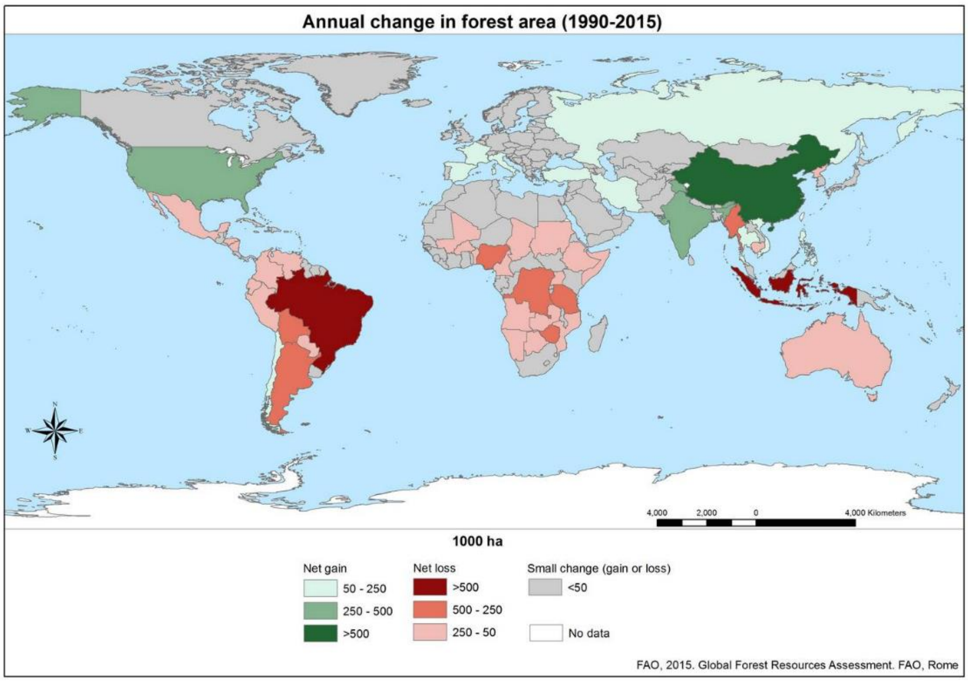

Figure 1 Annual change in forest area from 1990 to 2015 (Source: FAO 2015).

A wide definition of deforestation describes it as a long-term or permanent conversion of forested land to non-forested land (UNFCCC, 2006). Deforestation causes are commonly classified as direct (also named proximate) and indirect (named underlying). Direct causes involve any human activity, at local level, that directly and immediately drives to forest clearance. Indirect causes can affect forest decline both at local and global level, because they include underlying societal dynamics. Indirect causes drive the direct causes. Geist and Lambin (2002) analyzed 152 subnational case-study reports and described three dominant direct causes of deforestation: infrastructural extension, agricultural expansion, and wood extraction. Direct causes are driven by five underlying factors: demographic, economic, technological, policy and institutional, and cultural. Most of the causes are region specific and, in most cases, deforestation is determined by their different combination. As one can expect, deforestation drivers vary spatially and temporally: each country and region has its own intricate set of economic, social, and political circumstances determined by public and individual decisions. Under these assumptions, "no universal policy for controlling tropical deforestation can be conceived" (Geist and Lambin, 2002).

Forest degradation is even harder to define, and therefore to identify, than deforestation. In fact, it has different facets, often difficult to define by a single measure (Morales-Barquero et al., 2014; Thompson et al., 2013). A number of different definitions of forest degradation exist. A 2003 IPCC report reviews nearly 50 definitions of degradation in use and in the end suggests a definition that can meet the criteria discussed in the context of the Kyoto protocol: "A direct human-induced, long-term loss (persisting for X years or more) of at least Y% of forest carbon stocks [and forest values] since time T and not qualifying as deforestation or an elected activity under Article 3.4 of the Kyoto Protocol".

Since the acknowledgement by the 2007 Conference Of the Parties (COP) that forest degradation also leads to emissions and needs to be addressed (UNFCCC, 2008), it has been a topic of discussion (Mertz et al., 2012; Plugge and Köhl, 2012). At present, no certain estimates of carbon emissions from forest degradation exist for the entire tropics, though Houghton (2012) assessed that it may vary from 10% to 40% of the total net emissions from tropical forests between 1990 and 2012 ($\sim$1.4 PgC year^{-1}). The 2015 GFRA (FAO, 2015) defines the partial canopy cover loss (PCCL) as a proxy of degradation and assesses that the total area of PCCL in tropical climatic domain was 185 million ha from 2000 to 2012.

Complexities faced in defining degradation are even more profound when it comes to monitoring degradation. While deforestation is relatively simple to detect using space- or air-borne remote sensing platforms, degradation is far more challenging to observe remotely, even with high-resolution optical imagery (Morales-Barquero et al., 2014). Active sensors, such as RAdio Detection And Ranging (Radar) and Light Detection And Ranging (Lidar), which are able to penetrate both cloud and canopy cover, offer a good solution for monitoring stock level change in tropical forests (Ryan et al., 2012). However, the costs still hamper their application to vast tropical areas, even though their adoption in forest inventory is more efficient and convenient than field-based assessments alone (Tomppo et al., 2008).

It is also important to clarify that different forms of forest degradation exist. In many cases, forest degradation does not lead to deforestation. For example, one area can remain degraded for years, as for example local communities get fuel wood from it, and then, if the local wood extraction finishes, the forest will naturally re-increase its carbon stock level. Therefore, forest degradation drivers are often different from deforestation drivers. The GOFC-GOLD Sourcebook (2013) and Hosonuma et al. (2012) indicated four main causes of forest degradation: timber extraction and logging, fuelwood collection and charcoal production, uncontrolled fires, and livestock grazing. Deforestation and forest degradation differ for their driving forces and their consequences, so different actions have to be implemented to address them.

Solutions to reverse deforestation and forest degradation: the REDD+ approach

The REDD+ programme (Reducing Emissions from Deforestation and Forest Degradation) is an innovative approach to reduce CO_2 emissions from the forest sector. It is the most important action concerning the association between tropical forests and climate change. The innovativeness of REDD+ holds in its holistic approach in addressing deforestation and forest degradation drivers. The core ideas of REDD+ have never been executed nor conceived by previously implemented mechanisms.

At least three key features characterize REDD+ (Sunderlin and Atmadja, 2009). The first one is that REDD+ is a marked-based mechanism: it gives a monetary value to forest carbon. Since the first pilot initiatives aimed at avoiding deforestation and forest degradation, REDD+ projects have generated carbon credits traded in voluntary carbon markets. The basic idea is to pay forest-rich countries for preserving and enhancing their forest carbon stocks. In order to comply with the commitments made in the international negotiations and to compensate their emissions, developed countries have to provide developing ones with the finance to do so, by buying carbon credits produced through REDD+. The second key feature of REDD+ is the result-based approach; it means that payments to forest-rich countries (named non-annex I parties) depend on the actual abatement of carbon emissions from forests. Each ton of CO_2 equivalent not emitted in the atmosphere thanks to the REDD+ programme will generate a tradable carbon credit, only if its generation is measured, reported and verified, in accordance with the Bali Action Plan (UNFCCC, 2008). Finally, a new pivotal feature of REDD+ is the large amount of money that governments are committing to this mechanism (Sunderlin and Atmadja, 2009). Nevertheless, complex challenges remain to be resolved for effectively implementing each of the above-reported features.

REDD+ constitutes an achievement of the United Nations Framework Convention on Climate Change (UNFCCC), which has given importance to tropical forests on the global climate regime in the international community debate. UNFCCC parties started the discussion during the 11th COP held in Montreal, in 2005 (when the Kyoto Protocol came into force). Initially, only the reduction of emissions from deforestation (RED) was part of the debate. Two years later, in 2007, REDD+ was fully integrated into the global climate agenda with the addition of the second ‘D’ and the term ‘plus’. The ‘+’ allowed for four more activities to be added as eligible for support and funding under a REDD+ mechanism: reducing emissions from forest degradation, conservation of forest carbon stocks, sustainable management of forests, enhancement of forest carbon stocks.

Non-annex I countries willing to participate in REDD+ under either the Forest Carbon Partnership Facility (FCPF) or the UN-REDD Programme have to develop four core components in accordance with national circumstances and respective capabilities. The Readiness Preparation Proposal template provided by the FCPF and the UN-REDD Programme is a document designed to assist a country to prepare itself for involvement in REDD+. This document defines the following four core components: a national strategy or action plan; forest reference emission level (FREL) and/or reference level (RL); a robust and transparent national forest monitoring system; a plan for establishing a safeguard information system (Figure 2).

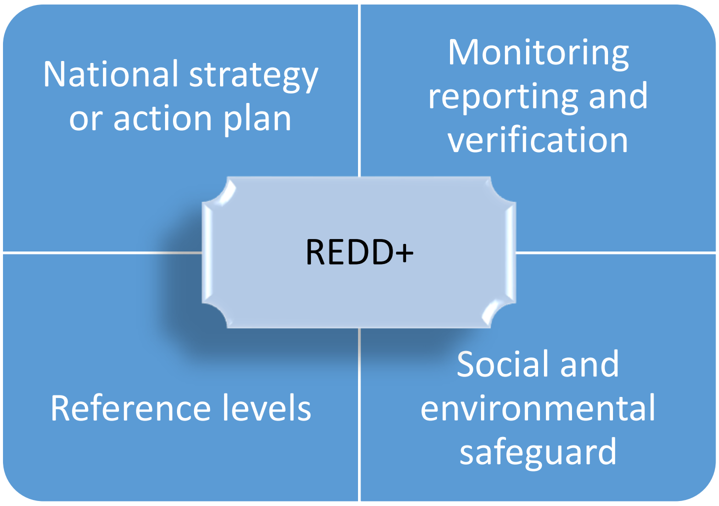

Figure 2 Core components to be developed by non-annex I countries that aim to undertake REDD+ activities under either the Forest Carbon Partnership Facility (FCPF) or the UN-REDD Programme.

The national strategy (also called action plan) provides a comprehensive understanding of political, social and economic dynamics affecting the activities to be undertaken. It is commonly designed in the readiness phase of REDD+ (i.e. the first phase), involving all the relevant stakeholders. The national strategy or action plan have to address, inter alia, “the drivers of deforestation and forest degradation, land tenure issues, forest governance issues, gender considerations and the safeguards” (UNFCCC, 2011).

REDD+ Safeguards

Along with benefits, REDD+ can also have environmental and social detrimental effects, named “risks”. To prevent and mitigate risks that can occur during the execution of REDD+ activities, appropriate measures have to be planned and implemented. REDD+ ‘Safeguards’ refer to policies, processes and measures that identify, analyze and manage risks and opportunities of REDD+ (Murphy 2011). Nine socio-economic and environmental risks of REDD+ implementation can be described, as reported in Figure 3 (Huettner, 2012).

Risk 1	• Pressure on carbon-poor lands with high biodiversity outside REDD+ areas
Risk 2	• Substitution of biodiversity-rich natural forests with plantations
Risk 3	• Biodiversity loss due to poaching wildlife and habitat loss in REDD+ areas
Risk 4	• Illegal logging in REDD+ areas due to weak law enforcement
Risk 5	• Land tenure issues and insufficient involvement of forest-dependent peoples
Risk 6	• Increase in land rents and food prices due to REDD+-induced scarcity of agricultural land
Risk 7	• Barrier for small-scale REDD+ projects due to high transaction costs
Risk 8	• Ineffective national REDD+ finance distribution due to governance challenges
Risk 9	• Non-permanence of REDD+ areas

Figure 3 Potential risks from REDD+ policies and programmes (adapted from Huettner, 2012).

Seven safeguards should be promoted and supported when undertaking REDD+ activities to prevent or mitigate potential risks and boost benefits (UNFCCC, 2011). The seven safeguards can be grouped into three categories (Barquín et al., 2014):

1) Governance

a) REDD+ activities are compatible with national and/or international programmes, conventions, and agreements.

b) National forest governance structures are transparent and effective.

c) All the relevant stakeholders are fully and effectively involved in REDD+ activities.

2) Social and environmental impact (including non-carbon benefits)

d) Respect for the knowledge and rights of indigenous peoples and members of local communities according to the United Nations Declaration on the Rights of Indigenous Peoples.

e) Protect and conserve, through REDD+, natural forests, biological diversity and their ecosystem services, in order to enhance social and environmental benefits.

3) GHG emissions integrity

f) Actions to address the risks of reversals.

g) Actions to reduce displacement of emissions.

Forest reference (emission) levels

The UNFCCC requests non-annex I parties to assess national forest reference emission level (REL) and/or reference level (RL). These benchmark the actual reduction of emissions ascribable to the implemented REDD+ activities. Hence, RELs and RLs — expressed in tons of carbon dioxide equivalent per year— gauge the progresses of REDD+ participant countries and will be technically assessed in the context of result-based payments.

Establishing RLs according to the IPCC principles for reporting of national emissions and removals of GHGs is one of the most complex and challenging REDD+ elements; they can decisively determine the success of REDD+ because they "affect the quantity, credibility, and equity of credits generated from efforts to reduce forest carbon emissions" (Griscom et al., 2009). The necessity to setting RLs is tightly linked to the concept of additionality, which envisages that REDD+ projects should go beyond business-as-usual, enabling emission reductions that would have not taken place otherwise. As a result, financial support is only available for avoiding emissions that would occur in the absence of REDD+.

There is no internationally standardized method for the setting of RLs under UNFCCC; several techniques can be implemented, as long as five principles are applied: transparency, completeness, consistency, comparability, and accuracy. However, the lack of a standardized method creates the potential risk that would lead to overcompensation and therefore reduces the cost-efficiency of REDD+ payments (Hargita et al., 2016).

Two categories of methods can be applied to design RLs: retrospective and prospective approaches (Huettner et al., 2009). Retrospective approaches take into account historical GHG emissions and removals and assume a linear trend; under these approaches adjustment factors for national circumstances are considered to allow inclusion of social and economic variables (Mollicone et al., 2007). Prospective methods use land-use-change models to predict the risk of deforestation and forest degradation (Brown et al., 2007). In any case, RL methods should be selected in accordance with national circumstances and capabilities. Until now, twenty-five countries have submitted a proposed forest reference emission level and/or forest reference level and are undergoing technical assessment processes (according to the UNFCCC website, visited on the 31st May 2017);

Measuring, reporting and verification

Any valid national, sub-national or local REDD+ project has to possess the tools to assess the amount of forest carbon, including its changes over time. The measurement of the reduction of emissions accomplished by the REDD+ project, as well as the system for reporting and verifying the emissions reductions, constitute the frame of MRV-systems (Measurement, Reporting, and Verification). The Bali Action Plan of the UNFCCC encourages all non-annex I parties to measuring, reporting and verifying emission reduction (Box 1). Measurements include activities of data collection concerning forest carbon inventory and land-use change analysis over the project lifetime. Precision and accuracy of the collected data have to be rigorously quantified. The IPCC reporting guidelines suggest transparent, consistent, accurate, comparable, and complete methods for reporting GHG emissions (IPCC, 2003). The reporting process entails calculating emissions and removals from the forest carbon inventory and the land use change analysis. The data collected over time have to be formally reported and finally will go through a process of verification that evaluates and, eventually, validates the information that is presented. Two land-use change experts, selected from the roster of the UNFCCC experts, perform this process (UNFCCC, 2013). The MRV system is one of the four fundamental components that countries willing to participate in REDD+ have to elaborate (Figure 2). Implementing a reliable MRV system is crucial; in fact, result-based payments are tightly linked to the quality of field assessments and remotely sensed data (Plugge et al., 2013).

Box 1 – MRV definitions

Measurement	Refers to two types of data: (i) data on land-cover change, usually assessed through remote sensing technology, termed 'Activity data'; (ii) data on forest carbon stocks, commonly derived from *in-situ* assessments based on statistical sampling design, are termed 'Emission factors' (Goetz et al., 2015).
Reporting	The measured forest-related emissions have to be periodically reported to the UNFCCC, in order to track REDD+ progresses. The reporting mechanism, that covers the whole project extension, utilizes a common reporting format and methodology, in order to ensure that information provided is complete, transparent, comparable and accurate (UNFCCC, 2013).
Verification	A panel of experts performs a thorough quality control to identify potential errors, flaws, and omissions. Results of the technical assessment are issued in a report (UNFCCC, 2013).

The measurements and reporting can be performed with different levels of accuracy and complexity. The IPCC propose a hierarchical structure, called the tiered approach: it implies increasing levels of accuracy of the method for estimating GHG emissions and removals for each source. The tier 1 approach employs default data and simple equations easily obtainable from IPCC guidelines or other international sources. Tier 2 uses region- or country-specific activity data and emission factors, with higher temporal and spatial resolution and disaggregated land-use category. Under tier 3, models and techniques specifically conceived to address national circumstances are applied; the great reduction of uncertainties requires very good forest inventory capacities. Tier 3 approaches envisage the combination of remotely sensed data calibrated over field measurements. This combination provides a reliable, practical, and cost-effective solution for developing and maintaining REDD+ MRV systems (De Sy et al., 2012). Optical sensors, Radar, and Lidar remote sensing techniques are the main sources of remotely sensed data used to extract information for forest biomass. Lidar helps to predict biomass in tropical forests with satisfactory accuracy. The mutually supportive combination of ground- and Lidar-based data was successfully applied in various forest biomes to estimate forest carbon stock (Mauya et al., 2015). Kaasalainen et al. (2015) analysed various aspects on the combined use of Lidar and Radar, highlighting their potential use for continuous global biomass mapping with improved accuracy.

Funding for REDD+

Finding a reliable source of financing is the key issue of REDD+ (Angelsen and Wertz-Kanounnikoff, 2008). The COP 19 established a work programme on REDD+ finance, and, in decision 9/CP.19, reaffirmed that finance may come from a wide variety of sources: public and private, bilateral and multilateral, including alternative sources. A conservative estimate reported that pledges and investments from public and private account for US$9.8 billion for the period between 2006 and 2014 (Norman and Nakhooda, 2015). The public sector committed the vast majority of funding (over 90%), which were channelled into bilateral country programmes and multilateral funds. Bilateral programmes represent two thirds of all internationally supported REDD+ activities (Streck, 2012); they facilitated the allocation of most of the resources to national governments in developing countries (Buizer et al., 2014). Norway is the largest contributor, followed by the United Kingdom, Germany, Japan and the United States.

Multilateral funds represent the second largest allocation of public financing. The latter includes, *inter alia*, the Amazon Fund, the Forest Carbon Partnership Facility and the UN-REDD programme. From 2008 to 2016, about US$4 billion was pledged to five multilateral climate funds that support REDD+ (Watson et al., 2016). Bilateral and multilateral schemes cover about 89% of total finance, while the remaining 11% is covered by private finance.

A much stronger engagement of the private sector is needed to meet the financial needs of REDD+. In fact, to support performance based payments at an effective level about US$ 30 billion per year required (UNEP, 2014). Another estimate reports that for halving global forest emissions between 2005 and 2030, from $17.2 to $28 billion per year could be necessary (Eliasch, 2008). To raise such a large amount of money, a new funding model comprising public-private partnerships is indispensable. This new model could be part of a new paradigm based on the principles of the Green Economy (UNEP, 2014). While achieving an inclusive green economy is a long-term challenge, filling the REDD+ financial gap needs urgent action, and a relatively faster way to involve the private sector could be to trade forest carbon credits both in voluntary and compliance markets. At present, carbon credits can only be traded in voluntary markets, but the vast majority of finance flows into compliance markets, which have prohibited the trading of forest carbon credits.

According to the market-based architecture of REDD+, part of the money for the result-based payments should come from the returns derived from the selling of credits on carbon markets. However, the financial market-based transactions and commitments to reducing carbon emissions from forestry and land-use practices still remain substantially insufficient (Goldstein, 2016). This drawback may compromise the success of the mechanism, considering that a global market-based framework was expected to financially support most of the activities. REDD+ funds are limited, furthermore, their effective allocation might be hampered by institutional, legal, political and economic barriers. For example, delays in the short-term disbursement of REDD+ funds and a mismatch of donor requirements and recipient needs render its fast progresses to be hardy achievable (Streck, 2012). These unfavorable economic conditions might improve: after the COP 21 held in Paris in December 2015, REDD+ has stepped into the spotlight and some positive signs emerged. Article 5 of the agreement reads, “Parties should take action to conserve and enhance, as appropriate, sinks and reservoirs of greenhouse gases […] including forests” and *suggests* a market approach for financing REDD+ activities. The formal inclusion of forests in the UNFCCC agreement is certainly a positive accomplishment; however, it is a starting point rather than an end goal. The Paris Framework neither allocates funding nor provides certain information on the source for result-based finance. Now it will be up to the next COP to figure out how to implement and boost actions on the ground. On the other hand, the ongoing activities that are being carried out under the REDD+ framework must go on; countries that have already started REDD+ national actions must be permitted to keep implementing measures and achieving their objectives, while alternative solutions to cope with the lack of resources must be found. *Inter alia*, a solution could be to take full advantage of the available resources, for example by adopting innovative techniques that improve the capability of achieving greater efficiency.

The cost of REDD+

REDD+ costs are grouped into three categories: opportunity cost, transaction costs, and implementation costs.

Opportunity cost: besides the negative environmental impacts of converting forests to other land uses, deforestation can generate a series of associated benefits. The opportunity cost is the forgone profit that deforestation would have generated, for example from timber and agricultural commodity sales. The opportunity cost of REDD+ defines the lost net benefit for not continuing with the business-as-usual logging or converting forestland.

Transaction costs: They are the costs involved in setting in motion and managing REDD+ policies, from the very early phases until the end of the project, e.g. identifying and selecting the project, partners and consultants; upfront capacity building; feasibility studies; negotiation, such as obtaining permits, arranging financing and transactions with carbon buyers; measuring, reporting and verification. These costs, usually expressed in $/t$CO_2$, cover the necessary expenses to establishing an operative REDD+ programme and display economies of scale.

Implementation costs: They are directly associated with the actions that reduce emissions. Some examples are: concrete actions that prevent logging, restoring vegetation in degraded areas, providing capacity building, infrastructure or equipment to develop alternative livelihoods to communities.

In reality, the categories of implementation and transaction costs are not always distinct; however, implementation costs are typically associated with reducing deforestation directly, whereas transaction costs are indirectly associated with it.

Even though several research studies have defined opportunity costs as the largest portion of REDD+ costs (The World Bank, 2011), trying to provide a general ranking of costs that applies to all countries constitutes a futile exercise for two reasons. First, assessing costs at global level is rather hard and “estimates are made less accurate by uncertain methodologies and untested assumptions” (Fosci, 2013). Second, costs can substantially vary according to the national context and specific location, for example the opportunity costs of land in remote areas may be less than transaction and implementation costs (Pagiola and Bosquet, 2009). Antinori and Sathaye (2007) presented an analysis of transaction costs for eleven forestry projects concerning forest preservation, restoration and afforestation projects (not REDD+ projects). The average transaction cost was 0.38 $/t$CO_2$; monitoring and verification costs represent 35% of the weighted transaction costs —which is the main component— ranging from 4%, for afforestation to 67% for forest restoration projects.

It is also possible to classify REDD+ costs according to the institution or the person that bears the costs. Overall, costs are incurred by buyers and sellers of REDD+ actions. These two broad categories can include countries, government agencies, international donors or buyers in carbon market, non-governmental organizations, research institutions, consultants-service providers, and individual actors (e.g. landholders) (Angelsen et al., 2013; Graham et al., 2016).

The present thesis investigates aspects related to MRV costs. The latter are conventionally included in the transaction costs and are incurred by the parties that implement the REDD programme (e.g. national and sub-national institutions) and third parties, such as verifiers, certifiers, and lawyers (Pagiola and Bosquet, 2009). Transaction costs are commonly considered minor compared to the other categories of costs; nonetheless, their importance could be substantially underestimated (Fosci, 2013). Moreover, implementing an effective MRV system will directly affect the generation of carbon credits, and so it influences the overall budget of the programme.

Part 2. Integration of the articles into the thematic context

The objective of the thesis is to provide a better understanding on approaches that could enable effective planning and implementation of monitoring activities. This thesis relies on three main pillars: innovation, inclusion, and efficiency in REDD+.

1) Scientific and technological innovations support MRV systems and provide appropriate instruments to design and execute REDD+. They can make a difference in generating carbon credits. At present, the considerable digital divide between developed and developing countries remains high, particularly concerning technologies used in forest inventorying and monitoring. Spreading innovation is a key intervention to promote both efficiency and inclusion.

2) The second pillar —inclusion— refers to the possibility that every country or province is given the opportunity of participating in REDD+. In the context of this thesis, inclusion is about the barrier to participation associated to low monitoring capacities and to limited availability of data, capital, technical infrastructure, or human capacities.

3) The third pillar concerns efficiency, which is fundamental, because most developing countries grapple with a shortage of resources, and there is a critical lack of finance in the REDD+ mechanism. The concepts of efficiency that are covered in this thesis are (i) techniques that enable a wise use of available data and resources, (ii) the analysis and description of approaches that produce large result-based payments (i.e. carbon credits generation) with minimum expense.

First article

The first article, published in January 2017 in the *Forests* journal volume 8, issue 1, was written by Di Lallo, with a substantial contribution made by Köhl. Köhl conceived the original idea that was developed by Di Lallo, who designed the study, created the model, and analyzed and interpreted the data. Köhl also helped to structure the study and develop the method; he coordinated the study, and substantially contributed to the quality control and critical revision of the manuscript. Lopez helped with the case study and the interpretation of some data. Mundhenk suggested the application of *random forests* and also provided technical content and revised the manuscript. Marchetti helped to coordinate the study and revised the manuscript.

Summary

The article presents a novel modelling approach that predicts the spatial location of forests threatened by near-future deforestation. Simulating forest-clearing dynamics is a key step in the context of REDD+. The importance of adopting reliable methods to simulate trends of business-as-usual deforestation scenarios is linked to the fact that result-based payments are made for improvements over business-as-usual scenarios. Modelling techniques using mathematical and statistical methods are also useful for identifying areas where REDD+ initiatives will have the greatest impact and for supporting domestic political measures to implement an informed and transparent funding-allocation mechanism. Moreover, combining forest-clearing dynamics with data on forest carbon stock enables the prediction of carbon-rich areas under the risk of losing their ecological values.

Several spatial modelling tools and approaches exist, or have been proposed, for identifying areas at risk of deforestation. However, many of the existing models can be not easily implemented in some tropical countries, due to limited data availability, organizational structure, or monetary resources. For this reason, we created a model, which using only available and easily accessible data, predicts the risk of deforestation with satisfactory accuracy for potential application in beginning phases of REDD+ projects. We tested the model using national-scale data from Nicaragua. The model is named PREDIT (PREdicting Deforestation In the Tropics).

PREDIT integrates inputs from different data layers (i.e. maps) using the random forests algorithm. The random forests algorithm is a decision tree–based method belonging to the family of machine learning. Decision tree-based methods are used in decision-making processes because they enable evidence-based, data-driven decisions. We adopted *random forests* given the strong non-linear relationships between the variables. We used available data sources from the time interval 1983–2011. Data from t1–t2 (i.e., 1983–2000) were used to calibrate the model and data from t2–t3 (i.e., 2000–2011) to test its accuracy. Ten independent variables (also called predictors) were used as a proxy of deforestation (Figure 4). They were selected by reviewing the available literature and according to the author's knowledge of the country; nevertheless, the availability of data was the major limitation in selecting the predictors. The dependent variables consist of two classes: 'forest areas' and 'deforested areas'. We performed PREDIT using two sets of predictor variables. In the first session, referred to as FourPA (Four Predictors Alternative), we included only the four predictors that mostly affect deforestation in Nicaragua. In the second session, referred to as TenPA (Ten Predictors Alternative), the set of all 10 available predictors was used (Figure 4).

FourPA

- Altitude
- Distance to cropland areas
- Slope
- Distance to pasture areas

TenPA

- Altitude
- Distance to cropland areas
- Slope
- Distance to pasture areas
- Forest density
- Population density
- Protected areas
- Forest type
- Distance to roads
- Distance to urban areas

Figure 4 Predictors used in PREDIT model. The model was run on two alternatives: (i) TenPA, which uses 10 predictors; (ii) FourPA, which uses four predictors, i.e. those that substantially influence forest-clearing dynamics.

The classification error for the two modeling alternatives (with four and ten predictors) was similar, so adding six predictors to the FourPA-model did not improve the overall accuracy, which was 76%. However, the overall accuracy is not an exhaustive indicator of model performance. Assuming the application of PREDIT in REDD+ projects, FourPA would be the preferred alternative, because it does not overestimate the risk of deforestation (i.e. it applies a conservative approach). In fact, one significant difference between TenPA and FourPA is that TenPA overestimate the risk of deforestation; it also explains the high value of Producer's accuracy (which defines the pixels correctly classified as "deforestation") (Table 2).

Table 2 Performance of the model in predicting areas subject to deforestation. The table shows statistics for the alternatives that use ten predictors (TenPA) potentially associated with deforestation and four predictors (FourPA) that certainly affect deforestation dynamics.

	Ten Predictors (TenPA)	**Four Predictors (FourPA)**
Overall accuracy	76%	76%
Producer's accuracy	0.80	0.69
User's accuracy	0.64	0.71
Figure of merit	55%	53%

We conclude that this modelling approach could find applications in REDD+. It can support countries involved in the early phases of REDD+. Particularly those countries that grapple with a critical lack of data, and that, while developing the capacity to build their own sound and accurate dataset, can take advantage of already available and easily accessible data.

Discussion in the thematic context

Forecasting future land-cover dynamics based on direct and indirect drivers of deforestation does not necessarily require extensive and expensive studies. Reliability and level of detail depend on the scope of the assessment and on local circumstances, such as financial availability and local technical capacity. Countries with low capacity in assessing and monitoring its forest resources, and the associated socio-economic dynamics, face serious challenges to join REDD+ due to the large investment at the beginning of the project. A lack (or inability) of access to financing can principally hinder REDD+ readiness implementation (Maniatis et al., 2013). Reforming forestry-related policies and building technical capacity are hard challenges as well; for example, investigating deforestation drivers and implementing a robust MRV system imply the existence of a well-tuned national forestry department. It may take years and large monetary investment. A stepwise approach —which envisages a gradual improvement of countries capacities as they progress toward more advanced REDD+ phases— could facilitate the implementation of REDD+ in countries lacking such capacities. This would enable a country to start implementing REDD+ activities while building its own internal structure; accordingly, it could reach a higher level of detail at advanced stages of the project. This stepwise approach is often necessary since the majority of tropical countries still lack capacities to implement a complete and accurate mechanism for measuring forest area change and performing a national forest inventory on growing stock and forest biomass (Food and Agricultural Organization, 2015).

While big challenges remain in developing forest inventory and carbon pool reporting capacities, important improvements have been accomplished in forest area change monitoring and remote sensing capacities: a recent study evaluated the capacities of 99 countries, reporting that 54 of the 99 have good to very good capacities (Romijn et al., 2015). A meaningful contribution to the improved capacity is ascribable to the increased availability of earth-observation data and the open access data policies; at present, as never before, a number of remotely sensed data are freely available over the internet to any user (Wulder et al., 2012). Countries willing to participate in REDD+ can benefit from the open policies. However, an increasingly large volume of data needs specific approaches; specifically, handling non-linear data with complex interactions, such as forest and environmental data, requires appropriate tools and software. Data mining, machine learning, and statistical methods possess the ability to analyze very large amounts of data, and are useful in creating predictive and inference models.

The innovative modelling approach (named PREDIT) presented in the first article combines open access remotely sensed data with open source software. The three pillars (efficiency, innovation, and inclusion) are perfectly embedded in the methodological approach presented in the first article. PREDIT is suited to a stepwise framework for developing REDD+. This effective combination can support countries involved in the early phase of REDD+ and would enable wider REDD+ participation: "it represents a starting point for countries that struggle with a critical lack of data, higher uncertainties, and competing interests" (Di Lallo et al., 2017). It is highly efficient as it uses free and open access data. Freely available techniques, such as PREDIT, can also have a critical role in promoting synergies across nations and can boost countries to agree to international treaties, such as REDD+ (Wulder et al., 2012).

Second article

The second article included in the cumulative thesis (Understanding Measurement Reporting and Verification Systems for REDD+ as an Investment for Generating Carbon Benefits) was published in July 2017 in the *Forests* journal, volume 8, issue 8. It was written by Di Lallo with a substantial contribution made by Köhl. Di Lallo and Köhl developed the idea, which was originally conceived by Köhl. Köhl also coordinated the study. Di Lallo analyzed the data and performed the simulation study. Mundhenk contributed to the analysis of data, the simulation study and revised the quality of the manuscript. Marchetti helped to coordinate the study, and critically revised the quality of the manuscript.

Summary

This article examines three key factors affecting the generation of forest carbon credits from REDD+. The factors are (i) setting Reference Levels (RLs); (ii) carbon credits supplying from emission reductions due to REDD+; (iii) uncertainties in forest carbon emission estimates. We conducted two analysis: a sensitivity analysis and a simulation study.

In the sensitivity analysis, the three factors affecting the avoided emissions (i.e. the forest carbon credits) were ranked according to their impact on the generation of carbon credits. We found that the generation of carbon credits mostly varies as a function of uncertainties in forest carbon monitoring (i.e. according to the monitoring technique adopted). Clearly, RLs influence the number of carbon credits that can be generated and the result-based payment that project managers or countries could receive, however, their actual weight in the mechanism was uncertain. Findings show that RLs impact on the accountable avoided emissions is almost as important as the uncertainties; while the amount of emissions actually reduced has a relatively minor impact.

In the simulation study, we analyzed the interrelationships between the cost of forest carbon monitoring, the associated precision, and the resulting accountable carbon credits. We explored the potential of two approaches for monitoring forest carbon in terms of reliability and costs. The first approach makes use of Lidar data and adopts a model-assisted technique; while the second consists of passive optical data and the use of stratified sampling.

Combining statistically rigorous sampling methods with Lidar data can significantly boost the accountable amount of forest carbon credits that can be claimed. Then we compared the potential result-based payments derived from the adoption of a model-assisted technique using Lidar data with a set of realistic costs. We found that investing in sound, recurrent MRV systems critically determines a country's potential to generate result-based payments. Therefore, potential result-based payments could pay-off the necessary investment in technology that would enable an accurate estimate of activity

data and emission factors. Conceiving an MRV system as an investment can encourage the implementation of well-defined, long-term monitoring strategies.

Discussion in the thematic context

We investigated three factors that influence the generation of carbon credits: setting reference levels (RLs), supplying emission reduction from avoided deforestation and degradation, and implementing an efficient monitoring system. A thorough understanding of the dynamics between these three factors helps to set up efficient projects —i.e. projects that produce large result-based payments. Findings of the second article show that: (i) uncertainties in forest monitoring mostly influence the potential credits received for reducing emissions and the resulting reward; (ii) uncertainties can be significantly reduced by adopting statistically sound sampling techniques and Lidar-based methods.

We indicated plausible and convenient options useful to analysts and decision-makers to understand how to take full advantage of the REDD+ opportunity. However, whether the MRV system is an effective investment or not can depend on several other factors; countries that decide to invest in innovative monitoring techniques have to carefully evaluate the tradeoff between reliability of a sound MRV and accountable carbon credits produced.

In the second paper, we also pointed out the pivotal role of innovative monitoring techniques, and their positive effect on efficiency of MRV systems. However, innovation is neither simply about the use of high-tech products or big data, nor just about external support and adoption of foreign technology. Innovation means promoting a well-designed, long-lasting strategy and a solid research and development programme. Conceived like this, innovation also promotes inclusion, as it can reduce gaps between developed and developing countries (OECD, 2012). However, it implicates a strong support from both private and public sectors. Even though the engagement the private sector has increased over the last few years, it is still far from being sufficient to cover the near-future REDD+ financial needs. Supporting a greater engagement of privates by introducing cost-effective measures is key for a successful execution of the REDD+ programme (Savaresi, 2016; Streck, 2012).

Developing countries rely on external sources of financing for implementing conservation policies through the REDD+ programme. The monetary support under the REDD+ regime is delivered at the readiness (ex ante) and at the verification phase (ex post), for the emissions effectively avoided. Ex ante funding is necessary, as preparing to perform long, extensive and expensive projects imply a strong engagement and substantial investments. Ex post payment is one novel feature that REDD+ has introduced in international forestry processes aimed at reducing tropical deforestation.

MRV costs (which are part of transaction costs) are mainly afforded at the beginning of projects, hence are charged on readiness funding. They can be very high and greatly influence the overall REDD+ budget. In addition, MRV systems influence uncertainties, which mainly determine the amount of accountable carbon credits, and thus the result-based payments. For this reason, adopting accurate, precise, long-term monitoring strategies is crucial, and conceiving MRV systems as an investment can encourage and incentivize tropical countries to do so.

Part 3. Conclusion of the cumulative dissertation

The debate on the reduction of emissions from deforestation (RED) emerged during the 11th COP, in 2005. Since the 2007 COP, held in Bali, tropical countries (non-annex 1 countries) started developing national strategies for Reducing Emissions from Deforestation and forest Degradation (Pistorius, 2012). In some cases, too high expectations were created, as many countries saw REDD+ as a fast, big transfer of resources to developing countries, or as a cheap way to reduce CO_2 emissions. This vision has never materialized, though REDD+ remains an effective and efficient climate change mitigation strategy. Following the enthusiastic reaction for the entrance of REDD+ in the international policy arena, many researchers, politicians, leaders, technicians and various stakeholders have raised concerns that the REDD+ programme will fail to deliver positive results. Clearly, those who expected that REDD+ would have been a quick and simple mechanism for climate mitigation were disappointed. After ten years of activity, is probably time to take stock of the key achievements of REDD+. However, we should not ask, "What are the right measures to reduce emissions from forests?" but rather "What makes REDD+ successful and able to deliver beneficial outcomes?". Bearing this question in mind, the doctoral research was mainly focused on technical challenges for measuring and monitoring forest areas and carbon stock. In particular, the thesis tried to answer the question by investigating innovative and cost-efficient techniques designed to help developing countries facing the first stages of REDD+.

Pursuing *efficiency* (representing the third pillar of this thesis) is vital considering the limited government budgets, development aids and the status of REDD+. On the one hand, developing countries involved in REDD+, which often struggle with scarcity of resources, aim to reduce emissions from deforestation and forest degradation and to improve their forest-related policies and governance; though it sometimes means to challenge deep-rooted national development paradigms and existing policy frameworks or policy objectives (Murdiyarso et al., 2012). On the other hand, there is the financial framework of REDD+, which remains uncertain, though some promising signs have emerged, such as the inclusion of the forest sector in the Paris agreement. However, REDD+ dependence on public funding is strong, and considering that it hardly provides adequate and predictable support, private investments are desirable. To encourage the involvement of the private sector as a key partner in REDD+, some parts of the programme would probably need to be redesigned in order to increase cost-effectiveness and reliability.

For an efficient allocation of funds, national and local institutions should identify areas that are prone to near-future deforestation. With the first article we highlighted that projects can take advantage from three elements: available data, methods to handle data, and free and open source software. The open access data policies lead to an increasing availability of freely and easily accessible forest-related data, which facilitate the participation to REDD+ of developing countries that still have to develop their own data sets. These countries can elaborate their own business-as-usual scenarios to identify and rank potentially suitable areas for REDD+ interventions by adopting the model presented in the first article. We are fully aware that our modelling approach does not shed light on the complex interrelationships amongst the multiple drivers underlying the deforestation processes, neither does it explain links between land-use change processes, their drivers and the involved actors —though understanding them is necessary for a correct implementation of REDD+ (Visseren-Hamakers et al., 2012). We proposed an objective, rapid and efficient way of checking on potential future forestland cover by using available geo-spatial information as a proxy for stakeholder activities.

Efficiency tightly relates to innovation: a key element to shift towards efficiency is the adoption of innovative techniques. For example, the use of big data by adopting novel and innovative types of analytics such as machine learning and artificial intelligence can improve the efficiency and effectiveness of REDD+.

The idea of efficiency formulated in the second paper is different, as it explores monitoring techniques that aim for a maximum generation of carbon credits with minimum expense. We found that Lidar-based monitoring techniques have a positive effect on the efficiency of MRV systems, as the uncertainties are reduced and, consequently, revenues flow derived from result-based payments can be larger than those achievable by using passive optical remote sensing. Supporting the use of Lidar in forest monitoring for the scope of REDD+ needs large investments. Promoting a fertile ground for investments and innovations can expand access to Lidar technology in developing countries. In addition to remote sensing-based forest monitoring methods and technologies, a number of studies have highlighted that the involvement of local people in monitoring activities (e.g. community-based forestry monitoring) can help to safeguard sustainability and equity in forest programmes, such as REDD+ (DeVries et al., 2016; Pratihast et al., 2014).

The third pillar introduced in this thesis is *inclusion*. The process to take part in REDD+ is long, several steps need to be taken, as well as having to meet rigorous requirements to access international funding opportunities. Strict regulations and protocols seek to ensure the effectiveness of REDD+. Whether a country is eligible as a 'REDD+ country' or not depends on a number of factors. For example, good governance, a sound legal framework for protecting the rights of indigenous people and clear land tenure laws are prerequisites for successful REDD+ project (Engel et al., 2010; Pettenella and Brotto, 2012). However, this thesis only focused on aspects concerning forest monitoring. Possessing an MRV system is one essential factor that can determine the successful planning and implementation of REDD+. Given the weak monitoring capacities, many tropical countries still use traditional forest inventories for forest monitoring systems (Mbatu, 2016). This can hinder the access to REDD+ to those countries that lack an effective accounting system to monitor and keep track of forest cover change and carbon emissions. However, to contribute effectively to climate change mitigation, the REDD+ mechanism needs to involve almost all tropical developing countries. The articles included in this thesis demonstrate that even countries with low monitoring capacities can start developing a project; furthermore, conceiving an MRV system as an investment can encourage them to implement a well-defined, long-term monitoring strategy.

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Annex 1. Scientific articles

Article
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REDD+: Quick Assessment of Deforestation Risk Based on Available Data

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Abstract: The evaluation of the future dynamics of deforestation is essential to creating the basis for the effective implementation of REDD+ (Reducing Emissions from Deforestation and forest Degradation) initiatives. Such evaluation is often a challenging task, especially for countries that have to cope with a critical lack of data and capacities, higher uncertainties, and competing interests. We present a new modeling approach that makes use of available and easily accessible data sources to predict the spatial location of future deforestation. This approach is based on the Random Forest algorithm, which is a machine learning technique that enables evidence-based, data-driven decisions and is therefore often used in decision-making processes. Our objective is to provide a straightforward modeling approach that, without requiring cost-intensive assessments, can be applied in the early stages of REDD+, for a stepwise implementation approach of REDD+ projects in regions with limited availability of data, capital, technical infrastructure, or human capacities. The presented model focuses on building business-as-usual scenarios to identify and rank potentially suitable areas for REDD+ interventions. For validation purposes we applied the model to data from Nicaragua.

Keywords: REDD+; tropical forests; spatial targeting; random forests; carbon; land-use change modelling

1. Introduction

Deforestation and forest degradation are the largest anthropogenic sources of CO_2 emissions into the atmosphere [1] other than fossil fuel combustion. Tropical forests are the cornerstones of climate change mitigation—they sequester more carbon at faster rates than temperate and boreal forests [2]. Carbon released from loss of forests accounts for at least 12%–20% of the global anthropogenic emissions of greenhouse gasses (GHGs) [3,4]. REDD+ (Reducing Emissions from Deforestation and forest Degradation) aims to mitigate climate change by abating carbon emissions from forests in developing countries (named non-Annex I Parties) through a wide set of activities [5]. A system of economic incentives prompts non-Annex I Parties to participate in the program [6]. Countries willing to participate have to adhere to a REDD+ national strategic plan providing a comprehensive understanding of the political, social, and economic dynamics affecting land-use change. The plan also provides guidance on the efficient allocation of the limited amount of available funding. To efficiently allocate funds, it is necessary to identify areas that are prone to near-future deforestation.

Three key criteria must be considered for effective and operational implementation of REDD+: the level of threat to service provision, the benefits, and the costs [7,8]. The decisive environmental service to consider when designing a REDD+ project on the ground is the reduction of GHG emissions [9]. Such a reduction has to be accretive, i.e., the progress must be achieved as part of the project and not be achievable without it, and it cannot result in leakage. To provide an advantageous cost-to-benefit ratio while ensuring accretion, it is important to locate projects in areas where forest carbon loss has already occurred or where significant deforestation and forest degradation are expected, i.e., areas where the level of threat to service provision is higher. Otherwise, no benefits will be generated, especially in countries in which business-as-usual projections show a low deforestation risk [10–12].

An accurate identification of deforestation risk requires, inter alia, data availability. Although the capacities of tropical non-Annex I countries to monitor forests and forest cover change are likely to improve over the next years, there are still a number of countries unable to implement the basic measures needed in the REDD+ context [13]. Hence, there is a lack of forest-related data for specific assessments of suitable REDD+ activity areas.

Several tools have been developed and used since the 1990s to simulate forest-clearing dynamics and to predict which areas are subject to the risk of losing carbon due to deforestation [14–19]. However, limited data availability can hamper their use in some developing countries [20–22]. In this paper we present a new approach based on the Random Forest algorithm [23]. Random Forest is a decision tree–based method belonging to the family of machine learning. Decision tree–based methods are used in decision-making processes because they enable evidence-based, data-driven decisions. Because a lack of data in developing countries may represent a barrier to the success of REDD+ projects, we adopted an approach that integrates a powerful machine learning technique (such as Random Forest), available geo-spatial layers, and easily accessible data sources. We call our model PREDIT (PREdicting Deforestation In the Tropics). Our approach attempts to overcome some of the current challenges in assessing locations of deforestation risk. Data from Nicaragua were used to evaluate the performance of our approach.

2. Materials and Methods

2.1. Random Forests

We selected a model approach that integrates inputs from different data layers using the Random Forest algorithm. Random Forest is a supervised technique, conceptually simple, and suitable for both regression and classification problems. Decision tree-based models recursively partition the entire dataset (i.e., all the predictors' possible attributes) into fairly homogeneous regions. In the terminology of tree models, such homogeneous regions are referred to as terminal nodes or leaves of the tree (Figure 1). When no further partitioning is required, the process of tree growing is concluded and the tree assigns a class to the dependent variable of interest. In machine learning terminology, it is said the decision tree 'votes' for a class.

While for regression trees the overall objective is to reduce the mean square error (i.e., the difference between the true value and the value predicted by the model), the objective of classification trees is to create nodes having a maximum homogeneity, also called the purity of the node. In fact, having impure nodes increases the probability of misclassification error. Node purity is expressed by the Gini index [24]:

$$G = \sum_{x=1}^{X} p_{mx}\,(1 - p_{mx}) \qquad (1)$$

where p represents the training observations (i.e., those used to calibrate the model) of the X classes in the mth region. The lower the Gini index, the more homogeneous the node is, and consequently the probability to assign an incorrect class to a test observation belonging to that node decreases. Thus, during the process of tree growing, the best split is the alternative providing the lowest Gini index value.

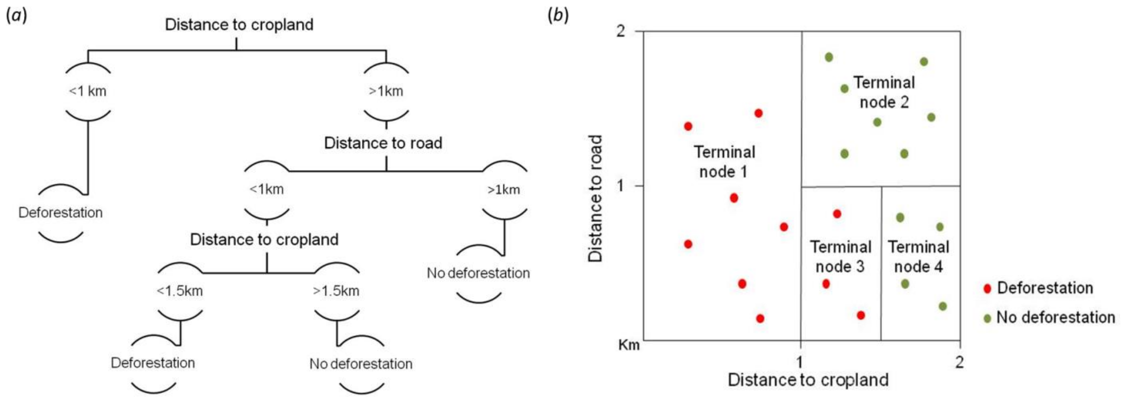

Figure 1. In this illustrative example land cover is predicted based on distance from cropland and road. Both pictures display the same decision problem using different representation systems: (**a**) shows the classification tree with three internal nodes and four terminal nodes; (**b**) shows the partition of the two-dimensional predictor space. In (**b**) the regions are entirely deforested or forested, a situation that is quite unusual in real-world models.

The random forests algorithm basically involves building a large number of classification trees on bootstrapped training samples. It is expressed by:

$$f(x) = \frac{1}{R}\sum_{r=1}^{R} f_r(x) \quad (2)$$

where $f(x)$ is the function of the dependent variable and R is the number of generated bootstrapped training trees, so $f_r(x)$ represents the rth bootstrapped training tree. This can also be expressed in a matrix form:

$$S_n = \begin{bmatrix} Pa_{S1}\, Pb_{S1} \ldots Pk_{S1} \\ \vdots \quad \vdots \quad \vdots \\ Pa_{Sn}\, Pb_{Sn} \ldots Pk_{Sn} \end{bmatrix} \quad (3)$$

where S_n is the nth bootstrap dependent variable, P_{aS1} is the predictor a of sample 1, P_{kS1} is the predictor k of sample 1, and $\{P_{aSn} \ldots P_{kSn}\}$ are the respective predictors $\{a \ldots k\}$ of the nth sample.

Finally, the class for which the greatest number of R individual training trees "vote" is used to predict the class for new observations that fall within the same region. Each prediction is expressed as a probability vector.

When using Random Forest, each decision tree is generated based on a random sub-sample (usually two-thirds) of the available observations. The remaining third of the data (not applied to calibrate the model) is called "out-of-bag" and serves as test data for computing an error rate. When trees are built, only a random subset of available k predictors is considered. Typically the number of predictors in the subset equals the square root of the total number of predictors. By defining $m \approx \sqrt{k}$ (where m is the number of predictors considered in a bootstrap sample), randomness is introduced into the tree-growing process, which assigns each predictor the same probability of being selected. This lowers the likelihood that stronger predictors will systematically affect the first split of the trees, a condition that would result in a series of highly similar and correlated trees [25]. The calibrated model that results is then used to predict the out-of-bag observations. The likelihood of classification error is therefore obtained from the out-of-bag estimation, which is an objective cross-validation-based accuracy estimate.

Some parameters must be defined by the user when calibrating Random Forests, including the total number of trees and the number of predictors sampled as candidates at each internal node. Another parameter is the "cut-off", which is the threshold value above which the probability of class A (e.g., deforestation) occurring is predicted and below which the occurrence of class B (e.g., forest) is predicted.

The Random Forest algorithm is widely used for data mining in many fields, but has been used only relatively recently in ecology and environmental studies [26]. However, to the best of our knowledge, there has so far been no study of its use in predicting the risks of future deforestation. For our study a decision tree-based model was adopted because the underlying relationships between the variables are not linear, and the categorical scale of attributes used is suitable for tree-based evaluation methods [24].

2.2. Data Used and Variable Selection

We used available data sources from the time interval 1983–2011. We included data from t1–t2 (i.e., 1983–2000) to calibrate the model and data from t2–t3 (i.e., 2000–2011) for validation. The whole dataset used for this study included 11 maps of Nicaragua: (1–3) three land cover maps for 1983, 2000, and 2011 respectively; (4–5) two population density maps; (6) a map of protected areas; (7–8) two road network maps; (9) one map of the urban settlements; (10) an elevation map; and (11) a slope map (Table 1). The 1983, 2000, and 2011 land cover maps are referred to as the 't1 reference', 't2 reference', and 't3 reference' maps, respectively. The predicted map for the year 2011 is called 't3 simulated map'.

The t1 reference map has a scale of 1:250,000. It was derived from 1977 and 1978 Landsat images classified by a supervised classification technique and complemented with ground observations [27]. Details of the methods used for adding the ground-based observations to the t1 reference map are not at our disposal. Although the quality of the t1 reference map has some drawbacks in comparison with more recent maps, the t1 reference map is the main map used for estimating land-use changes in Nicaragua of the last 30 years. This map is used by Nicaraguan institutions for official reports and statistics (e.g., the readiness preparation proposal). The t2 reference map was derived from 20 satellite images: 17 Landsat TM5 from many different years, and 3 Landsat TM7 from 2000 [28]. The classification was carried out by the ISODATA (Iterative Self-Organizing Data Analysis Technique Algorithm) unsupervised classification algorithm. Remotely-sensed data were supplemented by 120 field-plot observations [29]. The t3 reference map was derived from Landsat 7 Enhanced Thematic Mapper Plus (ETM+) satellite imagery. The satellite images, from 2011, were not ground-truthed; however, trained staff experienced in interpreting Nicaraguan vegetation from satellite images were employed in creating them [30]. The t1, t2 and t3 reference maps were officially released by the Ministry of Agriculture and Forestry (MAGFOR) and the Ministry of Environment and Natural Resources (MARENA) in Nicaragua.

Altitude and slope maps were extracted from the Digital Elevation Model (DEM) provided by HydroSHEDS [31]. The DEM has a resolution of three arc-seconds (approximately 90 m at the equator). Population density data were obtained from the Gridded Population of the World, Version 3, where density is expressed in terms of persons per square kilometre [32]. The World Database on Protected Areas [33], which is a global database of protected marine and terrestrial areas comprising both spatial vector data and attribute data (i.e., descriptive information), was used for data on protected areas.

Table 1. List of variables used to calibrate and validate the model.

Source Map	Data Format	Years Covered	Variable Extracted	Reference Unit	Source
Land cover	Vector	1983	- Distance to pasture areas - Distance to cropland areas - Forest type - Forest density	Meters Meters Broadleaved/coniferous Closed forest/open forest	[27]
Land cover	Vector	2000	- Distance to pasture areas - Distance to cropland areas - Forest type - Forest density - Forest cover change	Meters Meters Broadleaved/coniferous Closed forest/open forest Forest/deforestation	[28]
Land cover	Vector	2011	- Forest cover change	Forest/deforestation	[30]
Digital Elevation Model	Raster	-	- Altitude	Meters above sea level	[31]
Gridded Population of the World	Raster	1990, 2000	- Population density - Slope	Persons/km^2 Degrees	[32]
Protected areas	Raster	From 1980 to 2000	- Presence/absence of protected areas	Protected/No protected	[33]
Road network	Vector	1983, 2000	- Distance to road	Meters	[34,35]
Urban settlement	Vector	-	- Distance to urban areas	Meters	[36]

Ten independent variables (also called predictors in this article) and one dependent variable were extracted from the maps listed in Table 1. In Random Forest terminology, independent variables are called predictors and dependent variables are called response variables. The dependent variable, derived from the three land cover maps, is categorical and consists of two classes: (i) forest area and (ii) deforested area. Data from the three land cover maps of Nicaragua (1983, 2000, and 2011) were integrated through a GIS polygon-overlay analysis; the maps were overlaid to obtain the 1983–2000 and 2000–2011 forest cover change maps. The nominally-scaled dependent variable, i.e., the category of the dependent variable of each pixel, was binary: it was defined either as "forest" or "deforestation," according to the changes observed, with forests is defined as land with an area of more than 0.5 ha, trees higher than 5 m, and canopy cover of more than 10% [37]. The widely accepted definition of deforestation as "a long-term or permanent conversion of land from forest use to other non-forest uses" was adopted [38].

The independent variables consist of 10 spatially explicit predictors of deforestation. The availability of data was the major limitation in selecting the predictors. The predictors were chosen by reviewing the available literature and according to the author's knowledge of the country. While information on deforestation drivers at the continental level was taken from Hosonuma et al. [39], national information on Nicaragua was derived from the National Forest Inventory [40] and other sources [41–44]. The 10 predictors (Table 1) were chosen on the basis of the supposed relevant drivers of deforestation. Although some of the selected predictors may not be relevant to Nicaragua, we decided to include all of them to test the responsiveness of the model.

The proximity variables were computed using the Euclidean distance from each feature to the closest pixel. Three out of the 10 predictor variables were extracted from the national land cover maps available for 1983, 2000, and 2011: forest type, distance to cropland, and distance to pasture. The other predictors, such as road network and urban settlements, were extracted from remotely-sensed imagery and from publicly available sources (see Table 1 for references).

2.3. Modeling Using 10 and Four Predictors

We performed PREDIT using two sets of predictor variables. The processes of calibration and validation—which are explained in the next two sections—were carried out twice, each time using a different number of predictors (Table 2). Based on our knowledge, and on the of Readiness Preparation Proposal (RPP) developed by the Nicaraguan Ministry of Environment and Natural Resources [43], four predictors were selected as the most useful for inclusion in the model for predicting deforestation dynamics. In the first run, referred to as FourPA (Four Predictors Alternative), we included only these predictors. In the second run, referred to as TenPA (Ten Predictors Alternative), the set of all 10 available predictors was used.

Table 2. Ten predictors used in PREDIT model. The model was run on two alternatives: (i) TenPA, which uses 10 predictors; (ii) FourPA, which uses four predictors substantially associated with the dependent variable.

Screened Predictor Variables	
Used in TenPA	Used in FourPA
Forest density	Altitude
Population density	Distance to cropland areas
Distance to cropland areas	Slope
Protected areas	Distance to pasture areas
Forest type	
Altitude	
Distance to roads	
Distance to urban areas	
Slope	
Distance to pasture areas	

2.4. Model Calibration

The analysis was run using the Random Forest package of R, version 3.2.1 (R Foundation for Statistical Computing, Vienna, Austria) [45] and ArcMap 10.2.2 (Esri, Redlands, CA, USA). Three hundred data trees were grown using the Random Forest. Two and three predictors were sampled as candidates at each internal node to calibrate the model for FourPA and TenPA, respectively. Since our aim was to evaluate the model's ability to predict the risk of deforestation in the time interval t2–t3 (i.e., 2000–2011), we used training data from t1–t2 (i.e., 1983–2000) to calibrate the model (Figure 2). In total, approximately 105,000 pixels were sampled in forest areas from the reference t1 map; the shortest distance allowed between any of them was 90 m. For each sample pixel, we extracted data from the maps of predictor variables at time point t1 (Figure 3) and from the land-use class at time point t2, but no data about forest types at t1 were collected. The model was calibrated using observations for the predictor variables in 1983 and with the assumption that those conditions affected the dependent variable in 2000. An important aspect considered during the calibration phase was the imbalance in the relative frequencies of the classes, i.e., if one class of the dependent variable has fewer observations compared to the other classes. This issue can significantly influence model results. Considering that the area covered by the dependent variable class 'deforestation' is much smaller than the class 'forest', we applied post-stratification based on the dependent variable at t2 to reduce this class imbalance.

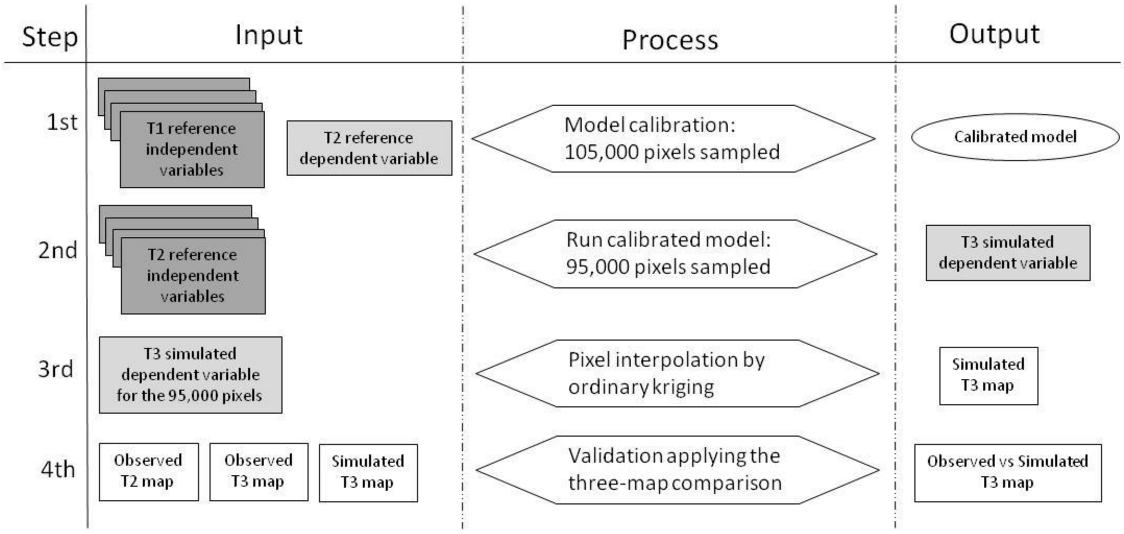

Figure 2. Summary of methods and data used in model building. The four steps were carried out twice: the first time including four and the second time 10 reference independent variables. Dark grey squares represent independent variable maps, light grey squares represent dependent variables, and white squares are maps of forest cover and forest cover change.

2.5. Model Validation

The validation process, which was carried out using data from the time interval t2–t3, included the following steps:

1. Approximately 95,000 sample pixels were generated by adopting a random sampling from the class “forest” at time t2.
2. For each pixel randomly selected, the corresponding value from every map of the independent variables at t2 was extracted.
3. The calibrated model and the fitted parameters used in the calibration procedure were used to predict the dependent variable at time t3 for the 95,000 pixels.
4. The t3-simulated map, which displays the predicted risk of deforestation, was created by interpolating the entire set of pixels using kriging.
5. The performance of the model was assessed by applying the three-map comparison technique and other statistical indicators [46].

Given that the aim of the procedure is to assess the risk of a pixel changing from “forest” to another land cover class, the validity of our model was assessed by random sampling of forest area at t2. Changes between t2 and t3 were estimated using the Random Forest algorithm and data fitted in the calibration phase. To predict the t3 map we used data preceding time t3. The predicted response of the dependent variable was expressed as the risk probability—ranging from 0 to 1—of each pixel in terms of undergoing deforestation. Risk is expressed in four probability classes—very low, low, moderate, and high. The probability threshold values that determine the risk class were applied as follows: very low ($p < 0.2$), low ($0.2 \leq p < 0.4$), moderate ($0.4 \leq p < 0.8$), and high ($0.8 \leq p < 1$). The thresholds were empirically derived considering the maximization of the overall accuracy of prediction for each risk class. In the analysis of the accuracy of the model, pixels belonging to the third and fourth classes of risk (i.e., moderate and high risk, respectively) are considered to be predicted as ‘deforested’.

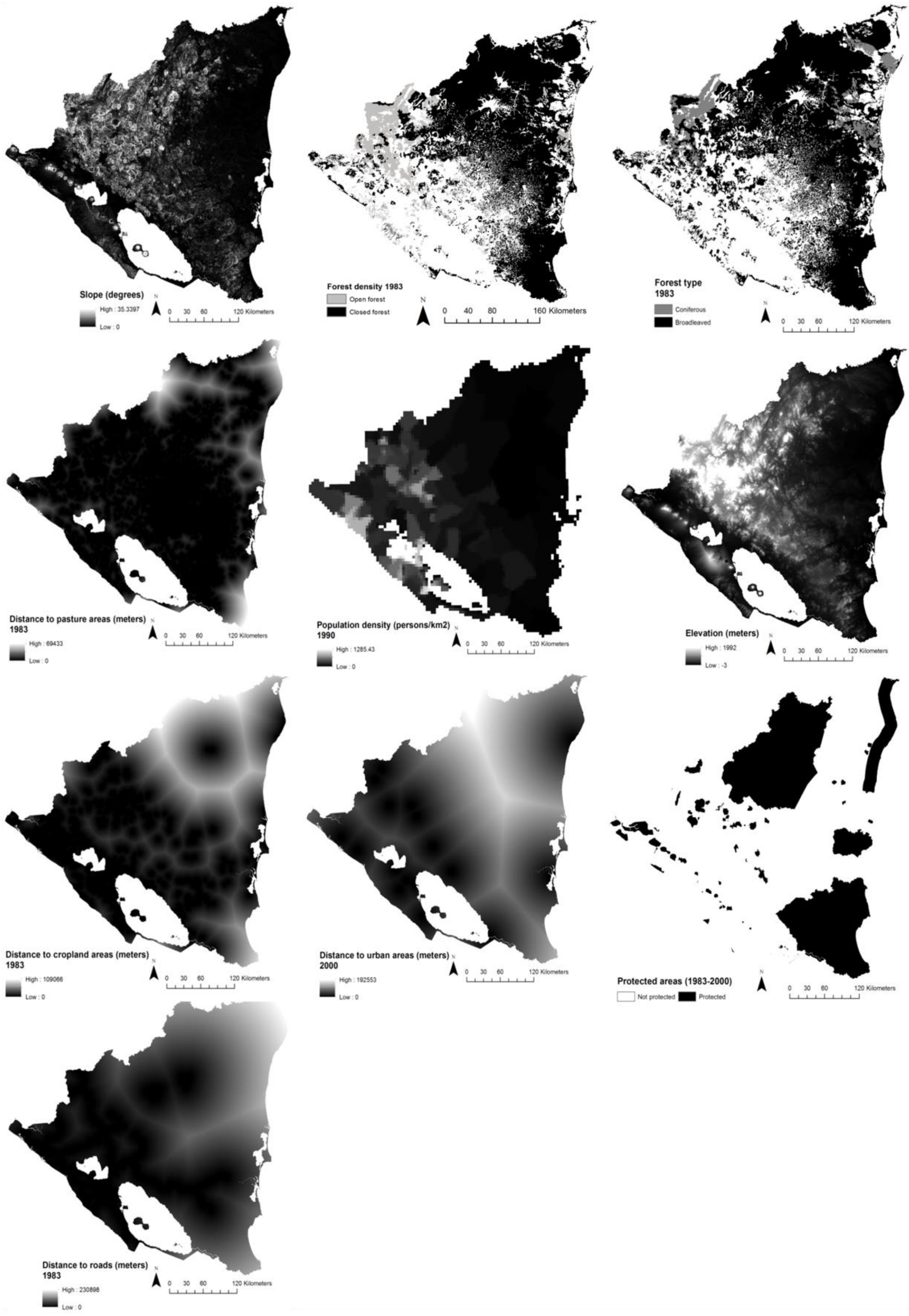

Figure 3. Spatial independent variables of Nicaragua used in the calibration of the model.

Ordinary linear kriging was applied to predict the risk of the dependent variable at a non-sampled location, i.e., for the whole forested areas in 2000 [47]. The simulated t3 map created using kriging has a pixel resolution of 150 m—higher resolution was not possible due to computational limitations. This map was validated using a technique that involves the overlay of three maps, which in this study were the t2 reference map, the t3 reference map, and the t3 simulated map. This three-map comparison [48] provides four components, two of which express correctness while the other two express prediction error: (i) reference deforestation correctly predicted (i.e., hits); (ii) reference forest permanence correctly predicted (i.e., correct rejections); (iii) reference change simulated as forest permanence (i.e., misses); (iv) reference forest permanence simulated as deforestation (i.e., false alarm). This validation technique compares the performance of the developed model with that of a null model that predicts pure persistence (i.e., no deforestation) [49]. Several methods based on these components describe and measure the performance of classification models. In this study we consider the following measures: figure of merit, allocation disagreement, quantity disagreement, producer's accuracy, and user's accuracy [47].

2.6. Study Area

Nicaragua is the largest Central American country, both in terms of land and rainforest area [41]. According to its national forest inventory, forests cover 25% of the total land area [40]. Despite some attempts to preserve its natural heritage, e.g., by establishing a number of protected areas over the past four decades [50], Nicaragua has lost almost half its forest cover since the 1950s and is still affected by deforestation, which has implications for local climate trends and agricultural productions [42,51].

The prime deforestation drivers in Nicaragua are animal husbandry and agriculture expansion, while agroforestry plays a minor role [43,52]. As in other Latin American countries such as Ecuador or Honduras, deforestation mainly follows an agricultural frontier, affecting considerable areas along the Caribbean and in the central north, which are still the regions with the largest stretches of natural forest. In September 2007, Hurricane Felix struck the northern region, or "Región Autónoma del Atlántico Norte"; over one million hectares of forests were affected and 512,165 ha were identified as strongly damaged, i.e., about 15% of the total forest cover of the country. PREDIT does not take into account climatic disturbances, and considering the extraordinarily large impact of Hurricane Felix, the three mostly affected municipalities were not included in the study area, i.e., Prinzapolka, Puerto Cabezas and Rosita.

3. Results

In all, 300 data trees were grown using the Random Forest algorithm. The maps in Figure 4 are the result of the three-map comparison technique (explained in Section 2.6); these maps visually represent model performances by showing the accuracy distribution of the land-change model. Areas characterized by a high risk of deforestation coincide with lowland forests, relatively gentle slopes, dense road networks and proximity to pasture and cropland areas.

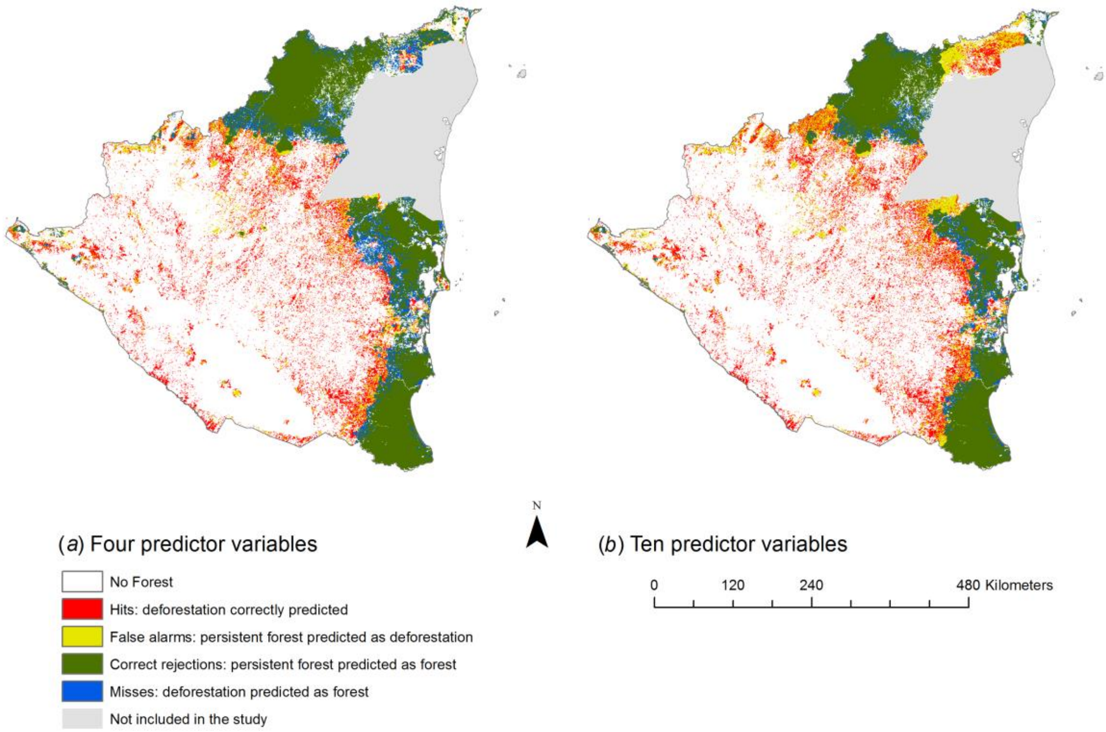

Figure 4. Distribution of agreement and disagreement for Four Predictors Alternative (**a**) and Ten Predictors Alternative (**b**), resulting from the comparison of three maps: the t2 reference map, the t3 reference map, and the t3 simulated map.

Accuracy is also reported in numerical terms in Table 3, which represents the confusion matrix between the simulated land-use changes and the reference changes. The classification error for the two modeling alternatives was similar. The additional six predictors included in TenPA did not improve the overall accuracy, which in both alternatives was 76%. However, the predictions of the two alternatives were different, as described through the measures of accuracy considered in this study. The deforestation correctly predicted by FourPA was lower than that predicted by TenPA (26% versus 30.6%), but the number of "false alarms" (i.e., persisting forest predicted as deforestation) was also higher in TenPA (17.3% versus 10.8%) (Figure 5). This means that TenPA classified more pixels as deforested and, accordingly, detected more deforestation than FourPA. The larger number of pixels classified as "deforestation" by TenPA was also evidenced by calculating the producer's and user's accuracy; in fact, the proportion of pixels incorrectly classified as "deforestation" (as defined by the user's accuracy) was higher in TenPA (Table 4). Figure 5 shows the four components of agreement and disagreement resulting from the validation process; values are expressed as the percentage of forest at t2 and are divided by classes.

Table 3. Error matrix obtained by the three-map comparison for FourPA and TenPA. Values are expressed in percentages.

	Reference					
	TenPA			**FourPA**		
	Forest	**Deforestation**	**Simulated Total**	**Forest**	**Deforestation**	**Simulated Total**
Forest	44.7	7.5	52.2	51.2	12	63.2
Deforestation	17.3	30.5	47.8	10.8	26	36.8
Reference Total	62	38	100	62	38	100

Table 4. Performance of the model in assessing the risk of future deforestation using a set of 10 predictors and using four out of 10 predictors.

	Ten Predictors (TenPA)	Four Predictors (FourPA)
Overall accuracy	76%	76%
Producer's accuracy	0.80	0.69
User's accuracy	0.64	0.71
Figure of merit	55%	53%

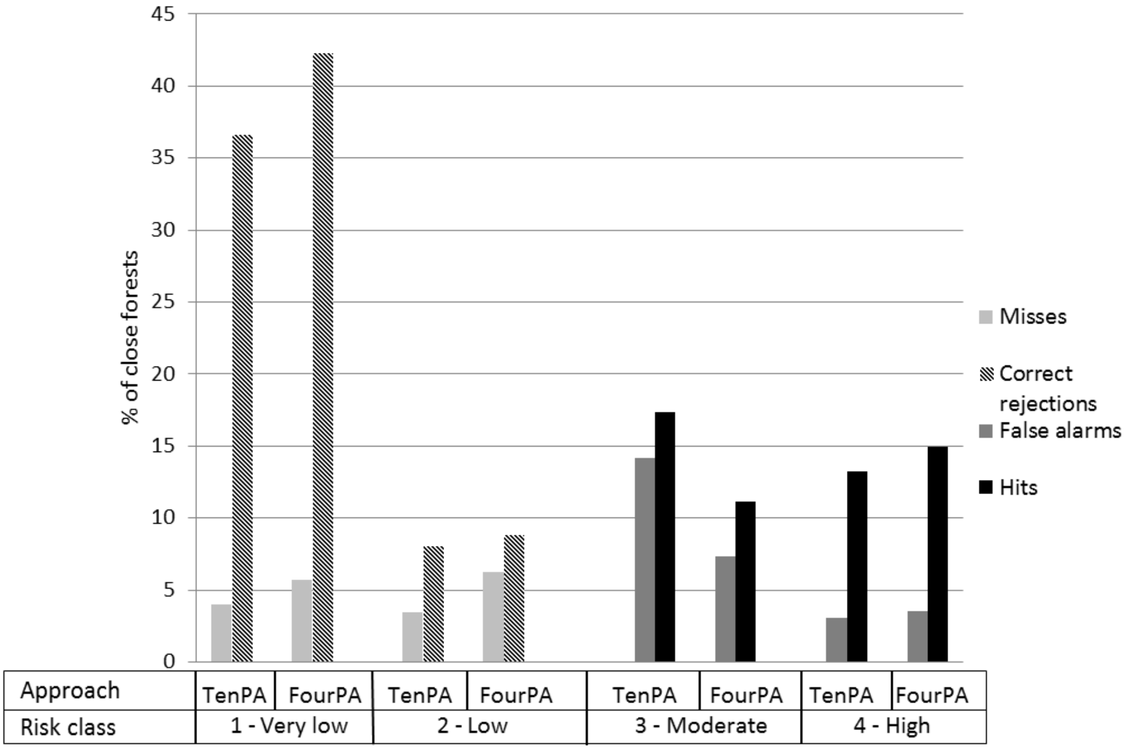

Figure 5. Elements of agreement and disagreement divided by the four classes of risk (i.e., very low, low, moderate and high). The accuracy components for both the modeling alternative with 10 (TenPA) and four (FourPA) predictors are reported for each risk class.

The performances obtained from the two variations (FourPA and TenPA) are summarized in Table 4, which shows the measures of the model accuracy assessment derived from the error matrix. The quantity of disagreement was obtained by counting the total simulated pixels that did not match their actual category in the reference maps. The quantity of disagreement accounted for 3% (FourPA) and 25.8% (TenPA) of the total number of pixels classified as observed deforestation in 2011. The higher value of the quantity of disagreement for TenPA is attributable to the overestimation of deforestation by this alternative (depicted in Figure 4 by the yellow-colored "false alarms"). For assessing the allocation disagreement, in addition to the absolute number of pixels, their spatial allocations in their respective categories was also considered. In other words, the allocation disagreement is the discordance between a pixel allocated into the simulated maps and a corresponding pixel in the reference maps. The 2011 map simulated with TenPA had a lower allocation disagreement than the map simulated with FourPA; the difference is attributable to the larger portion of deforestation correctly predicted by TenPA. In absolute terms, there were 674,001 total pixels in the reference map belonging to the category "deforestation"; the allocation disagreement was 383,606 and 264,220 for FourPA and TenPA, respectively.

The "figure of merit" is a statistical measurement used to assess the accuracy of land change models; it can range from 0% to 1%, where 100% indicates perfect prediction. In this study it is defined as follows:

$$\text{Figure of Merit} = \text{Hits/False alarms} + \text{Misses} + \text{Hits} \quad (4)$$

The figure of merit was 55% for TenPA and 53% for FourPA. The 2% difference can be considered negligible in this case; it would be incorrect to judge the accuracy of prediction of one alternative with respect to the other on the basis of this percentage. To comprehensively assess the performance of the model, all the statistical measurements reported in this paper must be considered and evaluated with reference to the final scope of the modeling application. Including 10 predictors does not increase or decrease the accuracy significantly, though one important difference is that in TenPA, the number of "false alarms" is higher. In REDD+ projects, adopting a conservative approach that does not overestimate the risk of deforestation is recommended; therefore, FourPA would be the preferred alternative.

4. Discussion

The risk of deforestation is generally assessed using data about the respective drivers of deforestation. Addressing them involves understanding the complex processes affecting interrelationships among political, institutional, economic, and cultural factors [53]. We present here a novel approach, called PREDIT, which is based on available data and which focuses on building business-as-usual scenarios to predict potentially suitable areas for REDD+ interventions. A strong point of this approach lies in its versatility and potential reproducibility in countries with limited available data or human, technical, or monetary resources. The approach does not focus on capturing the interrelationships of multiple drivers underlying the deforestation processes, which would be both time- and cost-intensive. However, it is an objective and rapid way of checking on potential future forest cover by using available geo-spatial information as a proxy for stakeholder activities.

We applied Random Forests which outperform classical methods (e.g., discriminant analysis or logistic regression) when there are strong interactions among variables, especially if they are non-linear [54]. Spatial autocorrelation, a problem common to parametric linear models, is reduced by the Random Forest algorithm (which is non-parametric). Based on a machine learning technique, PREDIT is highly flexible as it can handle categorical and continuous variables. Flexibility is an appreciable characteristic in spatial prediction models [25,55], though flexibility comes at the expense of interpretability. We are, however, not interested in making inferences or in creating a model that investigates and displays relationships among the dependent variable and the set of predictors for which interpretability is of significance; our goal is a pragmatic prediction of future events.

Performing the process twice, using two sets of predictors, also allowed us to screen the most relevant biophysical and demographic predictors affecting deforestation in Nicaragua. Considering our purposes, using four predictors (FourPA) provided better results than using 10 (TenPA), even though quantity disagreement was higher for FourPA. We seek to accurately identify areas where both deforestation and forest persistence might occur in the future. However, if the study had been aimed at predicting total carbon emissions, without referring to the location where they might occur, then knowing the allocation disagreement (i.e., the area where emissions would take place) would not have been fundamental. The reason including 10 predictors did not improve the prediction accuracy is likely related to the fact that the six predictors added in TenPA were not relevant drivers of deforestation in Nicaragua during the considered time interval. However, some drivers of deforestation can change over time, so a good predictor in 1983 might be a bad predictor in 2000. To analyze and explain all the potential reasons related to the different performances of the two alternatives (FourPA and TenPA), a comprehensive investigation of the land-use dynamics from 1983 to 2011 should be carried out, though such analysis goes beyond the scope of this paper.

To streamline the validation phase, we decided to categorize the probability of deforestation into four classes, though this also meant losing some information concerning risk. The threshold probability values assigned to determine the risk classes are subjective and should be evaluated by considering the final application of the model. For example, if the model is used to project a business-as-usual scenario to build reference levels (RLs), a conservative estimate should be used to minimize the possibility of overestimating deforestation. However, the creation of baseline scenarios useful to preparing RLs involves a series of complex and—often—"stochastic" circumstances. These circumstances increase uncertainties and can undermine the credibility and effectiveness of the mechanism [56]. In order to minimize uncertainties, improve accuracy, and provide completeness, field assessments are strongly recommended when preparing RLs.

We calibrated the model with data covering a time interval of 17 years (1983–2000), during which crucial political, social, and natural events took place in Nicaragua that led to extraordinary land-use changes. Nonetheless, the calibrated model exhibited satisfactory predictive accuracy within its domain of applicability; we expect that applying it in a less unstable context could yield better results. It must be underlined that predictive accuracy is only one of the various criteria used to assess the performance of a land change model and its potential applicability. To evaluate the actual applicability and the predictive performance of PREDIT to another area, several other environmental, political, economic and technical factors that might influence the performance of PREDIT [22] must be considered.

PREDIT has some limitations that could compromise its accuracy. Deforestation drivers may vary over a long time period, e.g., new driving forces not relevant in the calibration phase could, at a later time, become more important, and as a result the predictor variables used might lead to an error in predicting the location of future forest loss. PREDIT also does not predict the risk of deforestation for reforested and afforested areas.

The agreement between the simulated map and the reference map can be considered satisfactory for some payment for ecosystem services purposes, e.g., when identifying potential target areas for REDD+ projects. However, the model may perform differently depending on the location, time, and format of the data [46]. Nicaragua experienced a high deforestation rate for the period considered in this study; this situation might have facilitated a predictive model. In fact, recording small deforestation patches is far more challenging than detecting substantial changes of forest cover [57]. Thus it will be important to also test the model in areas where forest cover changes affect smaller areas.

5. Conclusions

Modeling deforestation is a key first step towards creating the basis for successful REDD+ initiatives, although it is, of course, only one of the numerous circumstances that determine whether a REDD+ project will be effective or not [58,59]. Our research was prompted by the necessity of forecasting the likelihood of deforestation, without reference to further complex assessments such as field measurements, social surveys, and stakeholder involvement. Predictive models focus on the general network of interaction among variables rather than investigating the roles and relationships of each one. This is different from how inference models work; with those models, the main objective is to understand how a dependent variable changes as a function of the independent variables [24,60].

PREDIT can be applied by decision-makers, researchers, and other stakeholders involved in REDD+. Besides its direct use in determining areas that risk losing their ecological importance, it has further potential functions. Using the model approach jointly with tools for estimating carbon stock and emissions will allow the identification of high-value areas where activities advocating forest monitoring should be strengthened. Significantly, the model can support countries involved in the early phases of REDD+. As developing a REDD+ program requires, inter alia, high-quality data, it is hoped that countries lacking data and technical capacity can adopt a gradual approach to engaging in REDD+ [22,61]. The approach presented in this article is suited to a stepwise framework for developing REDD+ [62]. It can aid in the operational implementation of REDD+ projects and in the design of action responses. Its adoption may be effective in the first phase of projects, when a country is still developing the capacity to build its own sound and accurate dataset. Adopting PREDIT or other similar tools would enable wider REDD+ participation; it represents a starting point for countries that grapple with a critical lack of data, higher uncertainties, and competing interests.

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Author Contributions: G.D.L. designed the study, developed the model, analyzed and interpreted the data, drafted the manuscript, and revised it critically; P.M., who conceived the application of Random Forest, also provided important technical content and revised the manuscript; S.E.Z.L. helped to identify the case study, contributed to the interpretation of data, and revised the manuscript; M.M. contributed to the early conception of the idea, helped to coordinate the study, and revised the manuscript; M.K. conceived the idea and helped to structure the study, helped to develop the method, coordinated the study, and substantially contributed to the quality control and critical revision of the manuscript. All the authors have read and approved the final manuscript.

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Understanding Measurement Reporting and Verification systems for REDD+ as an investment for generating carbon benefits

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Abstract: Reducing emissions from forests—generating carbon credits—in return for REDD+ (Reducing Emissions from Deforestation and forest Degradation) payments represents a primary objective of forestry and development projects worldwide. Setting reference levels (RLs), establishing a target for emission reductions from avoided deforestation and degradation, and implementing an efficient monitoring system underlie effective REDD+ projects, as they are key factors that affect the generation of carbon credits. We analyzed the interdependencies among these factors and their respective weights in generating carbon credits. Our findings show that the amounts of avoided emissions under a REDD+ scheme mainly vary according to the monitoring technique adopted; nevertheless, RLs have a nearly equal influence. The target for reduction of emissions showed a relatively minor impact on the generation of carbon credits, particularly when coupled with low RLs. Uncertainties in forest monitoring can severely undermine the derived allocation of benefits, such as the REDD+ results-based payments to developing countries. Combining statistically-sound sampling designs with Lidar data provides a means to reduce uncertainties and likewise increases the amount of accountable carbon credits that can be claimed. This combined approach requires large financial resources; we found that results-based payments can potentially pay-off the necessary investment in technologies that would enable accurate and precise estimates of activity data and emission factors. Conceiving of measurement, reporting and verification (MRV) systems as investments is an opportunity for tropical countries in particular to implement well-defined, long-term forest monitoring strategies.

Keywords: Reducing Emissions from Deforestation and Forest Degradation; MRV; Lidar; remote sensing; carbon accounting systems; reference emission level; uncertainty; sensitivity analysis

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1. Introduction

Since the first REDD-style project (the Noel Kempff Mercado Climate Action Project) initiated in 1997, the focus of REDD+ has broadened from the avoidance of deforestation as the “single largest opportunity for cost-effective and immediate reductions of carbon emissions” [1] to a holistic concept for sustainable development. Protecting biodiversity, enhancing local livelihoods, strengthening local people's rights, and improving forest governance are some of the widely discussed co-benefits that are embedded in REDD+ activities. However, the primary focus of REDD+ remains the reduction of carbon emissions associated with deforestation and forest degradation. For countries adopting a REDD+-regime, the most significant asset is to receive financial rewards for reducing emissions and enhancing carbon sinks. Results-based payments—also known as "carbon benefits"—constitute a key element that distinguishes REDD+ from other initiatives [2]. To generate payments, for any national or sub-national REDD+ initiative, the associated emission reductions have to be assessed. This includes the assessment of both changes of forest area (activity data) and changes of forest carbon stocks (emission factors). Activity data and emission factors have to be estimated by countries participating in REDD+ through the implementation of reliable measurement, reporting and verification (MRV) systems [3,4].

MRV systems have to be implemented in a challenging environment of reliable estimates on the one hand and of adequate assessment costs on the other. The reliability of any MRV system is driven by the quality of remotely sensed data, the intensity of in-situ assessments (i.e., sample size) and the soundness of models utilized, and is, thus, directly linked to cost. Consequently, increasing reliability is necessarily associated with increasing cost. Thus, the development and implementation of any MRV system can be considered as an optimization problem: which MRV-design results in the highest level of reliability for a given cost, or in the lowest cost for a desired level of reliability.

The Warsaw framework for REDD+ requires a country to implement a combined assessment approach that utilizes remote sensing data and in-situ assessments [4]. Associating field data and remote sensing provides an efficient solution to monitor the state and changes of forest carbon stocks [5,6]. Remote sensing of forest biomass involves different sensor types (e.g., Lidar, optical and radar), platforms (air- and space-borne), and processing techniques (e.g., unsupervised, supervised, and hybrid classification approaches) which substantially differ with respect to costs and performances. Even though these techniques gradually become more accessible, their implementation is still not viable, especially in vast tropical forest areas, due to poor investments in capacity building [7]. Overall, countries participating in REDD+ are developing their forest monitoring capacities, however, national forest inventories still need to be further improved [7,8]. The critical lack of funding in the REDD+ system restricts the possibilities to build capacities and to utilize high-resolution remote sensing sensors [9]. Although monitoring costs may be relatively small with respect to other categories of costs, they directly affect the success of REDD+ mechanisms; an effective monitoring system will reduce uncertainties and, as a result, eventually generate larger results-based payments [10].

From this perspective, a country may consider REDD+ as an investment providing long-term benefits and that will produce returns, and thus, exploit the opportunity that would allow a country to establish a monitoring system. Investing in sound, recurrent MRV systems critically determines a country's potential to generate results-based payments. Moreover, such investments can support forest policies reforms and promote sustainable forest management. REDD+ can be an opportunity for tropical countries to establish a better forest-related institutional framework and to improve management of forests at different levels [11,12].

Besides uncertainties in carbon estimates, other variables affect the amount of accountable carbon credits. A decisive role is played by the reference levels (RLs) and the planned reduction of business-as-usual emissions as a result of REDD+ activities. The reduction of past emissions rates results from the implementation on the ground of the five REDD+ mitigation actions (reduction of emissions from deforestation and forest degradation, conservation of forest carbon stocks, sustainable management of forests and enhancement of forest carbon stocks). A country should establish a target of emissions reduction according to its capacity to plan and execute the REDD+ activities and to the national RL [3]. The reduction of emissions actually determines the real removal of CO_2 from the atmosphere; however, payments depend on the generation of measurable, monitored, and verified tons of CO_2 emissions and removals.

The RLs, which are used as business-as-usual baselines, benchmark the quantity of emission reductions and removals–due to REDD+ activities–that can be estimated to evaluate progress of countries participating in REDD+. Therefore, the quantity of avoided emissions against the agreed RL stipulates the total amount of accountable carbon credits. Establishing reliable RLs (used throughout this paper as synonym for "REDD baselines") is crucial and challenging. Commonly used methods for establishing RLs include:

- historical rates of deforestation, degradation and emission factors, also using adjustment factors to allow inclusion of social and economic variables (named "national circumstances") [13], and
- projected deforestation and forest degradation rates using land-use-change models [14,15].

The debate on the implications of different methods is intense; the common view is that the selected RL method shapes the success of REDD+ and it should be selected according to the local circumstances, e.g., specific capabilities and data availability [16,17].

This paper analyzes the links between financial resources invested in MRV systems, the achievable reliability and the resulting amount of accountable carbon credits. Furthermore, in a simulation study, we investigated implications of different (i) reference levels, (ii) emission reductions due to REDD+ and (iii) uncertainties in emissions estimates, on the generation of carbon credits and the consequent potential financial benefits from alternative MRV systems. In addition, we studied investments in Lidar-based monitoring systems as a cost-efficient option for REDD+ projects.

1.1. State of the Art

1.1.1. Model-assisted design-based AGB estimation using remote sensing

Integrating ground-based observations with remotely sensed data is the most cost-efficient way to monitor the national state of forests [5]. Remotely sensed data —calibrated over field measurements— contribute to improve precision and to provide spatially explicit information [18]. When remote sensing data are used as auxiliary information, and are incorporated in a design-based framework by using a model, the resulting approach is called design-based model-assisted, or simply model-assisted approach [19]. In model-assisted approaches, auxiliary data from remote sensing are incorporated in the estimation process through regression models; it reduces the design variance of the field sample-based estimator of the population total above-ground biomass (AGB). When auxiliary data are highly correlated with AGB, the cost-efficiency of the estimation could be improved [6]. Particularly, for large-scale monitoring activities (e.g. at national and sub-national level), the combined approach (i.e. remote sensing and field measurements) reduces costs while ensuring accuracy and reliability [20]. Optical sensors, Radar, and Lidar remote sensing techniques are the main sources of remotely sensed data used to extract information for forest biomass [21,22]. According to circumstances and needs one sensor type can be more suitable than another can: there is no "one-sensor-fits-all" approach [23]. However, Lidar performance is significantly better than passive optical or Radar sensor used alone [21]. The coefficient of determination, R^2, provides a measure of (linear) regression performance, indicating the amount of variance explained by the model, and expressing the correlation between the auxiliary variable(s) and the variable(s) of interest. Therefore, the R^2 is also a measure of the contribution of remotely sensed data to forest biomass estimation, i.e. it is related to the reduction of standard error achievable by linking remotely sensed data to pure in-situ based estimation. A higher R^2 value means better precision of biomass estimation.

1.1.2. Cost-efficiency of Lidar-based methods

It is widely accepted that a combined Lidar and field-campaign approach provides precise estimates of AGB. However, the actual cost-effectiveness of such an approach is still intensively discussed. Due to its substantial cost, Lidar is still considered a hard alternative for large-scale forest monitoring in most tropical countries [24]. The application for large-scale assessments at successive occasions in tropical regions is apparently still far from being operational, and many countries may see the associated cost as a major obstacle for a routine application. However, only few studies have analyzed the actual trade-offs between efficiency and costs associated with the use of Lidar in carbon estimation [25,26]. There is uncertainty whether large investment in monitoring activities will result in higher returns through REDD+ results-based payments. Assessing the cost-effectiveness of model-assisted estimation of AGB using alternative remotely sensed data as auxiliary data will help to understand the actual feasibility and the major constraints for the design and implementation of targeted MRV systems.

1.1.3. Addressing uncertainties in REDD+: the Reliable Minimum Estimate

Quantifying uncertainties is of primary importance in the context of REDD+. The Intergovernmental Panel on Climate Change (IPCC) suggests the use of the reliable minimum estimate (RME) to quantify uncertainties in the estimates of emission factors and activity data [27]. Adopting the principle of conservativeness in REDD+ estimates was proposed by Grassi et al. [28] in order to "address the potential incompleteness and high uncertainties of REDD estimates, and thus to increase their credibility". The RME reduces the risk of overestimating the emissions reduction derived by a REDD+ project, which could lead to an overcompensation of emission reduction. The RME is defined as the difference between the lower limit of the confidence interval at the reference period (time 1) and the upper limit of the confidence interval at the commitment period (time 2) (Figure 1). The RME is the minimum quantity to be expected with a given probability and is a conservative way to handle uncertainties, related to all error types (e.g., sampling errors, measurement errors and modeling errors). While on the one hand the RME supports the credibility of estimates, its efficacious application depends on several factors, such as baseline emissions and the method used to set such baselines [29,30].

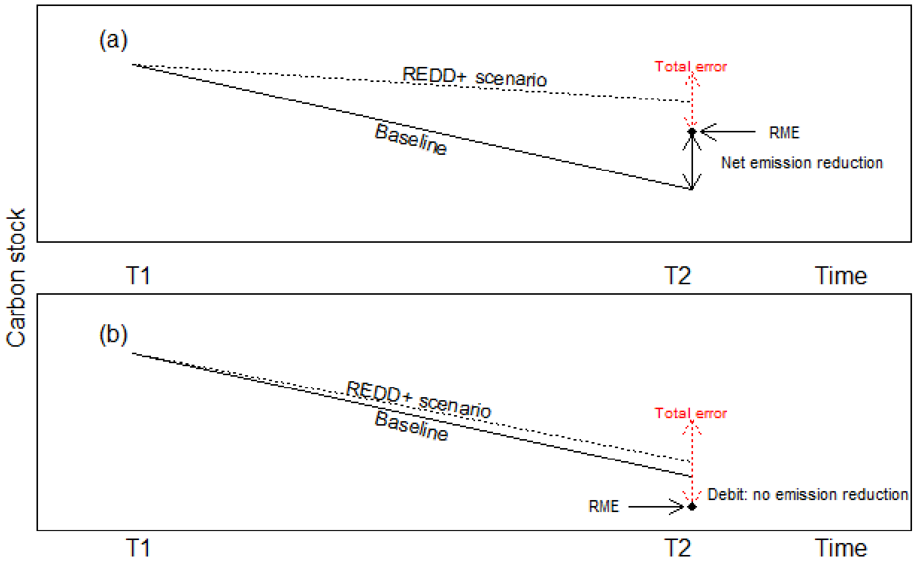

Figure 1. Projections of carbon emission under a business-as-usual baseline and a REDD+ scenario. In the upper figure (**a**) a positive reduction of emissions is shown. In (**b**) the projected REDD+ scenario emission reduction is smaller and the magnitude of the total error is larger; this condition leads to no improvement over the business-as-usual scenario. RME is reliable minimum estimate.

2. Materials and Methods

In the first part of the study, we estimated the aboveground carbon based on field-plot data from the national forest inventory of Puerto Rico. Starting from the forest inventory data, we simulated the integration of remotely sensed auxiliary data by adopting a model-assisted approach and a stratified sampling with optical data. In the second part of the study, we evaluated and compared a set of hypothetical scenarios, which differ for RLs, emission reductions, monitoring accuracy–derived from the first part–and costs. Finally, we analyzed implications of the various scenarios on the amount of carbon credits generated from reducing forest carbon emissions.

2.1. Data used

Two main sources of data were used: (i) forest inventory data from Puerto Rico and (ii) qualitative and quantitative data on the use of Lidar and passive optical sensors for biomass estimation extracted from peer-reviewed articles (Table S1).

2.1.1. Field data

The field plot data were collected during the third forest inventory of Puerto Rico [31,32]. The forested life zones in Puerto Rico are classified as subtropical dry, subtropical moist, subtropical wet and rain, subtropical lower montane wet, and subtropical lower montane rain. Totally 956 plots were sampled in the whole country, of which 288 were located within forested areas. In this study, we only considered plots located in moist forests and in wet and rain forests, which were 141 and 82, respectively (table 1). These two forested life zones would be the most suitable target areas for local REDD+ projects, as they are the most important in terms of area covered and carbon content. The permanent sampling unit installed is a cluster of four subplots, within which all trees with DBH ≥ 2.5 cm were measured [31]. Each subplot has a radius of 7.3 m, resulting in a sample plot area of 0.067 ha. We did not carry out any biomass and carbon assessment for each individual tree. For the simulations, we utilized aggregated plot level information, as reported in the forest inventory. Accordingly, the sample mean of the aboveground biomass (Eq. 1), the sample variance (Eq. 2), and the relative standard error (Eq. 3) were estimated as follows:

$$\hat{y} \quad = \quad \frac{\sum_{i=1}^{n} y_i}{n} \tag{1}$$

$$v(\hat{y}) \quad = \quad \frac{\sum_{i=1}^{n} (y_i - \hat{y})^2}{(n-1)} \tag{2}$$

$$SE_{\hat{y}} \quad = \quad \left(\frac{SD_{\hat{y}}/\sqrt{n}}{\hat{y}}\right) \times 100 \tag{3}$$

$$SD_{\hat{y}} = \sqrt{\frac{\sum_{i=1}^{n} |y_i - \hat{y}|}{n}} \tag{4}$$

where y_i is an observation on field plot, n is the sample size and SD is the standard deviation. Table 1 summarizes key statistics of interest for this study.

Table 1. Summary statistics for carbon stock in aboveground biomass of living trees with DBH ≥ 2.5 cm. Measurement and model error are not considered.

Forest Type	Plot (n)	Mean (tC ha^{-1})	Standard Error
Moist forests	141	56.84	4.77
Wet and rain forests	82	82.35	7.52
Total	223	66.22	4.17

Data are from third forest inventory of Puerto Rico. Measurement and model error are not considered. DBH: diameter at breast height.

2.1.2. Lidar data extraction

Field estimates of aboveground carbon density were used as a ground reference dataset to assess the potential gain in precision through the adoption of Lidar. The reduction in variance achievable with the integration of the regression estimator was assessed estimating the variance of the regression estimator:

$$\hat{v}_{srs}(\hat{t}_{reg}) = S_{\hat{y}}^2(1 - R^2) \quad (5)$$

$\hat{t}_{reg}$ is the regression estimator of Y, $\hat{v}_{srs}$ is the design variance estimator of $\hat{t}_{reg}$ under the simple random sampling, and $S_{\hat{y}}^2$ is the variance of $\hat{y}$.

No Lidar flight was conducted for the purpose of this study. We surveyed twenty refereed papers that used AGB estimation with Lidar sensors in tropical and subtropical rainforest biomes. We did not aim to provide a comprehensive review of Lidar applications in tropical forests; rather we collected sufficient information to provide our analysis with realistic and reliable estimates. For each paper we recorded, inter alia, the coefficient of determination (R^2), and used it to evaluate the contribution of remote sensing techniques to forest AGB and carbon densities prediction. The surveyed papers are listed in Table S1. The R^2 values for the reviewed studies range from 0.54 to 0.94, with an approximate mean of 0.8 and standard deviation of 0.11 [33–51]. This means that Lidar-based auxiliary variables correlate well with the field-based data. Firstly, we estimated the aboveground carbon stock based on field measurements alone and the variance (as in Equation (2)); secondly, we simulated the potential improvement in precision gained by using Lidar, assuming an R^2 of 0.8 by applying Equation (5).

2.1.3. Cost of carbon monitoring

Trying to approximate the exact cost of Lidar is a difficult task: it varies according to several factors. Moreover, most studies do not report costs in forestry applications. Lidar acquisition cost mainly depends on the type of platform used, area coverage and pulse density (also called pulses, points, returns, and echoes) [52]. Flight speed determines pulse density, which affects the accuracy of the forest structure metrics detected. Therefore, pulse density—i.e., speed and time of the flight—and accuracy are tightly related. The relationship between these two is not linear: they increase constantly, and beyond a certain pulse density level, accuracy remains nearly the same [52,53]. Published studies have demonstrated that a relatively modest reduction of laser pulse density had no effect on the precision of stem volume estimates [54,55]. Also in tropical areas, studies using pulse densities varying from 25 pulses/m^2 [40] to approximately 1.5 pulses/m^2 [20] reached similar results in terms of biomass prediction performance; however, several other factors can affect prediction performance, e.g., forest structure, terrain morphology, and models used. Overall, high pulse densities may not be necessary for estimation of forest biomass. Thus, relatively low-cost Lidar-data acquisition campaigns can lead to acceptable levels of accuracy for carbon stock estimates, and adopting low-pulse-density airborne laser scanner data for estimation of forest attributes at stand level could be cost efficient in forest inventorying [56]. Finally, a great impact on per unit area cost is attributable to economies of scales: the per-hectare costs decrease as the spatial extent of the flight increases.

We collected cost estimates from five studies and established accordingly two sets of costs to use in our study (Table 2). To show the effect of costs on aboveground carbon density monitoring in REDD+ context, we considered two plausible alternative costs of monitoring. In the first alternative, we assumed a smaller area inventory, typical for a REDD+ project. As this scenario implies higher costs per unit area, we selected expenses of \$5000 ha^{-1} for field-based sampling and \$8 ha^{-1} for Lidar. In the second scenario we assume a large forested area as in regional or national REDD+ monitoring; in this case, considering the associated benefits from economies of scale, the per hectare costs are set to \$500 and \$0.5 ha^{-1}, for field-based sampling and Lidar, respectively.

Table 2. Lidar acquisition and processing costs for forest monitoring.

Source	Spatial Resolution or Lidar Pulse Density	Coverage or Project Area (ha)	Acquisition and Processing Costs (in US\$)
Hummel et al. [57]	6.3 points/m^2 (mean pulse density)	12,650	5.6–9.3 US\$ ha^{-1}
Patenaude et al. [58]	-	2,800,000	4.15 US\$ ha^{-1} (only acquisition costs)
Wulder et al. [59]	90 cm (average horizontal distance between Lidar returns)	-	5 CND\$ ha^{-1}
Böttcher et al. [60]	-	13,600	4–5 US\$ ha^{-1} (plus additional 160 h processing time)
Asner et al. [20]	4 points/m^2 (mean pulse density)	National-scale (Perù)	0.01 US\$ ha^{-1}
Asner et al. 2011 [61]	50–70 kHz (pulse repetition frequency)	253,744	0.16 US\$ ha^{-1}
GOFC-GOLD [62]	-	-	0.5–1 \$ ha^{-1}

2.2. *Simulation approach*

We tested the adoption of two different approaches for MRV: the first approach assumes the use of Lidar data and the adoption of a model-assisted technique; the second approach utilizes stratified sampling with passive optical data. We evaluated costs-error implications of both approaches in accounting avoided emissions from deforestation and forest degradation in a REDD+ context under several potential scenarios. This resulted in three main methodological approaches and associated research questions:

(1) We created a series of subsamples from the 223 plots via bootstrapping. We simulated sampling with replacement for each sample size with 1000 iterations, starting from a sample size of 20 plots and increasing the size by one unit at a time, up to 223 plots. This resulted in a total of 204 different sample sizes and 204.000 iterations. Subsequently, the variance and the relative standard error of the estimate of aboveground carbon density (i.e., $\hat{y}$ in Equation (1)) were calculated for each iteration. Finally, the relationship between the relative standard error and the number of field plots was assessed.

(2) We investigated, by a scenario approach, how uncertainties expressed by the relative standard error obtained in step 1 determine the accountable avoided emissions. Each scenario is characterized by a different combination of (i) the accuracy of carbon monitoring (expressed by the relative standard error), (ii) the baseline carbon emissions from deforestation and forest degradation (i.e., RLs), and (iii) target for emission reductions as a result of REDD+ activities. The errors associated with the estimation of carbon stock changes were linked to the potential generation of carbon credits. Table 3 presents details of the scenarios implemented.

(3) Finally, the results of steps 1 and 2 were combined with a set of realistic monitoring costs. For the alternative monitoring systems, as presented in step 2, different levels of uncertainty and cost frameworks (see section 3.1.3) were realized and the achievable amounts of accountable avoided emissions calculated. This allows to study the cost-efficiency of alternative MRV-designs.

The above-described three steps were considered for two alternative monitoring approaches: (i) model-assisted estimation with Lidar remote sensing and (ii) stratified sampling with passive optical remote sensing. For each approach, the effect on the accountable generation of carbon credits was studied. In the model-assisted simulation, we assumed the availability of an error-free land-cover map, which allowed stratifying total land area in forest and non-forest. The estimate of the area of a certain forest type was based on the proportional number of sample plots located on that forest type. We simulated the integration of the field data and Lidar data through a model-assisted regression estimator, assuming an r^2 of 0.8. Lidar strips were assumed to be the same extension of the field plots.

In the simulation of stratified sampling, we assumed a combination of field assessments and remotely sensed optical data, which were assumed to be available wall-to-wall, providing auxiliary information for stratification. The alternatives are in line with Dec 14/CP 15 [64], as they utilize a combination of remote sensing for activity data and in-situ assessments for emission factors. The effect of the inclusion of different types of passive optical data on the accountable avoided emissions was evaluated considering two levels of classification errors: 3% and 20%. For combining uncorrelated uncertainties in area change and in carbon stock deriving from classification and sampling error, respectively, Equation (6) was used [65]:

$$E_{tot} = \sqrt{E_1^2 + E_2^2} \tag{6}$$

where E_1 is the classification error and E_2 is the sampling error.

Table 3. The defined set of values for the variables affecting the avoided emissions in the simulation study of Puerto Rico forestry data.

Relative standard error (%)	Baseline emission rate (or reference level) (%)	Emission reduction under REDD+ (%)
1.2-4	1	30
7-28	3	50
	5	75
	8	
	10	
	20	

2.3. Sensitivity analysis

Using results from the simulation study, the three variables affecting the avoided emissions were ranked according to their impact on the generation of carbon credits. In the sensitivity analysis, the "net avoided emission" is our variable of interest —i.e. the dependent variable— and is included as a function of three independent variables: standard error, RL, and target for emission reductions as a result of REDD+ activities. To describe and quantitatively assess the relationships between independent and dependent variables, we performed the Partial Rank Correlation Coefficient [66] using the sensitivity package of R, version 3.2.1 [67]. The Partial Rank Correlation Coefficient is based on regression analysis and measures the strength of the correlation between an input and an output variable, after removing any effect due to correlation of the other input variables. It ranges from -1 to 1, where -1 indicates a strong negative, 1 a strong positive, and 0 no correlation.

3. Results

The forest biomass carbon stock estimated from the 223 sample field-plots in the Puerto Rico forest dataset is 66.54 tons C ha^{-1}. We used this amount as reference measure to conduct the analysis. Relative standard errors of carbon density estimates decrease with increasing sample size. The relative standard error achievable with the model-assisted method and with the stratified sampling and passive remote sensing ranges from 1.5 to 4% and from 7 to 28%, respectively. The introduction of auxiliary data correlated with the response variable (r^2=0.8) in a model-assisted estimation significantly reduces the relative standard error (Figure 2).

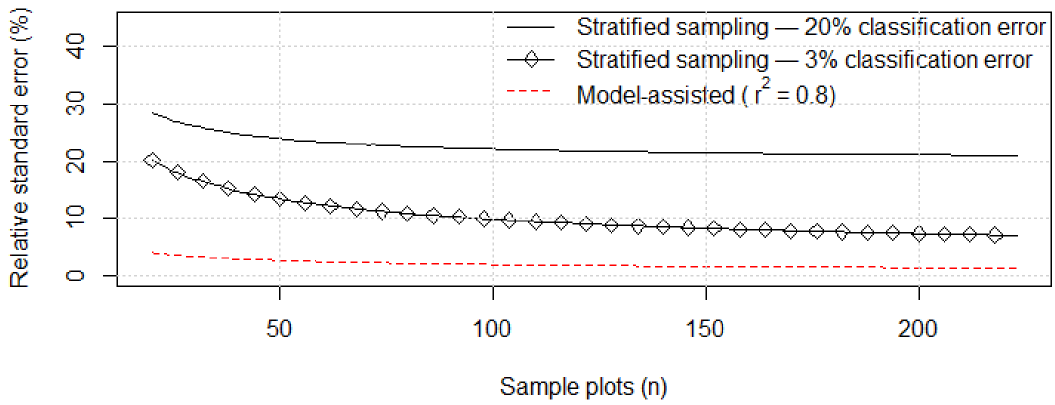

Figure 2. Percent standard error versus number of field sample plots in carbon estimates. The black lines show the error distribution for the estimation based on stratified sampling with passive optical remote sensing. The red dashed line shows the standard error attainable with a model-assisted estimation, assuming the adoption of a regression model with a coefficient of determination (r^2) of 0.8.

Combining the set of values assigned to the three variables that affect the generation of carbon credits (Table 3), 468 scenarios—i.e., possible permutations–were derived. However, only 52 out of 468 possible permutations had positive net avoided emissions at time 2 using the RME—i.e., generated carbon credits at the commitment period. It means that for the remaining 416 scenarios, the accountable emissions reduction produced by a REDD+ regime is smaller than or equal to the business-as-usual emission; therefore, they do not generate any carbon credit.

Figure 3 compares the relative standard error versus the accountable emissions reduction using Lidar data (Figure 3a) and passive optical data (Figure 3b,c). Results in Figure 3 are reported per hectare as this is the commonly adopted reference area used by scientists, field managers, and land-management professionals for carbon assessments [68]. The amounts of avoided emissions under a REDD+ scheme—which can be converted into accountable carbon credits—vary according to the MRV system adopted. Differences between Figures 3a–c demonstrate the effect of incorporating optical and Lidar-based auxiliary data in AGB estimation: the low relative standard error achieved under a model-assisted approach (Figure 3a) allows generating larger amounts of accountable avoided emissions. For example, under a model-assisted approach, credits can be generated even if the baseline emission rate is relatively low (e.g., 3%); conversely, using passive remote sensing, the minimum emission rate that would allow carbon credits generation is 20% (Figure 3b).

Larger amounts of credits are generated for larger quantities of baseline emission rates and emission reductions. Common to all scenarios is that when the baseline emission rate is 1% no carbon credit is generated (for that reason it is not displayed either in Figures 3 and 4). For low RLs (e.g., <10%), the accountable avoided emissions slightly vary as a function of emissions reduction. However, as the baseline emission rate increases, the accountable avoided emissions vary to a larger extent as emissions reduction change. This, concurring with findings from the sensitivity analysis (see last paragraph of Section 3), this demonstrates that the emission reduction has a relatively minor impact on the generation of carbon credits, particularly when the baseline emission rates are low.

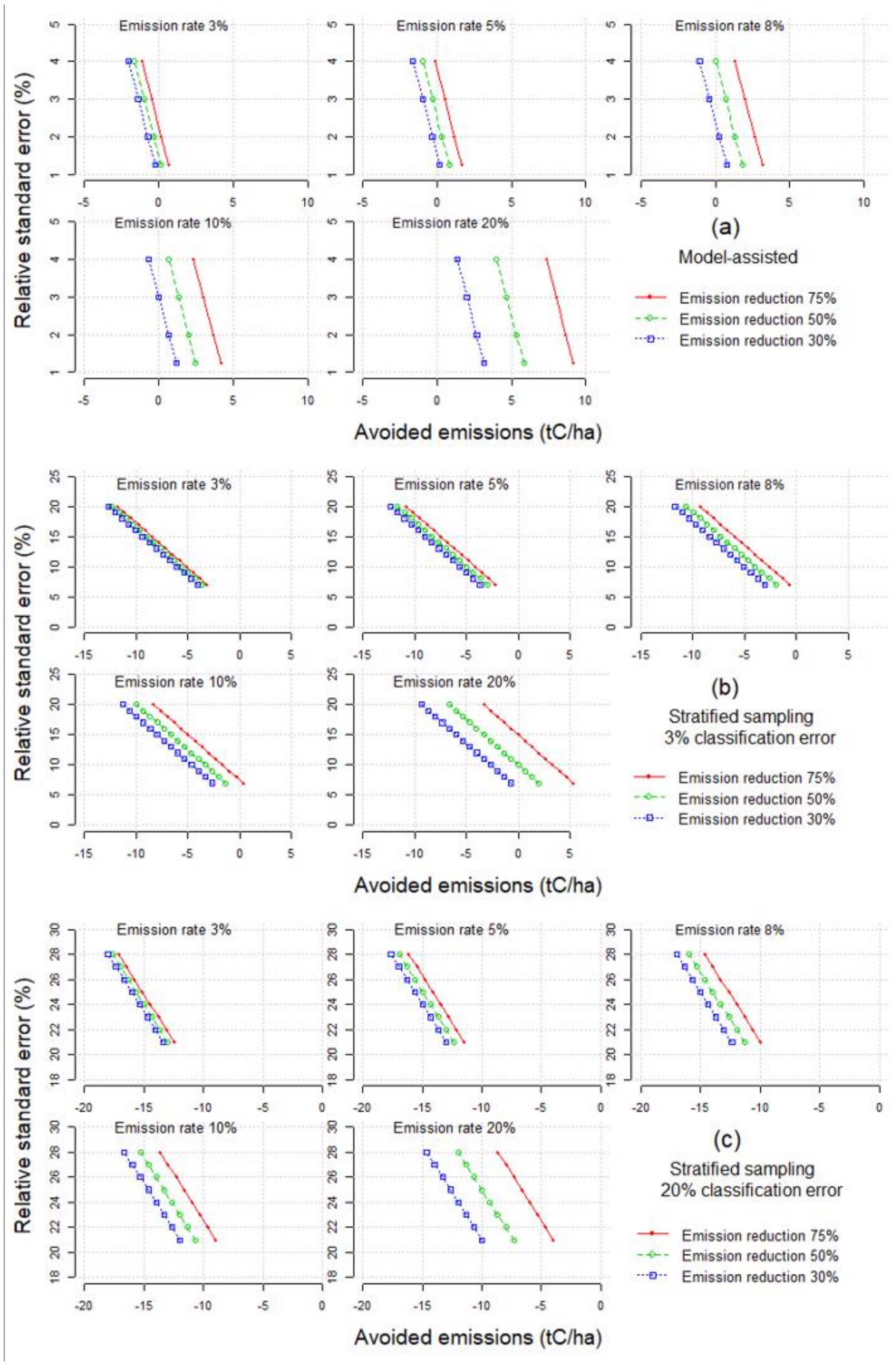

Figure 3. Comparison between the accountable avoided emissions versus the relative standard error achievable adopting three monitoring systems: (**a**) model-assisted approach with Lidar; (**b**) stratified sampling with passive remote sensing considering a 3% classification error; and (**c**) stratified sampling with passive remote sensing considering a 20% classification error. The figure shows the monitoring performances under different baseline emission rates (3%, 5%, 8%, 10% and 20%) and targets of emission reduction (30%, 50% and 75%). The three values of emission reductions are considered as percentage of emission reduction with respect to the reference levels. Negative values of avoided emissions indicate that emissions at t2 (commitment period) are larger than those at t1 (reference period), taking into consideration the principle of RME.

While Figure 3 shows per-hectare estimates, Figure 4 shows results for forested life zones considered in the study, i.e., Puerto Rico's moist forests, and wet and rain forests. Figure 4, which displays only the results of the model-assisted simulation, compares the cost of carbon monitoring and the accountable emission reductions generated for the respective costs. We did not include the simulation of stratified sampling with optical data in the analysis comparing monitoring costs and total avoided emissions, since there is no generation of carbon credits under such an approach, unless the classification error is 3% and the emission rate is above 20%. In fact, the simulation of stratified sampling with optical data that assumes a low classification error (3%) facilitates the generation of carbon credits only for emission rates above 20% (Figure 3b), while, under high classification error (i.e., 20%) (Figure 3c) no carbon credits would be generated in any of the assumed circumstances.

Figure 4 indicates that large amounts of avoided emissions are reached in all scenarios even with relatively low monitoring costs, i.e., when the monitoring costs are about \$20,000 and \$200,000, for low- and high-monitoring cost, respectively. The latter costs can be considered a turning point: beyond that, the avoided emissions do not increase significantly. For example, when the emission rate is 8% and the emissions reduction 50% (green line in the top right graph of Figure 4a), about 560 k tC can be accounted with an approximate cost of \$225,000; considering the same circumstance, increasing the costs by 80% would only increase the accountable carbon by 25%. This trend is common to all the considered scenarios. It suggests that beyond that turning point, greater investment in monitoring activities produces a minor reduction of the uncertainties, which does not result in an efficient generation of carbon credits.

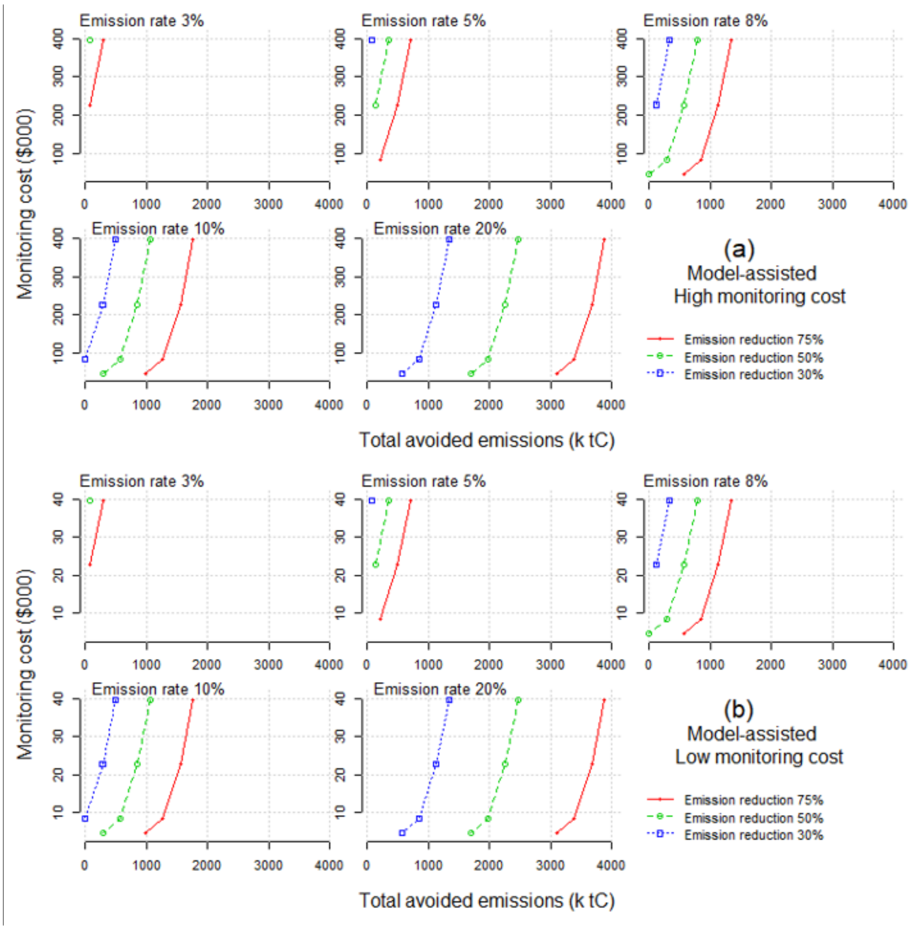

Figure 4. Total avoided emissions versus monitoring costs adopting a model-assisted technique. The figure shows how many tons of carbon can be generated for each alternative scenario and at what cost in case of high- (**a**) and low-cost (**b**) alternative.

In order to evaluate the viability of an MRV system as an effective investment, we calculated a fictive carbon-market price for a single ton of carbon that is needed to pay off at least the MRV costs (Table 4). We divided the total estimated cost of monitoring activities of the Puerto Rico's forest biomes considered in this study by the number of accountable avoided emissions (in tons of carbon) generated in any scenario. It allowed us to estimate the cost spent to monitor each ton of carbon and thus determine under which settings an MRV-system would be a useful investment. If the market price for a ton of carbon is higher than the costs reported in the fourth and fifth column, an MRV system would qualify as a useful investment for the given alternatives.

Table 4. Price paid for monitoring a single ton of carbon under different emission rates and monitoring scenarios.

Emission Rate (%)	Relative Standard Error (%)	Emission Reduction (%)	Cost of Monitoring a Single Ton of Carbon ($): Small Area Monitoring	Cost of Monitoring a Single Ton of Carbon ($): Large Area Monitoring
3	1.25	50	5.6	0.56
	1.25	75	1.4	0.14
	2	75	3.22	0.32
5	1.25	30	5.6	0.56
	1.25	50	1.12	0.11
	1.25	75	0.56	0.06
	2	50	1.61	0.16
	2	75	0.46	0.05
	3	75	0.41	0.04
8	1.25	30	1.22	0.12
	1.25	50	0.51	0.05
	1.25	75	0.29	0.03
	2	30	2.01	0.2
	2	50	0.4	0.04
	2	75	0.2	0.02
	3	50	0.3	0.03
	3	75	0.1	0.01
	4	75	0.08	0.01
10	1.25	30	0.8	0.08
	1.25	50	0.37	0.04
	1.25	75	0.22	0.02
	2	30	0.81	0.08
	2	50	0.27	0.03
	2	75	0.15	0.01
	3	50	0.15	0.02
	3	75	0.07	0.01
	4	50	0.17	0.02
	4	75	0.05	>0.01
20	1.25	30	0.29	0.03
	1.25	50	0.16	0.02
	1.25	75	0.1	0.01
	2	30	0.2	0.02
	2	50	0.1	0.01
	2	75	0.06	0.01
	3	30	0.1	0.01
	3	50	0.04	>0.01
	3	75	0.03	>0.01
	4	30	0.08	0.01
	4	50	0.03	>0.01
	4	75	0.02	>0.01

The reported costs also indicate the minimum price that should be paid per each ton of carbon sold in the carbon market, to cover at least the MRV system costs. The table shows the findings for the model-assisted simulation of monitoring Puerto Rico's moist forests, and wet and rain forests with Lidar remote sensing.

The sensitivity analysis allowed assessing the sensitivity of carbon credits generation with respect to factors' variation. The generation of carbon credits mostly varies as a function of errors. It confirms that the reduction of the standard error provides a decisive contribution in generating carbon credits; the RL has also a significant impact on the final avoided emissions. It is important to note that the amount of emissions reduction is the element with the smallest impact on the outcome.

4. Discussion

Based on field plot data, derived from the third forest inventory of Puerto Rico, we made a set of realistic assumptions to investigate the relationships between emission reductions under a REDD+ regime and some variables affecting such emission reductions. Setting reference levels (RLs), supplying emission reduction from avoided deforestation and degradation, and implementing an efficient monitoring system underlie effective REDD+ projects, because these factors determine the accountable emission reductions, and thus the carbon credits generation. We ranked these factors by conducting a sensitivity analysis and found that uncertainties in forest monitoring represent the factor that mainly affects carbon credits generation. Findings highlight the fundamental role of Lidar sensors in forest carbon monitoring, particularly in REDD+; combining statistical features of forest sampling with Lidar data enables a significant generation of carbon credits. Investing in MRV systems based on statistically-sound sampling designs, with quantifiable precision, and remote-sensing techniques contributes to reduce uncertainties and to increase the amount of accountable carbon credits that can be claimed.

Uncertainties in carbon estimates represent the factor that mainly affects the quantification of accountable emissions reduction and, therefore, can undermine the derived flow of benefits, such as the results-based payments to developing countries for avoiding deforestation [29,69]. The reduced uncertainties shown in the model-assisted simulation point out the potential contribution that Lidar data can give to REDD+ initiatives. Combining space- or air-borne imagery and field assessments offers an efficient way to monitor and map carbon stock, especially if large areas are considered [70,71]. This combination can have a twofold implication on REDD+ efficiency: for its lower costs of implementation–particularly in large-scale projects– and for the reduced uncertainties, which have a positive effect on the generation of measurable tons of reductions in CO_2 emissions. However, the efficiency and success of a national monitoring program rely on many elements, which can be grouped in four general areas of investigation: (i) measurement techniques and data collection; (ii) data compilation, analysis and processing; (iii) remote sensing techniques; and (iv) information management techniques [72]. Therefore, planning statistically rigorous sampling designs aimed at supporting field-measurement campaigns integrated with remote sensing data, is fundamental in forest inventory, as well as in MRV.

Even though we applied a conservative approach to estimate uncertainties of carbon stock change, monitoring avoided emissions through a model-assisted technique would enable generation of carbon credits under relatively low RLs as well. In fact, applying a conservativeness principle for MRV of carbon emissions–to not overestimate the reduction of emissions–can critically reduce the accountable amount of carbon credits that can be claimed [29,30]. We used the Reliable Minimum Estimate (RME) as a method to discount uncertainties, however, the presented results could have been significantly different if uncertainties were addressed using another method. Pelletier et al. [73] showed that the degree of conservativeness applied can strongly influence the overall creditable emission reductions, and stated that downstream discounts (i.e., conservative approaches) should only be applied if the uncertainties exceed a certain threshold. We used the RME method and did not test other ones (e.g., the FCPF Carbon Fund Approach, the KP Conservativeness Factors and the CDM Draft Proposal): comparing alternative approaches to address uncertainties and evaluating the effects on the potential carbon credits goes beyond the scope of this study but is an important subject for future studies. Additionally, at present, no internationally standardized regulations exist for the management of uncertainties in this field.

The relationship between monitoring costs and generation of carbon credits is not linear: increasing monitoring activities–and so the accuracy–beyond a certain threshold yields slightly larger generation of carbon credits. In this study, this threshold corresponds to a relative standard error of 2%. The relatively low error of carbon estimates assumed in this study depends, inter alia, on the biome homogeneity and the large sample size. However, the error trend simulated under the model-assisted approach is plausible [33,49]. We provided realistic figures of carbon monitoring costs according to data reported by the available literature. Clearly, these costs must be considered as indicative and should be interpreted with care because they might vary substantially from country to country; case-specific cost-benefit assessments are always essential.

Another critical aspect affecting the successful implementation of REDD+ projects is the method used to set the RLs. RLs have a larger influence than the actual reduction of emissions on the generation of carbon credits, and the impact of RLs is almost as important as the approach used to monitor forest carbon. Findings highlight the crucial role of RLs, and bring a new insight on their effect on the accountable emissions reduction. The necessity of establishing RLs has been a key issue in the political agenda. While politicians and scientists have been mostly focusing on evaluating and investigating feasible, sound and effective methods to setting RLs [17,74,75], the extent to which RLs affect the performance of REDD+ projects remains uncertain. What is known is that incorrectly-determined RLs can generate under- or over-compensation, which would reduce both cost-efficiency and incentive to reduce emissions through the five REDD+ activities [76]. Sheng et al. [77] presented one of the few studies (to the best of our knowledge) that analyzes "how rate of carbon emissions from deforestation and degradation is influenced by underreported emissions caused by asymmetric information and RLs". They claim that RLs are essential in the implementation of REDD+ and that overestimating RLs leads to an increase in actual emissions.

Whether the REDD+ program will support forest carbon as a climate change mitigation strategy or not will depend on a number of aspects, which differ nationally and regionally. We only considered some factors that contribute to a successful implementation of REDD+ projects; we are fully aware that several other variables also have large impacts on the generation of carbon credits and deserve careful consideration. Our study does not take into consideration all the social, economic and policy aspects, which may often be of greater importance than technical and scientific matters. Nevertheless, our findings can represent a basic guidance for countries willing to design an MRV system, and provide new insights and a better understanding of some key elements that affect carbon credits generation, and thus results-based payments.

5. Conclusions

We analyzed some key factors underlying effective REDD+ projects and assessed, under various realistic circumstances, the potential generation of carbon credits. Three key factors mainly involved in the generation of carbon credits were investigated: defining reference levels, supplying emission reductions due to REDD+ and designing effective MRV systems. Carbon credit generation significantly depends on the MRV-system adopted to assess aboveground carbon density, and applying a model-assisted technique strongly influences the potential generation of carbon credits.

Conceiving of an MRV system as an investment can encourage the implementation of well-defined, long-term monitoring strategies. Concurring with Pelletier et al. [73] we believe that the results-based payments could pay-off the necessary investment in technology that would enable an accurate estimate of activity data and emission factors. However, several barriers hinder fast progress. For example, finding stable, long-term sources of REDD+ finance remains a key outstanding issue.

In conclusion, we believe that to understand MRV systems as an investment for generating carbon benefits, a REDD+ market-based architecture is necessary. This architecture would promote the reduction of emissions and gather the finances necessary to do so [78]. However, concerns over measurement and monitoring of forest-related activities prevent REDD+ carbon credits to be exchanged in compliance markets. To address these concerns and create favorable conditions for a market-based approach, transparent, robust, and consistent carbon accounting rules have to be established. To achieve low uncertainties in carbon estimates, like those reported in this study, important investments in MRV should be incentivized. In this connection, knowledge and technology transfer—such as statistical sampling methods and Lidar—from developed to developing countries should occur more widely and faster, and international programs (such as REDD+) could effectively boost innovative monitoring techniques in forest-rich countries [79].

Supplementary Materials: The following are available online at www.mdpi.com/link, Table S1: Studies reviewed and key parameters collected.

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