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Determining a Carbon Reference Level for a High-Forest-Low-Deforestation Country

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Abstract: *Research Highlights*: A transparent approach to developing a forest reference emissions level (FREL) adjusted to future local developments in Southern Cameroon is demonstrated. *Background and Objectives*: Countries with low historical deforestation can adjust their forest reference (emission) level (FREL/FRL) upwards for REDD+ to account for likely future developments. Many countries, however, find it difficult to establish a credible adjusted reference level. This article demonstrates the establishment of a FREL for southern Cameroon adjusted to societal megatrends of strong population—and economic growth combined with rapid urbanization. It demonstrates what can be done with available information and data, but most importantly outlines pathways to further improve the quality of future FREL/FRL's in light of possibly accessing performance-based payments. *Materials and Methods*: The virtual FREL encompasses three main elements: Remotely sensed activity data; emission factors derived from the national forest inventory; and the adjustment of the reference level using a land use model of the agriculture sector. Sensitivity analysis is performed on all three elements using Monte Carlo methods. *Results*: Deforestation during the virtual reference period 2000–2015 is dominated by non-industrial agriculture (comprising both smallholders and local elites) and increases over time. The land use model projections are consistent with this trend, resulting in emissions that are on average 47% higher during the virtual performance period 2020–2030 than during the reference period 2000–2015. Monte Carlo analysis points to the adjustment term as the main driver of uncertainty in the FREL calculation. *Conclusions:* The available data is suitable for constructing a FREL for periodic reporting to the UNFCCC. Enhanced coherence of input data notably for activity data and adjustment is needed to apply for a performance-based payment scheme. Expanding the accounting framework to include forest degradation and forest gain are further priorities requiring future research.

Keywords: REDD+; Cameroon; reference level; deforestation; agriculture; forest baseline

1. Introduction

The REDD+ mechanism was designed to reward countries financially for reducing emissions from deforestation and forest degradation (DD), which significantly contributes to total greenhouse

gas (GHG) emissions worldwide [1]. REDD+ also includes the promotion of sustainable management of forests and increasing and conserving forest carbon stocks [2]. The underlying idea is that avoided deforestation offers a large and very cost-effective potential to curb GHG emissions [3,4]. To measure progress in this regard, a benchmark measure is needed to define how much would be emitted in the absence of REDD+ interventions. This benchmark is called a forest reference level (FRL) or forest reference emission level (FREL). The former refers to an accounting framework where forest gain is considered, the latter refers to forest loss only. FRL/FREL was institutionalized in the Warsaw Framework as one of the four elements required to participate in REDD+ [5].

The establishment of a FRL/FREL is preceded by a number of important policy-related decisions including a national definition of what constitutes a forest; the scale in terms of geographical coverage where FRL/FREL for sub-national jurisdictions or regions can be developed as an interim measure *en route* to developing a national baseline (Decision 1/CP.16 - FCCC/CP/2010/7/Add.1); the scope of the FRL/FREL in terms of the relevant activities causing changes in forest carbon stock, the carbon pools and the gases to be considered; and a reference period in the recent past. Together, these decisions provide the framework for measuring the area extent of change (activity data or AD) and emission factors (EF), which is the difference between carbon stored before and after conversion of forest to another land use. The combination of AD x EF for a given scale, scope, and period results in a historic baseline. Some countries such as Brazil and Indonesia used these historical baselines as their FREL, i.e., as the benchmark to measure their progress towards reducing future emissions from deforestation. Historical deforestation rates are very high for these two countries.

The thus established FRL/FREL can then be submitted to the United Nations Framework Convention on Climate Change (UNFCCC) for technical assessment. This is to assess the degree to which information provided is in accordance with the guidelines for submissions of information on FREL/FRL and offer a facilitative, non-intrusive, technical exchange of information on the construction of the FREL/FRL (FCCC/CP/2013/10/Add.1.). The information provided (including historical information) should be guided by the most recent Intergovernmental Panel on Climate Change (IPCC) guidance and be transparent, complete, consistent, and accurate (FCCC/CP/2011/9/Add.2).

Many countries and jurisdictions such as so-called high-forest-low-deforestation (HFLD) countries, which are characterized by high remaining forest cover and comparatively low rates of deforestation, dispose of atypical starting situations for REDD+ [6]. Historical rates of deforestation alone are inadequate to define an FRL/FREL for HFLD countries, especially in cases where there are clear indications of changes (increase) in drivers of DD. The risk of using a historical baseline in HFLD countries is that the efforts necessary to contain future deforestation could be underestimated. The FRL/FREL will therefore have to take socioeconomic development into consideration, which influence the trajectories of future drivers of change and the effort to be compensated will have to be based on the effectiveness of national/international policies and measures to address these.

However, the potential for inflation of the FRL/FREL and the subsequent creation of "hot air" when historical baselines are adjusted, have been the subject of much thinking about design principles [7–9] and criticism of applied methodologies [10–13]. How to define a benchmark for emissions remains an issue in the era of the Paris Agreement where many countries mention REDD+ in their Nationally Determined Contributions (NDC's) [14] and state that GHG emissions from land use, land-use change and forestry (LULUCF) are likely to increase in the future under the business-as-usual scenario [15,16]. Methodologies used to justify a perceived increase of future emissions vary greatly and often go unreported [15,16].

Engagement in REDD+ will ultimately depend on a country's capacity to demonstrate the level of emissions from forests with and without REDD+ interventions. The lack of data or capacity, or both, to measure, project, and monitor emissions has been put forward as a possible major hindrance, notably for African countries, to effectively participate in REDD+ [17–21], although the stepwise approach of improving reference levels as new and better data become available (See COP decision 12/CP17) recommended by the UNFCCC, largely facilitates the task. Globally, more than 30 countries have

already submitted FREL/FRLs to the UNFCCC for technical assessment, some of which have also claimed upwards adjustment [16]. The methodology used to justify the upwards adjustment is often poorly documented.

This paper focuses on the development of a virtual subnational FRL as an interim measure towards the development of a national FRL for Cameroon. Southern Cameroon serves as a case study area since it is facing a bundle of societal megatrends that are poised to have an impact on the still very high forest cover in coming years: The country's economy has recovered from the crisis of the early 2000s [22–24]; the local population is growing rapidly, especially in urban centers where the population tends to have different food consumption patterns; and the area is known as a bread basket for export to neighboring Gabon, Republic of the Congo, and Equatorial Guinea. These trends, combined with continued low agricultural yields, are generally expected to drive agriculture further into forest areas [25–28].

From the perspective of a stepwise approach towards the development of a national FREL, the study uses available datasets to establish an adjusted subnational FREL for Cameroon and critically analyses future steps for improving the FREL as the country aims to access performance-based finance. The working hypothesis underlying the adjustment term of the FREL is that there is a clear set of quantifiable variables related to the development of a society leading to forest conversion that can be projected into the future [29] while aiming at a high degree of transparency. The methodology for FREL development presented in this paper is easily replicable in other HFLD countries.

2. Materials and Methods

The study area is presented in Section 2.1 and a set of policy-related working definitions adopted by the country is presented in Section 2.2. These are the boundary conditions for the establishment of the subnational FREL. The virtual reference level for the reporting period 2020–2030 for the study area is computed based on historical emissions derived from activity data (Section 2.3) combined with emission factors (Section 2.4) and adjusted to national circumstances using a land use model (Section 2.5). The approach to sensitivity analysis of all components of the FREL is presented in Section 2.6.

2.1. The Study Area

The study area encompasses seven (out of a total of 58) administrative divisions located in the humid tropical part of southern Cameroon (Figure 1). It covers a total area of 9.3 million ha, which is equivalent to the land area of Hungary. The climate is dominated by ample rainfall of 1500–4000 mm per year, which allows for the growth of moist evergreen forests that cover close to 90% of the study area [30].

The population density of around 14 people per km^2 is relatively low and concentrated around the coast and in towns and villages along the road to the capital city Yaoundé, located around 50 km north of the boundary of the study region. The main drivers of deforestation in the region are shifting smallholder agriculture, agro-industrial plantations that mainly focus on tree crops and the expansion of transport infrastructure [31].

2.2. Working Definitions: Scale, Scope, Forest Definition, and Virtual Reporting Periods

Cameroon's draft national REDD+ strategy provides the theoretical working definitions that frame the conditions under which an FRL/FREL can be developed. In the scope of REDD+ in Cameroon, the term "forest" is defined by three criteria: Crown cover of 10% or more, an attainable tree height of 3 m or more, and a patch size of 0.5 ha or more. Mono-specific tree crops such as plantations of oil palm, rubber, and full-sun cocoa are explicitly excluded from the forest definition. The country also considers all eligible REDD+ activities (reducing emissions and increasing removals) in their draft strategy. All carbon pools should be considered in the establishment of the FRL, with an emphasis on accounting for significant pools at a Tier 2 level. CO_2 is the most relevant GHG in the forestry

sector but in specific cases CH_4 and N_2O may also be considered. The country has not formally fixed a reference period and a performance period.

The establishment of an FRL is further constrained by available data. First, there is no dataset available to reliably trace the degradation or gain of forests, which restricts the scope of this article to establishing an FREL of CO_2 emissions from deforestation only, where other gases potentially emerging from smaller fires are considered negligible. Pools are restricted to above and below-ground biomass due to the uncertainty associated with more liable pools. This study uses the periods 2000–2015 and 2020–2030 as virtual reference and reporting periods, respectively, based on the availability of relevant datasets. "Virtual" reference and reporting periods refer to the working definition made in the context of this article as opposed to the political decision that lies in the sovereignty of the country.

2.3. Remote Sensing of Activity Data

Activity data was derived from a countrywide reference land cover map for a base year (2000) and the assessment of forest loss over the reference period (2000–2015), clipped to the extent of the study area. The reference maps for 2000 and 2015 were developed using a hierarchical supervised decision tree-based wall-to-wall mapping methodology implemented in PCI Geomatica Software. The assessment was run on a composite of 10,517 terrain corrected (L1T) Landsat images (bands 3,4,5,7) with low cloud coverage sourced from the United States Geological Survey (USGS) Earth Explorer and resulted in seven thematic classes: (1) Primary and (2) secondary terra firma and (3) primary and (4) secondary swamp forests, (5) mangroves, (6) agro-industrial plantations of perennial crops, (7) non-forest land, and (8) forest loss since the year 2000. The workflow largely builds on a recent study conducted in the Democratic Republic of the Congo [32]. A minimum mapping unit of 0.5 ha compliant with the national forest definition was applied to forest loss areas to eliminate small-scale degradation and natural disturbances from the resulting deforestation map for 2000–2015. The assessment of accuracy, deforestation dynamics within the 2000–2015 period and identification of drivers of deforestation was performed using a stratified random sampling method [33,34]. To that end, 348 dated reference samples from Landsat and high-resolution images from Google Earth were collected, visually interpreted, and used to validate the reference and the forest change map, respectively [32]. The pre-defined protocol for the assessment of drivers of deforestation distinguishes eleven classes and is presented in Appendix B alongside a link to the online sample visualization.

2.4. Emission Factors from the National Forest Inventory

Emission factors were developed on the basis of the country's first, and thus far only, national forest inventory (NFI) performed during the years 2003–2004 [35]. Tree biomass in Cameroon was inventoried using 204 valid census tracts distributed according to a systematic stratified sample design across the country - 45 of which are located inside the study region. Tree biomass in both forest and non-forest (such as agroforests, fallows, tree plantations, etc.) areas was considered, although non-forest classes are only sparsely present in the final sample.

Re-analyzed for the purpose of REDD+, the NFI data allows for distinguishing carbon stocks in five land cover types in the study area: (1) Forest, (2) settlements, (3) grassland, (4) fallow land, (5) annual crops, and (6) perennial crops. Carbon stocks were calculated by combining data and information on tree diameter and tree height from the NFI with pan-tropical allometric equations [36] and proxy shoot-to-root ratios for moist tropical forests [37]. Emission factors were computed as the difference between initial forest carbon stocks of the living biomass and the carbon stocks left in the vegetation after forest conversion and presented in the results section. Further details on NFI data and assessments can be found in the background report [38].

2.5. Adjustment of the Reference Level to National Circumstances

Given that non-industrial agriculture is by far the main driver of deforestation in the region [39], the main adjustment of the reference level was calculated for non-industrial agriculture using a land

use model. The model's rationale builds on demand for agricultural products that needs to be satisfied by a matching supply. The model is implemented in MS Excel and is available for download from http://dare.iiasa.ac.at/56. It provides results in five-year intervals from 2000 until 2030 for each of the five agro-ecological zones of Cameroon [40] and the study area, and in terms of the contributions of the 15 most prevalent agricultural crops in the country (see a list of crops in the annex). The model comprises six computation steps, each of which is parameterized using available data for Cameroon: (1) Population, (2) food and feed consumption, (3) trade within Cameroon and with the rest of the world, (4) agricultural production, (5) cultivated area, and (6) resulting forest cover change.

2.5.1. Population

Demographic development plays a key role in the land use model. It is fed by national data and projections by division (third administrative level) and separately for urban and rural areas. In this study, towns with more than 50,000 inhabitants are considered urban areas. Population data for the years 1987 and 2005 is available from the national population censuses conducted by the Central Bureau of Census and Population Studies of Cameroon (BUCREP).

The population for reference year 2000 of the FREL is calculated based on 1987 census data and the average growth rate between 1987 and 2005. Existing population projections according to the shared socioeconomic pathway (SSP) [41,42] scenario number 3 of the SSP Framework were used to project the population growth available from the censuses to the future for the years after 2005 until the end of the virtual performance period in 2030. Rather than the middle-of-the road scenario SSP2, SSP3 is used as it is very close to the official national population projections [43]. SSP scenarios about future population growth for Cameroon are only available at the national level and were therefore used to project national data in the future only.

The data shows that the population in the study area has increased from 706,000 people at the time of the first census in 1987 to 1.05 million in 2005 with the share of the urban population increasing from 16% in 1987 to 22% in 2015. According to the SSP3 scenario, the population will increase further to 1.33 million by 2030, with 38% of the population living in urban areas.

2.5.2. Consumption

Living conditions and relative wealth in Cameroon are improving with an average of 4.2% GDP growth per annum over the last 10 years [44]. This has direct repercussions on people's dietary habits. Income growth and urbanization, for instance, lead to changes in consumption such as a more diverse diet that includes a larger share of animal protein, fats, and oils (a phenomenon known as Bennett's Law [45]).

Data on diets for the different regions of Cameroon comes from the UN World Food Program [46] and projected to the future using GDP projections from the World Bank and income elasticities for food consumption [47] that translate into future diets specific to Cameroon. These socioeconomic changes result in a projected increased per-capita consumption of beans and groundnuts (+35% each until 2030), bananas and plantains (+27%), as well as pork and poultry (+45%).

The resulting per capita consumption, combined with population projections result in an estimate of future food consumption that can be met either by local production, imports from other regions of the country, or imports from other countries.

2.5.3. Trade

The model considers flows of agricultural goods within Cameroon, as well as to and from neighboring countries and the international market. Trade of crops and foodstuff with third countries is documented by national publications [48] and the Food and Agriculture Organization Corporate Statistical Database (FAOSTAT). Statistics on internal trade within Cameroon are not available and therefore estimated as the complement of local agricultural production needed to feed the local population. The share of the consumption in each of the five agro-ecological zones (AEZ) and rural/urban area that is satisfied by each

source, that is local, each other AEZ or the rest of the world. This estimation is made according to three guiding principles: (1) The (over) supply status of a certain crop; (2) the proximity of the other regions with the importing region; and (3) it is assumed that imported goods from other countries mostly go to the urban areas. Further, the shares of imported versus locally produced food are assumed to be constant over time.

2.5.4. Agricultural Production

Production in each region is computed based on the local demand times the share that is domestically produced in case the region is a net importer, plus the sum of the shares of the region in the consumption of other regions times their projected level of consumption if the region is a net exporter. The local demand for crops is the sum of the demand for human consumption and for animal feed such as poultry.

A significant share of production is lost or wasted at different stages in the value chain [49,50]. This leads to a higher computed production compared to the computed consumption requirement. According to the Food and Agriculture Organization (FAO) [51], post-harvest losses reached 32% of the cassava production in 2010. For periods beyond 2010, constant post-harvest losses shares are assumed.

2.5.5. Harvested Area and Arable Land

Once the production level is computed, the harvested area results from dividing production by agricultural yields. Yields in the model are specified per administrative region based on data from the ministry of Agriculture's (MINADER), the AGRISTAT statistics report series, and counter-checked with country-level production data from FAOSTAT. Yields are kept constant at reported levels for future projections.

In order to compute the impact on arable land, two other parameters are used: (1) The average number of harvests per year and (2) the share of fallow land in total arable land. The average number of harvests per year is crop and region specific and is taken from the AGRISTAT reports over 2000–2004. The area that lies fallow is mainly driven by the fallow period, which varies with the population density, that is to say, fallow periods are shorter in densely populated areas [52]. Furthermore, fallow periods are longer in humid tropical regions than in drier savannah areas. In the model these are capped to two years (fallow multiplier: 1). A typology of fallow periods is presented in Table 1, where the resulting fallow coefficient is applied in the model. No fallow period is assumed for perennial crops such as oil palms, cocoa, rubber, and banana plantations.

Table 1. Typology of fallow duration as a function of population density in Cameroon. Source: Modified after Gillet et al. (2014).

Population Density (inhab./km^2)	Cultivation vs. Fallow Duration	Fallow Multiplier
<20	2y cultivation, 7y fallow	3.5
20–30	2y cultivation, 5y fallow	2.5
>30	2y cultivation, 3y fallow	1.5

At this stage, the model predicts the amount of arable land required to satisfy the demand for food and feed, which are the key drivers of deforestation, in intervals of five years.

2.5.6. Deforestation and Emissions

Forest clearing is a direct result of cropland expansion into forest areas. However, the share of cropland claimed from forests as opposed to other, non-forested lands varies from one region to another and is determined by the availability of non-forest land. For Cameroon, the share of new cropland claimed from forest ranges from 6% in the Far North region, which is dominated by open

vegetation, to 90% for the tropical humid zone [53]. For the study area in southern Cameroon, the same study finds a share of 85% of new cropland claimed from forest.

Next, projected deforestation is combined with carbon stocks for the land cover types presented in Section 3.2. Carbon stock values are derived from the first and thus far only NFI performed in 2003 [35] (see details in Section 2.4). In this context, the results of the NFI are preferred over those of other studies, since reporting for REDD+ requires a long-term monitoring framework where carbon stocks can be traced over time using one coherent methodology.

2.5.7. Model Validation—Comparison of Model Results with Observed Variables

Obtaining a good match of model results with independently observed data is key in terms of making a credible argument for an adjustment to national circumstances. To this end, checks that allow the comparison of intermediary model outputs at each calculation step with independent statistics—such as agricultural production computed by the model as described in 2.5—is compared with statistical data from the ministry of agriculture (MINADER) or the FAO.

The deforestation dynamics computed by the model are also compared to data from available remote sensing products such as that used to define activity data as described in Section 2.3 and independent global-scale remote sensing products [54,55] clipped to the extent of the study area.

2.5.8. Projecting Other Drivers—Industrial Agriculture and Infrastructure

The expansion of industrial agriculture and infrastructure in the context of Cameroon are based on discrete political decisions, and their future impact is estimated in terms of legal claims to land clearing. Legal claims to clearing land takes the form of sales of standing volumes (SSVs) that allow for unsustainable wood harvesting, and typically precedes the establishment of agro-industrial plantations and infrastructure projects [56,57]. That being said about land allocation, future land use in these areas is uncertain as only a small fraction of planned agricultural development projects in the country are actually implemented [58].

A total of 66,971 ha of SSVs that are almost entirely (97%) covered by forests are currently located inside concession areas flagged for the development of agro-industrial oil palm and rubber plantations, while another 17,980 ha are allocated around the Kribi deep water port to make way for port infrastructure. To account for the uncertainty associated with the development of these areas, it is conservatively assumed that only 10% of SSVs will be cleared and replaced by perennial crops and infrastructure for agro-industrial concessions and the deepwater port, respectively, by 2035.

Figure 1. Overview of land cover and land allocation in the study area. Land allocation in the form of agro-concessions (thick white outline) and unsustainable logging concessions (Sales of Standing Volumes - SSVs; thin white outline) are located at the coast and in the center of the area.

2.6. Sensitivity Analysis of Input Data and Methods

Monte Carlo methods iterate greenhouse gas calculations many times where input variables randomly take different values from the variables AD*EF*Adjustment (Adj hereafter) in each iteration according to a pre-defined probabilistic distribution. The resulting solution space for the FRL emerges from a random combination of input variables and therefore gives a complete picture of the uncertainties associated with the FRL calculation.

For the southern Cameroon case study, a Monte Carlo analysis with 1000 iterations was defined based on the arithmetic mean and the standard deviation at a 90% confidence interval for a normal distribution of the AD, EF, and Adj variables listed in Table 2. For the adjustment term, the variation comes from the deployment of alternative SSP scenarios. From the optimistic SSP 1 "Sustainability" with moderate population and GDP growth to the most pessimistic SSP 5 scenario "Conventional development", a gap of 9% for population, and 21% for GDP, respectively, can be observed for the year 2030. It should be noted that this is a somewhat simplified assessment for demonstration purposes: For AD it only considers smallholder deforestation, for EF two biomass pools (before and after conversion as opposed to land use specific ones) and various socioeconomic development scenarios leading to varying adjustment factors (as opposed to variation of each input variable).

Data describing the mean and the shape of AD is sourced from the remote sensing exercise described in Section 2.3, which is backed by 127 validation points. EF is composed of biomass in a forest before conversion (50 sample plots) and biomass after conversion (26 sample plots), where the latter is an average over annual and perennial cropland (see Section 3.2). The variation of the adjustment term is calculated from the standard deviation across the six scenarios of socioeconomic pathways for Cameroon (Table 2, Line 4 - Adj).

Table 2. Activity data, emission factor, and adjustment variables drive the uncertainty of a forest reference level.

Domain	Potential Source of Error to Analyze	Unit	Number of Samples	Mean	SD (CV)
AD	Deforestation observed 2000–2015	ha/year	127	10,602	1837 (17%)
EF	Forest biomass sampling	tCO$_2$/ha	45	490.13	35.39 (7%)
EF	Non-Forest biomass sampling	tCO$_2$/ha	26	174.99	48 (27%)
Adj	Potential development trajectories	Adjustment multiplier(dimensionless)	6	1.44	0.12 (42%)

SD = Standard Deviation; CV = Coefficient of Variation (SD/mean); Mean = Arithmetic mean; Adjustment multiplier: Applied to historical smallholder deforestation.

3. Results

3.1. Forest Loss during the Reference Period 2000–2015

Remotely sensed deforestation accounts for 219,948 ha (14,633 ha/yr or 0.16% per annum of the initial forest cover) over the period 2000–2015 with a standard error of 10.45%. The analysis of drivers of deforestation revealed that the expansion of industrial agriculture, notably palm oil and rubber plantations, contributed 30,128 ha (13.7%), while the expansion of infrastructure—notably the deep water port of Kribi and various projects involving the construction or upgrading of roads, contributed 10,260 ha or 4.7%. Non-industrial agriculture with 159,037 ha or more than 72%, contributed the most by far to forest loss during the reference period 2000–2015. Almost 10% of forest clearings cannot be clearly attributed to an anthropogenic driver and are therefore not further considered as relevant for REDD+ (Table 3).

Trend analysis further shows a strong increase from 36,807 ha of forest loss from 2000–2005, to 48,737 during 2005–2010 and 134,403 ha during 2010–2015. The relative standard error of remotely sensed forest loss at a 90% confidence interval is 60. These results are in the range of other remote sensing products available for Cameroon (Figure 2, different colored dots).

Table 3. Per-driver presentation of the area and proportion of remotely-sensed deforestation observed during the reference period.

Driver of Deforestation (2000–2015)	Area		Standard Error (%)
	(ha)	**%**	
Non-industrial agriculture	159,037	72.3	
Infrastructure	10,260	4.7	
Industrial agriculture	30,128	13.7	
Other	20,521	9.3	
Total	**219,947**	**100**	**10.45**

3.2. Emission Factors from the NFI

Emission factors are developed from the difference in above- and below-ground biomass between forest and the land use after clearing, as derived from the NFI. The highest EF is associated with the conversion of forest to built-up areas where all the forest carbon (490 tCO$_2$/ha) is lost (Table 4). Transitions of forest to grassland, annual crops, and fallow/wasteland are also emissions intensive. Perennial cropland houses more than half of the carbon stored in forests and therefore have a relatively low EF of 226.8 tCO$_2$/ha. Uncertainties are smallest in the forest class with a standard error of 4.3% but are significantly higher for the agricultural land cover classes that relate to the lower number of NFI sample plots located in these land cover classes.

Table 4. Emission factors and associated uncertainty for five land use transitions developed from the NFI.

Transition of Forest to	Emission Factor (tCO$_2$/ha) *	Standard Error (±%)
Annual crops **	347.7	14.1
Perennial crops	226.8	31.2
Fallow land	332.1	11.2
Grassland	462.3	5.9
Built-up areas	490.1	4.3

* Comprised of above ground biomass (AGB) and belowground biomass (BGB). ** Comprising 15 crops listed in Table A2 in the annex.

3.3. Adjustment of the Reference Level to National Circumstances

The rate of forest clearing is projected to increase in the future. This results in projected cleared areas of 15,900 ha/yr on average through 2020–2030 across all anthropogenic drivers of deforestation, which is 20% above the remotely sensed deforestation rate during the 2000–2015.

Non-industrial agriculture is responsible for the majority of the projected increase. Fueled by increases in population and consumption rates, the land use model predicts an increasing demand for land for the virtual performance period 2020–2030. This leads to projected forest loss from non-industrial agriculture of 14,600 ha/yr, which is 3900 ha/yr (+76%) higher than during the virtual reference period of 2000–2015 (Figure 2, left; light blue bar). This increase occurs gradually where the model for the period 2000-2015 estimates an average cleared area of 8300 ha/yr which then increases to 13,100 ha/yr during 2020–2025 and 16,100 ha/yr in the following period 2025–2030.

This expansion of non-industrial agriculture is mainly fueled by staple crops such as groundnuts, corn, cassava, plantains and bananas, and to a lesser extent by smallholder oil palm plantations and beans (Figure 2, right). Further drivers of deforestation include the expansion of infrastructure (almost

constantly at 2500 ha/yr accounting for 16% of total deforestation), and industrial plantations that contribute substantially (12,300 ha or 14% of total deforestation) but are assumed to slow down to 780 ha or 5% during the performance period. As a result, the overall projected deforestation for the virtual performance period is 3250 ha/yr (26%) higher than during the virtual reference period.
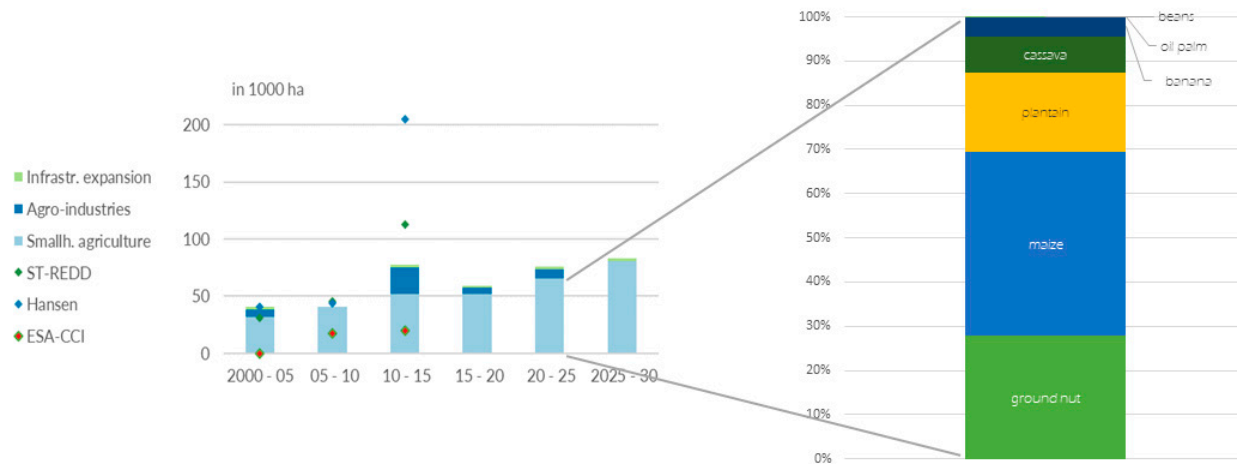

Figure 2. Reconstructed and projected deforestation from the land use model (stacked bars) as observed by three independent remote sensing products (diamond symbols) on the left and decomposition of modeled non-industrial agricultural drivers per crop (stacked % chart on the right).

Both historical and projected deforestation, as presented in Figure 2 are translated into emissions by applying the relevant emission factors derived from carbon stocks presented in Table 4.

The resulting forest reference level (Figure 3) for the virtual performance period 2020–2030 with 5.63 $MtCO_2$/yr is 1.26 $MtCO_2$/yr or 29% higher than the emissions for the reference period. This adjustment is driven by the expansion of smallholder agriculture, from which the associated annual emissions are projected to increase by 48% from 2020–2030, as compared to the virtual reference period 2000–2015.
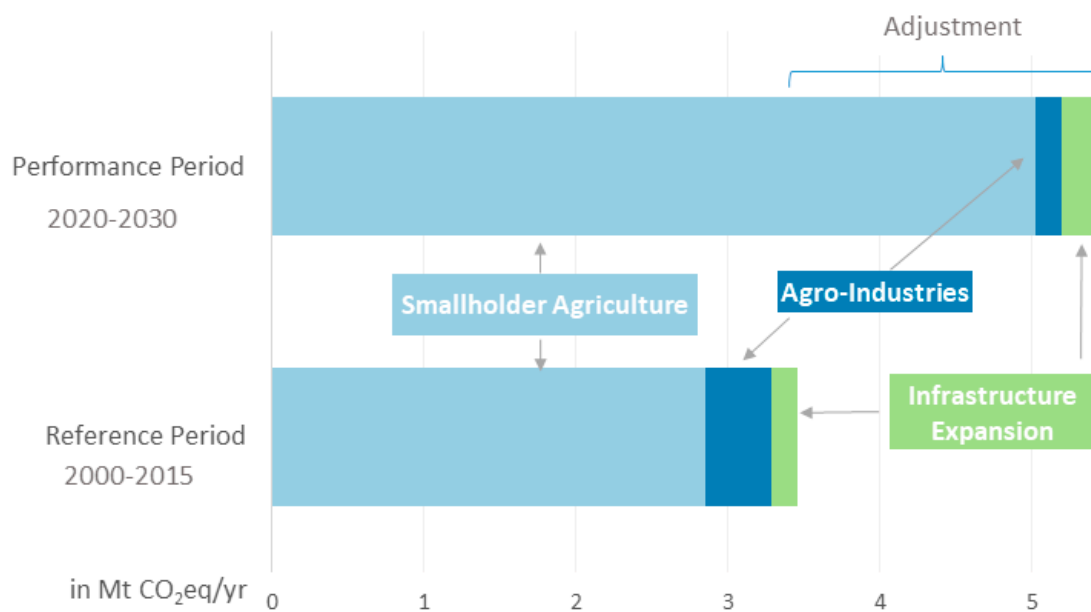

Figure 3. Projected emissions during the performance period (top bar) are 29% higher than emissions during the reference period (left bar); the increase is driven by expanding smallholder agriculture for which emissions are projected to increase by 48%.

3.4. Sensitivity of the Reference Level to Input Data

The spread of the results of the Monte Carlo analysis as shown in Figure 4. gives an indication of the sensitivity of the reference level calculation (AD*EF*Adj) where the adjustment term varies across five SSP scenarios. The resulting distribution is skewed to the right (with a skew factor of around 0.40) as can be expected due to the multiplication of normally distributed variables. The assumption of a normal distribution of the data can however be maintained since the skew factor is predominantly < 0.5 [59]. The mean FREL is 4.96 $MtCO_2$/year and the confidence interval is ± 2.19 $MtCO_2$/yr at a 90% confidence level (the z-score multiplier for the SD is 1.64). This means that the true mean value for the FREL lies between 2.73 and 6.78 $MtCO_2$/yr in 90% of the iterations. The aggregated variation of the reference level expressed as the coefficient of the variation (SD divided by the mean) is 27%.
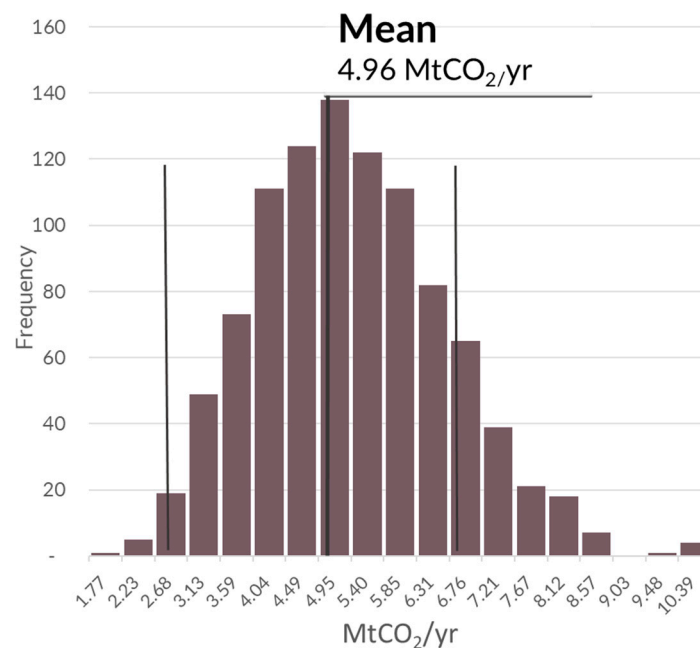

Figure 4. The results of 1000 Monte Carlo iterations of the reference level calculation; the mean (bold black line) lies within the 2-tailed standard deviation (α = 0.1; thin black lines).

4. Discussion

This article demonstrates the establishment of a forest reference emission level (FREL) adjusted to national circumstances using southern Cameroon as a case study. The results show that during the virtual reference period of 2000–2015, deforestation was mostly driven by the expansion of smallholder agriculture. Using a land use model based on food and feed consumption, deforestation is projected to the future using a virtual performance period spanning 2015–2030, thus leading to an adjusted FREL that lies 26% above historical emission levels over the virtual reference period. There is a great number of parameters in the land use model—population growth, agricultural yields, food losses, to name a few—that influence the future demand for land. A sensitivity analysis of activity data, emission factors, and the adjustment factor computed with the land use model using Monte Carlo techniques demonstrates that at a 90% confidence level calculated from 1000 calculation iterations, the FREL's coefficient of variation (CV) is ± 27%, while the CV of its single components varies between 7% and 43%. The remainder of this section is structured into two blocks: The first reviews the limitations of the approach and the uncertainties of the results, whereas the second block discusses the policy implications derived from the findings.

4.1. Uncertainties and Limitations of Approach and Results

Increasing domestic food consumption is the main driver of deforestation. This finding complements and confirms the conclusions of other pieces of research showing that the expansion of non-industrial agriculture is the principle driver of land conversion. This fact has been confirmed through various methodologies including analyses through the political economy lens [60–62], expert knowledge [25], analyses of the spatial drivers of deforestation [39,63], scenario trend projection [64] and, last but not least, a review of the Congo Basin countries' submissions to the UNFCCC [65]. In this study the non-industrial agriculture sector comprises smallholders and medium-sized "elites" landowners without distinction. Local or urban elites are gaining importance in the land use sector in Cameroon [63,66,67]. Not distinguishing between both agent groups is nevertheless justifiable because both groups respond to the same immediate market signals, which are subject to increasing demand for food and feed, as depicted in the land use model (Section 2.5). The results of this study show a relatively modest and even decreasing proportion of agro-industrial plantations. This is due to the conservative methodology adopted: Only clearings with a legal basis, provided by the allocation of sales of standing volumes, are projected to be cleared within the ten years timeframe of the study. This is in line with approved proposals for performance-based jurisdictional REDD+ funding provided by other countries [68,69]. Moreover, the allocation of new concessions is a political endeavor [70] with discretionary elements unknown to the public and therefore neither scale nor location can be predicted in sufficient detail to contribute to an FREL.

Consistency of the FREL with a GHG monitoring system is a challenge for many REDD+ countries [71]. A GHG monitoring system should allow the consistent tracking of AD, EF, and adjustments over time, meaning that each land cover transition should find its respective emission and adjustment factors. The currently available data does not allow for this consistency. This has to do with the aimed-for granularity of the analysis (Tier 3), which generally increases the complexity of monitoring [72] and in this case, over-stretches the degree of granularity of the available data.

For example, the national forest definition (Section 2.2) considers oil palm plantations as non-forest. Activity data (Section 2.3) map agro-industrial oil palm plantations but fail to map out the smallholder oil palm plantations that supply up to two-thirds of the national palm oil harvest [40,73] but are nonetheless classified as forest (if established before 2000) or deforestation in the currently available land cover map. This is mainly due to the technical difficulty of the task and the fact that technical advances in reliably mapping oil palm plantations at different scales have only recently become available [74,75]. Acknowledging this lack, the land use model used for the adjustment of the FREL (Section 2.5) relies on national statistics of oil palm supply rather than on the AD and uses emission factors (Section 2.4) developed for all perennial crops. However, the emission factor for perennial crops is partly derived from sample plots located within cocoa agro-forests. These are, however, considered forests according to the national forest definition (Section 2.2) and should therefore be accounted for as forest degradation. More generally, currently available AD data maps deforestation with unknown post-forest land use that inhibits the application of land use specific EF derived from the NFI, in other words no EF can be associated with remotely sensed deforestation but the land use following the clearing would need to be determined. Further, a definition of land use after conversion, rather than land cover, generally results in lower estimated deforested area as temporarily unstocked areas such as fallow are not considered [76]. Assessment of the land use should potentially be done a few years after clearing, to ensure the correct post-forest land use (or forest regrowth) is identified.

The uncertainty of the FREL calculation is considerable but within the range of results of comparable studies. The coefficient of variation as a measure of uncertainty in biomass estimates ranges from 7% for remaining forest to 27% for cropland. To put this in context, the IPCC recommends applying a default uncertainty of ± 75% for its default (Tier 1) emission factors. Global biomass maps—when aggregated to the national level for Cameroon—and the FAO's forest resources assessment (FAO FRA) yield relatively consistent results with differences across sources being in the range of 7% to 16% [77]. The authors however also note that on a local scale, differences across global maps

are significantly higher. The land use modeling approach to adjusting the FRL certainly increases the transparency of the adjustment term as compared to other approaches. It is an approach that requires a wide range of input data, which raises questions about data reliability beyond the scale of the sensitivity analysis performed in Section 2.6. The literature does notably point out potential problems with national datasets relating to population [78,79] and international trade [80]. Further, challenges relate to data on domestic trade, consumption rates and the characterization of complex multi-crop and multi cropping cycle systems, and the general political situation and stability that could evolve in the next 15 years.

Pertinent datasets and information are not available at present. The UNFCCC reporting guidelines stipulate that all significant gases, pools, and activities shall be covered [16] where the threshold for "significant" is often defined as 10% of total emissions [81]. Forest degradation is a significant source of emissions, as suggested by both qualitative national analyses [25,31] and global studies [25,82,83], the latter placing forest degradation in the range of 25% of total land-based emissions. The main drivers of forest degradation are—listed in decreasing order of available documentation—industrial logging aimed at the international timber market [57,84,85], cocoa encroaching into forests [86–88], informal logging for the domestic and regional timber market [89–96], and fuel wood collection [97,98]. None of these drivers of degradation is considered in this study because they are not assessed by activity data mapping and only the industrial logging and cocoa is tracked by national export statistics. In addition, it is not possible to retrieve emission factors for degradation from the one-time national forest inventory performed in 2003/2004. Moreover, not included is forest gain, which is the main element absent from many countries' submissions to the UNFCCC [65,71]. In the case of southern Cameroon, the forest definition (threshold ≥ 10% canopy cover), available AD and EF from the one-time NFI, as well as the dynamic nature of clearing and regrowth in the shifting cultivation landscape [95,99] make it challenging to effectively report on forest gain.

GHG reporting should be fit for the specific purpose. The virtual FREL described in this paper would qualify for the comparatively lenient requirements of jurisdictional REDD+ results reporting to the UNFCCC. This process is a facilitative, non-intrusive, technical exchange of information rather than a critical assessment of data and approach. However, this FREL requires further improvement, if the aim is to obtain performance-based payments such as those offered by the FCPF Carbon Fund [81]. This is notably due to the lack of coherence between AD, EF, and adjustment as listed above in this section and the resulting use of Tier 1 proxies in the absence of alternative national data. Further, the crediting period should start no longer than two years after the end of the reference period [81], not five years as is the case in this virtual reference level.

4.2. Policy Implications

As outlined in Section 2.1, a number of policy-related choices preceded the virtual FREL developed in this article. Most are straightforward as they adopted the widest possible definition. The forest definition and the scale of the project, however, deserve further discussion.

Forest definitions should be tailored to the specific policy question they address [100]. The current forest definition for Cameroon as stated in the forest code does not have any quantitative parameters. The definition used for the FAO forest resources assessment (FAO FRA) set a high bar of 30% canopy cover to what is considered forest. In contrast, the forest working definition in place for REDD+ and other climate change-related processes in Cameroon aims to cover the widest possible ranges of forest with a minimum canopy cover of 10%. The choice of either forest definition has minimal effects on the forest area in the dense evergreen forests of southern Cameroon which easily fulfill both canopy cover thresholds. It will, however, make a difference in the open forests of the savannah-like northern regions of the country [31,101]. More importantly, picking the appropriate forest definition is crucial for Cameroon as a whole to be or not be considered an HFLD country and is expected to provide preferential access to climate finance [81,102]. While the working definition of forests for REDD+ has not yet been officially adopted in political circles, the entire issue of multiple and conflicting forest

definitions raises questions of legitimacy given that each definition serves only the specific needs of the policy process that is en vogue at a given time [103,104].

High-level political risks are pending in the current project area that might drive future deforestation beyond the regular development trajectory. The development of the Heveasud plantation (Figure 1a,b), for instance, is not completed yet and information about the area to be cleared or logged unsustainably [57] in the future is not available. There have also been other development projects initiated but then stalled, such as the Mballam iron ore mine and the associated Kribi-Mballam railway stretching 500 km through thus far densely forested zones of the virtual project area [105,106]. On the other hand, considering these projects for the FREL is difficult to justify, given the low implementation rate of large-scale projects in the past [58]. The ongoing conflict in the Northwest and Southwest administrative regions of the country has had negative impacts on agricultural production and expansion in the conflict region, which might lead to some forest regrowth there. On the other hand, recent agricultural statistics point to a leakage of agricultural production away from the conflict zone to other parts of the country. Implicitly, the socioeconomic pathways underlying the Monte Carlo analysis likely cover the effects of this regional conflict.

To date, 39 countries have submitted FREL's, some of which have also claimed adjustment. The most commonly used approach in doing so is projecting trends of past deforestation into the future, which is generally considered a robust and conservative approach. Does the modeling approach presented here give rise to "*formulating incredibly high deforestation scenarios*" [13], as has been reported for other HFLD countries? Not for our case of Southern Cameroon. The average modeled deforestation for the virtual performance period 2020–2030 is 15,900 ha/yr, which is +50% above the reference period 2000–2015 but is exactly equal to deforestation observed in the period 2005–2015. Hence, shortening the reference period from 15 to the last 10 years (which is often the recommended duration of a reference period suggested by performance-based payment schemes [81]) would have the same effect on a reference level as deploying the mechanistic land use model, but without the benefits of having the breakdown per supply chain of the drivers of deforestation.

The scenarios underlying the most contested reference levels proposed for HFLD countries or regions (see for instance [10,13]) follow an ad-hoc narrative, i.e., "what would happen if … ?". This approach differs significantly from the bottom-up, data driven approach presented here, which stands in the scientific tradition of mechanistic land use modeling (for instance [29,107]). For other countries and jurisdictions to capitalize on this methodology, solid data on population, food, and feed consumption and agriculture and wood production are needed. For countries with a low population and low level of agricultural activity, the methodology presented here will yield in low adjustments of the reference level (see [108]).

5. Conclusions and Recommendations

This article aims at determining a transparent FREL adjusted to likely future developments and highlights significant uncertainties associated with this process. Adjustment of reference levels, such as other outcomes of international climate negotiations [109], are sometimes perceived as loopholes putting actual GHG reductions at risk [10]. In that sense, this article contributes to narrowing these loopholes by proposing a transparent approach to determining a FREL adjusted to future circumstances.

This section, consequently, focuses on making concrete suggestions for improving each element of the FREL with the ultimate objective of developing a FREL for a performance-based payment program.

To that end, the overall objective is to create a GHG monitoring system that consistently spans across all components (AD, EF, and adjustment) of a FREL, subject to TCCA principles and policy-related decisions described in Section 2.2.

Creating and improving the necessary data, information and infrastructure is costly and funding is limited. This section therefore aims to define priorities for future working directions.

5.1. Priorities for Improving Activity Data

The alignment of forest definition and AD mapping would also require differentiating natural forest from mono-specific plantations such as rubber and oil palms in the activity data. The technical feasibility of doing so has been demonstrated for other regions in Cameroon [27,110]. Further, the proof of concept is also made for distinguishing cocoa agroforests from full sun cocoa [111], which will be a requirement for aligning the forest definition and AD for REDD+ in the country.

The reference map of all six IPCC classes should place more emphasis on mapping agricultural land uses, given its role as a primary driver of deforestation. The reference map should split agriculture at least by annual and perennial crops with very different carbon densities (see Table 4). Radar-based systems with the capacity to penetrate clouds and detect canopy texture features (such as Sentinel 1) enable the differentiation of different crops and have been applied both in research [111–113] and in an operational context [111,114].

Forest loss mapping of all REDD+ activities: AD mapping should encompass all D's in REDD: Deforestation and forest degradation, as well as carbon stock enhancement.

Deforestation mapping should allow to trace the fate of cleared forest patches, as having data about land use after forest clearing is critical in terms of choosing the relevant emission factor. This will require a frequent update of the reference land cover map, which appears possible using radar sensors such as Sentinel 1 [111,112,115] and the definition of cut-off dates [116,117] given the often rapid consequential transitions between various land uses. For example, perennial plantains are often planted immediately after clearing [118] since they seem to benefit from the nutrient cocktail remaining in the wood ashes but after around three years they are replaced by other (often annual) crops. In short, spatially explicit tracking of drivers of deforestation and degradation across all relevant sectors will be needed.

Forest gain mapping will require long-term time series analysis to retrieve stand age data [119] combined with long-term forest inventory plots [120]. The inclusion of forest gain and/or forest stock enhancement would allow Cameroon to be one of the few REDD+ countries to report an FRL to the UNFCCC, which would testify to a significant improvement in reporting capacity [71]. It should also be noted that defining forest by a minimum crown cover of ≥ 10% might be an impediment to tracking forest gain in the dense forest areas of southern Cameroon [100].

Mapping of deforestation is mandatory. Activity data other than deforestation can be assessed according to two methods: remote sensing, which gives direct evidence of the extent and intensity of an activity [121–123], or through the use of proxy data. Using proxy data means that emissions from degradation are inferred from land use activity intensities, typically national statistics on forest use, such as national wood harvest. To assess emissions from selective logging, for instance, national wood harvesting data is combined with biomass expansion factors plus a logging damage factor to the remaining forest stand [57,124,125]. Proxy data are only as reliable as the statistics, which underpin them. Another, issue using proxy data is the overlap of different land uses in space and time. For instance, logging for timber and fuel wood for the local market occurs primarily in fallow areas [95], which have already been cleared once and accounted for as such and therefore pose the risk of double-counting.

The combination of both methods as demonstrated on the local scale [123] might improve results. Acknowledging the technical difficulty of detecting degradation, using forest fragmentation and the associated decrease in tree height and biomass in degraded forest edges has been proposed as a robust spatially explicit workaround [126].

5.2. Priorities for Improving Emission Factors and the Next NFI

A long-term network of forest inventory plots will be a requirement for measuring progress towards sustainable forest management and the enhancement of carbon stocks [120], which necessitates a rapid repetition of the NFI dating from 2003/2004.

Spatial misalignment errors of EF and AD should be avoided by using a stratified approach focused on moist and dry forest regions and systematic sampling inside the strata to ensure adequate coverage of forest types proportional to their area coverage with a higher density compared to the NFI from 2003/2004.

Implementation of a cost-effective NFI repetition cycle of 5-10 years building on the clusters and plots from the NFI 2003/3004 will be key to allow assessment of the change in carbon storage. A too long time-lapse since the last assessment should be avoided to not diminish the value of the NFI 2003/2004.

Densifying the sample grid is important in order to represent (1) all five agro-ecological zones of Cameroon, (2) all land use classes, and (3) drivers of deforestation and forest degradation with due statistical representation.

Forest degradation and enhancement of forest carbon stocks, as well as changes in the carbon stocks in remaining forests need to be, and can be, assessed by repeated measurements of the sample plots.

Balancing density and frequency: There should be a reasonable balance of the number of inventory plots and a short (ideally five-year) repetition cycle to enable a timely assessment of forest degradation and enhancement.

Technical and financial resources to the forest inventory unit in the ministry in charge of forestry should be made available to enable it carry out forest inventory in a repetitive manner 5.3. Adjustment to National Circumstances

Demographic dynamics are expected to be better represented by including data from the third national census of 2015. Alternatively, the possibility of using remotely sensed population data should be exploited [127].

Reliable agricultural statistics at the best possible granular level of detail should be collected. Previously, agricultural statistics were available at the department level in Cameroon but in recent years statistics are only available at the regional level—this is a major degradation of data availability.

Drivers of forest degradation should be represented in the model once relevant AD and EF data become available. This should encompass industrial and smallholder logging, cocoa, and fuel wood consumption.

5.3. From UNFCCC Reporting to Performance-Based Payments

The enhancement of coherence both at the institutional- and technical level are major priorities. Moreover, a content analysis of approved applications for performance-based payments from Central- and West Africa [128] and associated technical assessment reports have revealed simplification as an overarching strategy.

This is true for activity data mapping where a re-aggregated binary forest-non-forest land cover map, for example, yields higher accuracies than a thematic one [128]. This is also true for adjusting reference levels: Declaring deforestation for agro-industrial concessions in the most remote parts of the country as "planned" [68] might indeed appear more intuitive than going to lengths in elucidating the socioeconomic drivers underlying deforestation.

When it comes to ex-ante estimation of emissions reductions (ER's), the focus will probably need to be put on two to three well-organized supply chains (such as cocoa, oil palm, or industrial logging) with high potential to reduce emissions. The land use modelling approach offers a convenient framework for quantification potential ER's at the design stage of an ER program, notably for supply chains pursuing a land-sparing strategy. Thereby, projected yield increases resulting from REDD+ interventions translate into potential land sparing, moderated by a discount factors for imperfect translation of yield improvements to spared land. It should be noted, however, that the short-term policy framework of performance-based payment schemes (for instance, the FCPF prescribes a performance period of five years) will make effective implementation and results delivery by REDD+ a major challenge.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Results of the land use model in terms of cropland expansion 2000–2035 for the Southern Cameroon Area (in 1000 ha per 5-year period).

	2000–2005	2005–2010	2010–2015	2015–2020	2020–2025	2025–2030	2030–2035
Cassava	4.84	9.59	8.52	5.68	5.99	7.22	7.99
Mais	5.13	6.64	9.55	8.75	11.63	15.57	19.47
Beans	0.02	0.02	0.03	0.02	0.01	0.01	0.00
Millet/Sorghum	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Oil palm	0.34	0.33	0.52	0.51	0.60	0.67	0.73
Plantain	4.82	5.16	6.68	8.43	11.23	14.22	17.67
Ground nuts	4.57	4.61	6.31	7.63	9.24	10.22	11.66
Banana	1.44	1.21	2.07	2.10	2.68	3.37	4.10
Cacao	19.84	23.08	47.57	15.55	33.56	33.56	33.56
Cotton	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Appendix B

Table A2. List of crops represented in the model and classification as annual or perennial (only with regard to the Emission factor to apply).

Crop Name	Annual/Perennial (for EF Calculation)
Banana	Annual
Beans	Annual
Cassava	Annual
Cocoa	Perennial
Ground nut	Annual
Maize	Annual
Oil palm	Perennial
Plantain	Perennial
Rubber	Perennial

Appendix C

Table A3. Protocol used to drivers assessment.

Disturbance Class	Description of Disturbance
Infrastructure	Geometric areas with very high reflectance value
Croplands	Permanent small and medium-scale agriculture
Logging (Road, selective) – Industrial	Located inside allocated logging concessions; signs of logging infrastructure visible
Mining	Permanent openings with high, stable reflectance
Natural (Wildfires, windfalls, river meandering and other natural disturbances)	Immediate proximity to rivers; fires database
Non-industrial logging	Very short (annual) openings
Road construction	Linear shapes with high reflectance values
Smallholder clearing	Openings for smallholder agriculture (≤ca 1ha) visible for 2–3 years; remainder of all above

The collection of images is available from this website: http://glad.geog.umd.edu/Potapov/Cameroon/Cameroon_index_part2.html.

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