ENVIRONMENTAL RESEARCH
LETTERS

LETTER • OPEN ACCESS

A holistic approach to assessing REDD+ forest loss baselines through ex post analysis

To cite this article: Maren Pauly *et al* 2024 *Environ. Res. Lett.* **19** 124096

IOP Publishing Environ. Res. Lett. 19 (2024) 124096 https://doi.org/10.1088/1748-9326/ad616c

ENVIRONMENTAL RESEARCH
LETTERS

CrossMark

OPEN ACCESS

RECEIVED
18 March 2024

REVISED
8 July 2024

ACCEPTED FOR PUBLICATION
10 July 2024

PUBLISHED
2 December 2024

LETTER

A holistic approach to assessing REDD+ forest loss baselines through ex post analysis

Maren Pauly[1,*], William Crosse[1], Colin Moore[2], Kevin Brown[2], Oliver Griffin[2], Edward T A Mitchard[3,4], Jeremy Freund[5] and Joshua Tosteson[1]

[1] Department of Research & Evaluation, Everland LLC, New York City, NY, United States of America
[2] Wildlife Conservation Society, Washington, DC, United States of America
[3] Space Intelligence Ltd, Edinburgh, United Kingdom
[4] University of Edinburgh. School of GeoSciences, Edinburgh, United Kingdom
[5] Wildlife Works Carbon, Burlington, VT, United States of America
[*] Author to whom any correspondence should be addressed.

E-mail: maren.pauly@everland.earth, will.crosse@everland.earth, cMoore@wcs.org, kbrown@wcs.org, ogriffin@wcs.org, ed@space-intelligence.com, jeremy@wildlifeworks.com and joshua.tosteson@everland.earth

Keywords: forest, REDD+, nature based solutions, climate mitigation, climate change, forest conservation, baseline

Supplementary material for this article is available online

Abstract

The implementation of REDD+ (Reducing Emissions from Deforestation and Forest Degradation) projects has become a key Nature Based Solutions strategy to protect at-risk forests using the sale of verified emission reductions (carbon credits) as financing, generated by reducing forest loss against counterfactual baseline scenarios. Controversy over the reasonableness of such baseline scenarios has thrown this nascent market mechanism into disarray. While new technical approaches to baseline-setting that promise wider market acceptance are set to roll out in the coming years, existing projects are becoming unviable, as carbon credit buyers reduce investment due to lost confidence in the integrity of emissions reduction claims. Transparent, reproducible methods to assess existing REDD+ project baselines are needed in order to provide a clearer picture of the real impact of projects, and provide an objective basis on which investment decisions can be made today. Here we introduce such a method. In contrast to existing studies which utilize only one method to create a single 'control,' we integrate actual forest loss rates from a variety of control sites to establish a 'zone of reasonable accuracy (or ZORA)'. Application of our method in Cambodia, using two geospatial datasets (one global and one locally calibrated), shows that all three project baselines fall within or below ZORA. This approach is fully reproducible, and provides a transparent way for analysts to assess REDD+ baselines during this critical time when investment in forest protection must increase dramatically and without delay.

1. Introduction

REDD+ stands for 'Reducing Emissions from Deforestation and Forest Degradation,' a concept initially introduced by the UNFCCC under the Warsaw Framework for REDD +. As a market-based mechanism, it has been proven effective in protecting forests at risk, especially when implemented on a landscape scale by projects [1–4]. A voluntary market has been operating since the early 2000s, primarily under the Verified Carbon Standard (VCS) wherein ~100 REDD+ projects covering less than 1% of remaining tropical forests are currently registered [2, 5–8]. Based on the mitigation potential, cost-effectiveness, and impacts (biodiversity and community), the conservation of ecosystems through avoiding deforestation has been identified as one of the highest priorities for immediate action to mitigate climate change [9, 10]. Indeed, in tropical regions it may be the highest priority [11], as in many tropical countries *per capita* greenhouse gas emissions from burning fossil fuels remain low, whilst net forest loss rates are high [12].

Given the intrinsic uncertainty in predicting future deforestation [13] and the dependence upon such predictions for the quantity of REDD+ Verified Emissions Reductions that can be generated for offsetting purposes, the *ex post* assessment of REDD+ baselines can shed light on the reasonableness of emission reduction claims at a project level. Baselines have to date been developed by projecting forest loss measured over a historical reference period into the future through the duration of a baseline validity crediting period. While it is impossible to prove the 'accuracy' of a counterfactual scenario, the reasonableness of a baseline projection of forest loss may be assessed in hindsight by comparing the projection with actual deforestation that took place during the validity period in comparison or 'control' areas which are similar to the REDD+ project area, but did not feature any REDD+ activities.

To date, one principal methodology has been used to conduct *ex post* analysis of REDD+ project baselines—the Statistical Matching (or similar pixel matching) method [14, 15]. In this approach, analysts match REDD+ project area geospatial data variables with other areas of land within the same country, then evaluate the statistical correspondence between control site deforestation, project area deforestation, and predicted baseline deforestation. Two studies based on this approach have concluded that REDD+ project baselines systematically overstate the forest protection and emissions reduction impacts of the interventions, calling into question the efficacy of the REDD+ mechanism as a whole and contributing to a substantial reduction in investment [16, 17].

However, these studies have also sparked strong criticism, focused on inappropriate matching and control selection, inadequate communication of modeling and geospatial errors, and other methodological and analytic issues [18]. The critiques highlight that it is impossible to establish a perfect control for a given project area encompassing potentially many hundreds of thousands of hectares and thousands of people. As well, in any small-scale control area, forest loss may occur faster or slower than predicted within the context of the deforestation drivers that are present in the broader landscape. Because of these fundamental limitations, it is critical that more comprehensive methods, utilizing high quality geospatial data instead of low-resolution global geospatial datasets [19, 20], be used to assess REDD+ project baselines (supplementary information 1).

Here we present a holistic approach to assessing REDD+ baselines by developing, assessing, and integrating results from a number of different control sites, and applying the approach to three projects in Cambodia (the Keo Seima Wildlife Sanctuary REDD+ Project (KSRP), the Southern Cardamom REDD+ Project (SCRP) and the Tumring REDD+ Project (TRP)) using two different maps of forest cover change: Hansen *et al* [19] and a high accuracy, locally calibrated land cover dataset produced specifically for this purpose by Space Intelligence. We show how and why different control site selection methods produce widely variable results, and assess the performance of open-source datasets against higher quality data. We integrate the results of all approaches to establish the concept of a 'zone of reasonable accuracy,' a generally applicable, holistic metric against which other REDD+ project baseline deforestation rates may be assessed.

2. Methods

2.1. Data collection

2.1.1. Project data

Project area shapefiles and other documentation (project descriptions and monitoring reports) were downloaded from the VCS Registry for the REDD+ projects (supplementary table 1). Local drivers of deforestation were assessed based on the information provided in public project documentation, consultation with project developers and assessment of the Space Intelligence derived land cover and change maps developed for this study. According to the VCS methodologies these projects are registered under, Avoided Unplanned Deforestation baselines are established by predicting the business-as-usual deforestation (and resulting CO_2 emissions) within the REDD+ site ('Project Area') using a control area ('Reference Region', RR [21]). The RRs for two of the projects (SCRP, TRP) are the entire country of Cambodia as they allocated nested baselines from the Cambodia Forest Reference Level (FREL [22]) and the KSRP RR was defined using the VCS Methodology VM0015.

2.1.1.1. VCS selected project baselines

The SCRP and TRP utilized the FREL as the basis for the baseline deforestation rate using a proportional allocation approach (scaling emissions reductions based on the level of forest within the country vs. the project area). As the allocation of the FREL was based on total forest area within projects rather than forest at risk of deforestation, the baseline deforestation rate was the same as the FREL (2.38%/year). The published overall FREL accuracy is 81.23% [22], hence an uncertainty of ± 18.77% will be used (2.38 ± 0.45%/year).

The KSRP baseline predicted a total of 28 304 ha of forest loss within the first 10 years of the project: an average annual baseline deforestation rate of 1.70%. The reported mapping accuracy of the land classifications underlying the baseline was reported to average 93% and the confidence interval of the carbon stock was between ± 7.9% (dense forest) and ± 13.3% (open forest) [23]; hence the uncertainty of the baseline will be presented here as the sum of the fractional uncertainties (conservatively using the higher of the two carbon stock uncertainties)—resulting in a total baseline uncertainty of at ± 20.3% (1.70% ± 0.35%).

2.1.2. Geospatial data

2.1.2.1. Space intelligence forest change maps (SIFC)

25-meter resolution Land Cover maps covering the entire country of Cambodia were developed by Space Intelligence using Habitat Mapper™ (supplementary information 2.1) for 2010, 2015 and 2020.

From these, Forest Change maps (SIFC; forest to non-forest classes, and areas of stable forest and stable non-forest) were constructed to determine the rates of deforestation.

2.1.2.2. Hansen forest cover and change maps (HAN)

Hansen *et al* [19] forest cover and forest loss maps (30 m resolution, 10% canopy cover) version 1.10 were downloaded (https://storage.googleapis.com/earthenginepartners-hansen/GFC-2022-v1.10/download.html) for the relevant 10 × 10 degree granule covering Cambodia (hereafter referred to as 'HAN'; supplementary information 2.2). Annual forest cover was calculated by subtracting the annual forest loss from 2000 forest cover, cumulating the loss over time. This was calculated for the project areas, control areas, jurisdictions and country.

2.1.2.3. Map accuracy assessment

Independent Accuracy Assessments (IAAs) were designed based on best practices [24] to determine the accuracy of the SIFC and HAN maps. The strata used in the IAA were Stable forest, Forest loss, Forest gain and Stable non-forest. A stratified random sampling design was used as it is easily extensible and provides unbiased estimators for the accuracies and their variances [24]. A target sample size was estimated according to sampling theory (with a minimum of 100 samples for each class) and extended (proportionally to the areas of each class in the maps) to reduce the uncertainties in user's accuracies. The spatial assessment unit was defined as a square of 25 m side. Sample assessment was performed using visual assessment of Sentinel-2 and Landsat cloud free mosaics (RGB and false color), Planet NICFI and where available Google and Bing high resolution images. Analyst confidence assessments were used to eliminate points where the available data was insufficient to confidently assess the sample (supplementary information 2.3).

2.1.3. Control area selection

The predicted annual baseline forest loss for each project was compared to actual average annual forest loss within various control areas using the two different forest change datasets (HAN, SIFC) from project start (KSRP: 2010, TRP & SCRP: 2015) to 2020. These controls were selected using four different methods of varying complexity, outlined below.

2.1.3.1. Method 1: reference region (RR)

Method 1 utilized the project-defined Reference Regions (RRs). Based on the various VCS methodologies (VM0007, VM0009, VM0015; see supplementary table 1), the RRs should be matched with the project areas based on landscape factors (forest type(s), soil class(es), slope, elevation), transportation networks, human infrastructure (road, river, and settlement density), social factors and policies/regulations [21].

2.1.3.2. Method 2: proxy area (PrA)

We defined Proxy Areas as an alternative to the VCS methodology RRs. These PrAs were defined by having the same set of ministerial land tenure arrangements and legal status as the project area in question, within the same province and/or adjacent provinces with similar physiological characteristics.

2.1.3.3. Method 3: jurisdictional approach (JA)

For the jurisdictional approach, the province/state where the project is located is used as a control as per Pauly *et al* [25]. In the case of SCRP (where the project occupied a large portion (>40%) of the state), adjacent states were included in the analysis. The geospatial bounds of the REDD+ project areas were removed from the jurisdictional area to ensure REDD+ interventions were compared to surrounding non-REDD+ forests.

2.1.3.4. Method 4: statistical pixel matching (SPM)

A set of control pixels were defined for each project using covariates (supplementary information 3.1). Pixels rather than larger contiguous areas of land (as per West *et al* [14, 15]) were selected as smaller controls benefit from a larger number of potential matches. This is particularly useful in Cambodia, where contiguous areas of forest have disappeared in recent decades, reducing the number of large forest areas that can be used as REDD+ control sites.

The PrAs defined in Method 2 were used as the initial Area of Interest (AOI) for each project (supplementary information 3.4). Within these AOIs, a series of covariates known to influence the likelihood of deforestation were selected, including: distance to roads, distance to previous conversion, population density, elevation and slope; with distance to previous conversion known to be a particularly strong predictor of near-term deforestation [26].

For matching, the Coarsened Exact Matching methodology was employed [27] (supplementary information 3.2). Thereafter, standard measures of covariate balance (standardized mean difference and quantile-quantile plots) were used to assess the balance between project and non-project covariate distributions. The rates of deforestation (the proportion of matched pixels that were recorded as deforested in SIFC maps) were calculated for project and proxy areas. The average treatment effect in the treated (project) sample was determined using the risk ratio of deforestation in project and proxy sites, then bootstrapping to generate 95th percentile confidence intervals around this estimate. The annual forest change rates of the matched pixels was compared to the baseline deforestation rates for each project. Rosenbaum sensitivity analysis was performed as a way to determine the robustness of the matching to unobserved covariates [28] (supplementary information 3.3).

2.1.4. Defining a zone of reasonable accuracy

We defined a 'Zone of Reasonable Accuracy' (ZORA) based on the upper and lower uncertainty bounds of the mean annual forest loss that occurred within all the abovementioned control area methodologies for a single REDD+ project over the same defined period of time (supplementary information 4).

3. Results

3.1. Cambodia forest loss

Forest cover and loss within Cambodia differed between the SIFC and HAN datasets (figure 1, table 1). In 2010, forest cover in Cambodia was 10 064 948 ha according to SIFC and 7 788 491 ha according to HAN (supplementary table 2). Between 2010 and 2020, SIFC data estimated forest loss totaling 3 341 407 ha (33.20% ± 12.06% of total forest area, 3.32% ± 1.21%/year); primarily due to conversion of forest land to agricultural and plantation uses (supplementary figure 1). Over the same time interval, a considerably lower rate was estimated from HAN data (21.27% ± 12.71% total forest loss, 1.93% ± 1.15%/year). Relevant to the use of the Cambodia National FREL for the baseline setting of SCRP and TRP, the total country-level forest loss from 2015 to 2020 was 1 298 644 ha (3.24% ± 1.18%/year) according to SIFC since the project started; far less forest loss was captured by HAN over the same period (1.68% ± 1.00%/year).

The accuracy analysis indicated that SIFC better captures forest cover loss in Cambodia. HAN demonstrated a False Positive (FP) rate of 22.5% ± 8.7% and a Missed Detection (MD) rate of 37.3% ± 4.7%—a forest loss total error of ± 59.75% (supplementary information 2.3). Conversely, SIFC data had a FP of 23.6% ± 6.9% and MD of 12.7% ± 2.9%—a total error of ± 36.31%.

3.2. Baseline assessments

Across all baseline assessment methods and datasets, the actual deforestation rates varied widely—by an average of ± 2.97%/year, with TRP demonstrating the largest average results variance (± 5.00%/year) compared to KSRP (± 2.13%/year) and SCRP (± 1.79%/year). When comparing the same control areas using the HAN vs. the SIFC data, the SIFC data estimated an average deforestation rate (4.01%/year) more than 2-fold higher than HAN (1.93%/year).

3.3. Keo seima REDD+ project (KSRP)

Under Method 1 (RR), the average annual forest loss within the KSRP RR between 2010 and 2020 was 5.57% ± 2.02%/year according to SIFC and 1.09% ± 0.65%/year from HAN (figure 3). For Method 2, the KSRP PrA underwent a 2.49% ± 0.90%/year forest loss according to the SIFC data, which—similarly to the RR—was far higher than the forest loss rate detected according to HAN (0.97% ± 0.58%/year). Following Method 3, Môndól Kiri and Kratie provinces experienced forest loss rates of 2.70% ± 0.98%/year based on SIFC (HAN: 2.30% ± 1.37%/year). According to the SPM results, the distribution of points that had experienced conversion from forest to non-forest was spatially clustered (supplementary figure 5), with a high proportion clustered on the southern project border. Thus, the results demonstrate distinct differences when the adjacent Snuol Wildlife Sanctuary (SWS) was included (AOI_{KS2},AOI_{KS3}) vs. when it was excluded from the analysis (AOI_{KS1}); with the former two model runs encompassing the incoming deforestation frontier. Within the AOIs that included SWS, the average annual forest loss within the control points during the entire study period (2010–2020) was 1.68% ± 0.61%/year for AOI_{KS2} and 1.56% ± 0.57%/year for AOI_{KS3}; corresponding closely to the baseline deforestation rate used for the project. On the other hand, the model that excluded SWS (AOI_{KS1}) predicted only 0.59% ± 0.21%/year for the study period (2010–2020).

On average, the baseline assessments predict a baseline of 2.11% ± 1.01%/year; when only SIFC results are considered the average ex-post forest loss rate increases to 3.08% ± 1.11%/year. In both cases, the zone of reasonable accuracy (ZORA) is higher than the baseline established by the project (1.70% ± 0.26%/year).

3.4. Tumring REDD + project (TRP)

In the case of TRP, the RR underwent 3.52% ± 1.26%/year of forest loss according to SIFC, and 1.68% ± 1.01%/year according to HAN (figure 4). For Method 2, the selected TRP PrA suffered a total 7.58% ± 2.75%/year of forest loss according to the SIFC data; much higher than the forest loss detected by HAN (3.60% ± 2.15%/year). According to Method 3, SIFC data estimated a loss of 6.53% ± 2.37%/year within Kampong Thom, whereas HAN data only captured 2.53% ± 1.51%/year. For the SPM Method, the distribution of points that had experienced conversion from forest to non-forest was spatially clustered in the south and west, indicating an advancing front of deforestation moving towards the project area (supplementary figure 6). Within the two model runs, the

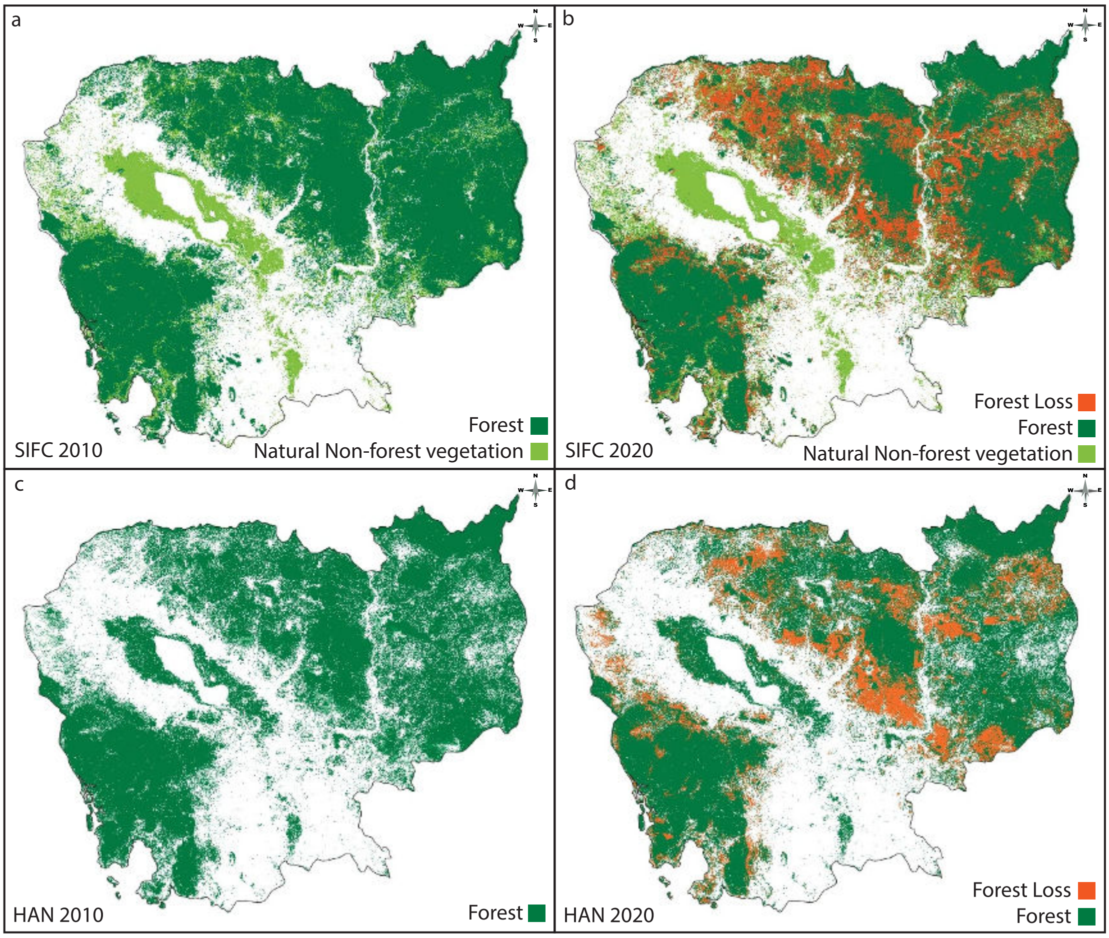

Figure 1. Forest cover and loss from Space Intelligence (SIFC) and Hansen *et al* (HAN) datasets for 2010 and 2020. Forest loss represents total 2010 forest cover lost between 2010 and 2020. Natural non-forest vegetation produced from SIFC only. More detailed land classifications from SIFC data in supplementary figure 1. Forest cover in 2010 was estimated at 10 064 948 ha (±1,027,806.83) from SIFC and 7788 491 ha (± 3,250,049.87) from HAN—decreasing to 6723 541 ha (± 686,590) and 6172 890 ha (± 2,575,878) in 2020 for SIFC and HAN, respectively.

annual forest loss within the matched pixels was very high; 7.29% ± 2.65%/year and 12.01% ± 4.36%/year for AOI_{TRP1} and AOI_{TRP2}, respectively.

Together, the baseline assessment methodologies show an average forest loss of 5.59% ± 2.68%/year; when only SIFC results are considered, this average increases to 7.41% ± 2.67%/year. In both cases, the ZORA is significantly higher than the project baseline (2.38% ± 0.45%/year).

3.5. Southern cardamom REDD+ project (SCRP)

Similar to the TRP, the SCRP RR underwent 3.52% ± 1.26%/year of forest loss according to SIFC; lower than HAN predictions (1.68% ± 1.01%/year). On a more localized level, the PrA and SPM baseline methods predicted far less deforestation, ranging between 0.22% ± 0.08%/year and 0.64% ± 0.23%/year for SIFC data. However, both the proxy and pixel-matched control areas include very little ELC land, predominantly consisting of protected areas. When this area is expanded to the jurisdiction (Method 3) the observed deforestation increases to between 1.33% ± 0.48%/year (SIFC) and 1.62% ± 0.97%/year (HAN) (figure 5).

Taken together, the results from all baseline assessments vary widely, depending on whether larger-scale deforestation drivers and known ELC-threats are taken into account. On average across all approaches, the ZORA for the SCRP baseline is 1.23% ± 0.73%/year (1.49% ± 0.54%/year for only SIFC results), which is on the lower end of the error threshold of the project's baseline (2.38% ± 0.45%/year).

4. Discussion

4.1. Zone of reasonable accuracy (ZORA)

Two REDD+ projects (TRP, SCRP) selected the national FREL as the baseline (2.38% ± 0.45%/year) whereas the third project (KSRP) developed a locally-calibrated risk map, resulting in a baseline forest loss rate of 1.70% ± 0.35%/year. Amidst this diversity of baseline-setting approaches, this multi-control site *ex post* analysis suggests that these Cambodian projects

Table 1. A summary of the baseline assessment results, comparing the Space Intelligence (SIFC) and Hansen *et al* (HAN) datasets in terms of forest cover (ha) at project start and average annual forest loss (%/year) from project start to 2020. Visualized in figure 2.

Parameters			KSRP	TRP	SCRP
Project area	SIFC	Forest cover project start (ha)	166 155.31 ± 16 967.36	40 820.56 ± 4168.49	438 162.63 ± 44 744.05
		Average annual loss (%)	0.73 ± 0.27	5.15 ± 1.87	0.04 ± 0.01
	HAN	Forest cover project start (ha)	128 901.69 ±53 789.23	33 548.25 ±13 999.31	363 011.38 ±151 480.57
		Average annual loss (%)	1.09 ±0.65	6.15 ±3.67	0.01 ±0.01
Jurisdiction	SIFC	Forest cover project start (ha)	2171 716.00 ±221 770.1	386 936.25 ±39 512.94	1376 960.56 ±140 611.7
		Average annual loss (%)	2.70 ±0.97	6.53 ±2.35	1.33 ± 0.47
	HAN	Forest cover project start (ha)	1447 498.63 ± 604 024.93	381 062.31 ± 159 013.03	1223 330.69 ± 510 482.16
		Average annual loss (%)	2.30 ± 1.37	2.53 ± 1.51	1.62 ± 0.97
Reference area	SIFC	Forest cover project start (ha)	586 180.00 ± 59 859.21	8022 186.00 ± 819 205.18	8022 186.00 ± 819 205.18
		Average annual loss (%)	5.57 ± 2.00	3.52 ± 1.26	3.52 ± 1.26
	HAN	Forest cover project start (ha)	445 499.19 ± 185 901.81	6924 921.19 ± 2889 691.88	6924 921.19 ± 2889 691.88
		Average annual loss (%)	1.09 ± 0.65	1.68 ± 1.01	1.68 ± 1.01
Proxy area	SIFC	Forest cover project start (ha)	726 164.75 ± 74 154.09	218 865.50 ± 22 349.99	719 206.88 ± 73 443.57
		Average annual loss (%)	2.49 ± 0.89	7.58 ± 2.73	0.64 ± 0.23
	HAN	Forest cover project start (ha)	466 014.63 ± 194 462.67	220 311.81 ± 91 933.65	772 058.31 ± 322 171.27
		Average annual loss (%)	0.97 ± 0.58	3.60 ± 2.16	0.15 ± 0.09
Synthetic controls	SIFC	Average annual loss (%)	0.97 ± 0.35	9.77 ± 3.51	0.45 ± 0.16
Average assessment results (Annual loss %)		SIFC + HAN	2.11 ± 1.01	5.59 ± 2.68	1.23 ± 0.73
		SIFC only	3.08 ± 1.11	7.41 ± 2.67	1.49 ± 0.54
Project baseline (%/year)			1.70 ± 0.35	2.38 ± 0.45	2.38 ± 0.45

are operating under baselines that fall within, or are conservative with respect to, the ZORA as defined herein.

4.2. Dataset quality implications

Across all projects, HAN data estimated far less forest loss across the baseline assessments (average: 1.92% ± 1.15%/year) than the locally calibrated SIFC data (average: 3.65% ± 1.33%/year); particularly for the RR of KSRP (HAN: 1.09% ± 0.65%/year, SIFC: 5.57% ± 2.00%/year). Since HAN data (or similar global, uncalibrated data) has been used for other previous REDD+ baseline assessment studies, this could have important implications on the results of such studies—potentially producing a higher delta between the actual forest loss in relevant controls and the selected baseline deforestation rate (concluding that baselines systematically overstated). Importantly, this likely impacted the reliability of studies wherein HAN forest cover data was applied as part of control selection [15]. The results in this study demonstrate the benefit of utilizing locally-calibrated land cover datasets as a basis for assessing REDD+ project effectiveness and the reasonable accuracy of baseline.

4.3. Unique deforestation risk factors in Cambodia

Forest clearing for agriculture is a key driver of deforestation in Cambodia, enabled by increased road density [29]. Native forests have given way to rubber, cassava, rice, and sugarcane, as both smallholder and

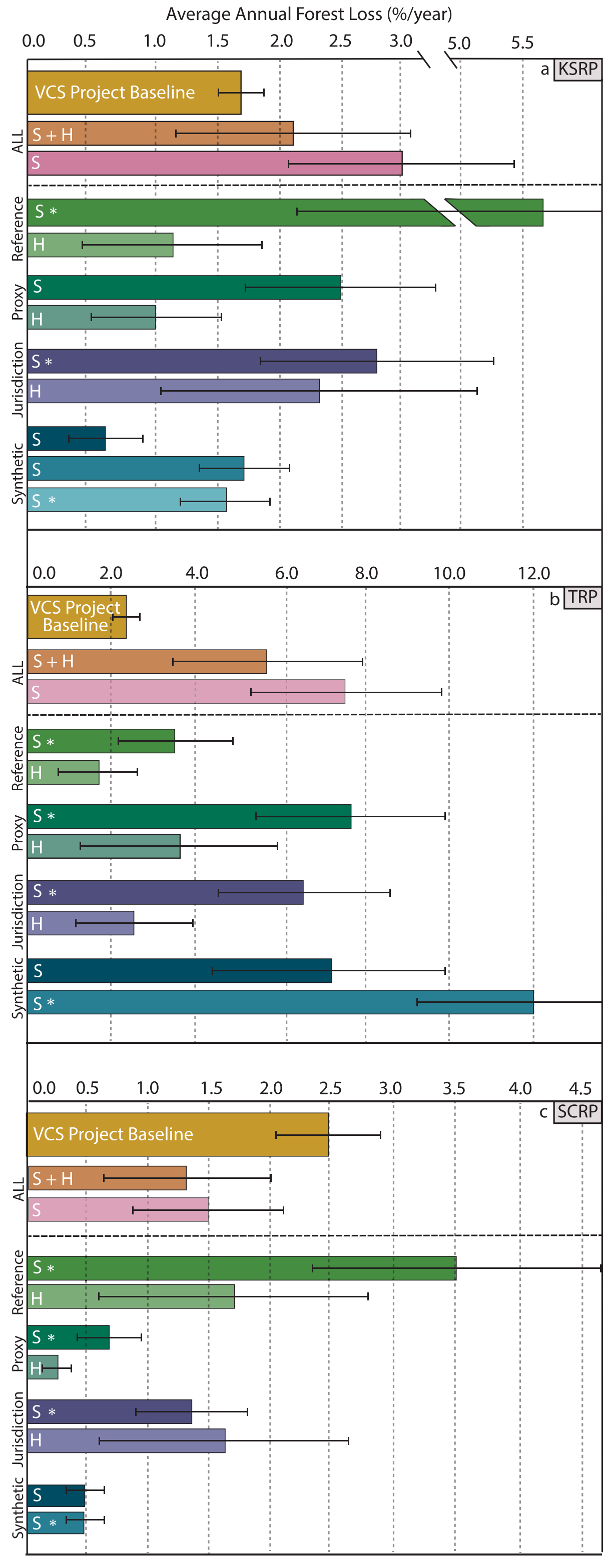

Figure 2. The selected project baseline deforestation rates for (a) Keo Seima REDD+ Project, (b) Tumring REDD+ Project, and (c) Southern Cardamom REDD+ Project compared to the baseline assessment method results using two geospatial datasets: SIFC ('S', Space Intelligence Forest Change) and HAN ('H', Hansen *et al* [19]). Baseline Assessment methodologies refer to: Method 1: Reference Region (RR, 'Reference'), Method 2: Proxy Area (PrA, 'Proxy'), Method 3: Jurisdictional Approach (JA, 'Jurisdiction'), and Method 4: Statistical Pixel Matching ('Synthetic'). The error bars of the baselines refer to the errors reported within the project documentation as described within the Results. Error bars of the baseline assessments reflect uncertainties of the datasets within the region mapped. Orange bar line represents the average annual forest loss predicted across all baseline assessment approach methods and the pink bar represents average across SIFC baseline assessment methods highlighted with an asterisk. Multiple options for Method 5 presented as per the various potential AOIs (Areas of Interest; see Methodology). The asterisk on the Synthetic method bar represents the most realistic AOI (see supplementary information: selection of AOIs).

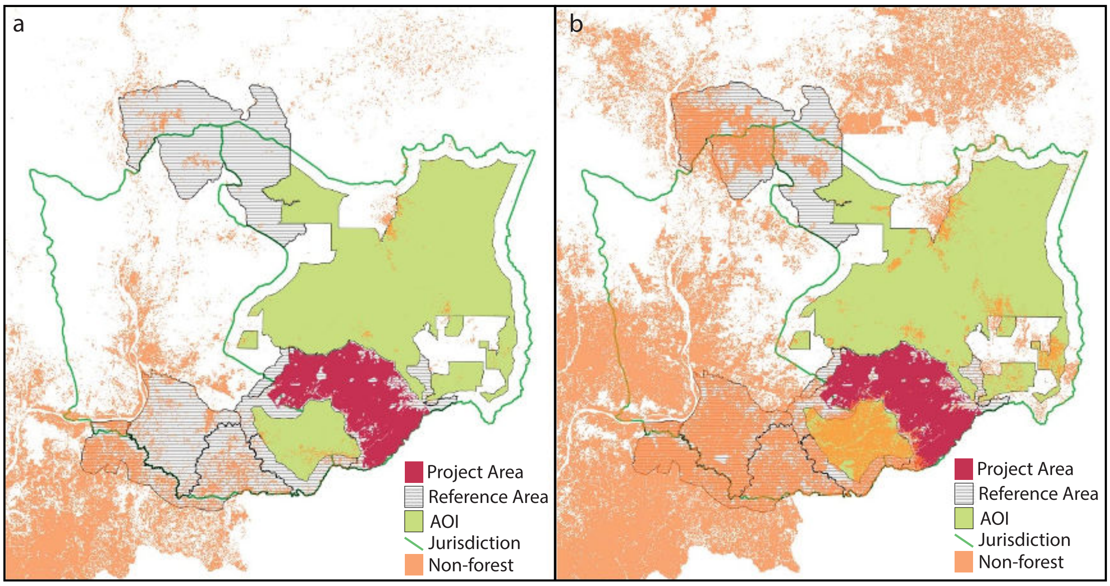

Figure 3. Forest loss represented by the progression of non-forest (plantations, agriculture and bare land) in (a) 2010 and (b) 2020 within the region of Keo Seima Wildlife Sanctuary REDD+ project. Largest AOI represented (AOI_{KS2}).

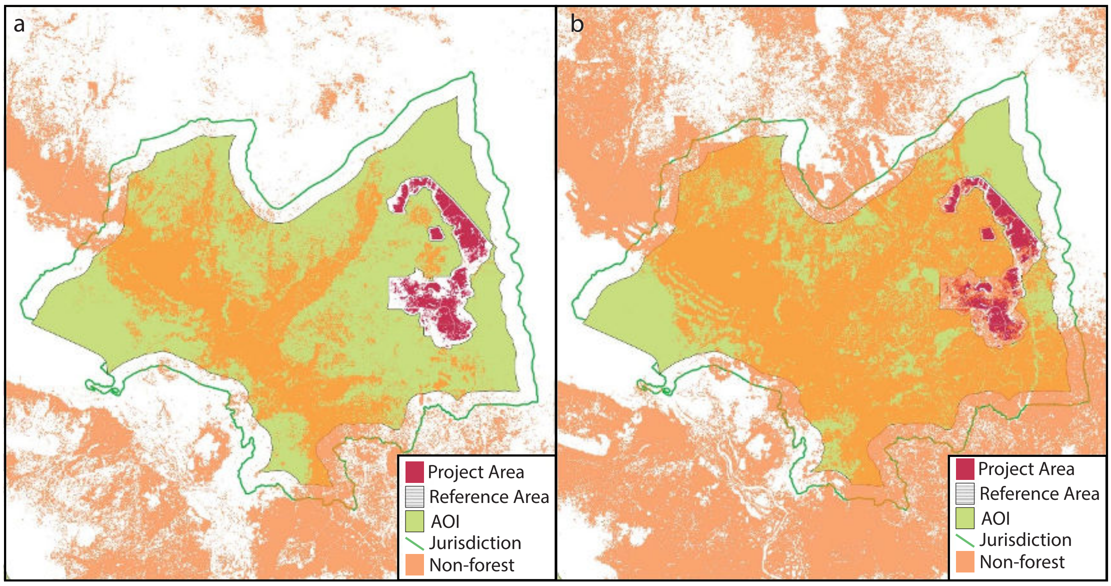

Figure 4. Forest loss represented by the progression of non-forest (plantations, agriculture and bare land) in (a) 2010 and (b) 2020 within the region of the Tumring REDD+ project. Largest AOI represented (AOI_{TRP1}).

large-agribusiness farming have continued to expand [30] through legal and illegal (i.e. land grabbing) approaches. Whilst land grabbing in the form of small-scale agricultural expansion is perhaps the most widely recognized form in the tropics, illegal logging has also contributed to deforestation and degradation, with valuable hardwoods such as rosewood and teak being targeted [31–33].

However, top-down ELC-based land grabbing is also an important driver of deforestation in Cambodia [34]. Deforestation is disproportionally high across ELCs which accounted for around 35% of agricultural land (estimated 2015; SIFC). Altogether, we find that between 2010 and 2020 Cambodia lost 33% of its forests, whilst plantations and agricultural land increased by nearly 2-fold (now superseding total remaining forest cover). In Cambodia, land rights are not strongly backed by dependable legal structures; as such, whilst the granting of new ELCs was officially suspended in 2012 (Directive 01 [35]), concession contracts continue to be granted by the government [36]; even within protected areas and other pristine forest landscapes, despite the posturing that ELCs should only be established within vacant or degraded lands [36, 37]. Recent research suggests that 95 ELCs have been granted within 18 protected areas over the last 20 years, currently covering a total of 12.5% of protected area land—resulting in

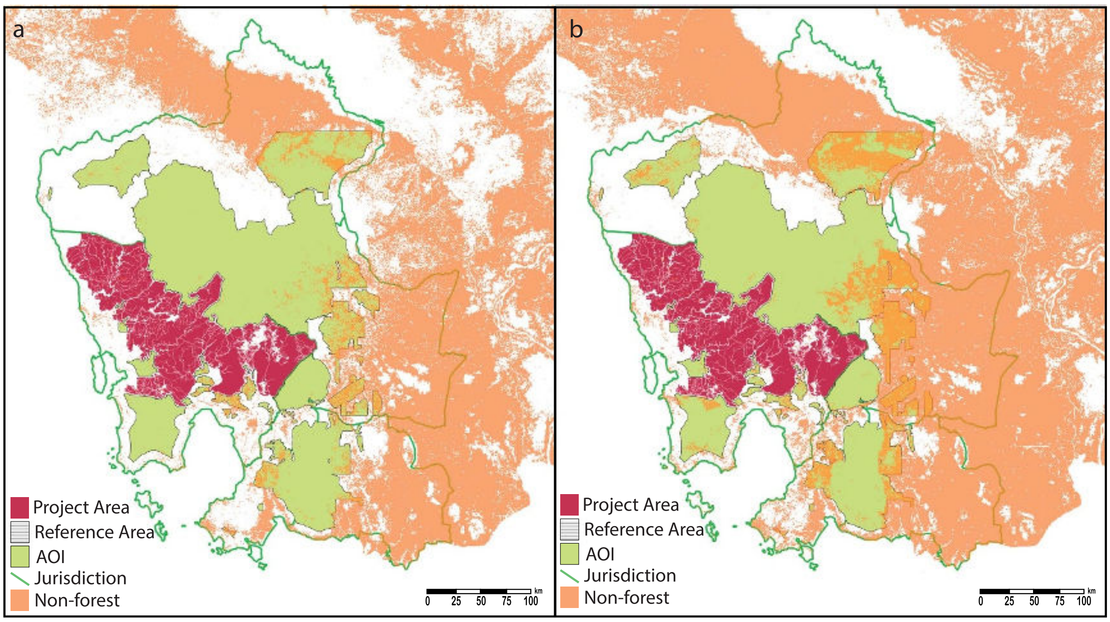

Figure 5. Forest loss represented by the progression of non-forest (plantations, agriculture and bare land) in (a) 2010 and (b) 2020 within the region of the Southern Cardamom REDD+ project. Largest AOI represented (AOI_{SCRP1}).

the downgrading and/or degazettement of 18 protected sites [38]. Accordingly, ELCs were included within control area selection as they represent a real threat to the REDD+ projects (supplementary information 5). The integration of ELCs in this study highlights that there can be critical factors impacting the 'reasonableness' of a baseline prediction, but which are not easily amenable to geospatial analysis.

4.4. Methodology limitations and the nature of counterfactuals in complex landscapes

Whilst this study underlines a series of different baseline assessment methods, it is still fundamentally impossible to validate the 'accuracy' of baseline deforestation predictions for a treatment area, as they are by definition what did not take place in reality. Beyond this fundamental constraint, other methodological issues illustrate the limitations associated with different approaches to control site selection.

For example, the RR approach is a relatively simple methodology to predict whether the baseline deforestation proceeded within the RR as expected at the time of project registration. However, given the fact that a single control site is used, validating the baseline deforestation rate by assessing ex-post RR forest loss is more a proof of the accuracy of the deforestation model outputs rather than an evaluation of whether the baseline deforestation rate applied to the project site was realistic.

For the PrA and SPM methods, there are many decision points in the development of this method which may profoundly impact the result. The selection of appropriate comparison areas is a critical step and should be based on a sound conceptual model of the intervention and counterfactual scenario [39, 40]. The approach taken here of selecting based on land management status is widely used and is simple and defensible and has been widely applied as a basis for assessments [28], yet it has not been adequately applied to the other REDD+ baseline studies [14, 15]. Within this framework, there does need to be scope for the consideration of the particular circumstances of a given comparison area at the project baseline to ensure it represents a realistic control. This analysis accounts for a subset of core covariates (e.g. slope, elevation, local population and distance to previous deforestation, roads and rivers) that are commonly accounted for in matching type analysis in academic literature [28, 40]; other factors could be added which pertain to both accessibility and utility of forest resources or land and resource user pressure (e.g. soil type, distance to a large city). Despite these complexities, when the method is applied at a fine (pixel) spatial resolution and the match quality is proven to be strong, then this method is thought to be highly accurate in establishing a realistic control.

The JA provides a more generalized control area that integrates the various deforestation rates of smaller land areas within the larger jurisdictional area surrounding a project, providing a more holistic indication of the deforestation risk present across the wider landscape. This approach becomes more limited to the extent that a project is located in very high or low deforestation risk areas within the jurisdiction. For example, the majority of KSRP is located within the southwestern corner of Môndól Kiri province, only a small section of the PA stretching into the adjacent Kratie province; with the former having much lower deforestation rates historically than the latter. The integration of both provinces into the JA assessment of KSRP is vital as Kratie encompasses the incoming deforestation frontier which has not yet penetrated across much of Môndól Kiri. Hence, a knowledge of deforestation frontiers and relative risk is important for the interpretation of results using this methodology.

Nonetheless, and of special interest to this study, the deforestation rates associated with the JA unsurprisingly match closely those associated with the ZORA for each studied project. Because the JA reflects an integrated picture of deforestation across all potential control sites within a wider area surrounding a project, we consider it a sufficient, and analytically simpler, basis on which to establish the ZORA for a given project.

5. Conclusions

Here we present a series of potential methods of selecting control areas and an initial definition of a zone of reasonable accuracy—both of which should be further tested in different landscapes. Each individual approach for creating control areas has its own strengths and limitations. The ZORA integration approach is a pragmatic, holistic way to assess the baseline on an *ex post* basis using a series of control areas. In the Cambodia context, we find the JA, which integrates across all potential control sites surrounding a project area, offers a simpler, effectively equivalent way to establish the ZORA for a given project.

In applying this approach, we demonstrate that the VCS baselines of three Cambodian REDD+ projects either fell within, or were below, their applicable ZORAs. These results contradict other studies in which single methodologies and uncalibrated data ultimately result in the conclusion that REDD+ baselines are systematically overestimated in general [14, 15], and specifically in the same sites in Cambodia [15]. Rather, the results here show that REDD+ project baselines in Cambodia are in line with, or lower than, observed deforestation when viewed holistically across a variety of comparison areas.

The study provides a transparent, replicable method that reduces bias, uses high quality, locally calibrated geospatial data, and provides a relatively simple, generally applicable standard basis for assessing the reasonable accuracy of a REDD+ project baseline. The method has high potential in the short term to provide quality assessments of carbon credits issued under existing REDD+ project baselines before new REDD+ carbon crediting methodologies that may be viewed as higher quality (particularly the VCS VM0048 [41]) come into force. Such assessments can provide a robust, objective basis for evaluating existing projects and unlocking urgently-needed conservation finance in this interim period, without waiting for new methodologies to emerge.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: Everland.earth.

ORCID iDs

Maren Pauly https://orcid.org/0000-0003-0470-2678
Jeremy Freund https://orcid.org/0009-0008-7478-2689

References

[1] Guizar-Coutiño A, Jones J P, Balmford A, Carmenta R and 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.* **36** e13970
[2] Gosnell G, Dickson R, Hu J, Hird T and Basnak M 2022 The REDD+ framework for reducing deforestation and mitigating climate change: overview, evaluation, and cost-effectiveness *Rethink Priorities* (available at: https://forum.effectivealtruism.org/posts/LmjsyFvQavLQnYSTp/the-redd-framework-for-reducing-deforestation-and-mitigating)
[3] Malan M, Carmenta R, Gsottbauer E, Hofman P, Kontoleon A, Swinfield T and Voors M 2024 Evaluating the impacts of a large-scale voluntary REDD+ project in Sierra Leone *Nat. Sustain.* **7** 1–10
[4] Pauly M, Crosse W and Tosteson J 2022 High deforestation trajectories in Cambodia slowly transformed through economic land concession restrictions and strategic execution of REDD+ protected areas *Sci. Rep.* **12** 17102
[5] Boyd W, Stickler C, Duchelle A E, Seymour F, Nepstad D, Bahar N and Rodriguez-Ward D 2018 *Jurisdictional Approaches to REDD+ and Low Emissions Development: Progress and Prospects* (World Resources Institute)
[6] Meyer C and Miller D 2015 Zero deforestation zones: the case for linking deforestation-free supply chain initiatives and jurisdictional REDD+ *J. Sustain. For.* **34** 559–80
[7] Pauly M and Tosteson J 2022 Safeguarding natural forests through the voluntary REDD+ scheme *Nat. Plants* **8** 861–6
[8] Piris-Cabezas P, Lubowski R N and Leslie G 2023 Estimating the potential of international carbon markets to increase global climate ambition *World Dev.* **167** 106257
[9] Cook-Patton S C *et al* 2021 Protect, manage and then restore lands for climate mitigation *Nat. Clim. Change* **11** 1027–34
[10] Duncanson L *et al* 2023 The effectiveness of global protected areas for climate change mitigation *Nat. Commun.* **14** 2908
[11] Lee H, Calvin K, Dasgupta D, Krinner G, Mukherji A and Thorne P 2023 Synthesis report of the IPCC sixth assessment report (AR6) *Intergovernmental Panel on Climate Change*
[12] Pacheco P, Mo K, Dudley N, Shapiro A, Aguilar-Amuchastegui N, Ling P Y, Anderson C and Marx A 2021 *Deforestation Fronts: Drivers and Responses in a Changing World* (WWF)
[13] Mitchard E T A 2018 The tropical forest carbon cycle and climate change *Nature* **559** 527–34
[14] West T A, Börner J, Sills E O and Kontoleon A 2020 Overstated carbon emission reductions from voluntary REDD+ projects in the Brazilian Amazon *Proc. Natl Acad. Sci. USA* **117** 24188–94
[15] West T A, Wunder S, Sills E O, Börner J, Rifai S W, Neidermeier A N and Kontoleon A 2023 Action needed to make carbon offsets from tropical forest conservation work for climate change mitigation (arXiv:2301.03354)
[16] Greenfield P 2023 Revealed: more than 90% of rainforest carbon offsets by biggest certifier are worthless, analysis

shows (The Guardian) (available at: www.theguardian.com/environment/2023/jan/18/revealed-forest-carbon-offsets-biggest-provider-worthless-verra-aoe) (Accessed 18 January 2023)
[17] Greenfield P 2024 Market value of carbon offsets drops 61%, report finds: negative scientific and press reports on the efficacy of carbon credit projects has led to a 'direct pullback in buyer investment' (The Guardian) (available at: www.theguardian.com/environment/article/2024/may/31/market-value-of-carbon-offsets-drops-61-aoe) (Accessed 31 May 2024)
[18] Mitchard E *et al* Serious errors impair an assessment of forest carbon projects: a rebuttal of West et al. (2023) (available at: https://ssrn.com/abstract=4661873) or http://dx.doi.org/10.2139/ssrn.4661873 (Accessed 12 December 2023)
[19] Hansen M C *et al* 2013 High-resolution global maps of 21st-century forest cover change *Science* **342** 850–3
[20] Vancutsem C, Achard F, Pekel J-F, Vieilledent G, Carboni S, Simonetti D, Gallego J, Aragão L E O C and Nasi R 2021 Long-term (1990–2019) monitoring of forest cover changes in the humid tropics *Sci. Adv.* **7** eabe1603
[21] VCS 2012 VCS module VMD0007: REDD methodological module: estimation of baseline carbon stock changes and greenhouse gas emissions from unplanned deforestation (BL-UP). Version 3.1
[22] Ministry of Environment (MoE), Royal Government of Cambodia (RGC) 2016 Initial forest reference level for Cambodia under the UNFCCC framework
[23] Wildlife Conservation Society 2015 Project description: REDD+ in Keo Seima WIldlife Sanctuary, Cambodia *VCS Version 3* (CCB Standards) 3rd edn V. 7.1
[24] Olofsson P, Foody G M, Herold M, Stehman S V, Woodcock C E and Wulder M A 2014 Good practices for estimating area and assessing accuracy of land change *Remote Sens. Environ.* **148** 42–57
[25] Pauly M, Crosse W, McCarron J, Raashid Z, Tosteson J and Michard E T A. 2024 REDD+ project baselines accurately correspond with observed forest loss globally (in review)
[26] Freund J, Pauly M, Gochberg W, Dangremond E and Korchinsky M 2024 A novel deforestation risk and baseline allocation model for the next generation of nested REDD+ projects (in review) *Sci. Rep.* 14
[27] Iacus S M, King G and Porro G 2012 Causal inference without balance checking: coarsened exact matching *Polit. Anal.* **20** 1–24
[28] Rasolofoson R A, Ferraro P J, Jenkins C N and Jones J P G 2015 Effectiveness of community forest management at reducing deforestation in Madagascar *Biol. Conserv.* **184** 271–7
[29] Riggs R A, Langston J D, Sayer J, Sloan S and Laurance W F 2020 Learning from local perceptions for strategic road development in Cambodia's protected forests *Trop. Conserv. Sci.* **13** 1940082920903183
[30] Piseth S, Monyoudom Y and Tynarath H 2021. Cambodia's agri-food trade: structure, new emerging potentials, challenges & impacts of Covid-19 *Food Security Policy Research, Capacity, And Influence (PRCI) Research Papers*
[31] Environmental Investigation Agency (EIA) 2019 State of Corruption: the top-level conspiracy behind the global trade of Myanmar's stolen teak
[32] Ayling J 2015 A regulatory approach to demand reduction in the illegal wildlife market *RegNet Research Papers No.82* (https://doi.org/10.2139/ssrn.2634303)
[33] Cerutti P *et al* 2018 Informality, global capital, rural development and the environment: mukula (rosewood) trade between China and Zambia *Research Report* (IIED)
[34] Rudi L M, Azadi H, Witlox F and Lebailly P 2014 Land rights as an engine of growth? An analysis of Cambodian land grabs in the context of development theory *Land Use Policy* **38** 564–72
[35] Royal Government of Cambodia (RGC) 2014 Directive No. 01 BorBor on the measures to strengthen and foster effectiveness for the management of ELCs
[36] Colchester M and Chao S, Updates on agribusiness and large-scale land acquisitions in Southeast Asia Brief# 1 of 8: regional overview
[37] Beauchamp E, Clements T and Milner-Gulland E J 2018 Exploring trade-offs between development and conservation outcomes in Northern Cambodia *Land Use Policy* **71** 431–44
[38] Ford S A, Persson J, Jepsen M R and Mertz O 2022 Sociopolitical drivers and environmental outcomes of protected area downgrading and degazettement in Cambodia *Reg. Environ. Change* **22** 114
[39] Schleicher J, Eklund J, D, Barnes M, Geldmann J, Oldekop J A and Jones J P 2020 Statistical matching for conservation science *Conserv. Biol.* **34** 538–49
[40] Pauly M 2023 Recent challenges in the retrospective evaluation of forest carbon credit baselines *Integr. Environ. Assess. Manage.* **19** 1394–7
[41] VCS Methodology VM0048: reducing emissions from deforestation and forest degradation, Version 1.0 (available at: https://verra.org/wp-content/uploads/2023/11/VM0048-Reducing-Emissions-from-Deforestation-and-Forest-Degradation-v1.0-1-1.pdf) (Accessed 27 November 2023)