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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

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; this reduces the design variance of the field sample-based estimator of the population's total aboveground 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 levels), 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]. Depending on circumstances and needs, one sensor type can be more suitable than another: 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].

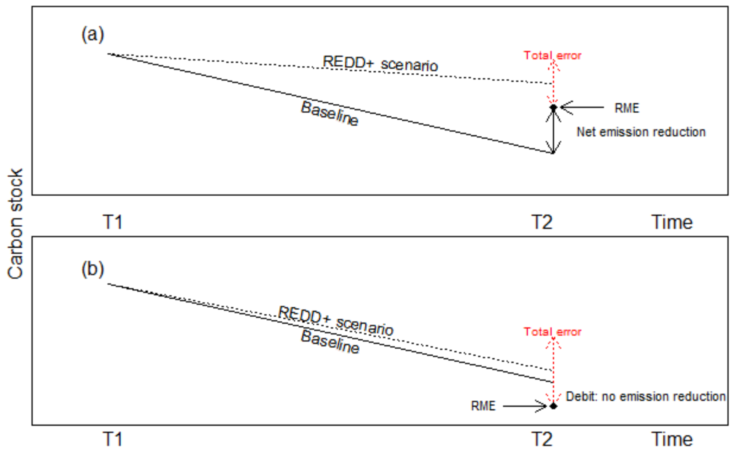

Figure 1. Projections of carbon emission under a business-as-usual baseline and a REDD+ scenario; In the upper figure (**a**) a positive reduction of emissions is shown; In (**b**) the projected REDD+ scenario emission reduction is smaller and the magnitude of the total error is larger; this condition 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 $\geq$ 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 (Equation (1)), the sample variance (Equation (2)), and the relative standard error (Equation (3)) were estimated as follows:

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

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

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

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

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 $\geq$ 2.5 cm.

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:

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

$\hat{t}_{reg}$ 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 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.

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	

The relative standard error values are based on the results of the simulation study (see Figure 2).

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 [63], 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 [64]:

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

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

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 [65] using the sensitivity package of R, version 3.2.1 [66]. 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).

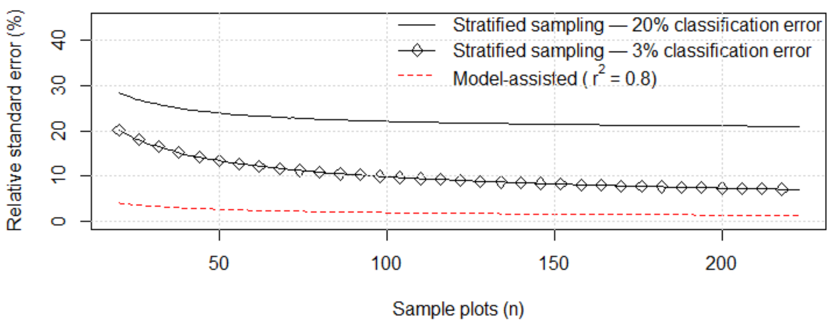

Figure 2. Percent standard error versus number of field sample plots in carbon estimates. The black lines show the error distribution for the estimation based on stratified sampling with passive optical remote sensing. The red dashed line shows the standard error attainable with a model-assisted estimation, 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 [67]. 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 Figure 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.

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.

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.

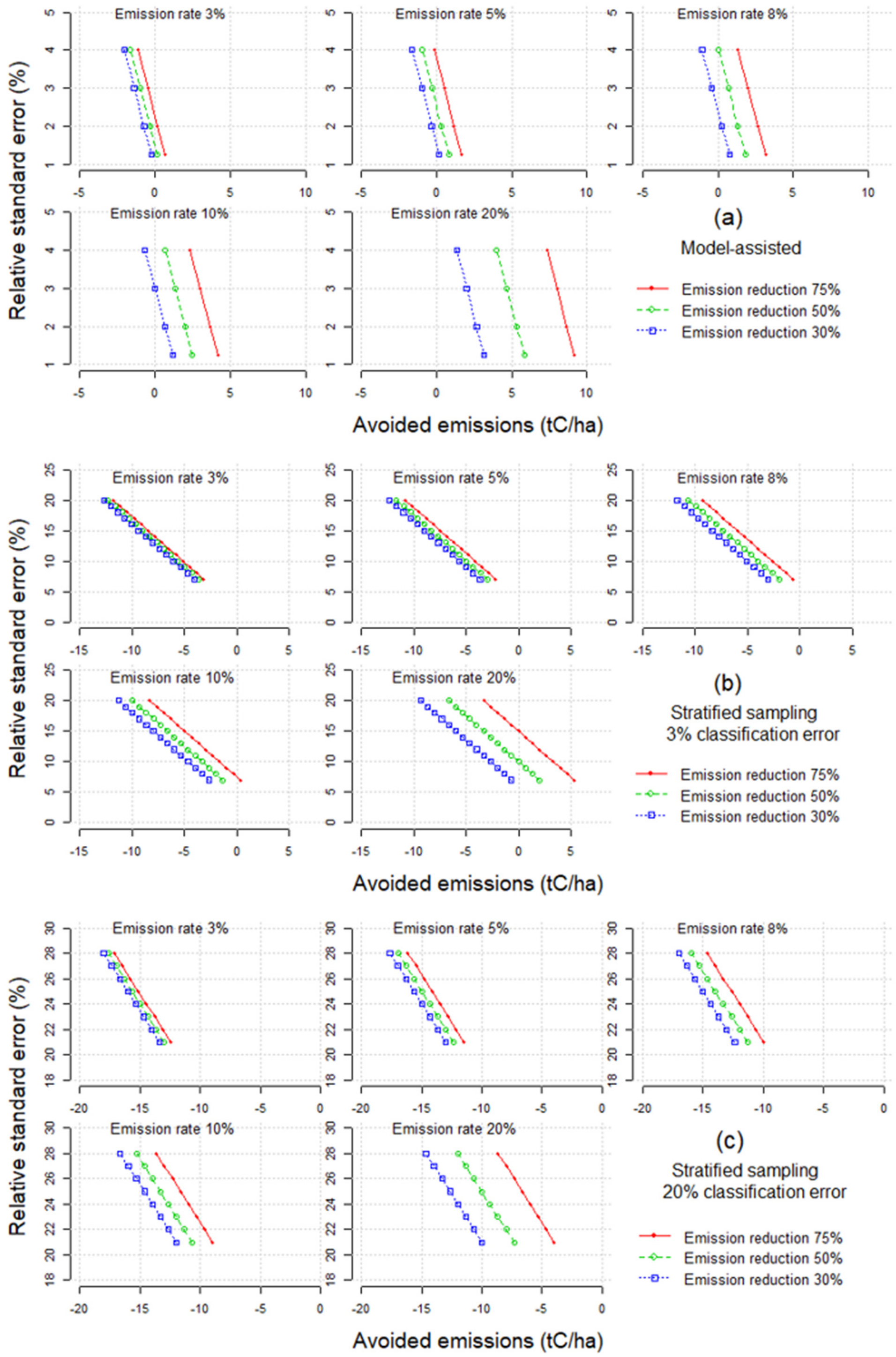

Figure 3. Comparison between the accountable avoided emissions versus the relative standard error achievable adopting three monitoring systems: (**a**) model-assisted approach with Lidar; (**b**) stratified sampling with passive remote sensing considering a 3% classification error; and (**c**) stratified 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.

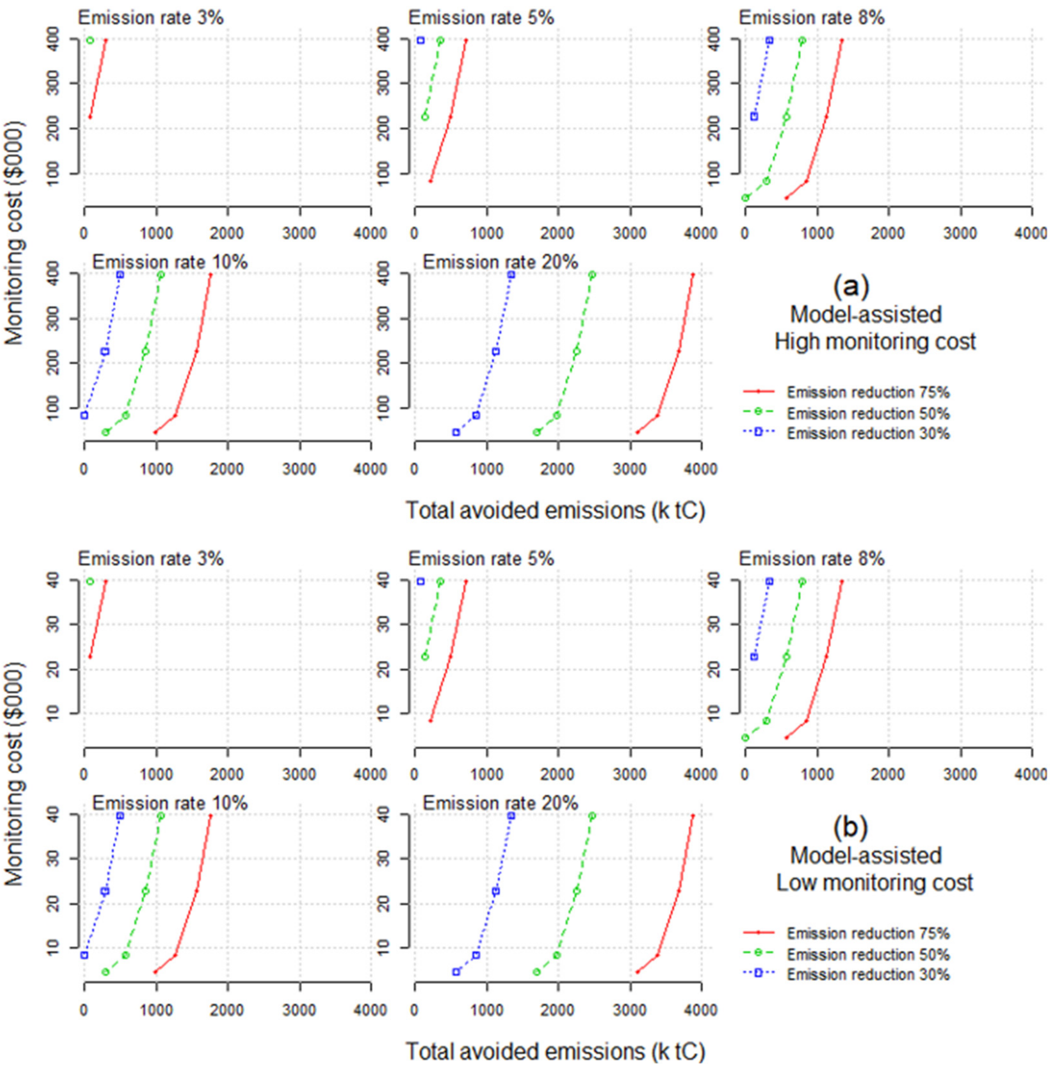

Figure 4. Total avoided emissions versus monitoring costs adopting a model-assisted technique. The figure shows how many tons of carbon can be generated for each alternative scenario and at what cost in case of high- (**a**) and low-cost (**b**) alternative.

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

Table 4. *Cont.*

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
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 [29,68]. 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 [69,70]. 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 [71]. 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. [72] 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 [17,73,74], 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 [75]. Sheng et al. [76] 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. [72] 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 [77]. 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 [78].

Supplementary Materials: The following are available online at www.mdpi.com/1999-4907/8/8/271/s1, Table S1: Studies reviewed and key parameters collected.

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