Application of the CCQI methodology for assessing the quality of carbon credits

This document presents results from the application of version 3.0 of a methodology, developed by Oeko-Institut, World Wildlife Fund (WWF-US) and Environmental Defense Fund (EDF), for assessing the quality of carbon credits. The methodology is applied by Oeko-Institut with support by Carbon Limits, Greenhouse Gas Management Institute (GHGMI), INFRAS, Stockholm Environment Institute, and individual carbon market experts. This document evaluates one specific criterion or sub-criterion with respect to a specific carbon crediting program, project type, quantification methodology and/or host country, as specified in the below table. Please note that the CCQI website Site terms and Privacy Policy apply with respect to any use of the information provided in this document. Further information on the project and the methodology can be found here: www.carboncreditquality.org

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Sub-criterion:	**1.3.2: Robustness of the quantification methodologies applied to determine emission reductions or removals**
Project type:	**Avoided unplanned deforestation**
Quantification methodology:	**VCS Methodology VM0006, Version 2.2** **Methodology for Carbon Accounting for Mosaic and Landscape-scale REDD Projects**
Assessment based on carbon crediting program documents valid as of:	**1 April 2024**
Date of final assessment:	**2 July 2024**
Score:	**1**

Assessment

Relevant scoring methodology provisions

"The methodology assesses the robustness of the quantification methodologies applied by the carbon crediting program to determine emission reductions or removals. The assessment of the quantification methodologies considers the degree of conservativeness in the light of the uncertainty of the emission reductions or removals. The assessment is based on the likelihood that the emission reductions or removals are under-estimated, estimated accurately, or over-estimated, as follows (see further details in the methodology):"

Assessment outcome	Score
It is very likely (i.e., a probability of more than 90%) that the emission reductions or removals are underestimated, taking into account the uncertainty in quantifying the emission reductions or removals	5
It is likely (i.e., a probability of more than 66%) that the emission reductions or removals are underestimated, taking into account the uncertainty in quantifying the emission reductions or removals OR The emission reductions or removals are likely to be estimated accurately (i.e., there is about the same probability that they are underestimated or overestimated) and uncertainty in the estimates of the emission reductions or removals is low (i.e., up to ±10%)	4
The emission reductions or removals are likely to be estimated accurately (i.e., there is about the same probability that they are underestimated or overestimated) but there is medium to high uncertainty (i.e., ±10-50%) in the estimates of the emission reductions or removals OR It is likely (i.e., a probability of more than 66%) or very likely (i.e., a probability of more than 90%) that the emission reductions or removals are overestimated, taking into account the uncertainty in quantifying the emission reductions or removals, but the degree of overestimation is likely to be low (i.e., up to ±10%)	3
The emission reductions or removals are likely to be estimated accurately (i.e., there is about the same probability that they are underestimated or overestimated) but there is very high uncertainty (i.e., larger than ±50%) in the estimates of the emission reductions or removals OR It is likely (i.e., a probability of more than 66%) or very likely (i.e., a probability of more than 90%) that the emission reductions or removals are overestimated, taking into account the uncertainty in quantifying the emission reductions or removals, and the degree of overestimation is likely to be medium (±10-30%)	2
It is likely (i.e., a probability of more than 66%) or very likely (i.e., a probability of more than 90%) that the emission reductions or removals are overestimated, taking into account the uncertainty in quantifying the emission reductions or removals, and the degree of overestimation is likely to be large (i.e., larger than ±30%)	1

Carbon crediting program documents considered

This assessment is based on an evaluation of the most important VCS documents applied under this methodology. It does not consider all VCS documents that may be applied in using the methodology. The following documents were considered:

1 Verra (2017): VCS Methodology VM0006. Methodology for Carbon Accounting for Mosaic and Landscape-scale REDD Projects. Version 2.2, 17 March 2017. https://verra.org/methodologies/vm0006-methodology-for-carbon-accounting-for-mosaic-and-landscape-scale-redd-projects-v2-2/

2 Verra (2023): VCS Methodology Requirements. Version 4.4, 4 October 2023. https://verra.org/wp-content/uploads/2023/08/VCS-Methodology-Requirements-v4.4-updated-4-Oct-2023.pdf

3 Verra (2017): VCS Agriculture, Forestry and Other Land Use (AFOLU) Requirements. Version 3.6, 21 June 2017. https://verra.org/wp-content/uploads/PREVIOUS-VERSION-AFOLU-Requirements-v3.6.pdf

4 CDM (2007): Tool for testing significance of GHG emissions in A/R CDM project activities. Version 1, active 4 May 2007 – 20 July 2012. https://cdm.unfccc.int/methodologies/ARmethodologies/tools/ar-am-tool-04-v1.pdf/history_view

5 Verra (2022): VCS Standard. Version 4.2, 20 January March 2022. https://verra.org/wp-content/uploads/2022/02/VCS-Standard_v4.2.pdf

6 Verra (2024): VCS Standard. Version 4.7, 16 April 2024. https://verra.org/wp-content/uploads/2024/04/VCS-Standard-v4.7-FINAL-4.15.24.pdf

Assessment outcome

The quantification methodology is assigned a score of 1.

Note that Verra is in the process of phasing out this methodology and replacing it by the methodology VM0048. Specific transition requirements specify for how long this methodology may continue to be used.

Justification of assessment

Project type

This assessment refers to the following CCQI project type:

- **Avoided unplanned deforestation**. This includes activities to avoid not legally authorized deforestation which occurs as a result of socioeconomic forces, such as subsistence agriculture of local communities, encroaching infrastructure, and illegal logging. In addition, forest degradation may be reduced. The activities are implemented on a dedicated project-level geographical area (not at jurisdictional level). Projects usually combine different activities to address drivers of deforestation, for example, by improving agricultural practices of local communities or providing alternative livelihoods. The project type reduces emissions by avoiding the loss of forest carbon stocks.

The CCQI project types, as described above, are applicable to the methodology. The methodology is applicable to projects that involve mosaic landscapes, with different patches of “cleared lands, degrades forest, secondary forests (…), and mature forests”. A key feature of mosaic landscapes is that forests are readily accessible to the potential agents of deforestation.

The methodology mentions that deforestation is a change from forest to another land use class such as the conversion of forest land to cropland, settlements, or to infrastructure. The methodology addresses drivers of deforestation (p. 11) which do not mention conversion of forest to grazing land. As this is a predominant driver for deforestation in tropical countries, this seems to be an important omission from the methodology.

The assessment of the methodology is hampered by a lack of appropriate referencing to other VCS documents. The exact version of the referenced document is not clear. References in the list of references do not include Internet-links or DOIs.

Selection of emission sources for calculating emission reductions or removals

The drivers of deforestation considered by this methodology identified on page 11 (section 4.1.1) seem to include a broad spectrum, including conversion for agriculture, commercial logging, and settlement. Roads are already largely present in mosaic landscapes, but these roads may be extended to further encroach upon forested areas. “Cattle grazing in forests” is also included primarily as a driver of degradation but not deforestation (i.e., conversion to grazing land).

The implications of including or excluding carbon pools and emission sources depend on the post-deforestation land uses predicted to occur in the baseline. If agriculture is the driver of deforestation, the land use following deforestation is likely to be agriculture. The patterns of agricultural use may differ by region but will largely coincide with the settlement driver in their effects. The land may be continuously used for agriculture, such as when palm oil plantations are established (e.g., in Indonesia) or if pastures are established following a period of crop cultivation (e.g., in Brazil). The land use may also be cyclical where a period of agricultural use is followed by a fallow period in which secondary forest may grow back (e.g., in the Democratic Republic of Congo). Following the fallow period, the area is often again cleared of its forest cover and cultivated, at the landscape level, which creates a mosaic of fallow, secondary forest of different ages, and agricultural fields. How much carbon is stored in the landscape (i.e., in trees, other vegetation and soils) depends on the length of the fallow period. If logging is the initial driver of deforestation, trees would be harvested and removed, and non-tree biomass may be damaged but would not be targeted for removal. The initial effect of logging is a degradation of the forest carbon stock, since usually the largest and more valuable trees are removed first. However, agriculture is often a secondary driver of deforestation, since the infrastructure created for logging increases access to forests and harvesting helps to prepare the land for agriculture. This is assumed to be the case for the development or expansion of roads as well. For these reasons, we assume for our analysis that ultimately the dominant post-deforestation land use is agriculture. We thus assume deforestation in the baseline scenario would in the long-term result in agriculture on these lands.

The methodology explains that carbon pools and emission sources may be excluded if insignificance can be demonstrated using the latest version of the CDM Tool for testing significance (section 8.4.3). The methodology states that the CDM Tool “should be used to test the significance of GHG emissions”. In section 5.1 it also states that “Insignificant emission sources may be excluded…if insignificance can be demonstrated…” using the CDM Tool. The CDM Tool referenced is currently inactive. The methodology identifies that project developers “should” test carbon pools and emission sources for significance if they seek to exclude a carbon pool or emission source. The methodology seems contradictory to how the significance test is used: on the one hand, the methodology states that the “sum of increases in emissions that may be excluded must be less than 5% of the emission reductions”; on the other hand, it seems to refer to this threshold in the context of individual emission sources, stating that "if it is determined that a specific GHG emission source will never reach this threshold and will never become significant, it may be omitted from the monitoring plan".

OE1 **Lack of clarity regarding the tool to demonstrate a pool or source is insignificant**: The methodology identifies a CDM Tool for demonstrating significance of GHG emissions that is inactive and no obvious replacement is made available. The methodology also seems unclear regarding how the threshold for insignificance should be used. Project developers could favorably interpret the methodology and pick and choose which carbon pools and emission sources they include or exclude, depending on the project circumstances. This may lead to overestimation of emission reductions. The fraction of projects affected by this issue is **unknown**. The impact on total credited removals or emission reductions is **unknown**. The variability in the degree of overestimation among projects is **unknown**.

The methodology specifies mandatory and optional carbon pools and sources of emissions and excludes certain pools and sources. The methodology seems to assume, but does not specify, that if carbon pools are included in the project boundaries that they are accounted for in both the baseline and project scenarios. The methodology states that it "requires accounting of all potential emissions of CO_2, N_2O and CH_4 from sources not related to changes in carbon pools, henceforward referred to as emission sources (Table 1)" but then the first entry in the methodology's Table 1 identifies that "Baseline Deforestation and Forest Degradation" is optional and is justified as "Emissions are related to changes in carbon pools." Baseline Deforestation and Forest Degradation is the only emission source listed in Table 1 related to the baseline while a list of emission sources is provided relating to the project. It is therefore unspecified whether these emission sources identified for the project scenario could also be accounted for in the baseline. In our analysis we assume that this omission means the project developers may interpret as they see fit and include baseline emission sources.

OE2 **Contradictory provisions add confusion to determination of inclusion/exclusion for emission sources**: The methodology requires the accounting of specified carbon pools and emission sources "not related to changes in carbon pools" but does not specify a requirement to account for emission sources that are related to changes in carbon pools. Emission sources included in the methodology's Table 1 (e.g., relating to the burning of woody biomass) necessarily relate to changes in carbon pools, yet they are marked as included or optionally included. These provisions directly contradict and add confusion that could cause a project developer to interpret the conflicting provisions favorably. This may lead to overestimation of emission reductions. The fraction of projects affected by this issue is **unknown**. The impact on total credited removals or emission reductions is **unknown**. The variability in the degree of overestimation among projects is **unknown**.

This assessment identifies the sources, sinks, and reservoirs and details their relevance in Table 1.

Table 1 Assessment of sources, sinks, reservoirs

Source, sink, or reservoir	Included? How?	Relevant for this assessment?
Carbon Pools		
Aboveground tree biomass	Mandatory for baseline and project.	Yes, major carbon pool affected by project activities.
Aboveground non-tree biomass	Mandatory when land cover under the baseline scenario is perennial tree crop.	Yes, major carbon pool affected by project activities. The methodology is for mosaic landscapes that suffered past degradation, thus denser forests will be intersected with shrubs and secondary forests and

Source, sink, or reservoir	Included? How?	Relevant for this assessment?
	Optional when land cover under the baseline scenario is not perennial tree crop (e.g., annual crop or pasture grass).	herbaceous regrowth of different ages. In the baseline scenario (post-deforestation land-use for agriculture), non-tree biomass such as shrubs are likely to be removed. Therefore, exclusion of this pool in the baseline scenario and the project scenario is likely to be conservative. Given that inclusion in the baseline and project scenario are both optional (if the baseline is not perennial tree crops), project developers can decide to include this pool.
Belowground biomass (note: methodology does not specify if this pertains to tree or non-tree biomass or both)	Optional	Belowground tree biomass is a primary source of emission reductions from the project activity. Exclusion of this pool in the baseline and project scenario would likely be conservative. Belowground non-tree biomass could be affected in different ways in the baseline scenario, depending on the agricultural practices. Non-tree biomass is likely to be removed and belowground biomass will be removed or disrupted to prepare the soil, resulting in a release of the stored carbon. However, while non-tree biomass may be initially disturbed and removed, it could also recover and potentially increase beyond the project scenario. Therefore, exclusion of this pool in the baseline and project scenario would lead to uncertainty. In most cases, however, we deem these effects to be negligible.
Deadwood	Optional	Major carbon pool affected by project activities. In the baseline scenario, slash deadwood would result from harvesting (which does not occur to the same degree in the project) but when the land use shifts to agriculture, deadwood would be burned or removed. The implementation of the avoided deforestation projects is likely to result in more naturally occurring deadwood than in the baseline. Exclusion of deadwood in the project and baseline scenario is therefore conservative.
Litter	Excluded	Excluded as per VCS AFOLU Requirements. In the baseline scenario, litter is likely to decrease due to removal of living biomass and deadwood for the purpose of site preparation for agriculture (e.g., biomass burning). Exclusion of this pool from the baseline and project scenario is therefore conservative.
Soil organic carbon (SOC)	Optional – but may only be included if land cover under the baseline scenario is comprised of annual cropping systems.	The methodology is not applicable to organic soils or peatland. In the baseline scenario, soil disturbance can be expected, leading to the release of SOC. In tropical regions, post-deforestation land use for agriculture is unlikely to increase SOC stocks. Therefore, exclusion of this pool from the baseline and project scenario is conservative.
Harvested Wood Products (HWP)	Mandatory	It is appropriate to include HWP in the baseline and project scenario.

Source, sink, or reservoir	Included? How?	Relevant for this assessment?
Emission sources		
Emissions from biomass burning	CO_2 excluded from project scenario	CO_2 emissions from fires are excluded because the methodology claims that they are already included in the changes of carbon pools. This does not account for biomass burning from carbon pools that are excluded. Exclusion of this source from the project scenario can therefore lead to overestimation.
	CH_4 and N_2O excluded from project scenario, except for CH_4 emissions relating to prescribed burning (as a project activity)	The methodology excludes CH_4 (except for emissions related to prescribed burning) and N_2O emissions because it states that emissions from unplanned fires are considered insignificant. Exclusion may result in overestimation depending on the project conditions if unplanned fire is significant in the project scenario. Also, in a mosaic landscape slash-and-burn agriculture (i.e., planned fires) could be practiced in the project scenario and not necessarily at lower rates depending on the project activities. Therefore, exclusion could lead to overestimation.
Emissions of CO_2 from the combustion of fossil fuels	Excluded from project scenario	Emissions of CO_2 from the combustion of fossil fuels may occur in the baseline related to harvesting and agriculture, or in the project related to monitoring and patrolling, it is uncertain whether CO_2 emissions from the combustion of fossil fuels decrease or increase as a result of the implementation of the project. Therefore, it is uncertain how exclusion of this source may affect calculated emission reductions. Non-CO_2 emissions from the combustion of fossil fuels are considered insignificant.
N_2O emissions – from enrichment planting and increased agricultural fertilizer use	Excluded from project scenario	The methodology assumes both of these sources to be negligible, but they may be significant. Exclusion in the project scenario, where fertilizer use does not increase compared to the baseline is appropriate and conservative. When fertilizer use increases due to project activities like enrichment planting or sustainable intensification of agriculture on existing agricultural land exclusion can lead to overestimation.
Livestock CH_4 and N_2O emissions	Included if stocking rate density on existing grazing land increases or cattle are shifted to a zero-grazing system (permanently housed instead of being allowed to graze). Optional under other circumstances.	CH_4 and N_2O emissions related to increases in stocking rates are determined to be significant and are mandatory to include. Under other project circumstances where inclusion is optional, if deforestation for livestock operations occurs in the baseline, then it is likely that livestock production will decrease due to the project or shift to other areas through activity shifting or market leakage (and remain at the same level as the baseline or decrease). Therefore, it is conservative to exclude this source from the baseline and project in these circumstances.

OE3 **CO_2 emissions from biomass burning are excluded**. CO_2 emissions from fires are excluded because the methodology claims that they are already included in the changes of carbon pools. This does not hold if biomass is burned from carbon pools that are excluded and therefore not accounted for. Therefore, exclusion of this source from the project scenario may lead to overestimation of emission reductions. The number of projects affected is **unknown**. The impact on total credited emission reductions is **unknown**. The variability in the degree of overestimation among projects is **unknown**.

OE4 **CH_4 and N_2O emissions from biomass burning are excluded.** Depending on the project conditions (e.g., region, pace of climate change impacts) unplanned fire may be a significant risk to the project area. Also, in a mosaic landscape slash-and-burn agriculture (i.e., planned fires) could be practiced in the project at levels equal to or beyond the baseline scenario. This may lead to overestimation of emission reductions. The number of projects affected is **unknown**. The impact on total credited emission reductions is **unknown**. The variability in the degree of overestimation among projects is **unknown**.

OE5 **N_2O emissions from increased fertilizer use are excluded.** When fertilizer use increases due to project activities like enrichment planting or sustainable intensification of agriculture on existing agricultural land emissions of N_2O will increase. Therefore, exclusion of this emission source may lead to overestimation of emission reductions. The number of projects affected is **unknown**. The impact on total credited emission reductions is **unknown**. The variability in the degree of overestimation among projects is **unknown**.

UE1 **Inclusion of aboveground non-tree biomass is optional**. In the baseline, deforestation would result in a lower amount of non-tree biomass than in the project. The exclusion of this pool would thus lead to underestimation of emission reductions. This issue applies to projects that opt to exclude aboveground non-tree biomass. The number of projects affected is **unknown**. For those projects where this issue materializes, the impact on total credited emission reductions is estimated to be **low** (less than 10%). The variability in the degree of underestimation is **unknown**.

UE2 **Inclusion of belowground biomass is optional**. The methodology is not clear whether belowground biomass relates to tree and/or non-tree biomass. We interpret the different provisions to mean that inclusion of each pool is optional. In the baseline scenario, deforestation would result in a lower amount of tree biomass than in the project scenario and the belowground tree biomass directly corresponds to the aboveground tree biomass. The exclusion of this pool would thus lead to underestimation of emission reductions. Belowground non-tree biomass could either decrease or increase due to the implementation of the project; however, these effects are deemed to be small. This issue applies to projects that opt to exclude belowground tree biomass. The number of projects affected is **unknown**. For those projects where this issue materializes, the impact on total credited emission reductions is estimated to be **low** (less than 10%). The variability in the degree of underestimation is **unknown**.

UE3 **Deadwood is an optional source**. Naturally occurring deadwood is likely to be lower in the baseline scenario than in the project scenario. Exclusion of this carbon pool therefore likely leads to underestimation of total credited emission reductions. This issue applies to projects that opt to exclude deadwood. The number of projects affected is **unknown**. For those projects where this issue materializes, the impact on total credited emission reductions is estimated to be **low** (less than 10%). The variability in the degree of underestimation is **unknown**.

UE4 **Litter is identified as an optional source.** Litter is anticipated to be lower in the baseline scenario than in the project scenario. Exclusion of this carbon pool therefore likely leads to underestimation of total credited emission reductions. This issue applies to projects that opt to exclude litter. The number of projects affected is **unknown**. For those projects where this issue materializes, the impact on total credited emission reductions is estimated to be **low** (less than 10%). The variability in the degree of underestimation is **unknown**.

UE5 **Soil carbon is identified as an optional source** (only allowed to be included if annual cropping system will be implemented in the baseline). Soil carbon is anticipated to decrease in the baseline scenario, resulting from soil disturbance caused by deforestation, and will at least be less significantly impacted under the project scenario. Exclusion of this carbon pool therefore likely leads to underestimation of total credited emission reductions. This issue applies to projects that opt to exclude soil carbon. The number of projects affected is **unknown**. For those projects where this issue materializes, the impact on total credited emission reductions is estimated to be **low** (less than 10%). The variability in the degree of underestimation is **unknown**.

UE6 **Emissions from livestock are optional under some project scenarios:** Livestock emissions within project boundaries are likely to decrease compared to a baseline scenario where deforestation occurs to enable livestock production. Excluding livestock emissions from baseline is therefore likely to result in underestimation of emission reductions. The number of projects affected is **unknown**. For those projects where this issue materializes, the impact on total credited emission reductions is estimated to be **low** (less than 10%). The variability in the degree of underestimation is **unknown**.

Un1 **Methodology does not consider emissions of CO_2 from the combustion of fossil fuels**: Given that CO_2 emissions from the combustion of fossil fuels may occur in the baseline related to harvesting and agriculture, or in the project related to monitoring and patrolling, it is uncertain – and likely variable among projects – whether these emissions decrease or increase as a result of the implementation of the project. This introduces uncertainty in the quantification of emission reductions. The number of projects impacted by this issue is **unknown**. For those projects where this issue materializes, this issue introduces a **low** (less than 10%) degree of uncertainty to the estimation of total credited emission reductions. The variability in the degree of uncertainty among projects is **unknown**.

Determination of baseline emissions

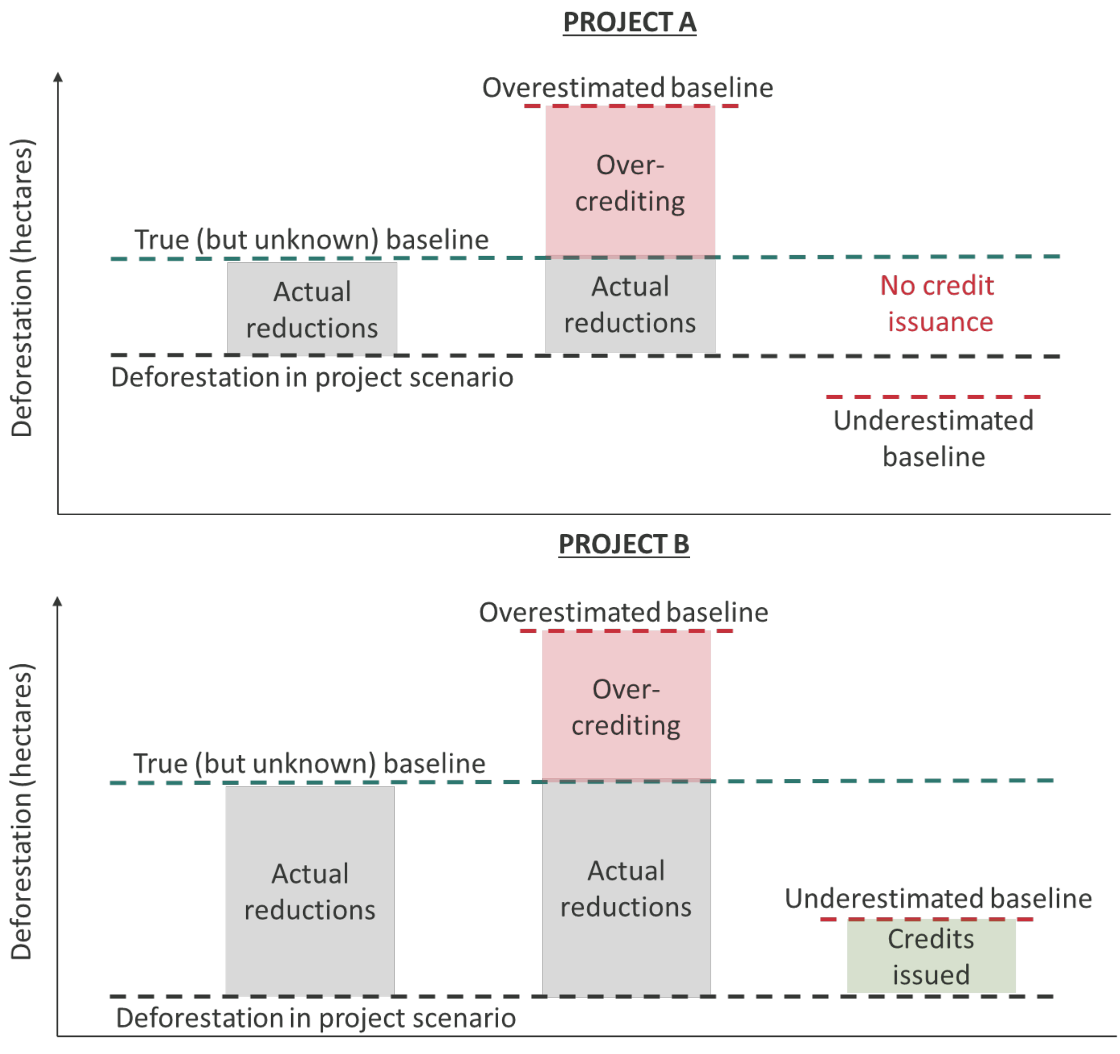
In the following, we first provide an overview of general challenges regarding the determination of baseline deforestation levels. This is followed by a summary of the issues identified with baseline determination under the older VCS methodologies assessed by CCQI (VM0006, VM0007, VM0009, and VM0015). We then turn to a detailed assessment of this methodology.

<u>*General challenges in establishing baselines for avoided deforestation projects*</u>

Establishing baselines for avoided deforestation projects is associated with very large uncertainty. Establishing baseline is always associated with uncertainty, as it is not directly observable what would have happened in the absence of a project. For avoided deforestation projects, uncertainty in establishing baselines is particularly high. The rate of future deforestation in a particular forest area depends on many unknown factors, such as changes in political, economic and social conditions. The literature suggests that changes in such “confounding” or “exogenous” factors can have a large impact on avoided deforestation (see, for example Miranda et al. 2024). Uncertainty in the underlying (historical) data used to establish baseline deforestation rates is another important source of uncertainty.

The divergence in estimates of baseline deforestation rates for the same projects is an indicator of the large uncertainty associated with predicting future deforestation rates for a specific project. For example, Guizar-Coutiño et al. (2022) and West et al. (2023) arrived at the different baseline deforestation estimates for the same projects. Similarly, some rating agencies built their own models to assess the quality of baselines and arrived at different deforestation baselines as the underlying projects. Aggregated estimates between rating agencies also differ (Calyx Global 2023; Sylvera 2023). Another indicator for the uncertainty is that even at jurisdictional level deforestation rates can vary considerably over time.

Figure 1 Implications of uncertainty in baseline deforestation levels



Large uncertainties raise challenges for ensuring attributability of the emission reductions to the project intervention. As the uncertainty in future deforestation scenarios is very high, this poses the risk that the calculated emission reductions could only partially be attributable to the project intervention and partially be an artefact of wrongly set baselines. This is illustrated in Figure 1 through two hypothetical projects. Project A reduces deforestation to some extent, by about one third. In this case, a large overestimation of the baseline would lead to significant over-crediting. A large underestimation of the baseline may lead to no carbon credit issuance at all, although the project reduces deforestation. This challenge is lessened for project B. Here the project reduces deforestation close to zero. In this case, an overestimation of the baseline leads to a lower degree of over-crediting relative to the actual reductions. Moreover, the project would still receive carbon credits if the baseline were significantly underestimated.

Two issues arise from this challenge:

1. **It is important to address the large uncertainty in predictions about future deforestation levels, by choosing a scenario that is conservative in the light of the uncertainty.** In theory, one could argue that over-crediting in one project may be compensated by under-crediting in other projects. However, projects with overestimated baselines have a competitive advantage over other projects. They receive more carbon credits than their actual emission reductions and can thus offer carbon credits at lower prices. By contrast, projects with underestimated baseline may not receive any carbon credits at all (as illustrated in Figure 1 above) or may only receive fewer carbon credits. Some of these projects may thus not succeed, or may fail later on, as they cannot generate sufficient revenues from carbon credits. This would lead to more carbon credits being generated from projects with overestimated baselines. Therefore, in a competitive market, unaccounted baseline uncertainty can undermine integrity across a portfolio of projects. Underestimation in some projects does therefore not compensate for overestimation in other projects. This is why many standard setting organizations, such as the Integrity Council for the Voluntary Carbon Market, require that uncertainty is addressed at the level of each individual mitigation activity and not only across a portfolio of projects and that all sources of uncertainty are considered. To address this issue, baselines need to be set at a sufficiently conservative level where the degree of conservativeness takes into account the level of uncertainty.
2. **It is important that projects have a significant impact on deforestation levels.** The larger the impact of project interventions on deforestation drivers relative to the impact of confounding or exogenous factors is, the more likely it is that the emission reductions are attributable to the project interventions. As shown in Figure 1 above, the implications of baseline uncertainty are mitigated if projects strongly and effectively reduce deforestation drivers. The available literature indicates that this may not always be the case for avoided unplanned deforestation projects. Projects often aim to create alternative sources of income for local communities, through improving existing agricultural techniques on existing farmland, developing agroforestry systems or establishing fisheries and aquaculture. However, in some cases, projects only reached certain groups and failed to address those communities which are most dependent on the forest as a source of income (Haya et al. 2023; Kapos et al. 2022), Another driver of deforestation are unclear land tenure structures, which some projects address through supporting land tenure reforms. However, research showed that improving land tenure is immensely difficult, as the local context and the individual interests of affected groups needs to be appropriately considered to ensure that the relevant groups receive tenure rights and to avoid that new tenure arrangements create conflict (Sunderlin et al. 2018; Alusiola et al. 2021). Lastly, projects oftentimes implement measures to prevent illegal logging, such as forest patrols, monitoring posts or marking forest boundaries. While these measures might reduce deforestation, they are not always implemented stringently enough (Nathan and Pasgaard 2017). To ensure that project activities are effective – and thereby mitigate the impact of baseline uncertainty – methodologies could require monitoring of the implementation of the project interventions or that projects must reduce deforestation to levels close to zero in order to receive carbon credits.

Summary of issues observed with the older VCS methodologies

All older VCS methodologies assume historical deforestation rates or trends to continue in the future. Different approaches exist for constructing baselines for avoided deforestation projects

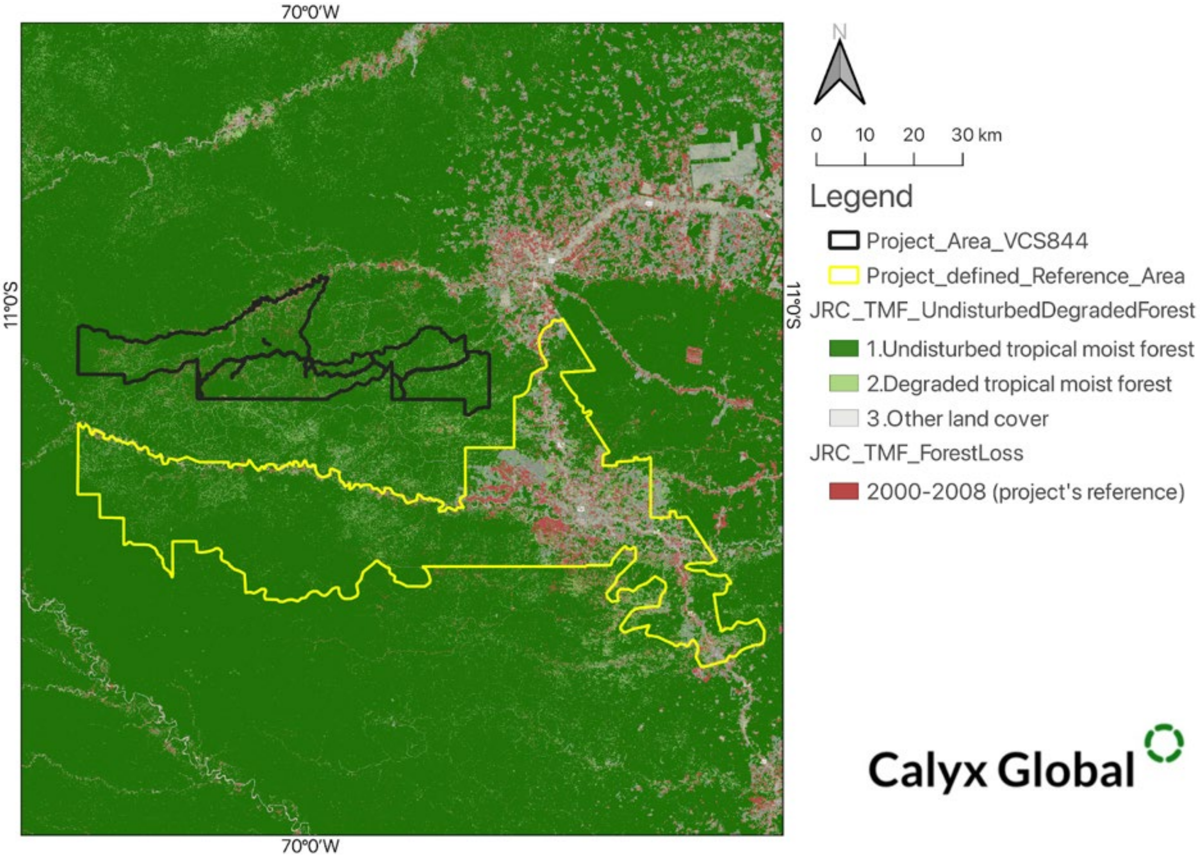
(West et al. 2023; Haya et al. 2023). The basic approach taken by all older VCS methodologies assessed by CCQI (VM0006, VM0007, VM0009, VM0015) is assuming that historical deforestation rates or trends observed in a reference area will continue in the future. The methodologies use historical information from a period covering the last 10 to 15 years prior to the project start date to establish historical deforestation rates or trends. The project-specific reference region to determine historical deforestation must be similar to the project area and methodologies provide criteria and ranges in which the project area and reference region may differ. These four methodologies use the historical average deforestation or different regression models for making a prediction about future deforestation or future forest cover (see Haya et al. 2023 for a detailed comparison of regressions used by the four assessed Verra methodologies).

Flexibility in establishing baseline deforestation rates. The four older VCS methodologies (VM0005, VM0007, VM0009 and VM0015) provide considerable flexibility on how to establish baseline deforestation rates. This allows project developers to make subjective choices that can lead to higher baselines (Haya et al. 2023). This holds in particular for the following choices:

- **Choice of the reference area or region:** The historical deforestation in a reference region is used to estimate the baseline deforestation rates. Although the methodologies provide criteria for ensuring that reference areas match the characteristics of the project area, these do not necessarily prevent project developers from choosing reference areas with high levels of historical deforestation (Seyller et al. 2016). Reference regions may especially be biased towards higher deforestation rates if the methodology provides different options to project developers to choose from or if deviations are explicitly allowed. For example, the methodology VM0007 stipulates that road density (m/km) may be up to 20% higher in the reference area than in the project area and roads are known to facilitate deforestation (see module VMD0007).
- **Approaches to projecting the historical deforestation trends into the future:** The projection of historical deforestation trends into the future may be done by using the average historical values or through models. If choice is given between approaches or within an approach, project developers may choose options that result in higher baseline deforestation rates.
- **Choice of the historical reference period:** The length of the historical reference period and how much time lies between its end date and the start of the project are two variables that influence the estimates of baseline deforestation. If the methodology allows for flexibility in choosing the historical reference period, project developers may choose a period that results in higher baseline deforestation rates.

This is illustrated in Figure 2 for the VCS project 844. The reference region (yellow lines) includes an area with roads and settlements in which significant deforestation has been observed in the reference period. The project area (black lines) is further away from roads and is thus likely to face much lower deforestation risks.

Figure 2 Project area and reference region used for estimating the rate of baseline deforestation for the project VCS844



Note: Figure provided by Calyx Global.

The available literature suggests that baseline deforestation rates derived from these older VCS methodologies have likely been overestimated by several hundred percentage points on average. Several studies have evaluated the impacts of projects by comparing the project areas to well matched control groups (West et al. 2023; Guizar-Coutiño et al. 2022; West et al. 2020). For example, West et al. (2023) estimate that only about 6% of the credits issued to the sampled projects represent actual emission reductions. Estimates by Guizar-Coutiño et al. (2022) are somewhat higher but still point to very significant overestimation. Inflated baselines are identified as the major cause of overestimation. Rating agencies that evaluated individual projects come to similar conclusions. Calyx Global (2023) evaluated 73 avoided deforestation projects and concluded that only four projects estimated a conservative baseline. Sylvera (2023) assessed more than 85% of avoided deforestation credits on the market and concluded that 31% of the projects were of "high-quality". Field-based case studies also find high risks of overestimation due to inflated baselines (see for example Seyller et al. 2016). Haya et al. (2023) applied the four older Verra methodologies assessed by CCQI (VM0006, VM0007, VM0009 and VM0015) to the same four projects and arrived at baselines that varied by a 1459% on average for the same project. This illustrates that the application of these methodologies to the same project can lead to greatly varying baselines. They also found that baselines used by project developers were consistently at higher end of the range of baselines they constructed by applying the four methodologies, suggesting that project developers made choices among the available options that led to higher baseline estimates.

Assessment of VM0006

This methodology uses historical carbon stock changes in a reference region to determine baseline emissions. Future baseline deforestation is estimated either by projecting the historical average or by applying a regression model. The baseline scenario for all projects is that ongoing or past changes in carbon stocks will continue into the future. The baseline encompasses deforestation and degradation, as well as increases in forest cover and forest regeneration. The baseline validity period was originally ten years and is six years since version 4.2. of the methodology (VCS Standard v4.2 and v4.7).

The analysis area for developing the baseline encompasses the reference region, the project area and the leakage belt. The reference region can include the project area and leakage belt, but this is not a requirement. It is expected to be "representative of the future trajectory of the project area in the absence of the project activities". The methodology provides a list of criteria for selecting a representative reference region. These include for example a minimum size (250,000 ha or the size of the project area), indications for setting the boundaries of the reference region according to natural, geopolitical, watershed or project area related boundaries, and the exclusion of areas where access of deforestation agents is limited. Areas of planned deforestation and areas where forest loss due to natural disturbances have occurred must be excluded from the reference region and project proponents must demonstrate that the reference region contains a minimum forest cover of 15% at the start of the reference period. Additionally, the reference region and the project area must have similar drivers of deforestation, landscape features (e.g. elevation, distribution of native forest, slope) and socio-economic and cultural conditions (e.g. land tenure rules, regulations and degree of urbanization). Project proponents must also assess the similarity of agents and drivers of deforestation and may adjust the reference area after this analysis to ensure that the same drivers and agents of deforestation are present in both areas.

The analysis of past deforestation and degradation is done using high to medium resolution remote sensing data. At least three points in time are analyzed representing the start, middle and end of the historical reference period. If less than three historical images are available, the project is not eligible. Project proponents are required to define land use classes and forest strata to improve the accuracy of carbon stock estimates. A list of expected transitions between land use classes is prepared in advance. An uncertainty deduction is applied according to the level of accuracy of forest classification. Accuracy is assessed by comparing a sample of predicted land use and land cover classes with other independent classifications and the use of a 'confusion matrix'. Sample locations must be spread throughout the analysis area and the land use or land cover class must be confirmed by ground truthing. If the accuracy of classification is less than 70%, the project is not eligible. A discount factor is applied if accuracy is below 85%. A discount is also applied if only three historical images are used for the analysis. The uncertainty in forest stratification and the associated carbon density is also considered through a discount factor. This discount factor also depends on the points in time for which carbon stocks have been assessed. A higher number of biomass inventories results in a lower discount.

Following the analysis of historical land use transitions, an analysis of drivers and agents of deforestation and degradation is carried out. The methodology defines which agents and drivers are eligible in the applicability conditions. Once agents and drivers are identified, their relative importance for carbon losses and their mobility are assessed. Then spatial variables that determine where land cover change will likely occur are identified.

Carbon stock densities for each land use and land cover class and the associated emission factors for each land use transition are determined based on sample plots, which may be permanent or temporary. For non-forest classes literature values can be used. The methodology requires calculating the combined error for the calculated carbon stocks of each land use class and forest stratum and to subsequently determine the level of uncertainty.

The approach for determining the baseline deforestation depends on the number of analyzed historical images. If three images are analyzed, delivering two deforestation rates, the average of these two rates is used as the baseline deforestation rate. If the analysis relies on more images, the baseline is calculated using a regression model as a function of time, fitted to the historical deforestation rate. The methodology refers to a beta regression, while according to Haya et al (2023) the equations used indicate the use of a linear regression. The baseline calculation also depends on the trend observed in historical deforestation. If deforestation is constant (no slope significantly different from 0 at the 95% confidence level), then the mean of the historical deforestation in the reference region is used (constant future deforestation rate). If the trend in historical deforestation indicates an increase over time (slope significantly over 0 at the 95% confidence level) then the regression model is applied, and the lower 95% confidence interval of the model serves as the baseline. If the trend in historical deforestation indicates a decrease (slope significantly below 0 at the 95% confidence level) then the regression model is applied and serves as the baseline. Baseline deforestation observed in the reference region is proportionally applied to the project area.

The methodology allows accounting for increased forest cover and for natural regeneration. One of the allowed project activities is assisted natural regeneration. Where projects aim to account for removals from increased forest cover and natural regeneration, increased forest cover and natural regeneration must be included in the baseline and project scenario. Like for the deforestation rate, the analysis of historic forest cover increase, and natural regeneration is done using historical land cover and land use imagery.

Once historical deforestation and forest increase rates are calculated, a statistical model that uses spatial driver variables is calibrated and applied. According to the methodology, this step serves to assess the impact of the spatial driver variables on historical land use change and to predict the likelihood of land use change. Project proponents can use any model in this step, but the methodology mentions logistic regression models. Indications for how to calibrate the model are provided. For quality assurance, the full model and all drivers must be significant at the 95% confidence level and a goodness-of-fit test comparing predicted and measured changes in land use and land cover must deliver a difference of maximum 15%. The model is then applied to predict the suitability for future deforestation. In the next step, aggregated classes and strata are aggregated into a “land-use change transition matrix” according to their suitability for deforestation. Although a spatially explicit deforestation model is applied, the baseline is not spatially explicit. As a final step, a forest scarcity factor is applied to account for a decline in the deforestation rates that occurs once the available area for deforestation falls below a certain threshold, according to the empirical observations and the forest transition theory.

OE6 **Flexibility in choosing the length of the historical reference period:** The methodology sets the maximum length of the historical reference period to 15 years, but otherwise indicates it can range from 10 to 15 years. Thus, it provides a degree of flexibility for project proponents to choose a point in time that could potentially lead to higher historical deforestation levels. This could thus lead to overestimation. The number of projects affected is **unknown** but could be high (more than two thirds of projects) given the incentive structure. For those projects where this issue materializes, the impact on total credited removals or emission reductions is estimated to be **high** (larger than 30%). The variability among those projects for which the issue materializes is **unknown**.

OE7 **Flexibility in the selection of the reference region:** The methodology provides considerable flexibility in the choice the reference region, including its location, size and initial forest cover. Although the methodology provides criteria for ensuring similarity and reducing bias, it does not provide concrete thresholds for when a level of similarity is sufficient. The methodology recognizes that it is "impossible" that any ruleset can prevent biased reference regions "under all project circumstances". The methodology states that it is the task of the validation/verification body to determine whether a reference region is "truly unbiased". The ability of verification bodies to do so may be limited due to information asymmetry. The selection of the reference region therefore remains subjective. Moreover, project proponents have the incentive to establish reference regions with features that result in higher historical deforestation and degradation. Overall, in our assessment there is a high risk that projects can select reference regions that lead to unrealistically high deforestation rates. The number of projects affected by this issue is **unknown** but could likely be high because project proponents have an incentive to choose reference regions that result in higher levels of historical deforestation. For those projects where this issue materializes, the impact on total credited emission reductions is estimated to be **high** (larger than 30%). The variability in the degree of overestimation among those projects for which the issue materializes is **unknown**.

OE8 **Flexibility in choosing imagery for determining historical deforestation in the reference region**: The methodology states that at least three images of forest cover in the reference region are required. Although an uncertainty deduction must be applied if only three images are used (factor 0.9), this does not preclude project proponents to pick and choose the most convenient images from three points in time. "(1) at minimum one image from 0-3 year before project start date, (2) at minimum one image from 4-9 years before project start date, and (3) at minimum one image from 10-15 years before project start date". This flexibility in choosing reference images potentially allows project developers to choose the reference images with higher average forest loss over the considered period and could thus lead to an overestimation of deforestation in the reference region. The number of projects affected by this issue is **unknown** but could likely be high because project proponents have an incentive to choose reference regions that indicate higher levels of historical deforestation. For those projects where this issue materializes, the impact on total credited emission reductions is **unknown**. The variability in the degree of overestimation among those projects for which the issue materializes is **unknown**.

Un2 **Calibration of the "forest scarcity factor":** The methodology considers the "forest scarcity principle" according to which "deforestation rates decrease upon the gradual depletion of forest resources". The inclusion of a scarcity factor is an element that contributes to avoiding overestimation because it allows to consider the reduction of deforestation rates that arise when the available area for deforestation decreases below a certain point. According to Haya et al. (2023), this calculation step contributes to a conservative baseline. However, the methodology provides flexibility for determining the scarcity factor. It states that it must be "calibrated using scientific literature in areas close to the project area that has followed a more advanced deforestation route" and it provides examples for such areas (neighboring countries, other provinces in the country), without providing additional criteria that ensure a representative choice. The equation to model the forest scarcity factor is shaped by two factors. First, how fast the deforestation rate decreases and second, the share of deforested area from the initial forest area at which the deforestation rate is 50% of the initial deforestation rate. To determine these two factors, project proponents may use historical remote sensing data in areas similar to the project area or peer-reviewed literature. Project proponents must only demonstrate that they used adequate data sources. Depending on the choice of scarcity factor, this issue could lead to over- or underestimation of credited emission reductions. The number of projects affected is **unknown**, as it depends on specific project conditions and choices made by project proponents. This issue introduces **medium** degree of uncertainty to the estimation of total credited emission reductions. The variability among those projects for which the issue materializes is **unknown**.

Un3 **Treatment of temporarily unstocked forest land**: Project proponents are required to provide a matrix of land use transitions. The default value for the period in which forest may be temporarily unstocked provided by the methodology is two years. In other words, if forest does not regrow within two years, the land use transition is counted as deforestation. However, forest may have regrown in the following years. Project proponents can choose another length for temporarily unstocked forest, depending on project-specific reasons. However, no criteria for assessing those reasons are provided. The short period of two years may lead to overestimation of deforestation, while longer chosen time periods may lead to underestimation (e.g., because land may be considered as temporarily unstocked forest for a longer period although deforestation occurred). The relevance of this issue depends on the number of historical images is used to determine historical land use transitions; the fewer images are used, the greater is the uncertainty. The issue is likely to affect all projects, given that projects are implemented in mosaic landscapes, where temporary unstocked forest can occur frequently, even if the areas are small. This issue is estimated to introduce a **low** degree of uncertainty to the estimation of total emission reductions The variability among those projects for which the issue materializes is **unknown**.

Un4 **Flexibility in defining the forest stratification model when degradation is included and lack of transparency**: Projects that include avoided deforestation must have a forest stratification model “unambiguously defined at validation”. The stratification remains fixed until the next baseline validation. The methodology provides several options for how this model may be constructed. It provides flexibility for the input data (optical remote sensing, radar and LiDAR measurements), whether ancillary data is used and which (climate, soil elevation, slope, proximity to roads, settlements or water bodies, land tenure status, etc.). The model itself may be rule-based, regression-based, or machine-learning based. No more guidance is provided for how to develop this model or what information needs to be provided so that validation and verification bodies are in a position to assess its quality. This issue applies to **all** projects. This issue is estimated to introduces a **low** degree of uncertainty to the estimation of total credited emission reductions. The variability among projects is **unknown**.

UE7 **Accuracy discount for uncertainty in land use and land cover classification:** A discount factor to address uncertainty in land use and land cover classification in historical maps is applied if the uncertainty is above 15% and below 30%. It increases with higher uncertainty. This could potentially lead to underestimation of total credited emission reductions and removals. Compared to other methodologies, VM0006 allows for a higher uncertainty, before the discount is applied. The number of projects affected is expected to be **low** since project proponents have an incentive to produce accurate classifications. Where this issue materializes (i.e., the uncertainty is larger than 15% and an uncertainty deduction is applied), the applied discount is between 20% and 30%, and the degree of underestimation is thus **medium** (between 10% and 30%). The variability in the degree of underestimation among projects is **unknown**.

Un5 **Accuracy discount for forest stratification:** Forest stratification reflects differences in carbon stock densities of different strata. Carbon stock densities are derived from sampling plots for the separate carbon pools. The uncertainty in forest stratification is assessed on the basis of sampling plots. The sampling plots for assessing uncertainty must be different from the ones used to for the forest stratification model, randomly selected and represent multiple time points. For the last requirement, measurements at different time points are required. Sample plots may be located only within the project area, if this does not lead to bias and if they are representative of the reference region. Two issues are considered for determining the discount factor. 1) The combined error in carbon stock density estimates and 2) the number of carbon stock density measurements (biomass inventories at different points in time). The discount factor for the combined error applies if the combined error is between 0.15 and 1. The discount factor for the number of measurements may decrease over the lifetime of the project, as more measurements become available, which is seen as an incentive for improved monitoring. The discount factor is 25% if only one measurement or two measurements are available, drops to 10% for three measurements and to 0 for more than three measurements. This could potentially lead to underestimation of total credited emission reductions and removals in the early stages of the project and to overestimation later on if bias in sampling design or other measurement uncertainty is not addressed as more measurements become available. Identifying bias in sample plot selection may be challenging for verification and validation bodies due to information asymmetry. The number of projects affected is **unknown**. This issue introduces medium degree of uncertainty to the estimation of total credited removals or emission reductions. The variability in the degree of underestimation among projects is **unknown**.

OE9 **Flexibility in choosing the temporal component for emission factors from deadwood and soil:** Emission factors for soil and deadwood must be gradually spread over time. The methodology proposes to use the default values from the IPCC GPG LULUCF 2003 guidelines, but project proponents may also choose their own temporal component if they can demonstrate the conservative nature "using peer-reviewed literature ore measurements conducted by the project proponent". Conservativeness must be demonstrated, but it is not clear how it will be assessed, and project proponents have an incentive to use this flexibility in their favor. The number of projects affected is **unknown.** For those projects where this issue materializes, the impact on total credited removals or emission reductions is estimated to be **low** (less than 10%). The variability among those projects for which the issue materializes is **unknown**.

Un6 **No uncertainty assessment for removals from forest cover increase and natural regeneration**: Section 8.1.5.2 of the methodology describes how relative forest cover and regeneration rates are estimated for each forest class or forest stratum. This is required to achieve "full symmetry in carbon accounting" when degradation is included in the baseline as well as for taking into account non-forest to forest transitions. This analysis is done using historical observations in the reference region. The section does not mention the need to assess uncertainty in the estimate and it is unclear whether the same procedure as for determining the land use and land cover classification is applied. Thus, this leads to uncertainty in the estimated removals. This issue applies to projects that include activities to address degradation and assisted natural regeneration. The fraction of those projects is **unknown**. This issue introduces a **low** degree of uncertainty to the estimation of total credited removals or emission reductions. The variability among those projects for which the issue materializes is **unknown**.

Un7 **No uncertainty assessment for statistical deforestation model for determining suitability of deforestation:** Section 8.1.5.3. of the methodology describes the steps for calibrating and validating a statistical model to predict the suitability for deforestation and degradation. This step serves to determine the likelihood of future deforestation and degradation. While this section includes steps and requirements to ensure the quality of the model (e.g. a goodness of fit test and significance at the 95% confidence level), there is no requirement for testing whether the selected model itself is adequate, which could be achieved through model comparison. It also does not require the use of a conservative approach and does not address the uncertainty associated with this modeling step. The suitability to deforestation is a proxy for deforestation risk, for which it has been shown that different models can deliver significantly different results and project proponents have an incentive to choose a model that provides financial benefits to the project (Haya et al 2023). The validation or verification body must confirm that the model is adequate for estimating the likelihood of deforestation. This issue applies to a **high** fraction of projects. The issue introduces a **high** degree of uncertainty to the estimation of total credited emission reduction. The variability among those projects for which the issue materializes is unknown.

Quantification of carbon stocks in the project and the baseline scenario

As an overarching issue, we observe that the methodology does not address uncertainty in determining carbon stocks in a systematic and appropriate manner. Accuracy requirements and uncertainty deductions are applied for some parameters (e.g., land use classifications) but not for other parameters that are associated with considerable uncertainty (e.g., allometric equations). The methodology does not define an overall minimum level of accuracy for the determination of carbon stocks in the baseline and project scenario and lacks a systematic approach to account for uncertainty. This could be implemented by calculating error propagations and applying an uncertainty deduction based on the total error or by ensuring that uncertainty is addressed for all relevant parameters (e.g., by choosing a conservative value that reflects the uncertainty). In our assessment, the lack of provisions to address uncertainty in an appropriate manner, combined with outdated approaches and flexibility for project developers to choose between different approaches, results in a very high uncertainty in the quantification of carbon stocks, with results that may significantly differ from actual carbon stocks existing in the projects.

Specifically, we identify the following elements of possible overestimation, underestimation or uncertainty with the approach in the methodology:

OE10 **Lack of appropriate definitions of forest, deforestation and degradation:** There is no requirement that the project proponents need to develop an appropriate definition of forest, deforestation and forest degradation for the project. Guidance would be necessary related to the choice of forest definitions (and related impacts on degradation) for different forest types, biomes or ecosystems and related to the definition of degradation, taking into account the specific features of the ecosystems in the project and the planned monitoring methods. Some projects implemented under the methodology use very low thresholds for canopy cover for humid tropical rainforests (e.g. 10% canopy cover for an humid Amazon rainforest in Peru which is the lower limit of the FAO forest definition). A 10% canopy cover is, however, far too low for a natural humid tropical rainforest where canopy cover of an intact forest may be 75-100%. The method also allows a very coarse stratification into the six IPCC land use classes. Such low choice of canopy threshold implies that 90% of the trees could be deforested, but the method would still classify the area as forest and multiply the area with a biomass factor for intact forests to quantify the carbon stocks prevented from deforestation. Thus, the lack of guidance related to a project-specific appropriate forest definition allows projects to define forests in a way that emissions from large-scale degradation /deforestation are not accounted for by the project. At the same time, the use of biomass stocks based on intact forests may significantly overestimate the emission reductions from deforestation. This is because the project may avoid deforestation in areas where the forest has already been severely degraded (e.g. leading to canopy cover of 20%). For the definition of 'mosaic', the methodology refers to the *VCS AFOLU Requirements*. This document describes that mosaic refers to a patchwork of cleared lands, degraded forests, secondary forests of various ages, and mature forests. In such a complex landscape, it is very important to use a clear definition of deforestation and degradation which is not part of the requirements. Fernández-Montes de Oca et al. (2022) show the importance of the definition of deforestation for the detection of deforestation. We assume that this issue affects **all** projects. The degree of overestimation of total credited emission reductions is **unknown**. The variability in the degree of overestimation among projects is also estimated to be **high**.

Un8 **Overall uncertainty assessment:** As an overarching issue, we observe that the methodology does not address uncertainty in determining carbon stocks in a systematic and appropriate manner. Accuracy requirements and uncertainty deductions are applied for some parameters (e.g., land use classifications) but not for other parameters that are associated with considerable uncertainty (e.g., allometric equations). The methodology does not define an overall minimum level of accuracy for the determination of carbon stocks in the baseline and project scenario and lacks a systematic approach to account for uncertainty. This could be implemented by calculating error propagations and applying an uncertainty deduction based on the total error or by ensuring that uncertainty is addressed for all relevant parameters (e.g., by choosing a conservative value that reflects the uncertainty). In our assessment, the lack of provisions to address uncertainty in an appropriate manner, combined with outdated approaches and flexibility for project developers to choose between different approaches, results in a very high uncertainty in the quantification of carbon stocks, with results that may significantly differ from actual carbon stocks existing in the projects. This issue applies to **all** projects. The level of uncertainty and variability among projects are **unknown**.

Un9 **Outdated methodological basis:** The methodology only refers to the IPCC Good Practice Guidance for Land Use, Land-Use Change and Forestry 2003 report as a source of biomass data, soil organic matter, natural regeneration, firebreaks, CH_4 from rice cultivation and other parts of the emission reduction estimation. This is an outdated source. There are four relevant updated methodology reports published by the IPCC:

- The 2006 IPCC Guidelines for National Greenhouse Gas Inventories;
- 2013 Supplement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories: Wetlands;
- 2013 Revised Supplementary Methods and Good Practice Guidance Arising from the Kyoto Protocol; and
- 2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories.

The newer reports include more specific and much more appropriate emission factors and other parameters, in particular for developing countries. The outdated references unnecessarily lead to higher uncertainties in the estimation. This issue applies to **all** projects. The level of uncertainty and variability among projects are **unknown**.

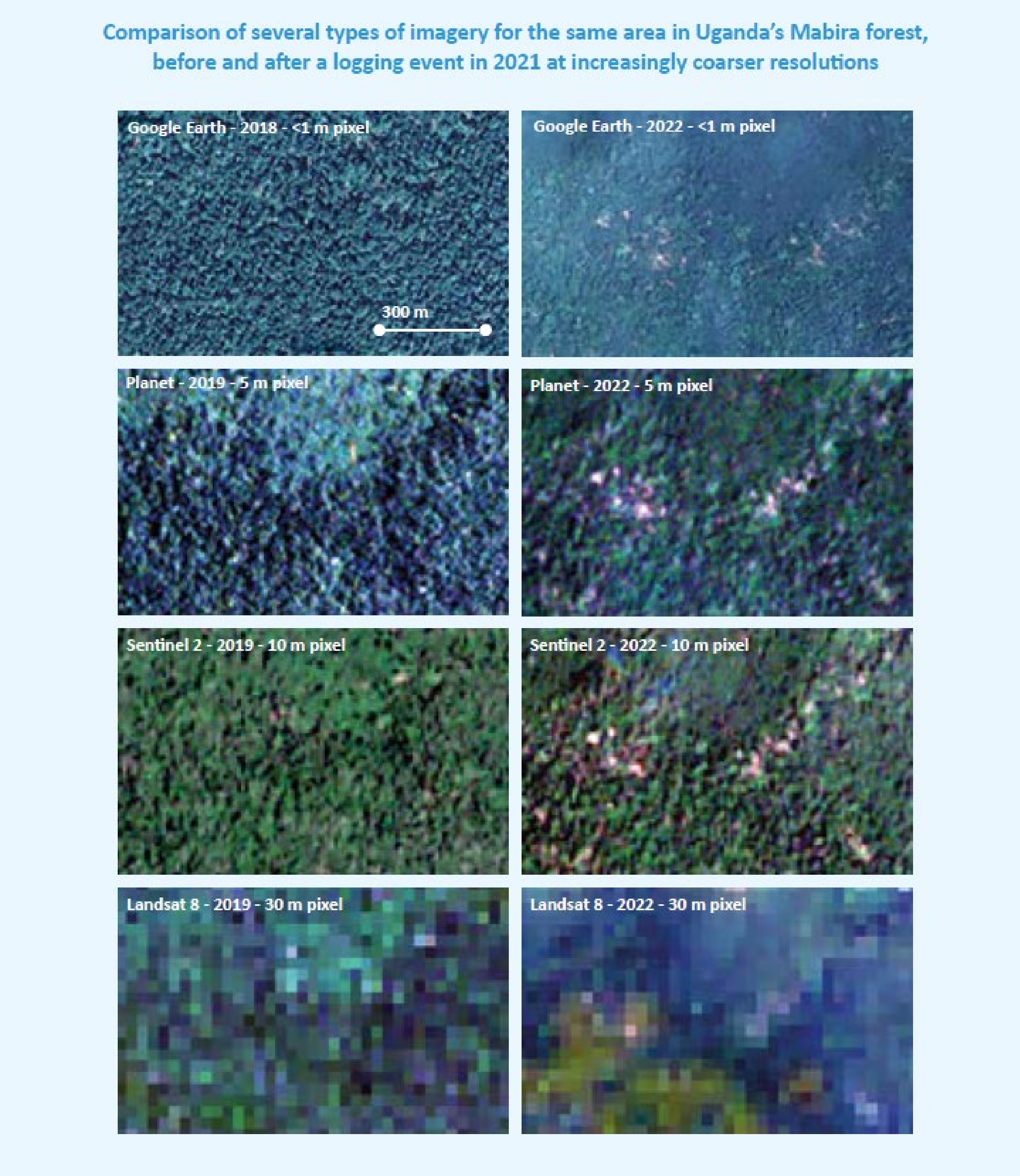
Un10 **Specific guidance missing for remote sensing:** The methodology does not provide specific guidance related to the use of satellite data and remote sensing methods or related to the quality assurance of data derived from remote sensing. Remote sensing methods have developed tremendously in the past decade and satellite data with high-resolution images has become freely available. This development is not reflected in the methodology. Any up-to-date methodology with acceptable uncertainty for avoided deforestation activities would need to develop more specific guidance for project developers related to remote sensing data. Through Norway's International Climate & Forests Initiative, for example, anyone can now access Planet Labs's high-resolution, analysis-ready mosaics of the world's tropics. Real and False-color mosaics of <5 m/px mosaics of the tropics with monthly cadence from August 2020 onwards (and an archive from December 2015 – August 2020 of Bi-Annual mosaics) offer a tremendously improved understanding of the forest areas, deforestation and forest degradation as it uses the Near Infrared (NIR) band. FAO has developed ready-to-use tools under OpenForis (http://openforis.org), e.g. CollectEarth, EarthMap or SEPAL that provide high accuracy remote sensing data. VM0006 allows medium resolution imagery from Landsat with 30 pixels. Figure 3 shows the difference in the quality of detection of logging events. Landsat 30 m pixels are the pictures in the lowest row. The examples show that in a mosaic landscape of different land use patterns, it is very difficult to detect changes in carbon stocks accurately with medium resolution imagery. The drastic improvements in remote sensing data for forest monitoring are not reflected in the methodology. It is essential to update and provide more specific guidance based on the latest science available.

The methodology focuses on consistency between historic analysis for the baseline and ex-post analysis during the project implementation. The accuracy that was used for ex-ante calculations must be used for ex-post calculations until the next baseline update which only occurs after 10 years. No guidance is provided about approaches to align less accurate data for historic periods with more accurate data that exists after 2015. Such guidance could significantly improve the accuracy of the detection of land use changes.

Some authors argue that remote sensing can be used to measure timber harvest over large areas, but for the quantification of carbon stock loss from low-intensity timber harvesting fuelwood collection, and understory thinning, it is necessary to rely on direct, ground level observation (Gao et al. 2020).

This issue introduces significant uncertainty in the quantification of carbon stocks. We assume that this issue affects a **high** fraction of projects, assuming that only few projects may use more accurate data as required under the methodology. The level of uncertainty and the variability among projects are **unknown**.

Figure 3 Example demonstrating the comparison of remote sensing images to detect logging in a forest in Uganda



Source: Neeff et al. (2023)

Un11 **Minimum mapping unit too large:** The minimum mapping unit is 1 hectare for remote sensing and classification procedures. The value of 1 ha is considered too high. The FAO forest definition uses 0.5 ha in its forest definition as minimum area (FAO 2018, p. 4) and 1 ha is the upper limit used of the range of 0.05-1 hectares chosen as minimum area by the UNFCCC for national forest definitions. The FAO definition and UNFCCC definition are elaborated for the cost-efficient mapping of an entire country, not for a specific project where the total areas are smaller and therefore smaller minimum mapping units should apply. This introduces further uncertainty, in particular in the context of 'mosaic' landscapes. We assume that this issue affects a **high** fraction of projects, assuming that only few projects use significantly higher resolutions. The level of uncertainty and the variability among projects are **unknown**.

OE11 **Insufficient guidance for ground truthing:** The calibration of medium-resolution remote sensing data is done with either direct field observations or "visually interpreted locations from remote sensing images" (Table 4). It is not mentioned that these remote sensing images should have a high resolution. The implemented projects show that frequently no direct field observations are used for ground-truthing and checking whether the remote sensing data has been correctly analysed. Ground-truthing with field observations is essential for quality assurance of project-level land classification. Visual interpretation of higher-resolution images is not a valid ground-truthing and calibration method. Ground truthing based on field observations should be mandatory and more specific guidance on the quantity and sampling methods for field observations should be provided. This issue introduces significant uncertainty. Moreover, it could also lead to an overestimation of emission reductions, as project developers may have leeway to interpret data in ways that provide larger emission reductions. We assume that this issue affects a **high** fraction of projects, assuming that only few projects use appropriate ground truthing approaches. The degree of overestimation and variability among projects are **unknown**.

Un12 **Insufficient guidance on forest stratification:** Minimum stratification in the methodology are the six land use classes of the IPCC. This is insufficiently accurate for avoided deforestation projects, in particular in mosaic landscapes where a large variety of land use classes exist in parallel that represent different carbon stocks. When the six IPCC land use classes are used, there would only be one general forest class. For a mosaic landscape forests it is important to stratify further, e.g. into natural forest and forest plantations, but also between intact primary forest and different type of degraded forests. The stratification is important to link the detected areas of the forest strata with the appropriate biomass factors for the strata. Without further stratification, biomass factors used will be associated with very high uncertainties. This issue introduces significant uncertainty. This issue is likely to apply to all projects. The level of uncertainty and the variability among projects are **unknown**.

Un13 **Outdated guidance on harvested wood products:** The methodology is using an outdated method based on Winjum et al. (1998) for the estimation of carbon stored in wood products, despite the fact that more recent IPCC methods exist, in particular in the 2019 Refinement to the 2006 IPCC Guidelines for National GHG Inventories. The suggested method is not in line with the IPCC methods because it entirely ignores any country-specific data on wood products which are generally available for all countries from FAO wood statistics. Instead, the method uses default fractions for the carbon stored in different wood products and default parameters for the oxidation in four wood product classes for three climate regions. The IPCC Guidance states that, in order to calculate storage in harvested wood products, country-specific information on the utilization of wood as material needs to be available. If this is not the case, it should be assumed that the wood is oxidized within short periods after harvesting.

The methodology uses a wood product called "other industrial round wood" which does not exist in the IPCC methods and the international classification system for wood products which is used in FAO statistics. Industrial roundwood is roundwood without fuelwood and charcoal and is the material of origin for sawnwood, wood-based panels and paper and paperboard. It therefore does not make sense to estimate “other industrial round wood” separately. This seems to lead to some double counting of harvested wood products.

The decay of wood products follows a first order decay function which is not reflected in the standard ratio of “remaining wood products between 5 and 100 years after initial harvest” in Table 19 of VM0006. The impact of this issue is proportional to the levels of harvested timber in the baseline and the actual project period. For a project, it would certainly be possible to track the main pathways of the harvested timber (whether it is delivered to sawmills for construction purposes or to pulp and paper production) and use these pathways for the calculation of carbon stored in wood products. The outdated standard factors introduce additional uncertainties. Overall, due to these issues, the estimation of carbon stored in harvested wood products may differ substantially from the real release or sequestration to or from the atmosphere. This issue is likely to apply to **all** projects. The level of uncertainty and the variability among projects are **unknown**.

UE8 **Uncertainty deduction factors:** Table 5 on p. 28 includes uncertainty deduction factors for the LULC classification as a function of accuracy attained. For an accuracy of ≥85% for the correct land use classification, no deduction applies. A project is not eligible if the land use accuracy detection is < 70%. For projects where the accuracy falls within the range of 70% to 85%, the deduction could contribute to an underestimation of emission reductions. The fraction of projects affected is **unknown**. For those projects where deductions are applied, the deduction factors would imply a **medium** degree of underestimation of total emission reductions. The variability among projects is unknown.

We note, however, that he accuracy levels used in Table 5 are rather low and recommend that higher values should be required without deduction factors because technologies have been developed considerably and a more precise determination of LULC classification is possible. The accuracy of land classification in national GHG inventories at the scale of entire countries is usually much higher than these thresholds, thus a higher accuracy level should apply at project level.

OE12 **Flexibility in choosing allometric equations:** Allometric equations are used to estimate the volume or biomass of trees based on parameters that are more easily to measure (e.g., height and trunk diameter at breast height). Allometric relationships can be determined based on destructive sampling of trees. Given the costs of destructive sampling, carbon crediting projects usually use literature sources of allometric equations. The quality of allometric relationships is best if the determination is site- and species-specific and from the same or a similar location. The determination of aboveground biomass through allometric equations is associated with considerable uncertainty, in particular in the case of tropical forests where the choice of allometric equations has been identified as a main source of error. Three important shortcomings have been identified: equations are constructed from limited samples; they are sometimes applied beyond their valid diameter range; and they rarely take into account the wood’s specific density (Martínez-Sánchez et al. 2020; Chave et al. 2004; van Breugel et al. 2011).

VM0006 allows the use of locally developed allometric equations as well as the use of the IPCC GPG for LULUCF (p. 130). The methodology does not provide a clear ranking and preference of site- and species-specific sources. More recent developments to achieve improved data on allometric equations are not taken into account. For example, the

GlobAllomeTree platform was created in 2013 to share and provide access to tree allometric equations. Since then, wood densities, biomass expansion factors, and raw data have been added to the platform. The FAO, CIRAD, and University of Tuscia, and many other organizations all over the world have contributed both their data and expertise. Due to the lack of prioritization towards better sources for allometric equations, the project proponents can potentially choose less accurate sources if they lead to higher calculated emission reductions.

This was found by Haya et al. (2023) who analyzed a sample of avoided deforestation projects using the methodologies VM0006, VM0009, VM0007 and VM0015 and observed that the allometric equations chosen by the project developers resulted in above-ground carbon estimates that were 15.4% higher than the average of their set of best-fit equations. This result suggests that project developers have likely taken advantage of the methodologies' flexibility to choose allometric equations that lead to high estimates of forest carbon and more emission reductions.

The fraction of projects affected by this issue is **unknown**. Where this issue materializes, the degree of overestimation is estimated to be **medium** (up to 30%), given the experiences observed with this and VCS methodologies by Haya et al. (2023). The variability in the degree of overestimation among projects is likely to be **high**.

OE13 **Flexibility in determining belowground biomass:** Belowground biomass is usually estimated using root-to-shoot ratios for trees as a relationship between aboveground biomass and roots. Direct measurement is very time-consuming; therefore, methodologies usually apply values from literature and IPCC Guidelines. Root-to-shoot ratios vary with tree species, age, tree size and climate. Therefore, it is important to select a scientific source that is as specific as possible for the forests and trees in the project region.

The guidance in VM0006 allows using default root-to-shoot ratios from the outdated IPCC GPG for LULUF, next to using relationships obtained from destructive sampling or from local studies. The methodology does not provide a prioritization for using more conservative estimates. Due to the lack of prioritization, the project proponents can potentially choose less accurate sources if they lead to higher calculated emission reductions.

This was observed with the methodologies VM0006, VM0009, VM0007 and VM0015. Haya et al (2023) compared the choice of root-to-shoot ratios for randomly selected VCS avoided deforestation projects with alternative peer-reviewed methods. On average, the projects' choice of root-to-shoot ratio was 37% higher than the mean of alternatives. They also found ratios applied in projects from literature that were not conservative, but much higher than alternative estimates. This suggests that project developers and verifiers did not conduct a careful comparison with literature sources. Similar to the estimation of aboveground biomass, this result shows that the flexibility provided by the methodologies was used by project developers to determine higher emission reductions.

This issue is likely to affect a **high** fraction of projects. Where this issue materializes, the impact on total credited emission reductions is estimated to be **low** (up to 10%), given that below-ground biomass usually is a smaller part of the overall emission reductions. The variability in the degree of overestimation among projects is likely to be **high**.

OE14 **Overestimation of the carbon fraction in biomass:** The carbon fraction in biomass is the percentage of total dry aboveground biomass that is carbon and is applied to the estimates of aboveground biomass derived from the allometric equations. For tropical trees, Martin et al. (2018) derived a best estimate of 0.456 based on a global synthesis of over 2,000 wood carbon concentration measurements. For tropical woodland trees Ryan et al. (2011) determined 0.47 as the most appropriate value. This value is also used as a global default value in the 2006 IPCC Guidelines (Volume 4, Chapter 4, Table 4.3). Martin et al. emphasized that the ubiquitous use of 0.5 for the carbon fraction introduces a systematic error in forest carbon accounting that leads to an 8.9% overestimate in tropical forests. VM0006 uses a default value of 0.5 which is therefore likely to lead to over-crediting. This issue is likely to apply to a **high** fraction of projects. For those projects where this issue materializes, the impact on total credited removals or emission reductions is estimated to be **low** (less than 10%). The variability in the degree of overestimation among projects is estimated to be **high**.

We note that projects registered under the methodology commonly failed to disclose key information about forest carbon accounting in their project documents. For instance, the raw tree data and forest inventories compiled by developers are commonly not disclosed. The quantification of carbon stocks cannot be replicated on the basis of the information made available. In our assessment, the lack of transparency and possibility to replicate the emission reduction calculation poses a risk for overestimation, as errors in the calculation or unreasonable assumptions cannot be identified by third parties. In 2022, however, Verra introduced new requirements that suggest that any spreadsheets of emission reduction calculations should be provided (VCS Registration and Issuance Process). Moreover, stakeholders request project documents that are missing from the Verra Registry (VCS Standard). We suggest that the VCS documents could be more specific about the type of data that should be provided (e.g., forest inventories). It would also be useful if the data is shared in a way to assist comparison across projects in public data repositories with standardized metadata and data formats, as well as assigning a citable digital object identifier (DOI) to ease citation tracking.

Determination of leakage emissions

In the following, we first provide an overview of general challenges regarding the determination of leakage emissions. As the VCS methodologies use partially similar approaches to quantify leakage emissions, we then provide an overview of commonalities and differences among the five VCS methodologies assessed by CCQI (VM0006, VM0007, VM0009, VM0015 and VM0048). We then turn to a detailed assessment of this methodology.

<u>*General challenges in establishing baselines for avoided deforestation projects*</u>

The main leakage risk for avoided deforestation projects arises from potential increases in deforestation elsewhere. This may occur due to “activity shifting” or “market leakage”. Activity-shifting leakage arises when a deforestation driver is displaced from the project area and leads to deforestation elsewhere. For instance, if timber production is the primary driver, activity leakage occurs if the deforestation agents relocate harvesting from the project area to surrounding areas. Market leakage occurs when avoiding deforestation alters market conditions by reducing the production of a traded commodity relative to the baseline, thereby creating incentives for others to intensify deforestation outside the project area (Streck 2021).

Leakage emissions are methodologically difficult to estimate. Depending on the type of leakage, different ways exist to estimate leakage effects. Activity shifting is often estimated by observing changes in deforestation in areas surrounding the project, which Verra refers to as leakage areas or leakage belts. Measurement tools to quantify such leakage effects can encompass onsite measurement or remote sensing to estimate changes in forest area and carbon stocks, along with interviews conducted within the local community (Henders and Ostwald 2012).

Market leakage is usually estimated with economic models used to determine shifts in the market equilibrium and the subsequent impacts of these changes on leakage (Henders and Ostwald 2012). The assessment of market leakage presents a distinctive set of difficulties, as it involves evaluating the impact of market forces and the adaptability of regional forest production rates in response to these influences. This undertaking is intricate, time consuming, expensive and it possess challenges in estimation (Guizar-Coutiño et al. 2022; Kuik 2013; Man-Keun et al. 2014). Moreover, models heavily rely on input data and are exceptionally responsive to alterations in the parameters chosen by researchers, introducing a degree of uncertainty (Filewod and McCarney 2023).

Assessing market leakage is also challenging as size of leakage effects can vary significantly. A meta-analysis by (Pan et al. 2020) highlights this complexity, revealing an average leakage rate of 39.6% for forestry projects but with significant variation (from 0 to 75%). This indicates that market leakage effects can be influenced by specific factors like the project location and economic factors integration. Given that leakage can manifest at local, national, or international levels, determining the suitable geographic parameters for its estimation is difficult (Henders & Ostwald 2012).

Market leakage can be very large for avoided deforestation projects. Conservation activities restricting land availability have a high risk of increasing prices for commodities such as timber which can lead to deforestation outside the project's boundary. Filewod and McCarney (2023) summarize that leakage estimates for developed nations are typically at least 70% of reduced output measured in terms of either forestry production or carbon stocks and that lower values (50% or less) have been found in developing country context. The meta-analysis by Pan et al. (2020) reveals an average leakage rate of 39.6% for forestry projects but with significant variation. Research by Atmadja et al. (2022) revealed, 28 out of 62 projects showed leakage effect with rates varying from 1% to 33%. These low leakage rate have been identified as being specific for small countries with rather limited access to timber and capital markets. Filewod and McCarney (2023) and Haya et al. (2023) further emphasize how the global market for wood products and a country's levels of integration into the market can be a significant factor in determining leakage rates.

By contrast, activity leakage may not exhibit higher deforestation rates. A study by Guizar-Coutiño et al. (2022) analyzed activity leakage across 40 VCS-REDD+ projects and found minimal leakage with only 3 projects indicating increased deforestation rates while two actually demonstrated a decrease. Furthermore, Alix-Garcia et al. (2012) reported a 50% reduction in deforestation rates in Mexico with low activity leakage of 4%. These findings suggest that the risk of activity leakage may much smaller than the risk of market leakage.

Summary of commonalities and differences among VCS avoided deforestation methodologies and issues identified in the literature

Quantification methodologies use a variety of approaches to account for leakage. All assessed VCS methodologies account for leakage from activity shifting and market effects, except for VM0015 which only considers leakage from activity shifting. To estimate activity shifting, satellite image analysis is used to detect any increase in deforestation rates in designated leakage zones around the project, often referred to as “leakage belts”. An increase in deforestation rates in these leakage areas must be accounted for through leakage deductions. The methodologies differ in how projects need to establish the geographical boundaries of these leakage areas and how “baseline” deforestation rates in these leakage areas are estimated.

To account for market leakage, the methodologies use default leakage rates. These default leakage rates were specified in the VCS AFOLU requirements which were later integrated in the VCS Methodology Requirements. The rates are 20%, 40%, and 70%, depending on the ratio of the project's merchantable biomass to total biomass, in comparison to the area to which the displacement occurs. The methodologies differ in how they account for leakage (Haya et al. 2023):

- **Relevant deforestation drivers:** The methodologies differ in which drivers of deforestation are considered relevant for market leakage: VM0006 requires accounting for market leakage only when illegal logging that supplies national or international markets is identified as a deforestation driver. VM0007 requires market leakage deductions when timber, fuelwood, or charcoal production are identified as drivers. VM0009 requires market leakage deductions when any commodity accounted for in the baseline scenario is displaced. VM0015 does not explicitly account for market leakage. VM0048 requires accounting for market leakage when timber, fuelwood, or charcoal are identified as drivers.
- **Application of default values:** The methodologies also differ in how the default values are applied in the quantification of emission reductions. VM0006 applies the leakage deduction to total emissions reductions, whereas VM0007 applies it just to the emissions associated with the displaced timber harvest, and VM0009 applies it to the portion of emissions reductions from aboveground merchantable trees. VM0048 applies the leakage deduction for market leakage to the carbon emissions associated with the timber harvesting in the baseline.
- **Alternative approaches:** VM0009 allows project developers to pursue alternative approaches to quantify leakage emissions with due justification whereas the other methodologies do not allow for such approaches.

Altogether, this suggests that the general VCS requirements for accounting for market leakage have been applied in different ways across methodologies.

Leakage deduction applied by projects appear overall too low. The available evaluations of individual projects using the methodologies VM0006, VM0007, VM0009 and VM0015 suggest that most projects do not apply any leakage deductions. Calyx Global (2023)assessed 70 projects covering 94% of the avoided deforestation credits that have been verified as of December 2022 and found that about 60% of the project claims zero leakage. Similarly, Haya et al. (2023) found that 59% of projects did not take any leakage deductions. Case studies suggest that projects which are at risk of activity or market leakage avoided leakage deductions by using various arguments for exceptions, questionable justifications, and made use of lax requirements in the methodologies).

Where projects apply leakage deductions, these are relatively low. An analysis of 73 projects using the methodologies VM0006, VM0007, VM0009 and VM0015 reveals that the median leakage deduction applied by all projects (including those claiming zero leakage) are 2.6% for activity shifting and 4.4% for market leakage. Zero or low leakage claims are quite prevalent: 55 out of the 73 projects claimed zero leakage from activity shifting and 54 claimed zero market leakage. For those that apply the deduction, total leakage rates are under 25% (Haya et al. 2023). This implies that the projects are likely to underestimate market leakage effects.

Methodologies do not account for international leakage. Any project activities that displace commodities which are linked to the global market can lead to international leakage (Haya et al. 2023). None of the VCS methodologies account for international leakage. However, several studies indicate that a decrease in harvesting of timber or other commodities within project boundary often can induce more harvesting or deforestation in other countries (Gan and McCarl 2007; Murray et al. 2004; Sohngen 2009).

Assessment of VM0006

This methodology estimates the following sources of leakage:

1. **Activity shifting leakage by geographically constrained drivers**: This refers to agents that may shift their deforestation activities to the project's surrounding areas, potentially leading to increased deforestation in those areas. The leakage must be assessed by calculating deforestation and forest degradation rates in the area where agents are likely to be displaced. The area is referred to as a “leakage belt”.
2. **Activity shifting leakage by geographically unconstrained drivers:** This refers to the relocation of agents to the project area, which may result in deforestation in the baseline scenario. Due to the implementation of the project, these agents may shift to other areas, potentially causing land-use changes in these areas.
3. **Market leakage:** Market leakage is considered when illegal logging activities supplying timber to national or international markets are identified as a driver.
4. **Emissions from leakage prevention measures:** This relates to emissions caused by measures to prevent leakage. A number of optional leakage prevention activities are specified under VM0006, namely assisted natural regeneration activities, cookstove and fuel efficiency activities, harvest activities in the project area, the intensification of annual production systems, flooded rice production systems, or an increase in livestock stocking rates.

We identify the following potential sources of overestimation, underestimation or uncertainty with this approach:

OE15 **No accounting for market leakage for drivers other than timber:** The VM0006 methodology requires market leakage deductions to be applied only when illegal logging that supplies national or international timber markets is identified as a deforestation driver. This approach fails to consider other important deforestation drivers which are relevant for national and international markets, such as charcoal, fuelwood or agricultural production. For instance, beef, soybean or palm oil production are important drivers for deforestation within national boundaries and can impact the levels of imports or exports (see, for example, Pendrill et al. 2019). Failing to consider other commodities than timber could therefore result in overestimation of emission reduction. This issue is likely to affect a **high** fraction of projects. The impact on total credited removals is **unknown.** The variability in the degree of overestimation among projects is estimated to be **high.**

OE16 **Flexibility in defining the leakage belt:** The methodology allows project developers to define and adjust the leakage belt based on observed changes in deforestation patterns or socioeconomic activities. It also allows modifications to the leakage belt and periodic reassessment if any new project parcels are added. This may allow developers to exclude places where activity shifting is most likely to occur and may result in overestimation of emission reductions. The fraction of projects affected, and the degree of overestimation are unknown. The variability in the degree of underestimation among projects is estimated to be high.

OE17 **Low market leakage discount factor:** The methodology prescribes a market leakage deduction factor between 0% to 25%, depending on the effect that the project activity has on the harvested timber volume. The more harvest levels are reduced, the higher is the market leakage discount factor. This range is lower than literature estimates of market leakage effects (see above) This could potentially lead to underestimation of total credited emission reductions. The fraction of projects affected is estimated to be high. The degree of overestimation is unknown. The variability in the degree of overestimation among projects is likely to be high.

UE9 **No accounting of any negative leakage:** In principle, it is conceivable that avoided deforestation projects could also reduce deforestation outside the project area. This could occur if the measures taken to reduce deforestation drivers not only affect the project area but also surrounding areas. The methodology does not account for any such "negative" leakage effects. Any decrease in deforestation observed in the leakage belt is not accounted for as a negative leakage term. This could potentially lead to underestimation of total credited emission reductions. The fraction of projects affected, and the degree of underestimation are estimated to be **low**. The variability in the degree of underestimation among projects is likely to be **high**.

OE18 **Overestimation of baseline deforestation and degradation rates in the leakage area:** The methodology calculates baseline deforestation rates in the leakage area by taking the "size-wise proportion of the deforestation/degradation rates in the project area under the baseline scenario" (section 8.3.2). This approach assumes that deforestation occurs at the same rate across the leakage area as in the baseline scenario for the project area. As baseline deforestation rates are likely to be overestimated (see discussion further above), it is likely that baseline rates in the leakage area are also overestimated, leading to underestimation of leakage from activity shifting. The fraction of projects affected is estimated to be **high**. The degree of overestimation is **unknown**. The variability in the degree of overestimation among projects is likely to be **high**.

Summary and conclusion

Table 2 summarizes the results of the assessment and, where possible, presents the potential impact on the quantification of emission reductions for each of the previously discussed elements.

Table 2 Relevant elements of assessment and qualitative ratings

Element	Fraction of projects affected by this element[1]	Average degree of under- or overestimation where element materializes[2]	Variability among projects where element materializes[3]
Elements likely to contribute to overestimating emission reductions or removals			
OE1: Lack of clarity regarding the tool to demonstrate a pool or source is insignificant	Unknown	Unknown	Unknown
OE2: Contradictory provisions add confusion to determination of inclusion/exclusion for emission sources	Unknown	Unknown	Unknown
OE3: CO_2 emissions from biomass burning are excluded	Unknown	Unknown	Unknown
OE4: CH_4 and N_2O emissions from biomass burning are excluded	Unknown	Unknown	Unknown
OE5: N_2O emissions from increased fertilizer use are excluded	Unknown	Unknown	Unknown
OE6: Flexibility in choosing the length of the historical reference period	Unknown	High	Unknown
OE7: Flexibility in the selection of the reference region	Unknown	High	Unknown

1 This parameter refers to the likely fraction of individual projects (applying the same methodology) that are affected by this element, considering the potential portfolio of projects. “Low” indicates that the element is estimated to be relevant for less than one third of the projects, “Medium” for one to two thirds of the projects, “High” for more than two third of the projects, and “All” for all of the projects. “Unknown” indicates that no information on the likely fraction of projects affected is available.

2 This parameter refers to the likely average degree / magnitude to which the element contributes to an over- or underestimation of the total emission reductions or removals for those projects for which this element materializes (i.e., the assessment shall not refer to average over- or underestimation resulting from all projects). “Low” indicates an estimated deviation of the calculated emission reductions or removals by less than 10% from the actual (unknown) emission reductions or removals, “Medium” refers to an estimated deviation of 10 to 30%, and high refers to an estimated deviation larger than 30%. “Unknown” indicates that it is likely that the element contributes to an over- or underestimation (e. g. overestimation of emission reductions in case of an omitted project emission source) but that no information is available on the degree / magnitude of over- or underestimation. Where relevant information is available, the degree of over- or underestimation resulting from the element may be expressed through a percentage range.

3 This refers to the variability with respect to the element among those projects for which the element materializes. “Low” means that the variability of the relevant element among the projects is at most ±10% based on a 95% confidence interval. For example, an emission factor may be estimated to vary between values from 18 and 22 among projects, with 20 being the mean value. “Medium” refers to a variability of at most ±30%, and “High” of more than ±30%.

Element	Fraction of projects affected by this element[1]	Average degree of under- or overestimation where element materializes[2]	Variability among projects where element materializes[3]
OE8: Flexibility in choosing imagery for determining historical deforestation in the reference region	Unknown	Unknown	Unknown
OE9: Flexibility in choosing the temporal component for emission factors from deadwood and soil	Unknown	Low	Unknown
OE10: Lack of appropriate definitions of forest, deforestation and degradation	All	Unknown	High
OE11: Insufficient guidance for ground truthing	High	Unknown	Unknown
OE12: Flexibility in choosing allometric equations	Unknown	Medium	High
OE13: Flexibility in determining belowground biomass	High	Low	High
OE14: Overestimation of the carbon fraction in biomass	High	Low	High
OE15: No accounting for market leakage for drivers other than timber	High	Unknown	High
OE16: Flexibility in defining the leakage belt	Unknown	Unknown	High
OE17: Low market leakage discount factor	High	Unknown	High
OE18: Overestimation of baseline deforestation and degradation rates in the leakage area	High	Unknown	High
Elements likely to contribute to underestimating emission reductions or removals			
UE1: Inclusion of aboveground non-tree biomass is optional. The number of projects affected is unknown	Unknown	Low	Unknown
UE2: Inclusion of belowground biomass is optional	Unknown	Low	Unknown
UE3: Deadwood is an optional source	Unknown	Low	Unknown
UE4: Litter is identified as an optional source	Unknown	Low	Unknown

Element	Fraction of projects affected by this element[1]	Average degree of under- or overestimation where element materializes[2]	Variability among projects where element materializes[3]
UE5: Soil carbon is identified as an optional source	Unknown	Low	Unknown
UE6: Emissions from livestock are optional under some project scenarios	Unknown	Low	Unknown
UE7: Accuracy discount for uncertainty in land use and land cover classification	Low	Medium	Unknown
UE8: Uncertainty deduction factors	Unknown	Medium	Unknown
UE9: No accounting of any negative leakage	Low	Low	High
Elements with unknown impact			
Un1: Methodology does not consider emissions of CO_2 from the combustion of fossil fuels	Unknown	Low	Unknown
Un2: Calibration of the "forest scarcity factor"	Unknown	Medium	Unknown
Un3: Treatment of temporarily unstocked forest land	All	Low	Unknown
Un4: Flexibility in defining the forest stratification model when degradation is included and lack of transparency	All	Low	Unknown
Un5: Accuracy discount for forest stratification	Unknown	Medium	Unknown
Un6: No uncertainty assessment for removals from forest cover increase and natural regeneration	Unknown	Low	Unknown
Un7: No uncertainty assessment for statistical deforestation model for determining suitability of deforestation	High	High	Unknown
Un8: Overall uncertainty assessment	All	Unknown	Unknown
Un9: Outdated methodological basis	All	Unknown	Unknown
Un10: Specific guidance missing for remote sensing	High	Unknown	Unknown
Un11: Minimum mapping unit too large	High	Unknown	Unkown
Un12: Insufficient guidance on forest stratification	All	Unknown	Unknown

Element	Fraction of projects affected by this element[1]	Average degree of under- or overestimation where element materializes[2]	Variability among projects where element materializes[3]
Un13: Outdated guidance on harvested wood products	All	Unknown	Unknown

The table shows that there are many potential sources of overestimation, underestimation, and uncertainty. Based on our assessment of the elements in the table, we conclude that the methodology is likely to lead to overestimation of emission reductions or removals and that the degree of overestimation is likely to be large (i.e., larger than 30%). This corresponds to a score of 1 according to the CCQI methodology (see page 2).

In our assessment, overestimation of baseline deforestation rates is the largest integrity risk. The flexibility provided by the methodology for choosing the length of the historical reference period (OE6), selecting the reference region (OE7) and choosing historical imagery for determining historical deforestation (OE8) are the most important issues that contribute to a likely overestimation of expected deforestation in the baseline. Moreover, establishing the baseline is associated with very large uncertainty. Two important issues that contribute to uncertainty in the baseline are the lack of uncertainty assessments for estimated removals from forest cover increase (Un6) and for the model used to determine the suitability of lands for being deforested (Un7). The uncertainty deduction related to the classification of lands in historical images (UE7) is a potential source of underestimation.

We also find that leakage effects are likely to be underestimated, in particular because accounting for market leakage is limited to timber (OE15) and the discounts for market leakage appears relatively low (OE17). Lastly, there is a large risk that biomass carbon stocks are overestimated, partially due to the use of outdated data and partially due to the flexibility provided to project developers in determining carbon stocks (OE11 to OE14). We also note that the exclusion of some carbon pools and emission sources may lead to underestimation for some projects (UE1 to UE6) but this underestimation is estimated to be significantly smaller than the risks of overestimation.

References

Alix-Garcia, J. M.; Shapiro, E. N.; Sims, K. R. E. (2012): Forest Conservation and Slippage: Evidence from Mexico's National Payments for Ecosystem Services Program. In: *Land Economics* 88 (4), pp. 613–638. DOI: 10.3368/le.88.4.613.

Atmadja, S. S.; Duchelle, A. E.; Sy, V. de; Selviana, V.; Komalasari, M.; Sills, E. O.; Angelsen, A. (2022): How do REDD+ projects contribute to the goals of the Paris Agreement? In: *Environ. Res. Lett.* 17 (4), p. 44038. DOI: 10.1088/1748-9326/ac5669.

Calyx Global (2023): Turning REDD+ into Green, Improving the GHG integrity of avoided deforestation credits, 2023. Online available at https://calyxglobal.com/assets/files/resources/643a3d3a8a28e_Turning%20REDD%20into%20Green_v0101.pdf, last accessed on 20 Mar 2024.

Chave, J.; Condit, R.; Aguilar, S.; Hernandez, A.; Lao, S.; Perez, R. (2004): Error propagation and scaling for tropical forest biomass estimates. In: *Philosophical transactions of the Royal Society of London. Series B, Biological sciences* 359 (1443), pp. 409–420. DOI: 10.1098/rstb.2003.1425.

FAO - Food and Agriculture Organization of the United Nations (2018): Terms and Definitions FRA 2020, Global Forest Resources Assessment 2020 Working Paper 188. Rome, 2018. Online available at https://www.fao.org/3/I8661EN/i8661en.pdf, last accessed on 16 May 2024.

Fernández-Montes de Oca, A.; Ghilardi, A.; Kauffer, E.; Gallardo-Cruz, J. A.; Núñez, J. M.; Sánchez-Cordero, V. (2022): Harmonizing Definitions and Methods to Estimate Deforestation at the Lacandona Tropical Region in Southern Mexico. In: *Remote Sensing* 14 (10), p. 2319. DOI: 10.3390/rs14102319.

Filewod, B. and McCarney, G. (2023): Avoiding carbon leakage from nature-based offsets by design. In: *One Earth* 6 (7), pp. 790–802. DOI: 10.1016/j.oneear.2023.05.024.

Gan, J. and McCarl, B. A. (2007): Measuring transnational leakage of forest conservation. In: *Ecological Economics* 64 (2), pp. 423–432. DOI: 10.1016/j.ecolecon.2007.02.032.

Gao, Y.; Skutsch, M.; Paneque-Gálvez, J.; Ghilardi, A. (2020): Remote sensing of forest degradation: a review. In: *Environ. Res. Lett.* 15 (10), p. 103001. DOI: 10.1088/1748-9326/abaad7.

Guizar-Coutiño, A.; Jones, J. P. G.; Balmford, A.; Carmenta, R.; Coomes, D. A. (2022): A global evaluation of the effectiveness of voluntary REDD+ projects at reducing deforestation and degradation in the moist tropics. In: *Conservation Biology* 36 (6). DOI: 10.1111/cobi.13970.

Haya, B. K.; Alford-Jones, K.; Anderegg, W. R. L.; Beymer-Farris, B.; Blanchard, L.; Bomfim, B.; Chin, D.; Evans, S.; Hogan, M.; Holm, J. A.; McAfee Kathleen; So, I.; West, T. A. P. et al. (2023): Quality Assessment of REDD+ Carbon Credit Projects, Berkeley Carbon Trading Project, 2023. Online available at https://gspp.berkeley.edu/research-and-impact/centers/cepp/projects/berkeley-carbon-trading-project/REDD+, last accessed on 18 Mar 2024.

Henders, S. and Ostwald, M. (2012): Forest Carbon Leakage Quantification Methods and Their Suitability for Assessing Leakage in REDD. In: *Forests* 3 (1), pp. 33–58. DOI: 10.3390/f3010033.

Kuik, O. J. (2013): REDD Policies, Global Food, Fiber and Timber Markets and 'Leakage', In J. Gupta, N. van der Grijp, & O. J. Kuik (Eds.), Climate Change, Forests and REDD: Lessons for Institutional Design (pp. 207-228).: Routledge. Online available at https://www.taylorfrancis.com/chapters/edit/10.4324/9780203077221-10/redd-policies-global-food-fibre-timber-markets-leakage-onno-kuik.

Man-Keun, K.; Peralta, D.; McCarl, B. A. (2014): Land-based greenhouse gas emission offset and leakage discounting. In: *Ecological Economics* (105), 2014, pp. 265–273. Online available at https://doi.org/10.1016/j.ecolecon.2014.06.009.

Martin, A. R.; Doraisami, M.; Thomas, S. C. (2018): Global patterns in wood carbon concentration across the world's trees and forests. In: *Nature Geosci* 11 (12), pp. 915–920. DOI: 10.1038/s41561-018-0246-x.

Martínez-Sánchez, J. L.; Martínez-Garza, C.; Cámara, L.; Castillo, O. (2020): Species-specific or generic allometric equations: which option is better when estimating the biomass of Mexican tropical humid forests? In: *Carbon Management* 11 (3), pp. 241–249. DOI: 10.1080/17583004.2020.1738823.

Murray, B. C.; McCarl, B. A.; Lee, H.-C. (2004): Estimating Leakage from Forest Carbon Sequestration Programs. In: *Land Economics* 80 (1), pp. 109–124. DOI: 10.2307/3147147.

Neeff, T.; Vollrath, A.; Lindquist, E.; García, J.; Fox, J.; Sandker, M.; Nakalema, T. (2023): Estimating emissions and removals from forest degradation, An overview of country experience. Food and Agriculture Organization of the United Nations, 2023. Online available at https://doi.org/10.4060/cc5803en.

Pan, W.; Kim, M.-K.; Ning, Z.; Yang, H. (2020): Carbon leakage in energy/forest sectors and climate policy implications using meta-analysis. In: *Forest Policy and Economics* (115), 2020. Online available at https://doi.org/10.1016/j.forpol.2020.102161.

Pendrill, F.; Persson, U. M.; Godar, J.; Kastner, T.; Moran, D.; Schmidt, S.; Wood, R. (2019): Agricultural and forestry trade drives large share of tropical deforestation emissions. In: *Global Environmental Change* 56, pp. 1–10. DOI: 10.1016/j.gloenvcha.2019.03.002.

Ryan, C. M.; Williams, M.; Grace, J. (2011): Above- and Belowground Carbon Stocks in a Miombo Woodland Landscape of Mozambique, Biotropica Volume 43, Issue 4 pp. 423 - 432, 2011. Online available at https://doi.org/10.1111/j.1744-7429.2010.00713.x, last accessed on 20 Mar 2024.

Seyller, C.; Desbureaux, S.; Ongolo, S.; Karsenty, A.; Simonet, G.; Faure, J.; Brimont, L. (2016): The 'virtual economy' of REDD+ projects: does private certification of REDD+ projects ensure their environmental integrity? In: *Int. Forest. Rev.* 18 (2), pp. 231–246. DOI: 10.1505/146554816818966273.

Sohngen, B. (2009): An Analysis of Forestry Carbon Sequestration as a Response to Climate Change, COPENHAGEN CONSENSUS ON CLIMATE. AED Economics, Ohio State University, 2009. Online available at https://cfaes.osu.edu/sites/aede/files/publication_files/Analysis%20of%20Forestry%20Carbon.pdf.

Streck, C. (2021): REDD+ and leakage: debunking myths and promoting integrated solutions. In: *Climate Policy* 21 (6), pp. 843–852. DOI: 10.1080/14693062.2021.1920363.

Sylvera (ed.) (2023): The State of Carbon Credits 2023, How the market can move forward, 2023. Online available at https://www.sylvera.com/resources/the-state-of-carbon-credits-report., last accessed on 29 May 2024.

van Breugel, M.; Ransijn, J.; Craven, D.; Bongers, F.; Hall, J. S. (2011): Estimating carbon stock in secondary forests: Decisions and uncertainties associated with allometric biomass models. In: *Forest Ecology and Management* 262 (8), pp. 1648–1657. DOI: 10.1016/j.foreco.2011.07.018.

West, T. A. P.; Börner, J.; Sills, E. O.; Kontoleon, A. (2020): Overstated carbon emission reductions from voluntary REDD+ projects in the Brazilian Amazon. In: *Proceedings of the National Academy of Sciences of the United States of America* 117 (39), pp. 24188–24194. DOI: 10.1073/pnas.2004334117.

West, T. A. P.; Wunder, S.; Sills, E. O.; Börner, J.; Rifai, S. W.; Neidermeier, A. N.; Frey, G. P.; Kontoleon, A. (2023): Action needed to make carbon offsets from forest conservation work for climate change mitigation. In: *Science (New York, N.Y.)* 381 (6660), pp. 873–877. DOI: 10.1126/science.ade3535.

Winjum, J. K.; Brown, S.; Schlamadinger, B. (1998): Forest Harvests and Wood Products: Sources and Sinks of Atmospheric Carbon Dioxide. In: *Forest Science* 44 (2), pp. 272–284. DOI: 10.1093/forestscience/44.2.272.