Title

Methodological issues with deforestation baselines compromise the integrity of carbon offsets from REDD+

Authors

West, Thales AP
Bomfim, Barbara
Haya, Barbara K

Publication Date

2024-07-01

DOI

10.1016/j.gloenvcha.2024.102863

Global Environmental Change 87 (2024) 102863

Contents lists available at ScienceDirect

Global Environmental Change

journal homepage: www.elsevier.com/locate/gloenvcha

Methodological issues with deforestation baselines compromise the integrity of carbon offsets from REDD+

Thales A.P. West [a,b,*], Barbara Bomfim [c,d], Barbara K. Haya [d]

[a] Institute for Environmental Studies (IVM), Vrije Universiteit Amsterdam, Amsterdam, The Netherlands
[b] Centre for Environment, Energy and Natural Resource Governance, University of Cambridge, Cambridge, UK
[c] Climate and Ecosystem Sciences, Lawrence Berkeley National Laboratory, Berkeley, CA, USA
[d] Goldman School of Public Policy, University of California, Berkeley, Berkeley, CA, USA

ARTICLE INFO

Keywords:
Carbon credit
Additionality
Avoided deforestation
Nature-based solutions

ABSTRACT

The number of voluntary interventions seeking to generate carbon offsets by reducing deforestation and forest degradation, generally known as REDD+ projects, has increased significantly over the past decade. Offsets are issued based on project performance in comparison to a baseline scenario representing the expected deforestation in a project area in the absence of REDD+. Baselines from most ongoing REDD+ projects were established following four methodologies approved by the largest voluntary carbon offset certification scheme worldwide, the Verified Carbon Standard (VCS) from Verra. These methodologies often rely on oversimplified assumptions about deforestation that remain overlooked by project developers, certification bodies, and buyers. Here, we explore what these methodological assumptions are and their implications. We then construct alternative deforestation baselines for four ongoing VCS-certified projects using the four VCS-REDD+ methodologies and examine how they differ. Overall, we observe large discrepancies among the project baselines. On average, the highest baseline value we calculate for each project is more than 14 times greater than the lowest value across the four projects studied. This illustrates the lack of robustness and consistency across the VCS-REDD+ methodologies. The results also call into question the additionality of carbon offsets issued based on these methodologies. New baseline methods need to be urgently developed if voluntary REDD+ projects are to reliably estimate their additional contribution to climate change mitigation. The incorporation of causal inference methods represents current best practices in measuring the efficacy of REDD+ interventions. Regrettably, these methods remain largely overlooked by project developers, certification standards, and governmental and international bodies. Dynamic baselines developed by independent analysts could potentially enable project developers to distinguish the impacts of the REDD+ intervention from confounding factors and properly estimate additionality.

1. Introduction

Reduced Emissions from Deforestation and forest Degradation (REDD+) attracted significant attention as a strategy to mitigate climate change following the discussions that started at the 11th Conference of Parties (COP11) to the United Nations Framework Convention on Climate Change in 2005 (UNFCCC; Thompson et al., 2011). Since then, while governments worked on institutional REDD+ arrangements at national and subnational levels (Börner et al., 2018; FAO, 2019; UN-REDD, 2021), multiple decentralized, voluntary REDD+ projects became operational worldwide (Wunder et al., 2020). These projects are largely funded through the commercialization of carbon offsets in voluntary carbon markets (West, 2016a). Currently, the volume of offsets issued by REDD+ projects represents the largest share of transactions in the voluntary carbon market, involving project developers and thousands of buyers interested in neutralizing their greenhouse gas emissions (GHG; So et al., 2023; Donofrio et al., 2021; The World Bank, 2021). Moreover, there are efforts in place to scale and integrate the GHG emission reductions claimed by these projects into cap-and-trade markets and Nationally Determined Contributions to climate change mitigation committed under the Paris Agreement (Blum and Lövbrand, 2019; FAO, 2019; Lee et al., 2018; McAfee, 2022; Taskforce on Scaling Voluntary Carbon Markets, 2021; Verra, 2021).

The effectiveness of voluntary REDD+ projects at reducing GHG

* Corresponding author at: Institute for Environmental Studies (IVM), Vrije Universiteit Amsterdam, Amsterdam, The Netherlands.
E-mail address: t.a.pupowest@vu.nl (T.A.P. West).

https://doi.org/10.1016/j.gloenvcha.2024.102863
Received 16 May 2023; Received in revised form 22 May 2024; Accepted 25 May 2024
Available online 10 June 2024

emissions from unplanned (illegal) deforestation is measured against a baseline (or counterfactual) scenario, representing the expected deforestation in the absence of REDD+ activities (Bos et al., 2017; West et al., 2018). In general, the higher the baseline deforestation, the more offsets a project can claim. Because deforestation can be affected by a number of factors that change over time, the use of *ex-post* methods—based on observable data from control units (i.e., areas not exposed to REDD+ activities) rather than forecasts—is considered the best practice for creating credible counterfactuals and assessing project performance (Balmford et al., 2023; Guizar-Coutiño et al., 2022; West et al., 2020a; 2023). That is because such *ex-post* approaches can account for potential bias from confounding factors that change over time and affect both project and control units similarly, e.g., changes in governance or agricultural commodity prices (Ferraro and Hanauer, 2014).

In contrast, the baseline methodologies adopted by most existing voluntary REDD+ projects—VM0006 (Terra Global Capital, 2017), VM0007 (Avoided Deforestation Partners, 2020a), VM0009 (Wildlife Works and ecoPartners, 2014), and VM0015 (Pedroni, 2012a)—are based on *ex-ante* approaches. According to these methodologies, approved under the Verified Carbon Standard (VCS) certification scheme from Verra (Verra, 2019), baselines are usually simplistic forecasts that ignore the influence of confounding factors. For example, these forecasts can be based on extrapolations of historical deforestation trends or averages observed over a 10-year period, disregarding changes in political or economic contexts known to influence deforestation (Assunção et al., 2015; Busch and Ferretti-Gallon, 2017; Lambin et al., 2014; West and Fearnside, 2021). As a result, simplistic *ex-ante* baselines can easily become unrealistic. Furthermore, because project sites are largely covered by forests (i.e., areas virtually without deforestation), deforestation baselines are informed by the historical deforestation observed at a broader spatial scale, known as the *reference region*. While VM0006 and VM0009 tend to measure historical deforestation rates in the reference region and proportionally apply these—in the form of annual averages or forecasts from statistical models—to the project area to create its baseline, the most popular methodologies, VM0007 and VM0015, include an additional step based on spatial, "pixel-level prioritization." Under this approach, the baseline deforestation is not proportionally allocated to the project site, but rather spatially allocated across the reference region using a deforestation-risk (or suitability) map. These maps are produced based on relationships between historical deforestation patterns and observable spatial attributes within the reference region, e.g., distances to roads and rivers, presence of protected areas, elevation, slope, and soil type (Sloan and Pelletier, 2012; West et al., 2019). Annual baseline deforestation rates are then allocated across the reference region starting with the pixels with the highest estimated risk. Only the deforestation allocated inside project boundaries throughout the lifetime of the project is considered part of the project's baseline scenario. However, several algorithms can be employed for the construction of deforestation-risk maps, e.g., logistic regressions and artificial neural networks, often resulting in "equally valid," and yet contradicting, spatial configurations (Lin et al., 2011; Soares-Filho et al., 2013; West et al., 2020b). As a result, VM0007 and VM0015 offer extra opportunities for baseline "gaming" given that configurations that allocate more baseline deforestation inside the project areas are financially more attractive than others (e.g., Soares-Filho, 2012). Previous studies found that *ex-ante* project baselines tend to be overestimated compared to those constructed using best-practice *ex-post* methods (West et al., 2020a, 2023).

Here, we explore the methodological reasons why the *ex-ante* baselines adopted by voluntary REDD+ projects tend to result in unreliable counterfactual scenarios. First, we examine the key assumptions underlying the four most adopted VCS-REDD+ methodologies. Then, we employ those key methodological assumptions to illustrate their implications by creating alternative *ex-ante* deforestation baselines for four operational REDD+ projects around the world.

2. VCS-REDD+ methodologies

2.1. VM0006: *"Methodology for carbon accounting for mosaic and landscape-scale REDD projects" (v.2.2)*

VM0006 is a VCS-REDD+ methodology for projects located in regions where deforestation follows a "mosaic" configuration (Terra Global Capital, 2017), where mainly small-scale deforestation agents and drivers "are spread out across the forest landscape" and "most areas of the forest landscape are accessible to human populations" (Verified Carbon Standard, 2017). In VM0006, baseline deforestation is based on a historical average or trend observed in the project's reference region and is proportionally applied to the REDD+ project area (Table 1). A spatial allocation of the deforestation baseline is only required if the project area has more than one forest stratum (with different carbon stocks) or if more than one post-deforestation land-use class (e.g., pastureland and palm oil plantation) is considered in the baseline scenario (also associated with different carbon stocks).

According to VM0006, the estimation of the baseline deforestation rate is based on "beta regressions," fitted to historical deforestation data.[1] These regressions are mainly a function of time (i.e., years prior to project start), but can include other covariates related to deforestation, such as protection status and distance to roads. If a model can be constructed for which all covariates are significant (p-value ≤ 0.05), the lower limit of the 95 % confidence interval of the regression model's forecast can be used as the deforestation baseline; otherwise, the baseline must be based on a historical average (Table 1). The baseline deforestation is further discounted by two "forest scarcity factors," rendering the baseline more conservative. In effect, as the project area becomes increasingly deforested, the baseline deforestation rates also decline due to the discounting from the forest scarcity factors (Equation (1)). According to VM0006, the use of these factors is justified based on the forest transition theory, which postulates deforestation rates to decrease with socioeconomic development and shifts in the labor market (Köthke et al., 2013; Rudel et al., 2005).

While VM0006 is complex, the calculation of the baseline deforestation can be simplified to:

$$D_{PA,t} = d_{RR}(t) \times \frac{PA}{RR} \times \frac{1}{1 + e^{s_1\left(s_2 - \frac{NFA_t}{PA}\right)}} \tag{1}$$

where $D_{PA,t}$ is the baseline deforestation in the REDD+ site in year t (ha), which is a function of $d_{RR}(t)$, representing either an annual deforestation average or a forecast from a "beta regression" (or linear regression) model based on historical deforestation data from the project's reference region, adjusted by the proportional size of the project area (PA) in relation to its reference region (RR), and discounted by the forest scarcity factors s_1 and s_2. In turn, the scarcity factors are a function of the non-forest area (NFA_t) proportion within PA; s_1 represents the deforestation rate of decay, whereas s_2 is the relatively cleared area at which deforestation is expected to reach 50 % of the initial deforestation rate in the project region.

[1] As defined in VM0006, beta regressions are "commonly used to model variables that assume values in the standard unit interval (0; 1)," where the dependent variable is beta-distributed with a mean related to a set of regressors through a linear predictor with unknown coefficients and a link function (Terra Global Capital, 2017, p. 48). However, such a definition of beta regressions is not compatible with the equations, steps, and examples provided throughout VM0006 on the calculation of baseline deforestation rates (Terra Global Capital, 2017, pp. 48–52). It is our understanding that, despite its definition, the term "beta regression" is in fact used in the methodology to describe a linear regression model (hence, the use of the term in quotes throughout the text).

Table 1
Overview of REDD+ methodologies approved under the Verified Carbon Standard.

Factor	VM0006	VM0007	VM0009	VM0015
Minimum size of the reference region	250,000 ha or the size of the project area (whichever is greater)	For RRD*: $7500 \times PA^{-0.7}$, where PA is the project area (ha); the area of forest in the RRL* must be ± 25 % of the area of the RRD*	Greater than or equal to the project size	Suggested: 5–7 times larger than >100,000-ha projects; 20–40 times larger than <100,000-ha projects
Reference region's forest cover at the project start	≥15 %	100 % for RRD*; ≥50 % for RRL*. The area of forest in the RRL* must be within a ±25 % range of the corresponding values in the RRD*	N/A	N/A
Shared characteristics between project area and reference region	Drivers of deforestation; landscape configuration (forest type, elevation, slope); and socio-economic and cultural conditions (land-tenure status, policies/regulations, degree of urbanization). Generally, the reference region values linked to these attributes should fall within a ±10 % range of the corresponding values in the project area	Agents of deforestation; landscape factors (forest class, soil type, slope, elevation); transportation networks and human infrastructure (roads, navigable rivers, settlements, etc.); social factor (presence of gangs or guerillas, the ethnic composition of local populations); policies and regulations. Generally, the values linked to these attributes should fall within a ± 20 % range of the corresponding values in the project area for the RRD* and within a ±30 % range for the RRL*	Drivers of deforestation; location and mobility of deforestation agents; landscape configuration (topography, land use/cover, soil type, infrastructure, market distance, land tenure). The reference region values linked to these attributes do not need to fall within a predefined range relative to the corresponding values in the project area	Agents and drivers of deforestation; infrastructure drivers; any spatial drivers expected to influence the project area (resettlement programs, mining and oil concessions, etc.); landscape configuration and ecological conditions (forest/vegetation classes, elevation, slope, rainfall); socio-economic and cultural conditions (legal status of the land, land use); enforced policies and regulations. Generally, the reference region values linked to these attributes should fall within a ± 10 % range of the corresponding values in the project area
Estimation of baseline deforestation rate	Historical average or "beta regression" (as a function of time) fitted to historical deforestation data from the reference region. Annual baseline deforestation rates from the reference region are then proportionally applied to the project area and discounted by "forest scarcity factors"	Under the "simple historic" approach: based on historical average or linear/non-linear regression (as a function of time) fitted to historical deforestation data from the RRD* and proportionally applied to the RRL*. Under the "population driver" approach: based on per-capita historical deforestation, extrapolated from household survey or population census data. Under both approaches, the baseline deforestation rate at the project level is a function of the spatial allocation of the baseline deforestation estimated at the reference-region level across the reference region	Logistic regression (as a function of time) fitted to random samples observed throughout a historical period within the reference region. The relative deforestation forecast (%) is then annually applied to the project area	Historical average, linear/non-linear regression (as a function of time) fitted to historical deforestation data from the reference region, or other (simulation) modeling approaches. The baseline deforestation rate at the project level is a function of the spatial allocation of the baseline deforestation estimated at the reference-region level across the reference region
Statistical requirements for the estimation of baseline deforestation rate	Average historical deforestation is used if the estimated time parameter of the regression model is insignificant ($p \leq 0.05$). If not, the lower limit of the 95 %-confidence interval of the forecast must be used when trending upwards	Under the "simple historic" approach: regression model must be significant ($p \leq 0.05$), with $r^2 \geq 0.75$, and unbiased (i.e., lowest possible residuals). Under the "population driver" approach: regression model must be significant ($p \leq 0.05$), with $r^2 \geq 0.50$, and unbiased (i.e., with a minimal trend in residuals)	N/A	N/A
Baseline deforestation allocation	Conducted at the project area level (only relevant if multiple forest strata and/or post-deforestation land-use classes are considered). Allocation is informed by a deforestation-risk map based on the spatial driver of historical deforestation. Any suitable method can be used to construct the risk map	Conducted at the RRL* level. Allocation is informed by deforestation-risk maps based (at minimum) on the landscape (e.g., soil type, slope, elevation), accessibility (e.g., distance to rivers, roads), anthropogenic (e.g., distance to sawmills, settlements, cleared land), and land tenure and management factors (e.g., protected areas, concessions). Internationally peer-reviewed algorithms are eligible to prepare the risk maps. Several risk maps should be prepared and the most accurate should be selected based on model validation outcomes. Only the deforestation allocated within project boundaries is part of the project's baseline scenario	N/A	Conducted at the reference region level. Allocation is informed by deforestation-risk maps based on the spatial driver of historical deforestation. Risk maps must be constructed with a peer-reviewed model. Several risk maps should be prepared and the most accurate should be selected based on model validation outcomes. Only the deforestation allocated within project boundaries is part of the project's baseline scenario

(*continued on next page*)

Table 1 (*continued*)

Factor	VM0006	VM0007	VM0009	VM0015
Validation of baseline deforestation allocation	If a regression model is used, the full model and all covariates must be significant (p-value $\leq$ 0.05). One-third of the data must be exclusively used for the validation of the spatial allocation model. A goodness-of-fit score $\geq$85 % is required	Based on the Figure of Merit method for the comparison between simulated and observed land-use/ cover maps. The minimum threshold for the Figure of Merit is defined by the relative historical deforestation level in the RRL*. Exceptions are allowed if supported by the literature	N/A	Based on any appropriate method for the comparison between simulated and observed land-use/ cover maps. If the Figure of Merit method is used, the minimum validation threshold is defined by the relative historical deforestation level in the reference region

*VM0007 adopts two reference regions: one for projecting the rate of baseline deforestation (“RRD”) and the other for the allocation of baseline deforestation (“RRL”).

2.2. VM0007: “REDD+ methodology framework” (v.1.6)

VM0007 is a VCS-REDD+ methodology composed of several modules (Avoided Deforestation Partners, 2020a). The VMD0007, “Estimation of baseline carbon stock changes and greenhouse gas emissions from unplanned deforestation and unplanned wetland degradation (v.3.3),” is the module dedicated to the construction of unplanned deforestation baselines (Avoided Deforestation Partners, 2020b). This module provides two approaches to calculate baseline deforestation rates: “simple historic” and “population driver” (Table 1). Under the “simple historic” approach, baseline deforestation rates are based on the historical deforestation observed within a project’s reference region specifically selected to inform baseline deforestation rates (RRD); these rates can be based on historical averages or forecasts from statistically significant (linear, exponential, or logarithmical) regression models that are a function of time (i.e., associated with p-values $\leq$ 0.05 and $R^2 \geq$ 0.75). Under the “population driver” approach, rates are instead informed by a historical *per-capita* deforestation rate observed within a geopolitical unit where the REDD+ project site is located (e.g., a municipality or population census unit); this approach requires historical information about population size (e.g., from household surveys or census data), as well as a projection of population growth, which is then is used to forecast baseline deforestation rates based on a correlation between historical population size and deforestation (see VMD0007 for details).

In VM0007, baseline deforestation rates are estimated at the reference region level but are not proportionally allocated to the REDD+ project site as in VM0006 (Table 1). Although there may be exceptions, the baseline deforestation is ultimately a function of the spatial allocation of the RRD-informed rates across a second reference region encompassing the project area, namely the “reference region for projecting location of deforestation” (RRL). Only the RRL deforestation allocated inside project boundaries is considered part of the project’s baseline scenario.

The spatial allocation of the baseline deforestation across the RRL is informed by a deforestation-risk (or suitability) map, which can be constructed in a variety of ways. Generally, spatial algorithms establish relationships between historical deforestation patterns observed within the RRL (i.e., the dependent variable) and biophysical and socioeconomic factors mapped across the landscape, e.g., soil type, slope, elevation, accessibility, tenure status, etc. (i.e., independent variables), returning a raster map with estimated “likelihoods” of deforestation at the pixel level. According to VM0007, any “international peer-reviewed algorithm” is eligible for use. Once a deforestation-risk map is constructed, baseline deforestation rates are annually allocated to the pixels with the highest likelihood of deforestation until the total expected area of baseline deforestation is reached. Because the number and type of independent variables included in the spatial algorithm can substantially alter the estimated pixel-level likelihood of deforestation, and thus the final configuration of the baseline map itself, VM0007 requires several risk maps (and baseline maps) to be produced. In the end, the map associated with the highest accuracy, based on the outcome of model validation metrics, should be adopted as the project’s official baseline scenario.

According to VM0007, the validation of the deforestation baseline maps should be based on the Figure of Merit method (Pontius, 2018). This method is based on map comparisons, where the output from the allocation algorithm (i.e., the simulated baseline map) for a specific historical period is compared to an observed, “real world” map. For example, a deforestation allocation algorithm (or model) can be calibrated based on the historical patterns of deforestation observed from 2001 to 2010 within the RRL. This algorithm can then be used to allocate the expected deforestation from 2011 to 2020 across the RRL. The Figure of Merit then compares the simulated RRL map of 2020 with an actual observed RRL map of 2020 and calculates a level of agreement between the two as a way to measure the accuracy of the allocation algorithm. The Figure of Merit can range from 0 % (when no simulated pixel-level deforestation matches what was observed in the real world) to 100 % (for a perfect match). According to VM0007, the minimum Figure of Merit threshold for the spatial algorithm (or model) to pass validation is defined by “the net observed change in the reference region for the calibration period of the model. Net observed change must be calculated as the total area of change being modeled in reference region during the calibration period as percentage of the total area of the reference region” (Avoided Deforestation Partners, 2020b, p. 28). Still, exceptions are allowed if supported by the literature.

2.3. VM0009: “Methodology for avoided ecosystem conversion” (v.3.0)

The estimation of baseline deforestation rates in VM0009 is similar to that in VM0006; they are based on the historical deforestation observed across the project’s reference region, which is then proportionally applied to the project area (Wildlife Works and ecoPartners, 2014). However, according to VM0009, estimates are based on the forecast of a logistic regression model fitted to random samples collected from the reference region through time prior to the start of the project (Table 1). The logistic regression in VM0009 is a function of time, but, similar to VM0006, can also include additional covariates related to deforestation (e.g., population and road densities). Yet, because VM0009 provides little guidance on how these covariates should be constructed and used, they tend to be ignored by project developers.[2] Unlike VM0006, VM0009 does not use discounts such as the forest scarcity factors, nor require the lower limit of the 95 % confidence interval of the forecast to be adopted for conservativeness.

As in a standard logistic regression model, baseline deforestation in VM0009 can be generally defined as:

$$D_{PA,t} = \frac{1}{1 + e^{-\mu(t,\theta)}} \tag{2}$$

where $D_{PA,t}$ is the baseline deforestation in the REDD+ site in year t (%), which is a function of time t and, optionally, other covariates related to deforestation (θ).

[2] As of March 2022, only two VCS-certified projects included one additional covariate (i.e., population density) other than “time” (Haya et al., 2023).

Mathematically, the use of logistic regressions can lead to inflated baselines in two ways. First, the exponential growth behavior of the logistic functional form before its inflection point (i.e., concave upward), can potentially lead to a sharp increase in baseline deforestation within the first years of the project. Second, the intercept of the logistic regression can lead to an artificial spike in baseline deforestation at year zero of the project. This is because the time variate in the logistic regression model according to VM0009 is relative to the project start date, e.g., t = − 10, −9, …, −1 (Wildlife Works and ecoPartners, 2014, pp. 76–78). Despite these functional issues, VM0009 claims to be grounded on the "economic theory of resource consumption (i.e., ecosystem conversion) within a discrete area over time" (Wildlife Works and ecoPartners, 2014, p. 191).

2.4. VM0015: "Methodology for avoided unplanned deforestation" (v.1.1)

The construction of unplanned deforestation baselines in VM0015 is rather similar to the "simple historic" approach from VM0007 and how the allocation of the baseline deforestation is conducted and validated (Pedroni, 2012a). In addition to allowing the use of a historical deforestation average observed within the project's reference region and linear or non-linear regression models to forecast the baseline deforestation rates, VM0015 explicitly allows the use of any other (simulation) modeling approach (e.g., Vitel et al., 2013; Table 1).

The main difference between VM0007 and VM0015 is that the latter does not have an alternative "population driver" option. Furthermore, when baseline deforestation is based on a historical average rather than a model forecast, annual deforestation rates are proportionally applied only to the remaining forest area within the reference region over time. Thus, even though VM0015's average proportional rate of deforestation (% year^{-1}) remains constant, the absolute deforestation rate (ha year^{-1}) shrinks over time, as:

$$D_{RR,t} = \left(A_{RR} \times \frac{PA}{RR}\right) \times FA_t \tag{3}$$

where $D_{RR,t}$ is the baseline deforestation in the project's reference area in year t (ha), which is a function of the historical annual deforestation rate average (%) in reference region (A_{RR}), adjusted by the proportional size of the project area (PA) in relation to its reference region (RR), and discounted by the remaining forest area within the project site at time t (FA_t). This formulation implies an exponential decay of the deforestation rate over time across the reference region, in line with the forest transition theory (Köthke et al., 2013; Rudel et al., 2005).

When baseline deforestation is forecasted with the use of a model, VM0015 requires time-varying discounts to be applied to the forecasts which are a function of the remaining forest area "eligible" for deforestation within the reference region based on biophysical constraints across the landscape (Pedroni, 2012a, pp. 44–47). As a result, baseline deforestation rates estimated based on VM0015 can be more conservative than those based on VM0007. Still, unlike VM0006 and VM0007, VM0015 does not have explicit requirements about the statistical robustness of regression or simulation models used to forecast the baseline deforestation (Table 1). Similar to VM0007, VM0015 requires spatial allocation of the baseline deforestation across the reference region, as well as validation of the allocation algorithm employed, but it allows for the use of alternative model validation methods other than the Figure of Merit (although that is the only validation method mentioned in VM0015). Again, only the baseline deforestation allocated within project boundaries is considered part of the project's baseline scenario.

3. Methods

We systematically scrutinized and empirically tested the key assumptions used for the construction of unplanned deforestation baselines underlying the four VCS-REDD+ methodologies discussed above and their implications. We selected four VCS-certified voluntary REDD+ projects and constructed alternative deforestation baselines based on the key methodological assumptions underlying VM0006, VM0007, VM0009, and VM0015. Each of the selected projects adopted a different VCS-REDD+ methodology and had been rigorously evaluated in previous studies (West et al., 2020a; 2023). The four selected projects, according to their VCS identification numbers, were: Project 1112 from Brazil (based on VM0007); Project 1396 from Colombia (based on VM0006); Project 934 from the Democratic Republic of Congo (DRC; based on VM0009); and Project 944 from Peru (based on VM0015).

For each project, we created seven alternative baselines, one from VM0009 and two from each of the others by adopting different methodological options allowed by each VCS-REDD+ methodology. Because Project 934 did not provide information on its baseline deforestation rates, those were estimated based on a forest carbon stock of 876.7 Mg CO_2 ha^{-1} obtained from the project's certification report (DNV Climate Change Services, 2012) and the project's reported *ex-ante* annual baseline emission reductions (Wildlife Works, 2012).

Voluntary REDD+ project areas (in the form of spatial polygons) were obtained from the VCS project database (Fig. 1). We replicated the projects' reference regions with similar sizes and shapes as reported in the official project descriptions (CarbonCo et al., 2014; Conservation International-Peru, 2015; ecoPartners et al., 2014; Wildlife Works, 2012). We employed a buffering approach to create Project 934′s reference region instead of replicating its actual area because the latter is located ~650 km from the project site and does not comply with the requirements of other VCS-REDD+ methodologies. We also note that Project 934′s official reference region is apparently more heavily populated and closer to major markets than the project site, and exposed to different policy contexts and drivers of deforestation (Seyller et al., 2016).

We employed two algorithms from the Land Use Modeler/TerrSet software (v.18.2; Eastman, 2016) to create the deforestation-risk maps underlying the baselines from VM0007 and VM0015. This software is a commonly adopted land-use/cover change simulation model among project developers. The two algorithms were the Multi-Layer Perceptron (MLP), a feedforward artificial neural network, and SimWeight, a similarity-weighted, instance-based machine-learning tool (see Eastman, 2016, and Sangermano et al., 2010, for details). In summary, both algorithms estimate deforestation risk at the pixel level by establishing empirical relationships between historical deforestation patterns (e.g., observed from 2001 to 2010) and spatial variables (e.g., distance from roads, elevation, and protected area cover)—and as in most simulation models, results can be rather sensitive to the underlying data used for calibration, as well as the analyst's decisions. Table S1 describes the variables used to construct the deforestation-risk maps for this study, matching the ones also considered by the project proponents. Deforestation data for Projects 934, 944, and 1396 were obtained from the Global Forest Change dataset (Hansen et al., 2013) for the 2001–2021 period, whereas the data for Project 1112 were obtained from a reprocessed version of the MapBiomas land-use/cover dataset (Souza et al., 2020), which more closely matches Brazil's official deforestation rates (see West et al., 2020a, for details).

In order to create the alternative deforestation baselines for each project in the study using the VCS-REDD+ methodologies, additional assumptions needed to be adopted. For the baselines based on VM0006, two sets of values were adopted for parameters s_1 and s_2: (i) both as 0.25 and (ii) both as 0.75; these sets of values cover a wide range of deforestation contexts and were found to result in the widest ranges of baseline deforestation compared to other realistically reasonable sets we tested (results not shown). Due to population data constraints, we restricted the construction of the alternative baselines based on VM0007 to the "simple historic" approach. Last, following the standard practices adopted by project developers, additional model covariates related to deforestation (represented by the θ parameter from Equation (3)) were

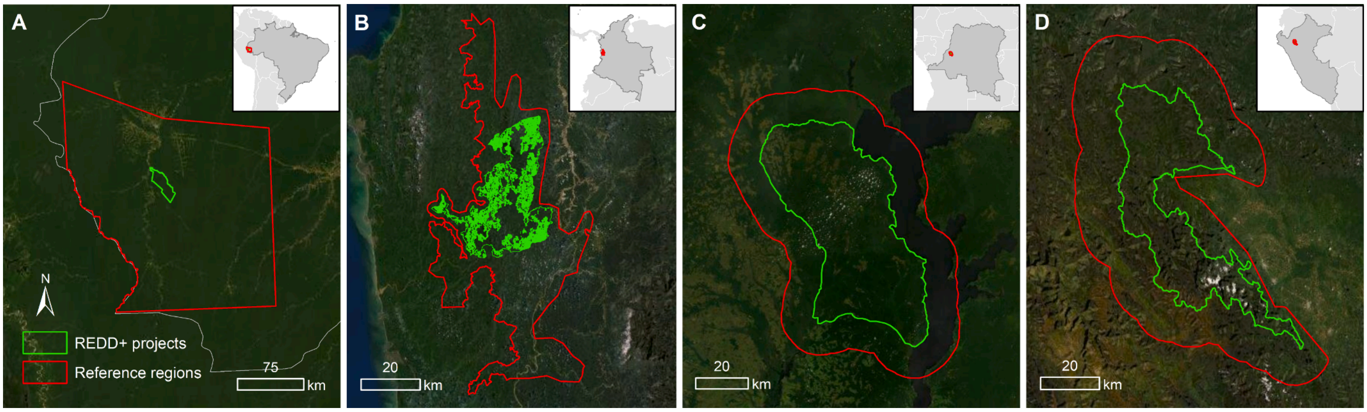

Fig. 1. REDD+ project locations (inner borders): (A) Project 1112 from Brazil; (B) Project 1396 from Colombia; (C) Project 934 from the Democratic Republic of Congo; and (D) Project 944 from Peru. Reference regions (outer borders) were constructed based on the information available from the official project descriptions, with the exception of Project 934, whose official reference region is located ~650 km from the project area.

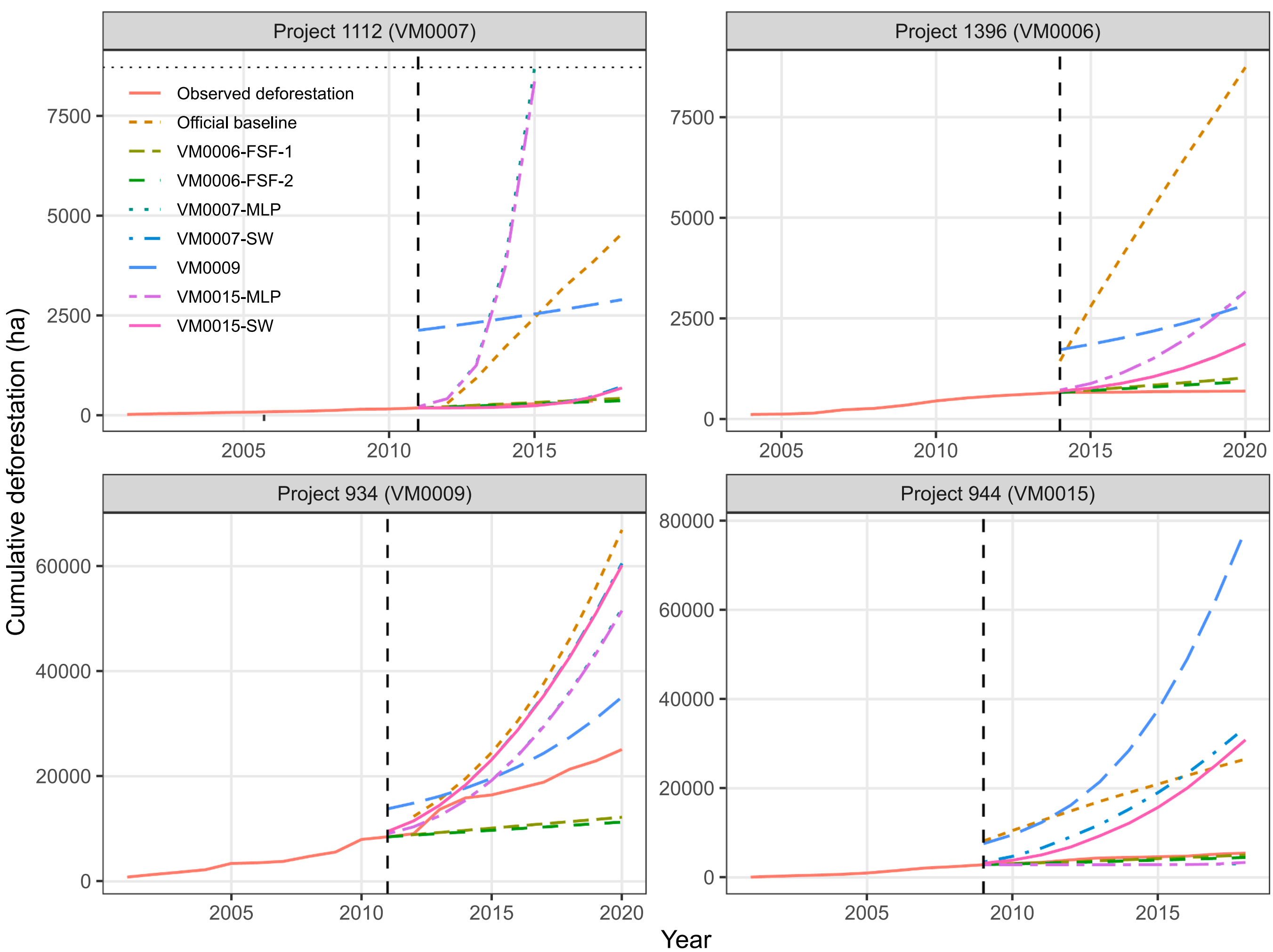

Fig. 2. Variation in *ex-ante* cumulative deforestation baselines of voluntary REDD+ projects from different VCS-REDD+ methodologies (VM0006, VM0007, VM0009, and VM0015) versus the observed deforestation in the project sites (red solid lines). Dashed black lines separate the historical period used for the construction of the baselines (left side) from the baseline periods when the projects started (right side). Official baselines constructed by project developers based on the methodology reported in parenthesis (ochre dashed lines). FSF-1 and FSF-2 refer to different sets of the "forest scarcity factor" parameters of VM0006. Multi-layer perceptron (MLP) and SimWeight (SW) are the algorithms employed for the spatial allocation of the baseline deforestation in VM0007 and VM0015. The horizontal dotted line in the Project 1112 panel is a cutoff adopted to improve visualization. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

not included in the logistic regressions from VM0009.

The time parameter estimates from VM0006′s, VM0007′s, and VM0015′s regression models were only significant for Project 944 (Tables S3 & S4). Thus, deforestation baseline rates were based on historical averages for Projects 934, 1112, and 1396 under VM0006, VM0007, and VM0015, but based on forecasts for Project 944. As expected, all logistic regression models from VM0009 returned significant time parameter estimates (Table S5).

4. Results

For all projects, we found large discrepancies in baseline deforestation across the four VCS-REDD+ methodologies (Fig. 2). In the most extreme case, Project 1112′s alternative baselines ranged from 363 ha to 8713 ha of cumulative deforestation through 2018, with the official project baseline set as 4547 ha for the same period. The variability in alternative baselines for Project 944 was also significant, ranging from 3092 ha to 77,943 ha through 2017, with the official project baseline estimated at 26,528 ha for the period. Project 934′s alternative baselines ranged from 11,271 ha to 60,512 ha, versus our estimated 66,896 ha as the official baseline, through 2020. Finally, Project 1396′s alternative baselines ranged from 931 ha to 3166 ha, compared to 8735 ha from the project's official baseline, also through 2020.

Overall, VM0006 returned the most conservative baselines (but likely because our calculations were based on forecasts from linear, as opposed to beta, regression models, as discussed above), whereas VM0007 and VM0015 produced the least conservative scenarios. Among the methodologies, VM0006 was the one that most closely represented a simple linear extrapolation of historical deforestation trends. The spatially explicit baselines from both VM0007 and VM0015 were substantially influenced by the algorithm employed for the construction of their underlying deforestation-risk maps (i.e., SimWeight or MLP; Figures S1–S17), as best illustrated by the Project 1112 case (Fig. 2). For that project, the baselines from VM0007 and VM0015 based on the MLP allocation algorithm were orders of magnitude higher than the baselines from VM0006 and VM0009. We also found small differences in deforestation baselines between VM0007 and VM0015 when the same allocation algorithm was adopted (Fig. 2 & Figures S2–S17).

Among all methodologies, VM0009 was the only one associated with artificial spikes in baseline deforestation at year zero of the REDD+ project (driven by the intercepts of the underlying logistic regressions, as discussed above). Project 944 best illustrates the potential for the initial exponential growth behavior of logistic regressions to substantially inflate baseline deforestation under VM0009. In contrast, we found that the range of different values adopted for the forest scarcity factors of VM0006 had relatively little impact on baseline deforestation. Overall, most of the alternative baselines (23 out of 28) were more conservative than the official project baselines in terms of cumulative deforestation at the end of the evaluation period of each project (Fig. 2). Similar patterns are observed when we focus exclusively on the project's first five years of operation for a fairer comparison across projects and methodologies (Table 2).

Table 2
Comparison of cumulative baseline deforestation of voluntary REDD+ projects from different VCS-REDD+ methodologies (VM0006, VM0007, VM0009, and VM00015) during the projects' first five years of operation. Percentages reported in parentheses represent how much the alternative baseline differs from the official project baseline (i.e., alternative baseline divided by the official baseline). Values approximately indicate the proportion of credits that would have been issued had the project used the alternative baseline. FSF-1 and FSF-2 refer to different sets of the "forest scarcity factor" parameters of VM0006. Multi-layer perceptron (MLP) and SimWeight (SW) are the algorithms employed for the spatial allocation of the baseline deforestation in VM0007 and VM0015.

Baseline method	Cumulative deforestation during the project's first five years of operation (ha)			
	Project 1396 (VM0006)	Project 1112 (VM0007)	Project 934 (VM0009)	Project 944 (VM0015)
Official baseline	6428 (100 %)	3199 (100 %)	30,544 (100 %)	17,056 (100 %)
VM0006-FSF-1	900 (14 %)	354 (11 %)	10,535 (35 %)	3742 (22 %)
VM0006-FSF-2	840 (13 %)	311 (10 %)	10,020 (33 %)	3518 (21 %)
VM0007-MLP	1955 (30 %)	8713 (272 %)	23,970 (78 %)	2843 (17 %)
VM0007-SW	1265 (20 %)	320 (10 %)	28,887 (95 %)	11,853 (69 %)
VM0009	2373 (37 %)	2649 (83 %)	21,799 (71 %)	21,466 (126 %)
VM0015-MLP	1953 (30 %)	8362 (261 %)	23,901 (78 %)	2843 (17 %)
VM0015-SW	1263 (20 %)	313 (10 %)	28,809 (94 %)	9334 (55 %)

5. Discussion

Our results illustrate critical issues with key methodological assumptions for the construction of deforestation baselines behind the four most adopted VCS-REDD+ methodologies for voluntary avoided deforestation projects worldwide. Overall, we found the VCS-REDD+ methodologies to result in unreliable and inconsistent baselines, compromising their suitability for assessing project performance and thus additionality. Furthermore, each methodology offers substantial flexibility in creating baseline scenarios that could be exploited by project developers intending to maximize credit generation. Our review and empirical analysis unmistakably reveal that current VCS-REDD+ methodologies constitute intricate approaches for establishing simplistic—and often unrealistic—reference levels for the project sites, rather than creating credible counterfactuals (Bos et al., 2017; Ferraro & Hanauer, 2014; Guizar-Coutiño et al., 2022). And despite critical flaws behind the baseline methodologies, each carbon offset issued according to these methodologies is controversially promoted and traded as equivalent to one metric ton of CO_2 that has not been emitted to the atmosphere but would have been in the absence of the REDD+ intervention. The ongoing policy discussions to scale and integrate offsets potentially derived from flawed REDD+ methodologies into national GHG inventories, emission reduction commitments, and cap-and-trade markets could create an illusion of greater success in our climate change mitigation efforts than is warranted and harm meaningful efforts to mitigate climate change by diverting investments into ineffective solutions (Blum & Lövbrand, 2019; FAO, 2019; Lee et al., 2018; McAfee, 2022; Taskforce on Scaling Voluntary Carbon Markets, 2021; Verra, 2021; West et al., 2020a; 2023).

For each project, deforestation baselines differed substantially across all four VCS-REDD+ methodologies. On average, the highest baseline value we calculated for each project was more than 14 times greater than the lowest value across the four projects studied. Such large variations raise a concern about whether the claimed reductions in forest loss in fact occurred and, consequently, the environmental integrity of the carbon offsets—which are a function of the project performance relative to the baseline. Our findings unveil the potential driving factors for the inflated baselines identified in *ex-post* impact evaluations and other project assessments in the literature (Calyx Global, 2023; Delacote et al., 2022; West et al., 2020a; 2023). The disparities between the projects' official baselines and our alternative scenarios can be partially attributed to differences among datasets, but also methodological flexibility and, in some cases, unclear descriptions of specific methodological steps or procedures.

Unquestionably, the subjectiveness and flexibility in the VCS-REDD+ methodologies could be exploited by profiteers in the form of baseline "gaming" (Angelsen, 2017; Ehara et al., 2021; Mertz et al., 2018; Rifai et al., 2015). Overall, we observe significant discrepancies among the project baselines. The bluntest example of methodological flexibility is illustrated by the construction of the underlying deforestation-risk maps in VM0007 and VM0015, which has a direct and often significant impact on deforestation baselines. These maps can be highly sensitive to the method and data used in the analysis (e.g., Ehara et al., 2021; Lin et al., 2011; Sloan and Pelletier, 2012; Soares-Filho, 2012, 2013; West et al., 2020b) and yet, different-risk maps of the same region could potentially be considered "equally valid" from a model validation perspective according to VM0007 and VM0015 (Pedroni, 2012a; Avoided Deforestation Partners, 2020b). For example, a review of the Figure of Merit validation scores associated with nine voluntary REDD+ projects found the highest score (or accuracy) to be 11.7 %—with three other projects with scores lower than 1 %—and still, those project baselines were deemed "validated" (West, 2016b). The current, and seemingly arbitrary, low threshold for the Figure of Merit validation (see Table 1) becomes even more problematic if compared to the original requirements from both VM0007 and VM0015: 40 %, 60 %, and 80 % for projects located in landscapes with frontier, transition, or mosaic deforestation configuration, respectively (Avoided Deforestation Partners, 2011, p. 27; Pedroni, 2012b, p. 64). The first versions of VM0007's baseline module even stated that "where these minimum standards are not met the project shall be considered ineligible" (Avoided Deforestation Partners, 2011, p. 27). While high Figure of Merit scores are not common in the land-use/cover change modeling literature (e.g., Pontius et al., 2008; Sloan and Pelletier, 2012), extremely small values severely compromise the usefulness of *ex-ante* baseline scenarios as a means to measure project performance and issue carbon offsets.

The VCS-REDD+ methodologies also offer some flexibility in the selection of reference regions (as long as minimum requirements are met), which would also influence deforestation baselines. This could potentially explain the null project impacts and the location bias issue reported by Delacote et al. (2022) for voluntary REDD+ interventions in the Brazilian Amazon. Other factors used for baseline construction, such as the logistic regression's sampling procedure from VM0009, the identification of biophysical deforestation constraints in VM0015, and even the forest scarcity factors from VM0006 and other default values, also largely rely on the analyst's decisions and thus can be subjective or even deliberately biased, including "cherry picking" of the literature (e.g., Seyller et al., 2016).

At the time this research was conducted, Verra was working on a new, consolidated methodology for voluntary avoided unplanned deforestation interventions that would replace all existing VCS-REDD+ methodologies, including the four covered in this study (Climate Focus, 2023). The consolidated methodology (VM0048), released on 27 November 2023, significantly constrains much of the methodological flexibility discussed above (Verra, 2023). According to the new methodology, deforestation baselines will be based on historical averages, rendering them more conservative than baselines informed by upward-trending forecasts, such as those from logistic regression models. Similar to VM0007 and VM0015, the new methodology relies on the use of deforestation-risk maps, which can be highly influenced by modeling choices, as demonstrated in this study. Still, risk maps will be developed by independent third-party contractors at a subnational, jurisdictional scale (i.e., using whole jurisdictions as reference regions), thereby removing the responsibility and flexibility from project developers to possibly "cherry pick" reference regions and create individual—and potentially inflated—project baselines.

While these actions represent a substantial improvement over existing VSC-REDD+ methodologies, developers could still potentially choose project areas that would unlikely be deforested because of factors known by them, but which jurisdictional deforestation-risk maps may have failed to capture. Furthermore, these deforestation-risk maps, combined with simplistic ("static") forecasts of baseline deforestation rates, may eventually become outdated due to changes in the landscape, governance, and the economy. Crucially, the proposed methodology remains inadequate in addressing dynamic changes in deforestation drivers (i.e., controlling for confounding factors), as it continues to rely on a problematic *ex-ante* approach for baseline construction. This approach lacks the capacity to serve as a robust foundation for measuring project performance rigorously, demonstrating additionality, and thereby ensuring the integrity of carbon offsets from voluntary REDD+ interventions (Balmford et al., 2023; Bos et al., 2017; West et al., 2020a; 2023).

The adoption of *ex-post* methods that monitor deforestation in non-project (i.e., control) areas and use those as the basis to assess project performance would drastically increase the credibility of REDD+ offsets (Balmford et al., 2023; Guizar-Coutiño et al., 2022; West et al., 2020a; 2023). Nevertheless, "good" controls for the project sites may be difficult to find and could become outdated over time (e.g., if converted to protected areas or allocated to legal agricultural production). Econometric approaches based on the use of autoregressive and exogenous factors, e.g., macroeconomic indicators—as demonstrated in Wang et al. (2023) for sustainability-linked bonds in the Brazilian Amazon—could also potentially solve, or at least alleviate, some of the inherent problems with the use of "static" baseline methodologies. However, relying on such "dynamic" baseline approaches would heighten the financial risk for project developers, introducing uncertainty about the expected project performance and its offset generation potential. Alternatively, more reliable baseline scenarios could potentially be constructed if based on more advanced simulation modeling frameworks, and properly designed, calibrated, and validated land-use/cover change models, as demonstrated in Vitel et al. (2013). Irrespective of the methodological approach chosen, the complete disclosure of baseline calculations and underlying assumptions, facilitating third-party assessment of project baselines, stands as another pivotal step in bolstering market confidence in voluntary REDD+ interventions and offsets.

6. Conclusion

We systematically scrutinized the key underlying assumptions behind the four most adopted baseline methodologies for voluntary REDD+ projects worldwide. Results from the empirical analyses demonstrate how major differences in methodological assumptions result in large baseline discrepancies, indicating a generalized lack of robustness and consistency. Since baselines directly influence the number of offsets that projects can claim, our results also question the environmental integrity of carbon offsets based on those methodologies. If voluntary REDD+ interventions are to credibly offset GHG emissions and contribute additionally to climate change mitigation, new baseline methodologies need to be urgently developed. The new methods must be robust enough to guarantee—at least to a satisfactory degree—that every issued carbon offset is equivalent to at least one ton of CO_2 that has not been emitted into the atmosphere. Otherwise, claims of achieving net-zero emissions by individuals, organizations, and governments through carbon offsets from REDD+ interventions will persistently lack credibility.

This study offers new insights about some of the underlying reasons why voluntary REDD+ projects appear to fall short of delivering the benefits they claim to have achieved (Calyx Global, 2023; Delacote et al., 2022; Guizar-Coutiño et al., 2022; Haya et al., 2023; West et al., 2020a; 2023). It suggests that the current process of baseline construction according to the VCS-REDD+ methodologies is more akin to storytelling and arbitrary modeling choices than to genuinely accounting for the threats of deforestation. While Verra's consolidated methodology addresses many problems with the methodologies examined in this study, it fails to address the most fundamental challenge of rigorous performance assessment by unwarrantedly disregarding the influence of confounding factors on project outcomes. Furthermore, "vintage" offsets from VM0006, VM0007, VM009, and VM0015 continue to be actively traded in the voluntary carbon market. While the root cause of the problem remains overlooked by the offset industry and regulators, offsets from voluntary REDD+ interventions may be causing more inadvertent harm than good to our efforts to mitigate climate change (Carton et al., 2021; McAfee, 2022; Seyller et al., 2016; Haya et al., 2023).

It is imperative that baseline methodologies (1) ensure parameter selection leads to conservative offset estimates, i.e., at the lower bound of uncertainty, (2) meticulously eliminate conflicts of interest from modeling decisions, and, most importantly, (3) adopt rigorous *ex-post* methods to credibly measure performance and additionality. The ability to discern the impacts of REDD+ interventions amid confounding factors and to accurately estimate additionality hinges on the proactive adoption of dynamic baselines. The integration of causal inference methods, coupled with enhanced data transparency, not only represents a significant opportunity but is also essential to elevate the credibility of gauging the effectiveness of REDD+ initiatives. These valuable methods can no longer be disregarded by project developers, certification standards, as well as governmental and international bodies. Still, more empirical research is needed to identify how causal inference methods can be best employed for the evaluation of REDD+ interventions.

CRediT authorship contribution statement

Thales A.P. West: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Barbara Bomfim:** Writing – review & editing, Writing – original draft, Conceptualization. **Barbara K. Haya:** Writing – review & editing, Writing – original draft, Resources, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgements

This research was funded by Carbon Market Watch as part of the Quality Assessment of REDD+ Carbon Credit Projects report, prepared by the Berkeley Carbon Trading Project at the University of California, Berkeley Goldman School of Public Policy.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.gloenvcha.2024.102863.

References

Angelsen, A., 2017. REDD+ as result-based aid: General lessons and bilateral agreements of Norway. Rev. Dev. Econ. 21, 237–264. https://doi.org/10.1111/rode.12271.
Assunção, J., Gandour, C., Rocha, R., 2015. Deforestation slowdown in the Brazilian Amazon: prices or policies? Environ. Dev. Econ. 20, 697–722. https://doi.org/10.1017/S1355770X15000078.
Avoided Deforestation Partners, 2011. REDD Methodological Module: Estimation of baseline carbon stock changes and greenhouse gas emissions from unplanned deforestation (BL-UP), v.2.0. Voluntary Carbon Standard, Washington, D.C.
Avoided Deforestation Partners, 2020a. VM0007 REDD+ Methodology Framework (REDD+MF), v.1.6. Verra, Washington, D.C.
Avoided Deforestation Partners, 2020b. VM0007: Estimation of baseline carbon stock changes and greenhouse gas emissions from unplanned deforestation and unplanned wetland degradation (BL-UP), v.3.3. Verra, Washington, D.C.
Balmford, A., Brancalion, P.H.S., Coomes, D., Filewod, B., Groom, B., Guizar-Coutiño, A., Jones, J.P.G., Keshav, S., Kontoleon, A., Madhavapeddy, A., Malhi, Y., Sills, E.O., Strassburg, B.B.N., Venmans, F., West, T.A.P., Wheeler, C., Swinfield, T., 2023. Credit credibility threatens forests. Science 380, 466–467. https://doi.org/10.1126/science.adh3426.
Blum, M., Lövbrand, E., 2019. The return of carbon offsetting? The discursive legitimation of new market arrangements in the Paris climate regime. Earth Syst. Gov. 2, 100028 https://doi.org/10.1016/j.esg.2019.100028.
Börner, J., West, T.A.P., Blackman, A., Miteva, D.A., Sims, K.R., Wunder, S., 2018. National and subnational forest conservation policies—What works, what doesn't. In: Angelsen, A., Martius, C., de Sy, V., Duchelle, A., Larson, A., Pham, T. (Eds.), Transforming REDD+: Lessons and New Directions. Center for International Forestry Research (CIFOR), Bogor, pp. 105–116 https://doi.org/10.17528/cifor/007045.
Bos, A.B., Duchelle, A.E., Angelsen, A., Avitabile, V., De Sy, V., Herold, M., Joseph, S., de Sassi, C., Sills, E.O., Sunderlin, W.D., Wunder, S., 2017. Comparing methods for assessing the effectiveness of subnational REDD plus initiatives. Environ. Res. Lett. 12 https://doi.org/10.1088/1748-9326/aa7032.
Busch, J., Ferretti-Gallon, K., 2017. What drives deforestation and what stops it? A meta-analysis. Rev. Environ. Econ. Policy 11, 3–23. https://doi.org/10.1093/reep/rew013.
CarbonCo, TerraCarbon, Carbon Securities, I.S.R.C. Investimentos e Acessória, 2014. The Russas Project. Bethesda.
Carton, W., Lund, J.F., Dooley, K., 2021. Undoing equivalence: Rethinking carbon accounting for just carbon removal. Front. Clim. 3, 1–7. https://doi.org/10.3389/fclim.2021.664130.
Climate Focus, 2023. Methodology for Reducing Emissions from Deforestation and Forest Degradation (v.0.1). Verra. Washington, D.C.
Conservation International–Peru, 2015. Alto Mayo Conservation Initiative. Lima.
Delacote, P., Le Velly, G., Simonet, G., 2022. Revisiting the location bias and additionality of REDD+ projects: The role of project proponents status and certification. Resour. Energy Econ. 67, 101277 https://doi.org/10.1016/j.reseneeco.2021.101277.
DNV Climate Change Services, 2012. VCS Validation Report: The Mai Ndombe REDD+ Project. Oakland.
Donofrio, S., Maguire, P., Myers, K., Daley, C., Lin, K., 2021. Markets in Motion: State of the Voluntary Carbon Markets 2021, Installment 1. Forest Trends' Ecosystem Marketplace, Washington, DC.
Eastman, J.R., 2016. TerrSet Manual. Clark University, Worcester.
Ecological Carbon Offsets Partners, LLC (ecoPartners), Offsetters, ClearSky, Climate Solutions, 2014. Rio Pepe y ACABA REDD+ Project. Chocó.
Ehara, M., Saito, H., Michinaka, T., Hirata, Y., Leng, C., Matsumoto, M., Riano, C., 2021. Allocating the REDD+ national baseline to local projects: A case study of Cambodia. For. Policy Econ. 129, 102474 https://doi.org/10.1016/j.forpol.2021.102474.
FAO—Food and Agriculture Organization of the United Nations, 2019. From reference levels to results reporting: REDD+ under the United Nations Framework Convention on Climate Change. 2019 update. Rome.
Ferraro, P.J., Hanauer, M.M., 2014. Advances in measuring the environmental and social impacts of environmental programs. Annu. Rev. Env. Resour. 39, 495–517. https://doi.org/10.1146/annurev-environ-101813-013230.
Global, C., 2023. Turning REDD into Green: Improving the GHG Integrity of Avoided Deforestation Credits. Leadville.
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. Conserv. Biol. 1–13 https://doi.org/10.1111/cobi.13970.
Hansen, M.C., Potapov, P.V., Moore, R., Hancher, M., Turubanova, S.A., Tyukavina, A., Thau, D., Stehman, S.V., Goetz, S.J., Loveland, T.R., Kommareddy, A., Egorov, A., Chini, L., Justice, C.O., Townshend, J.R.G., 2013. High-resolution global maps of 21st-century forest cover change. Science 342, 850–853. https://doi.org/10.1126/science.1244693.
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, K., So, I., West, T.A.P., Withey, L., 2023. Quality Assessment of REDD+ Carbon Credit Projects. Berkeley Carbon Trading Project, University of California, Berkeley. Available at: https://gspp.berkeley.edu/research-and-impact/centers/cepp/projects/berkeley-carbon-trading-project/redd (Accessed on September 25, 2023).
Köthke, M., Leischner, B., Elsasser, P., 2013. Uniform global deforestation patterns —An empirical analysis. For. Policy Econ. 28, 23–37. https://doi.org/10.1016/j.forpol.2013.01.001.
Lambin, E.F., Meyfroidt, P., Rueda, X., Blackman, A., Börner, J., Cerutti, P.O., Dietsch, T., Jungmann, L., Lamarque, P., Lister, J., Walker, N.F., Wunder, S., 2014. Effectiveness and synergies of policy instruments for land use governance in tropical regions. Glob. Environ. Chang. 28, 129–140. https://doi.org/10.1016/j.gloenvcha.2014.06.007.
Lee, D., Llopis, P., Waterworth, R., Roberts, G., Pearson, T., 2018. Approaches to REDD+ Nesting: Lessons Learned From Country Experiences. World Bank, Washington, DC.
Lin, Y.-P.-P., Chu, H.-J.-J., Wu, C.-F.-F., Verburg, P.H., 2011. Predictive ability of logistic regression, auto-logistic regression and neural network models in empirical land-use change modeling - a case study. Int. J. Geogr. Inf. Sci. 25, 65–87. https://doi.org/10.1080/13658811003752332.
McAfee, K., 2022. Shall the American Association of Geographers endorse carbon offsets? Absolutely not! Prof. Geogr. 77, 171–177. https://doi.org/10.1080/00330124.2021.1934879.
Mertz, O., Grogan, K., Pflugmacher, D., Lestrelin, G., Castella, J.-C., Vongvisouk, T., Hett, C., Fensholt, R., Sun, Z., Berry, N., Müller, D., 2018. Uncertainty in establishing forest reference levels and predicting future forest-based carbon stocks for REDD+. J. Land Use Sci. 13, 1–15. https://doi.org/10.1080/1747423X.2017.1410242.
Pedroni, L., 2012a. VM0015 Methodology for Avoided Unplanned Deforestation, v.1.1. Voluntary Carbon Standard, Washington, D.C.
Pedroni, L., 2012b. VM0015 Methodology for Avoided Unplanned Deforestation, v.1.0. Voluntary Carbon Standard, Washington, D.C.
Pontius, R., 2018. Criteria to confirm models that simulate deforestation and carbon disturbance. Land 7, 105. https://doi.org/10.3390/land7030105.

Pontius, R.G., Boersma, W., Castella, J.C., Clarke, K., Nijs, T., Dietzel, C., Duan, Z., Fotsing, E., Goldstein, N., Kok, K., Koomen, E., Lippitt, C.D., McConnell, W., Mohd Sood, A., Pijanowski, B., Pithadia, S., Sweeney, S., Trung, T.N., Veldkamp, A.T., Verburg, P.H., 2008. Comparing the input, output, and validation maps for several models of land change. Ann. Reg. Sci. 42, 11–37. https://doi.org/10.1007/s00168-007-0138-2.

Rifai, S.W., West, T.A.P., Putz, F.E., 2015. "Carbon Cowboys" could inflate REDD+ payments through positive measurement bias. Carbon Manag. 6, 151–158. https://doi.org/10.1080/17583004.2015.1097008.

Rudel, T.K., Coomes, O.T., Moran, E., Achard, F., Angelsen, A., Xu, J., Lambin, E., 2005. Forest transitions: towards a global understanding of land use change. Glob. Environ. Chang. 15, 23–31. https://doi.org/10.1016/j.gloenvcha.2004.11.001.

Sangermano, F., Eastman, J.R., Zhu, H., 2010. Similarity weighted instance-based learning for the generation of transition potentials in land use change modeling. Trans. GIS 14, 569–580. https://doi.org/10.1111/j.1467-9671.2010.01226.x.

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? Int. For. Rev. 18, 231–246. https://doi.org/10.1505/146554816818966273.

Sloan, S., Pelletier, J., 2012. How accurately may we project tropical forest-cover change? A validation of a forward-looking baseline for REDD. Glob. Environ. Chang. 22, 440–453. https://doi.org/10.1016/j.gloenvcha.2012.02.001.

So, S.I., Haya, B.K., Elias, M. (2023). Voluntary Registry Offsets Database, v7.1. University of California Berkeley, Berkeley Carbon Trading Project. Available at: https://gspp.berkeley.edu/research-and-impact/centers/cepp/projects/berkeley-carbon-trading-project/offsets-database (accessed March 4, 2023).

Soares-Filho, B.S. 2012. Delusional REDD baselines. Measurement, Reporting and Verification in Latin American REDD+ Projects Workshop. Center for International Forestry Research (CIFOR), Petrópolis.

Soares-Filho, B., Rodrigues, H., Follador, M., 2013. A hybrid analytical-heuristic method for calibrating land-use change models. Environ. Model. Softw. 43, 80–87. https://doi.org/10.1016/j.envsoft.2013.01.010.

Souza, C.M., Shimbo, Z.J., Rosa, M.R., Parente, L.L., Alencar, A., Rudorff, B.F.T., Hasenack, H., Matsumoto, M., Ferreira, G.L., Souza-Filho, P.W.M., de Oliveira, S.W., Rocha, W.F., Fonseca, A.V., Marques, C.B., Diniz, C.G., Costa, D., Monteiro, D., Rosa, E.R., Vélez-Martin, E., Weber, E.J., Lenti, F.E.B., Paternost, F.F., Pareyn, F.G. C., Siqueira, J.V., Viera, J.L., Neto, L.C.F., Saraiva, M.M., Sales, M.H., Salgado, M.P. G., Vasconcelos, R., Galano, S., Mesquita, V.V., Azevedo, T., 2020. Reconstructing three decades of land use and land cover changes in Brazilian biomes with Landsat archive and Earth Engine. Remote Sens. 12, 2735. https://doi.org/10.3390/rs12172735.

Taskforce on Scaling Voluntary Carbon Markets, 2021. Phase 1- Final Report. Institute of International Finance, Washington, DC.

Terra Global Capital, 2017. VM0006 Methodology for Carbon Accounting for Mosaic and Landscape-Scale REDD Projects, vol 2.2. Verra, Washington, DC.

The World Bank, 2021. State and Trends of Carbon Pricing 2021. The World Bank, Washington, DC.

Thompson, M.C., Baruah, M., Carr, E.R., 2011. Seeing REDD+ as a project of environmental governance. Environ. Sci. Policy 14, 100–110. https://doi.org/10.1016/j.envsci.2010.11.006.

UN-REDD, 2021. 12th Consolidated Annual Progress Report of the UN-REDD Programme Fund. UN-REDD Programme, Geneva.

Verified Carbon Standard, 2017. Agriculture, Forestry and Other Land Use (AFOLU) Requirements (v.3.6). Washington, D.C.

Verra, 2019. VCS Standard v.4.0. Washington, D.C.

Verra, 2021. Jurisdictional and Nested REDD+ (JNR) Program Guide. Washington, D.C.

Verra, 2023. VM0048 Reducing Emissions from Deforestation and Forest Degradation, v.1.0. Washington, D.C.

Vitel, C.S.M.N., Carrero, G.C., Cenamo, M.C., Leroy, M., Graça, P.M.L.A., Fearnside, P.M., 2013. Land-use change modeling in a Brazilian indigenous reserve: Construction of a reference scenario for the Suruí REDD Project. Hum. Ecol. 41, 807–826. https://doi.org/10.1007/s10745-013-9613-9.

Wang, D., Gurhy, B., Hanusch, M., Kollenda, P., 2023. Could sustainability-linked bonds incentivize lower deforestation in Brazil's Legal Amazon? Policy Research Working Paper. World Bank Group, Washington, D.C.

West, T.A.P., 2016a. Indigenous community benefits from a de-centralized approach to REDD+ in Brazil. Clim. Policy 16, 924–939. https://doi.org/10.1080/14693062.2015.1058238.

West, T.A.P., 2016b. On the Improvement of Tropical Forest-based Climate Change Mitigation Interventions. University of Florida.

West, T.A.P., Börner, J., Fearnside, P.M., 2019. Climatic benefits from the 2006–2017 avoided deforestation in Amazonian Brazil. Front. For. Glob. Chang. 2, 52. https://doi.org/10.3389/ffgc.2019.00052.

West, T.A.P., Börner, J., Sills, E.O., Kontoleon, A., 2020a. Overstated carbon emission reductions from voluntary REDD+ projects in the Brazilian Amazon. Proc. Natl. Acad. Sci. 117, 24188–24194. https://doi.org/10.1073/pnas.2004334117.

West, T.A.P., Fearnside, P.M., 2021. Brazil's conservation reform and the reduction of deforestation in Amazonia. Land Use Policy 100, 105072. https://doi.org/10.1016/j.landusepol.2020.105072.

West, T.A.P., Grogan, K.A., Swisher, M.E., Caviglia-Harris, J.L., Sills, E.O., Roberts, D.A., Harris, D., Putz, F.E., 2018. Impacts of REDD+ payments on a coupled human-natural system in Amazonia. Ecosyst. Serv. 33, 68–76. https://doi.org/10.1016/j.ecoser.2018.08.008.

West, T.A.P., Monge, J.J., Dowling, L.J., Wakelin, S.J., Yao, R.T., Dunningham, A.G., Payn, T., 2020b. Comparison of spatial modelling frameworks for the identification of future afforestation in New Zealand. Landsc. Urban Plan. 198, 103780 https://doi.org/10.1016/j.landurbplan.2020.103780.

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. Science 381, 873–877. https://doi.org/10.1126/science.ade3535.

Wildlife Works and ecoPartners, 2014. VM0009 Methodology for Avoided Ecosystem Conversion, v.3.0. Verra, Washington, D.C.

Wildlife Works, 2012. The Mai Ndombe REDD+ Project. San Francisco.

Wunder, S., Duchelle, A.E., de Sassi, C., Sills, E.O., Simonet, G., Sunderlin, W.D., 2020. REDD+ in theory and practice: How lessons from local projects can inform jurisdictional approaches. Front. For. Glob. Chang. 3, 1–17. https://doi.org/10.3389/ffgc.2020.00011.