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Integrated assessment of deforestation drivers and their alignment with subnational climate change mitigation efforts

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ABSTRACT

Efforts to reduce emissions from deforestation and forest degradation and enhancing forest carbon stocks (REDD+) have evolved over the past decade. Early REDD+ programs and local/subnational projects used various interventions (i.e. enabling measures, disincentives and incentives), implemented by government, the commercial and non-commercial private sector, but are currently understudied vis-à-vis their effectiveness to address site-specific drivers of deforestation and forest degradation (DD). We assess how well REDD+ interventions addressed DD at five project sites in Peru (1), Brazil (1), Vietnam (1) and Indonesia (2). Our study design includes an integrated assessment of remotely sensed, spatially modelled, and locally reported drivers. First, we observe follow-up land use from high resolution imagery as proxy for direct deforestation drivers. Second, spatial Random Forest modelling of DD drivers allows for influence quantification of topographic, climatic and proximity variables at each site. Third, we report direct and indirect DD drivers from pre-intervention surveys and semi-structured interviews with five REDD+ implementers, 40 villages and 1200 households. Data gathered included perceived changes in forest cover and quality, and their causes. We found general agreement between observed, modelled and reported local DD drivers, yet some were inadequately addressed by interventions. Intra-site differences in drivers underscores the importance of analysing micro-level DD drivers. Our interdisciplinary approach reveals the complexities of local direct and indirect DD drivers, and the complementarity of remotely sensed, spatially modelled and locally reported methods for driver identification. A better understanding of the alignment between DD drivers and REDD+ interventions is vital for practitioners and policy makers to enhance the effectiveness, efficiency, equity and co-benefits of REDD+ at the local level.

1. Introduction

Deforestation and other land use changes contribute significantly to carbon emissions (IPCC, 2006). Efforts to reduce emissions from deforestation and forest degradation and to enhance carbon stocks (REDD+) were embedded in the Paris Agreement (UNFCCC, 2015). To design effective policies, it is important to know: what land use change activities are happening; who are the agents linked to these changes; and what underlying forces are at play?

Numerous conceptual models can be used to understand the drivers of deforestation and forest degradation and their interactions. Geist and Lambin (2002) focus mainly on distinguishing proximate (*direct*) and underlying (*indirect*) causes, whereas Wood and Porro (2002) put more emphasis on the distinction between biophysical and socioeconomic factors at different spatial scales. The approach of Kaimowitz and Angelsen (1998) is more similar to Geist and Lambin's, although the focus differs by concentrating on the economics behind the immediate and underlying factors. It is important to monitor drivers of deforestation and forest degradation (DD) at the local level because they differ across space and time (Rudel, 2007; Rudel et al., 2009; Defries et al., 2010; Hosonuma et al., 2012; De Sy et al., 2015; Curtis et al., 2018).

The methods to assess drivers are nested in different scientific disciplines. They range from visual assessment of land use, land cover, and changes therein (LULCC) (e.g. De Sy et al., 2015), socioeconomic survey data collected in the field (e.g. Walker et al., 2002), to machine learning

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techniques assessing the relative importance of spatial factors explaining land cover change (e.g. Zanella et al., 2017). Each of these methods has its strengths and weaknesses in terms of the driver elements (e.g. agent, location, extent) that it can accurately assess. Remotely sensed imagery can help to identify the land cover following deforestation, which can then be used as proxy for the direct driver (De Sy et al., 2015). Recent technical innovations in remote sensing and forest-relevant monitoring techniques have resulted in national and global datasets with increasing levels of coverage, spatial and temporal detail and accuracy (Bos et al., 2017), which can capture changes in forest cover, including land uses following deforestation. Socio-economic data can complement these remote sensing techniques in helping to identify the agents or underlying factors at play. Spatial modelling with machine learning techniques, such as Random Forest modelling, provide powerful tools to reveal underlying spatial factors influencing DD. When used in isolation, however, they lack the ability to provide a meaningful interpretation of these results. Rather than compare the capabilities of each of the methods, we argue that an assessment of their complementarity is more valuable as combined, interdisciplinary approaches provide better understanding of the processes at stake than single-source approaches.

Information on drivers can help determine the appropriate policy interventions to address those change processes (Finer et al., 2018). As the activities leading to DD differ between continents and countries (Hosonuma et al., 2012; De Sy et al., 2015), there is no single intervention to address all drivers effectively (Seymour and Harris, 2019). Similarly, REDD+ interventions vary greatly in terms of type and implementer. Ideally, interventions are tailored to the local context (Godar et al., 2014; Austin et al., 2019), which requires an integrated assessment of relevant drivers. Information on drivers is therefore beneficial in all stages of the REDD+ design, implementation and evaluation (De Sy et al., 2018). Incorporating this type of information is not straightforward, however, as recurrent monitoring is complex and costly.

The objectives (i.e. linkages *between* the triangles in Fig. 1) of this study are, (1) to assess the complementarity of different data sources in providing DD drivers information; (2) to identify the most prevalent DD drivers in our study sites; and (3) to identify possible (mis)matches between the pre-identified DD drivers and REDD + interventions. The aim of this study is not to assess how successful these interventions are in addressing these DD drivers, as this requires an impact assessment, which goes beyond the scope of this study. In order to reach our objectives, we will address the following research questions (i.e. the elements *within* the triangles in Fig. 1):

1 To which land cover and land uses are forests converted, based on high resolution imagery?
2 What are the most important topographic, climatic and proximity variables explaining deforestation, based on a Random Forest Model?
3 What are the dominant locally reported direct and indirect DD drivers, based on household, village, and key informant interviews?
4 Which DD activities and agents are targeted by the REDD+ interventions?

2. Materials & methods

2.1. Conceptual framework

Fig. 2 shows the conceptual framework of this study, which builds upon existing LULCC models as discussed in the previous section, but puts the activity inducing DD at the centre. In this way, we provide a holistic approach that can be used in both spatial and non-spatial assessments.

In our conceptual model, drivers are defined as the interplay of agents, land activities and underlying forces that lead to DD. Agents refer to entities performing land activities on the ground and include smallholders and communities, large agricultural land holders, large scale agribusinesses and logging or mining companies. Activities are human actions that lead to forest change (e.g. agricultural expansion, logging, infrastructure expansion) often referred to as *direct drivers* (see for example De Sy et al., 2018). Environmental factors consist of biophysical or topographic elements that allow or limit certain activities (e.g. slope, availability of soil minerals, etc.) but which in essence cannot be influenced by humans through policies or other interventions. Underlying forces, such as economic and political processes, are often complex and can interact with each other. They directly or indirectly influence the decision-making of the agents (e.g. farmers, government agencies, agricultural or mining companies etc.) who are performing the activities.

REDD+ interventions can be categorized into three types (i.e. enabling measures, disincentives and incentives), which can be applied by different types of implementers (government, non-government, and private sector actors) at different levels (e.g. (sub)national programs vs. local level REDD+ projects). While incentives (e.g. payments for environmental services) and disincentives (e.g. command-and-control measures) aim to change agents' decision-making in terms of forest change activities, enabling measures (e.g. tenure clarification, environmental education) can influence agents, and thus indirectly their activities, or underlying forces.

2.2. Study areas

In our study we focus on five sites, located in four countries in Latin

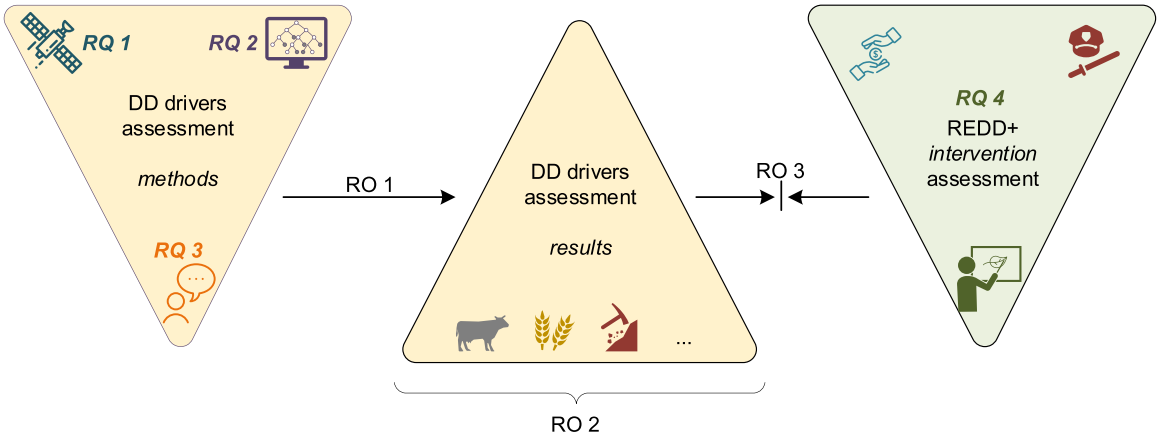


Fig. 1. Relationship between research objectives (RO), and research questions (RQ).

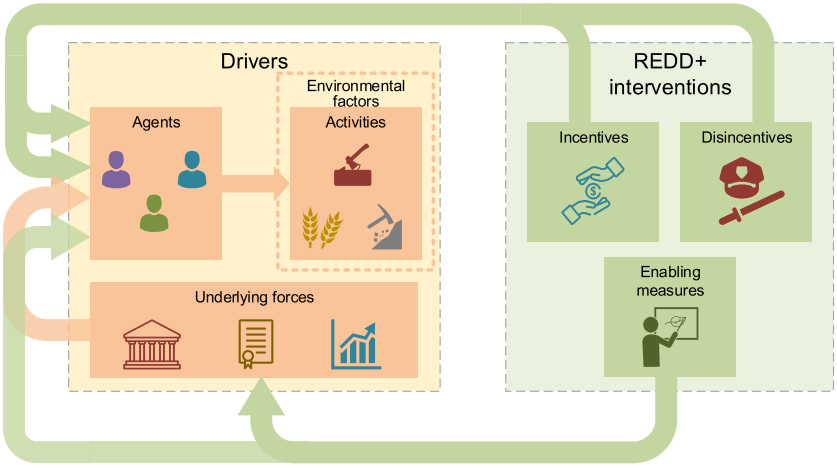


Fig. 2. Conceptual framework. Orange arrows represent interactions between different driver elements. Green arrows represent how different REDD + interventions envision to influence these elements or its interactions.

Fig. 3. Study areas.

Table 1
Site characteristics.

Country	Site	Initiative area (in km^2) [6]	Area of interest (approximately, in km^2)[7]	Ecozone (FAO)	REDD + start year	REDD + end year	Implementer type
Brazil	Transamazon[1]	260	48,000	TRF[8]	2013	2017	NGO
Peru	Madre de Dios (MDD)[2]	3,088	11,000	TRF[8]	2009	*Ongoing*	Private sector
Indonesia	KCCP[3]	144	20,000	TRF[8]	2008	*Ongoing*	NGO
Indonesia	Katingan[4]	1,083	36,000	TRF[8]	2009	*Ongoing*	Private sector
Vietnam	Cat Tien[5]	669	8000	TRF[8]/ TMDF[9]	2009	2012	NGO

[1] Sustainable Settlements in the Amazon (IPAM).
[2] REDD + Project in Brazil Nut Concessions (BAM & FEPROCAMD).
[3] Ketapang Community Carbon Pools (FFI).
[4] Katingan Peatland Restoration & Conservation Project (PT.RMU).
[5] Cat Tien National Park Pro-Poor REDD + Project (SNV).
[6] As reported by the initiative (source: Sills et al., 2014, Appendix 2).
[7] Areas covered by the remote sensing and spatial modelling part of the study, includes the initiative area and a large surrounding buffer zone.
[8] Tropical rainforest.
[9] Tropical moist deciduous forest.

America and Asia (Fig. 3, Table 1). These five sites are part of CIFOR's Global Comparative Study on REDD + (GCS REDD +), and were selected to represent a wide range of intervention types ((dis)incentives and enabling measures), implementer types (non-governmental organizations (NGOs) and private sector), and geographies across the tropics (CIFOR, 2017). Further, data availability constraints concerning the availability of different forest change map products affected the final selection (Bos et al., 2019). The initiatives will be described in more detail in section 3.4.

2.3. Summary of workflow

The workflow of this study is visualized in Fig. 4. In this section, the elements are introduced briefly, and will be discussed in more detail in the following sections.

This study consists of three parts, that is, assessments of (1) DD drivers, (2) REDD + interventions, and (3) their alignment. The DD drivers analysis uses three methods which build upon different data sources. Here, insights from high resolution imagery, spatial modelling and socio-economic surveys jointly provide insights in the DD drivers of the study sites. The REDD + intervention assessment builds upon village level survey data and a database containing information on REDD + interventions in the different study sites. The DD drivers analysis formed the basis for the assessment of the complementarity of different (disciplinary) methods and datasets. Finally, we assessed the alignment of the REDD + interventions with the DD drivers at the five sites.

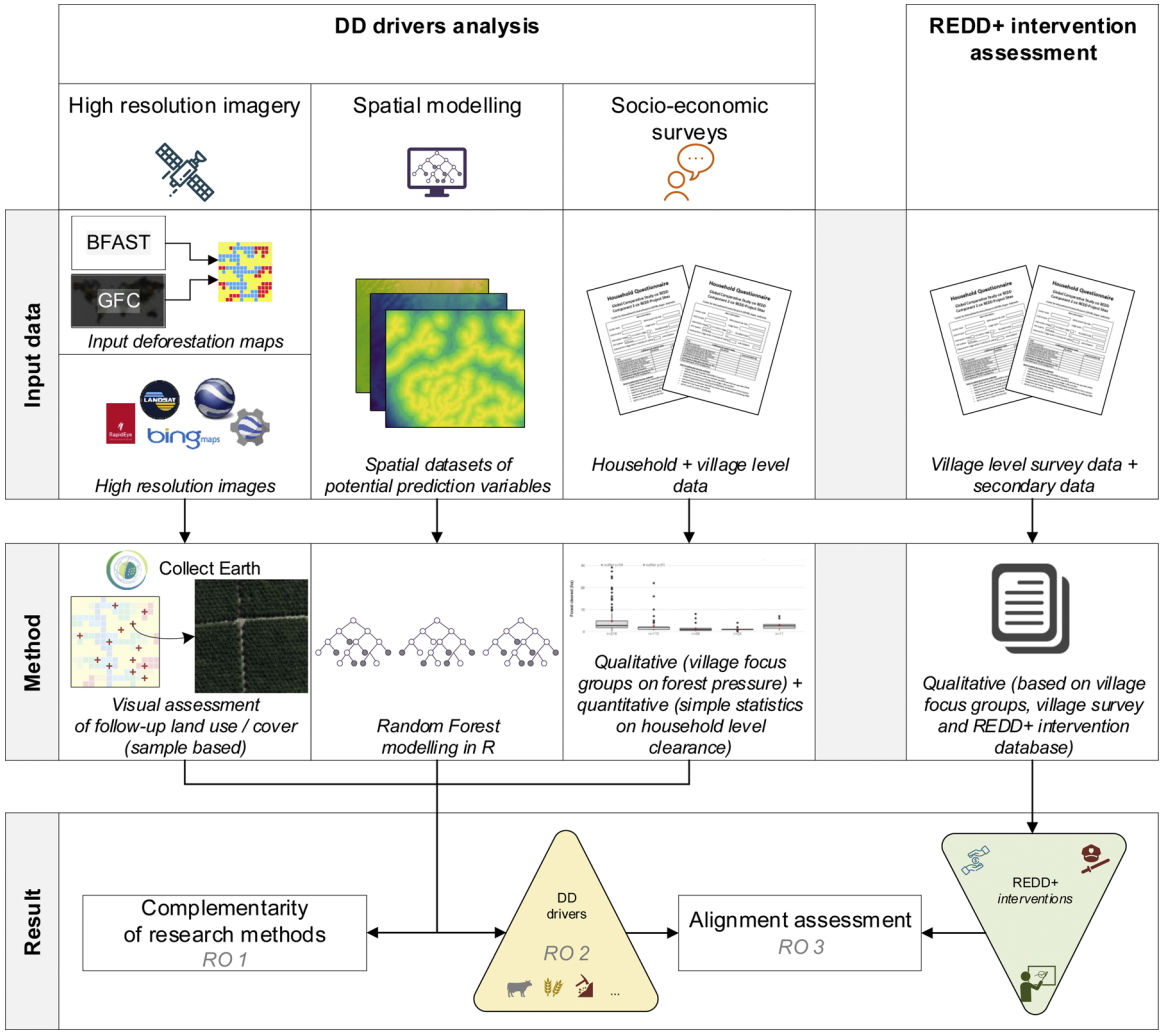


Fig. 4. Workflow DD drivers, REDD + intervention and alignment assessment.

2.4. Remotely observed land cover and land use patterns after DD using high-resolution imagery

For the first research question (Fig. 1, Section 1), we used tree cover loss data based on a combination of the Global Forest Change (GFC) dataset (Hansen et al., 2013, version 1.3) and the Breaks For Additive Seasonal and Trend (BFAST) algorithm (Verbesselt et al., 2010, 2012). For methods and sampling design regarding the forest loss detection, we refer to Bos et al. (2019)[1] . We define deforestation as a conversion from land above a certain tree cover percentage and covering more than a certain minimum mapping unit[2] to land with very limited or no tree cover. Therefore, we follow the land cover definition of deforestation, which is more practical to assess, rather than a land use definition of deforestation (Seymour and Busch, 2016). BFAST and GFC data were temporally aligned for each site based on the minimum overlapping time period for the two datasets, resulting in 2001–2014 for Brazil-Transamazon, Peru-MDD and Indonesia-KCCP, 2001–2015 for Indonesia-Katingan and 2004–2014 for Vietnam-Cat Tien. These time frames were also applied in the spatial modelling part of this study. Forest degradation refers to a decrease in quality of certain features of the forests while the predominant land cover and land use remains forest. In this study, degradation is exemplified by a reduction in tree cover, while still exceeding the threshold of the corresponding forest definition.

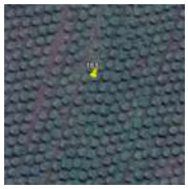
Follow-up land use or land cover after DD was used as proxy for the direct driver of deforestation[3] . To assess land use following deforestation, we assessed the forest loss samples from Bos et al. (2019), and determined follow-up land use using high-resolution imagery, consisting of Google Earth (2001–2019) and RapidEye (2010; 2014) imagery. In addition, time series data of Landsat TM (2001–2015) was

[1] In the original study, the sample size was 270 pixels for each of the sites, and included both forest loss and stable forest pixels. For this particular study, we only focussed on the forest loss pixels, which led to slightly different sample sizes for each of the sites, that is, n = 197 for Brazil-Transamazon; n = 203 for Peru-Madre de Dios; n = 206 for Indonesia-KCCP; n = 203 for Indonesia-Katingan; and n = 227 for Vietnam-Cat Tien.

[2] Following national forest definitions, source UNFCCC (2019). For specific thresholds used, see Bos et al. (2019). Forest definition used for Brazil-Transamazon is > = 10% tree cover and a minimum mapping unit of 0.5ha.

[3] We acknowledge that in certain areas, the first follow-up land use may not always reflect the main driver of forest clearance (e.g. in Amazonian areas where forest loss is often followed by cropping, but long term land use consists of pasture. Likewise, in Indonesia, deforestation can be followed by rice crops, while this is only temporary until their rubber trees mature), but emphasize that longitudinal high resolution imagery or other methods such as household level surveys may better reveal these type of processes. In general, in this study we aim to report the long-term driver, but given the relatively short time frame of our study, for recent forest clearance detections, we cannot rule out to have detected the temporary or intermediate follow-up land cover/use rather than long-term drivers.

Table 2
Observations and corresponding aggregated classes of follow-up land use and land cover.

	Aggregated class			
	Degradation	Tree plantations	Agriculture	Other
Observations	• Burned areas • Selectively logged areas (but remains predominantly forest) • Regrowth (partial)	• Rubber[1] • Palm oil[1] • Large scale tree plantations	• Crops • Cattle pastures • Shrub mix farm • Small scale agroforestry systems (incl. orchards, coffee etc)	• Mining • Water • Change in river flow • Hydropower reservoir • Road infrastructure • Buildings
Example				

[1] To align with findings from the socioeconomic data we decided not to aggregate these under the "agriculture" class, as according to reported data, agents linked to these conversions often differ from agents for (subsistence or small scale cash crop) agriculture.

assessed to clarify certain land use patterns. Although the spatial resolution of these data is limited (30 m), in cases of large-scale land conversion (such as tree crop plantations) and limited availability of high-resolution imagery, Landsat TM was often sufficient to validate follow-up land use. For recording the follow-up land use, we developed a survey using Open Foris Collect (Open Foris, 2019). For each sample, the confidence level was recorded. When a sample's land use or land cover was confirmed with multiple imagery data sources, a high confidence level was given. Samples for which no decisive follow-up land use or land cover could be given due to data limitations or other reasons were assessed by an additional independent remote sensing expert or local expert. When uncertainty remained, samples were marked with a low confidence level. Follow-up land use classes were aggregated into four classes (Table 2). The relative size of each class was calculated using Stehman's methods, while taking into account unequal sample class distributions (Stehman, 2014; Bos et al., 2019).

2.5. Spatial modelling of underlying factors associated with forest loss

For the second research question, we created a random forest model to assess the relative importance of predefined spatial variables to predict deforestation. A random forest model (RF) is a non-parametric method based on classification or regression tree learning. Unlike many other spatial models, RFs are known for their robustness, reduced risk of overfitting, capability to deal with non-linear relationships between prediction variables, and ability to address interactions without explicitly defining them in the model (Breiman, 2001). The forest loss data (response variable) used differed across the sites, and was based on the map product with the highest accuracy as found in Bos et al. (2019)[4] . The predictor variables used are described in Table 3. These topographic, climatic and proximity variables are known to influence economic returns and benefits that shape the land use and land cover change processes (e.g. Kaimowitz and Angelsen, 1998; Wood and Porro, 2002; Geist and Lambin, 2002; Ferretti-Gallon and Busch, 2014), but their relative importance may differ across different contexts.

Variable importance of these predictor variables was used as proxy for underlying forces of deforestation. Classification trees were computed for a binary categorical response variable (forest loss and stable forest). For each of the sites, 5% of non-NA pixels were sampled for training data, resulting in training datasets of sizes ranging from approximately 250,000–770,000 pixels per study site. To weigh all misclassifications equally in the trained RF, balanced training samples were generated so that 50 % of the training samples consisted of forest loss, and 50 % of stable forest. For each site, the random forest consisted of 500 classification trees. The spatial predictor variables selected for this study were elevation, slope, distance to roads, distance to waterways, distance to existing agriculture, average annual temperature and average annual precipitation, which are common variables in deforestation assessments (Ferretti-Gallon and Busch, 2014). Following Breiman (2001) and using the randomForest package (Liaw and Wiener, 2018) in R, the relative variable importance using the Mean Decrease in Accuracy (MDA) was calculated by (1) computing the out-of-bag statistic with the data for the i-th predictor variable intact, (2) permuting the data for the i-th predictor variable (i.e. the contents of the i-th prediction variable are randomly shuffled), (3) recalculating the out-of-bag statistic using the permuted data for the i-th predictor, (4) calculating the difference. This procedure was repeated for all seven prediction variables. Accuracies of the prediction maps were calculated following Olofsson et al. (2014).

2.6. Socio-economic survey data for perceived direct and indirect drivers of deforestation

For the third research question (Fig. 1, Section 1) we used data on reported direct and indirect DD drivers. These data were gathered during semi-structured interviews with REDD + implementers, village-level focus groups (mixed gender and women's only), and household surveys. The surveys were conducted in 2010–2011 and targeted approximately 1200 households in 40 villages. Data gathered included forest regulations; perceived causes of forest cover/quality change; and household level clearance of forests and its purpose. A complete overview of the questions asked and methods applied can be found in the technical guidelines (Sunderlin et al., 2010, 2016).

Survey data from village focus groups and household interviews were cleaned, aggregated and visualized using R. Simple descriptive statistics were calculated for the main household variables, while a qualitative assessment was done for the data collected from the village surveys. The assessment focussed on the following themes and variables: area (size) per land use, purpose of clearing, principal crop and crop type after clearing, forest area and forest quality change and perceived (exogenous) causes of forest cover change.

[4] The Global Forest Change dataset (Hansen et al., 2013) was used for Brazil-Transamazon, Peru-Madre de Dios, and Indonesia-KCCP. The combined dataset *sensitive-early* (Bos et al., 2019) was used for Indonesia-Katingan and Vietnam-Cat Tien.

Table 3
Prediction variables for Random Forest model.

Variable	Type	Unit	Source
Elevation	Topographic	Meters	CIAT-CSI SRTM (Jarvis et al., 2008)
Slope	Topographic	Degrees	Derived from elevation, see above.
Annual precipitation	Climatic	Millimetres	WorldClim 2 (Fick and Hijmans, 2017)
Annual mean temperature	Climatic	Temperature Celsius	WorldClim 2 (Fick and Hijmans, 2017)
Distance to agriculture	Proximity	Meters	ESA Climate Change Initiative Land Cover Map (2015)
Distance to roads	Proximity	Meters	OpenStreetMap
Distance to waterways	Proximity	Meters	OpenStreetMap

2.7. Assessment of REDD+ interventions and alignment with DD drivers

Data from a survey of village interventions were used to document the most relevant REDD+ interventions at each site (Sunderlin et al., 2016). During the second phase of fieldwork (2013–2014), the research team first compiled a list of all interventions that aimed to conserve or restore forests that were documented in the study villages in earlier interviews with implementers and village focus group discussions. That list was refined with REDD+ implementers, and then with key informants in all study villages following the methods outlined in Sunderlin et al. (2016). REDD+ interventions included not only those implemented by the REDD+ proponent, but also (sub)national policies and programs that affected local forest use at the study sites. For each REDD+ intervention, information on agent (target stakeholder (group)), sector (e.g. forest, agriculture), and level ((sub)national or local) were recorded to assess the degree of alignment with the DD drivers results as found in the earlier parts of the study.

3. Results

3.1. Forest change patterns observed with remote sensing

Table 4 gives an overview of the relative shares of forest area conversions. The aggregated classes in Table 4 are broadly defined, but there are cross-site differences within those classes. That is, agriculture in Brazil is marked by pasture lands mainly, while in Indonesia-Katingan this is mainly cropland, including rice. In Indonesia-KCCP, tree plantations constitute of oil palm plantations, unlike the tree plantations in Vietnam Cat-Tien. Fig. 5 shows some of these cross-site differences within the four classes. Site-specific findings are given below. Two of the 1350 samples were given a low confidence level (SM1). SM2 gives an overview of the spatial distribution of the samples per site and their reported forest conversion classes.

3.1.1. Brazil-Transamazon

The class *degradation* (n = 13) constitutes mostly (n = 11) of samples that were characterised by regrowth after forest disturbance. All samples marked as *agriculture* (n = 177), were pastural lands, often marked with cattle and cattle tracks. The samples marked as *other* (n = 7) were roads, buildings, or other infrastructures.

3.1.2. Peru-MDD

Samples classified as *degradation* were characterised by small scale disturbances after which some degree of regrowth was visible in the subsequent years. *Agriculture* consisted mainly of pastural lands (n = 83) and to a lesser degree crops (n = 16). Although the *other* class was relatively small (i.e. 6% of the total area of forest deforested, Table 4), the spatial distribution of this class gave some clear insights (SM2), with patches of mining, clearly distinguishable near the main river.

Table 4
Area proportion (%) of follow-up land use and land cover classes.

	degradation	tree plantations	agriculture	other
Brazil-Transamazon	10 %	0 %	87 %	3 %
Peru-MDD	59 %	0 %	35 %	6 %
Indonesia-KCCP	32 %	50 %	15 %	3 %
Indonesia-Katingan	51 %	24 %	16 %	9 %
Vietnam-Cat Tien	14 %	30 %	42 %	14 %

3.1.3. Indonesia-KCCP

Degradation in this site consisted of forest affected by fires, and logging after which regrowth occurred with a mixture of trees and small shrubs. *Tree plantations* consisted primarily of large-scale oil palm plantations, although often only marked several years after the deforestation disturbance was detected. *Agriculture* consisted of rice paddies and other crops. Conversions marked as *other* (n = 11) were mostly cases of mining (n = 7), and some conversions to infrastructure.

3.1.4. Indonesia-Katingan

Samples marked as *degradation* consisted mostly of partially logged plots and degraded forest at oil palm plantation edges. To a lesser degree, fires were noted, as well as some cases of partial regrowth after forest disturbance. *Tree plantations* consisted mostly (60 out of 62 cases) of oil palm plantations. Samples with *agriculture* were mostly small-scale croplands. The *other* class consisted of infrastructure (buildings) (n = 3) and some cases of bare land (n = 5) for which no other follow up land use was detected.

3.1.5. Vietnam-Cat Tien

Samples marked as *degradation* consisted of forests with clearly visible selective logging, and to a lesser degree recurrent disturbed forests with intermediate regrowth. A considerable amount of samples (n = 44) were marked as large-scale monocultural *tree plantations*. *Agriculture* consisted mainly of cropland (n = 110), including bushy crops, coffee and cashew trees. To a lesser degree, pastural lands were found (n = 12) and some mixed areas with cropland and small-scale plantations (n = 6). The *other* class consisted of infrastructure (buildings and roads, n = 8), and flooded areas due to the building of a new hydropower dam (n = 8).

3.2. Spatial modelling

The spatial distribution for each of the prediction variables, as well as comparisons between forest loss and stable forest pixels per site can be found in SM3. Error matrices and corresponding error-adjusted areas were estimated and accuracies were calculated for all model predictions based on a comparison between the models' predictions and the input deforestation maps. The accuracies are listed in Table 5, the error matrices can be found in SM4. In general, the random forest models predicted deforestation well using the spatial layers as predictors, with overall accuracies exceeding 86 %. The relative high overall accuracies build confidence in the random forest models in general, as low accuracies in the models' predictions would also suggest that the variable importance findings would be less meaningful. The relatively low user's accuracies of forest loss class for Peru-MDD and Indonesia-KCCP indicated that the models overestimated forest loss at those sites. Here,

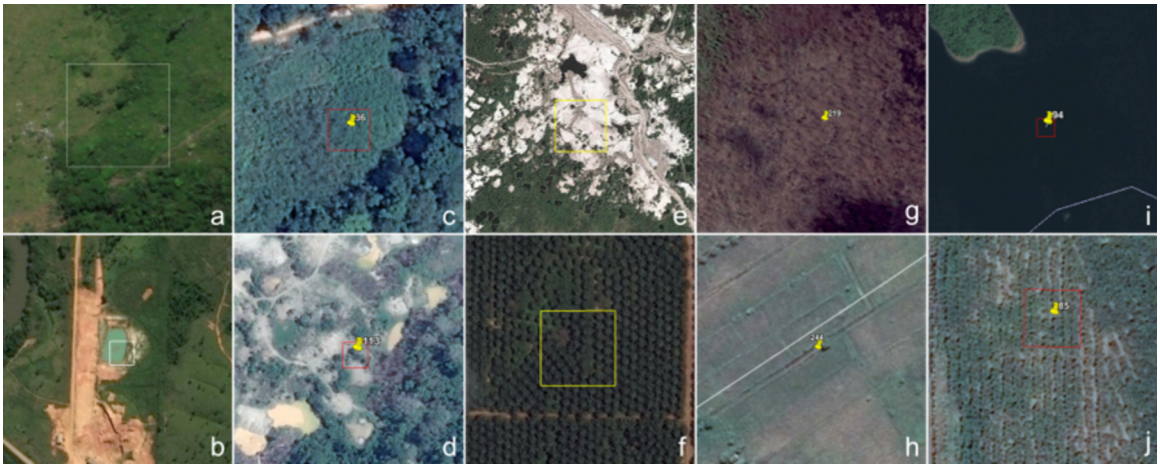


Fig. 5. Examples of DD activities encountered. Brazil-Transamazon: (a) agriculture (pasture) and (b) other (infrastructure). Peru-MDD: (c) degradation and (d) other (mining). Indonesia-KCCP: (e) other (mining) and (f) tree plantation (oil palm). Indonesia-Katingan: (g) degradation (fire) and (h) agriculture (crops). Vietnam-Cat Tien: (i) other (hydropower reservoir) and (j) tree plantation.

Table 5
Accuracies of Random Forest Model predictions.

	Brazil - Transamazon		Peru - MDD		Indonesia - KCCP		Indonesia - Katingan		Vietnam - Cat Tien	
	Loss	Stable	Loss	Stable	Loss	Stable	Loss	Stable	Loss	Stable
UA	93.5 %	84.8 %	34.1 %	99.9 %	57.3 %	97.6 %	74.7 %	94.6 %	66.3 %	96.5 %
PA	96.3 %	75.5 %	98.5 %	89.8 %	90.7 %	85.0 %	89.1 %	86.4 %	90.6 %	85.1 %
OA	91.8 %		90.3 %		86.0 %		87.3 %		86.4 %	

UA User's accuracy; PA Producer's accuracy; OA Overall accuracy.

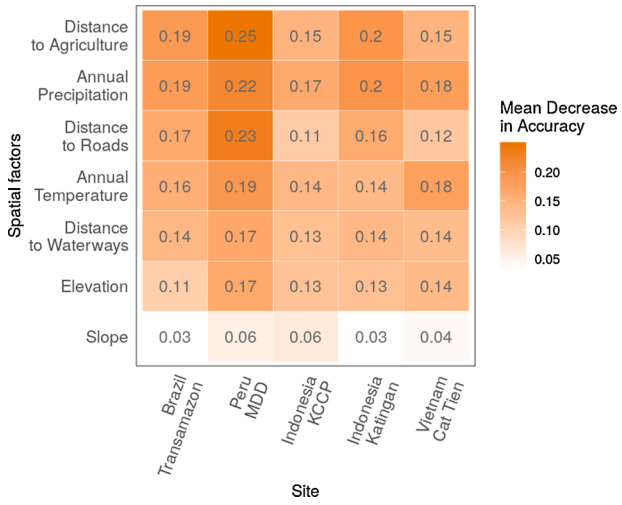


Fig. 6. Random Forest models variable importance.

the random forest models' predictions were thus well capable of modelling the spatial patterns of forest loss when using the available information from the prediction variables, but they were less capable of estimating the magnitude of forest loss.

The mean decrease in accuracy (MDA) is an indicator of variable importance[5]. Fig. 6 shows that in general, distance to existing agriculture, annual precipitation (i.e. micro-climate differences), and distance to roads are important spatial factors for explaining deforestation, although there are differences between sites. In Peru-Madre de Dios for example, the relative importance of distance to agriculture as deforestation predictor is higher than in Vietnam-Cat Tien, where it is ranked as the third-highest explanatory factor.

Local variability in annual precipitation turned out to be important across all sites, which can also be derived from the density plots (SM3), which show distinct differences in precipitation between the groups of stable forest and forest loss pixels. Yet, local variability in annual precipitation may be correlated with other variables both included in, and excluded from these models. In general, the topographical factors of slope and elevation were least important.

3.3. Socio-economic survey data for perceived direct and indirect drivers of deforestation

3.3.1. Perceived forest area and forest quality change at village level

During the mixed gender focus group discussions, the majority of villages reported a decrease in *forest area* in the past two years[6] . Forest quality was defined as the availability of goods and services of the forest related to density of woody material, forest health, and biological productivity and diversity, and is thus a proxy for forest degradation. The majority of the villages reported a decrease in *forest quality* in the past two years, with Vietnam-Cat Tien being the exception[7] .

[5] MDAs refer to accuracies of single tree models, and should not be confused with the model accuracies of the map accuracies of the model's predictions as presented in Table 5.

[6] There were eight village level focus groups at each site (total n = 40). Decreased forest area was reported in six villages in Brazil-Transamazon and in Indonesia-Katingan, seven in Peru-MDD and in Indonesia-KCCP. Only in Vietnam-Cat Tien, a minority of the villages reported a decrease in forest area (n = 2).

[7] For the same 40 village level focus groups, the majority of the villages in Brazil-Transamazon (n = 7), Peru-MDD (n = 8), Indonesia-KCCP (n = 8) and Indonesia-Katingan (n = 6) reported a decrease in forest quality. In Vietnam-Cat Tien, three villages reported no forest quality change, while the remaining five

Table 6
Overview of perceived forest pressure sources at village level per site.

Brazil-Transamazon	Peru-MDD	Indonesia-KCCP	Indonesia-Katingan	Vietnam- Cat Tien
• Incoming migrants (farmland) • Logging companies (small & large scale) • Seasonal migrants • People from neighbouring villages • Agro-industrial farms (cattle)	• Unclear tenure rights (in- and outside Brazil nut concession areas) • Logging companies • Incoming migrants for papaya plantations and timber (areas in vicinity of roads) • Gold mining (remote areas)	• Industrial companies (pulp, paper, soy, cattle) • Swidden agriculture • Large food estate (rice, by the government) • Oil palm plantations (selection of villages) • Illegal gold mining (selected villages) • (Legal) logging for housing infrastructure • Logging by timber companies • Poaching	• Oil palm plantation • Small scale mining • Agricultural land expansion • Infrastructural developments • Poaching • Small scale logging • Large scale cattle • Rubber plantation (firms) • Timber plantation	• Small scale agriculture • Small scale (illegal) timber harvesting

3.3.2. Perceived forest pressure sources at village level

During the mixed gender and women focus group discussions, participants were asked to report their perceived forest pressure sources in their village area and surroundings. These pressures include both agents, activities and facilitating conditions. The pressures mentioned are summarized in Table 6 in no particular order.

3.3.3. Forest clearance and purpose by households

The previous section reported both exogenous and endogenous pressures on the villages' forests. Here, we focus on household level clearing of forests as reported in the household surveys, which represents endogenous pressures. Yet, these results do not show the relative importance of endogenous pressures in the sites.

The results are visualised in Fig. 7. Whether or not households clear forests differs greatly between the sites. While in Brazil-Transamazon > 75 % of interviewed households report forest clearing in the past two years, in Vietnam-Cat Tien this is < 5 %. Also, the mean and median area of forest cleared differs widely, although there are large differences between the spreads within sites, as Brazil-Transamazon and Peru-MDD contain more outliers above the boxplots' maxima. In all sites, household clearance is mostly for cropping. In the South American sites, relatively few households report a relatively large area cleared for pasture[8], while in the Southeast Asian sites this regards clearance for tree plantations such as oil palm and rubber plantations[9] (Fig. 7d). Still, it is worth noting that especially the reported clearance for tree plantation is sensitive to the moment of survey data collected, as households reported not to clear for tree plantations regularly. For example, in the survey round of a few years later (not reported here), the amount of forest cleared for tree plantations in Indonesia-KCCP was significantly larger compared to the results of the first survey round as presented in Fig. 7.

3.4. REDD + Interventions

Table 7 shows an overview of the REDD + interventions as discussed below. Together with the information on deforestation drivers (Section 3.1-3.3), Table 7 was used for the identification of (mis)matches between interventions and drivers in Section 4.3.

3.4.1. Brazil-Transamazon

From 2012–2017, the *Sustainable Settlements in the Amazon* project targeted smallholders in the Transamazon Highway region (Eastern Brazilian Amazon) to promote sustainable agricultural practices and was implemented by the NGO Amazon Environmental Research Institute (IPAM). In 2000, forest cover was 95.4 % but 19.2 % points were lost during 2001–2012 (Sunderlin et al., 2014b). Smallholders sampled had 69 % forest cover on their landholdings in 2010 (Duchelle et al., 2014), earning their income mostly from cropping and livestock, and clearing forest mostly for crops (Cromberg et al., 2014b). Interventions focused on more sustainable agriculture and economic compensation (Simonet et al., 2019).

Three main interventions were applied, which all focused on local small-to-medium sized farmers: 1) direct cash payments conditional on forest conservation and fire-free agricultural production; 2) investments in alternative production; and 3) support for farmers to comply with environmental regulations. Most interventions thus featured change in land use strategies (land-saving strategies) and compensated direct forest protection. At the same time, federal command-and-control policies had significantly curbed deforestation – from all sectors and actors alike (Börner et al., 2014). Yet, ultimately the Brazilian Forest Code was also reformed in ways that particularly pardoned smallholder deforestation, thus loosening somewhat command-and-control leverages on smallholders (Cromberg et al., 2014a; Simonet et al., 2019).

3.4.2. Peru-Madre de Dios

The objective of the REDD + project in Madre de Dios, Peru is to provide incentives for Brazil nut concessionaries to conserve the forests on which they depend. This area is heavily forested (99 % in 2000) with very low deforestation, that is only 0.3 % point loss from 2001 to 2012 (Sunderlin et al., 2014b). Brazil nut producers in the area glean most of their local income from forests, including Brazil nuts and timber (Garrish et al., 2014). The project began in 2009 as a collaboration between the private company Bosques Amazonicos and the local Brazil nut producers' federation and targeted 405 concessionaries over 308,757 ha (BAM, 2012). It was validated by VCS in 2012 and sold 1.5 million verified carbon units through the voluntary market.

Bosques Amazonicos, FEPROCAMD and a local Peruvian NGO provided extensive technical support to Brazil nut producers to help them comply with national forest management regulations, specifically related to the formulation of annual operational and 5-year management plans for their concessions. However, the main planned interventions of the REDD + project – namely implementation of a forest monitoring and surveillance system, construction of a local nut processing plant to increase the market value of harvested nuts, and eventual payments

(*footnote continued*)
did not know or did not answer.

[8] In Brazil-Transamazon, 25 households (10 % of respondents) together reported approximately 190 ha of clearance for pasture, which equals 19 % of reported forest area cleared. In Peru-MDD, 7 households (3 % of respondents) together reported approximately 74 ha of clearance for pasture, which equals 25 % of total reported forest area cleared.

[9] In Indonesia-KCCP, 5 households (2 % of respondents) together reported approximately 4 ha of clearance for tree plantations, which equals 5 % of total reported forest area cleared. In Indonsia-Katingan, 12 households (5 %) together reported approximately 15 ha of clearance for tree plantations, which equals 56 % of total reported forest area cleared. In Vietnam-Cat Tien, 1 household (< 0.5 %) reported 3 ha of clearance for tree plantations, which equals 9 % of total reported forest area cleared.

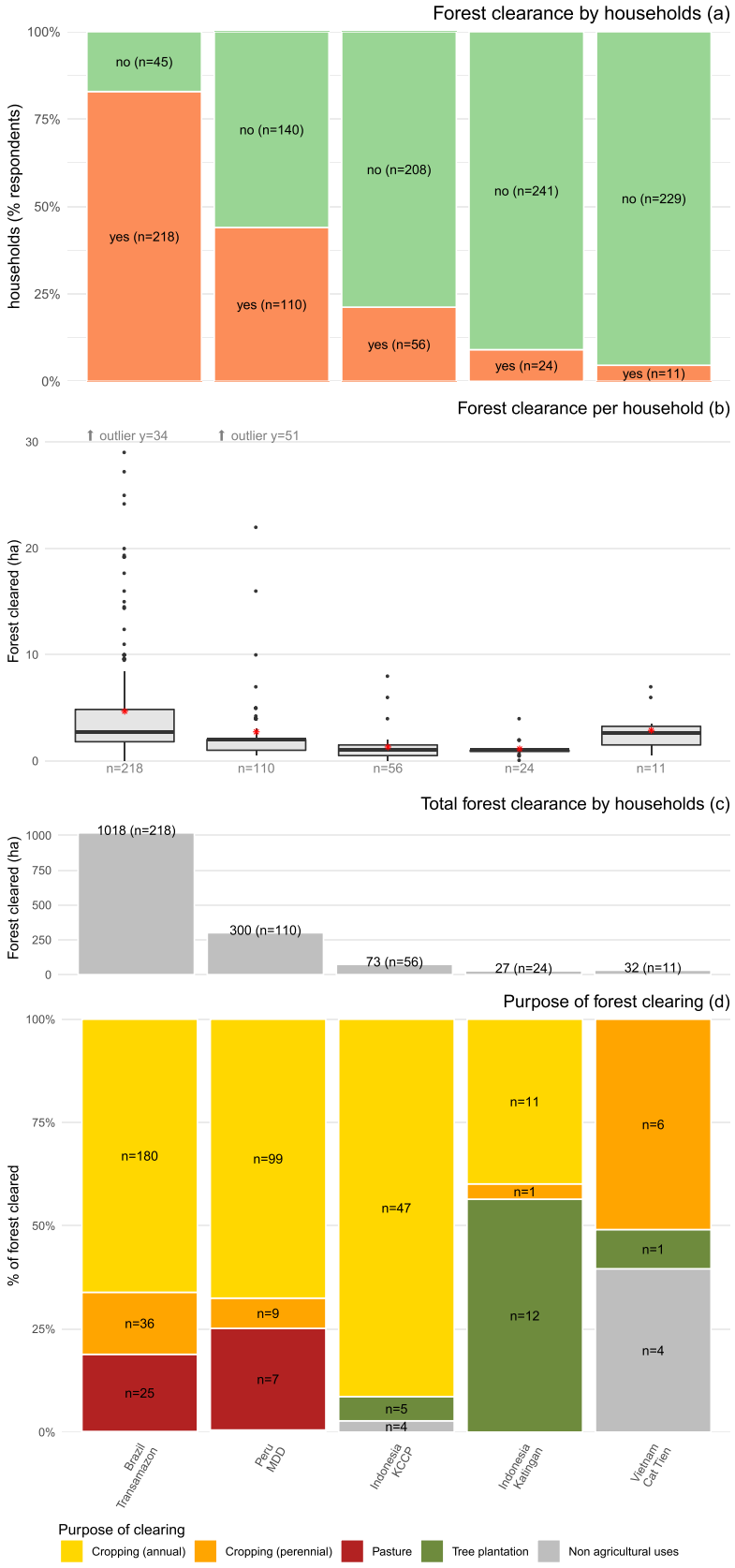


Fig. 7. Reported forest clearance and purpose by households.
(a) Shows the response to the question "did your household clear any forest during the past 2 years?" (b) Forest clearance (area) by households that reported > 0 ha clearance. Upper and lower extremes of whiskers represent Q3 + 1.5* interquartile range (IQR) and Q1–1.5*IQR respectively, where IQR = Q3 − Q1. Red asterisk represents the mean. (c) Total forest clearance by households (respondents only) per site (d) Follow up use of forest area cleared. *n* represents number of respondents per purpose category.

Table 7
Overview of intervention types per site.

	REDD + interventions aggregated by category																			
	Disincentives			Incentives						Enabling measures						Other				
	Restrictions on forest access/conversion			Forest enhancement			Livelihood enhancement			Environmental education			Tenure clarification							
	Agent	Sector	Level	Agent	Sector	Level	Agent	Sector	Level	Agent	Sector	Level	Agent	Sector	Level				Agent	Sector	Level
Brazil-Transamazon	LH/SH	*	N/S/L				SH	AC/AP/F	L	SH	AC/AP/F	L	SH	AC/AP/F	N/S/L						
Peru-Madre de Dios	SH	F	N/L				SH	F	L	SH			SH	F	N/L						
Indonesia-KCCP	SH	F	L	SH	F	N/L	SH	F/AC/TP	L	SH	F	L	SH	F	L						
Indonesia-Katingan	SH	F	L/S	SH	TP	L	SH	TP/Fi/F	L/N	SH	F	L	LH	F	L				G	O	S
Vietnam-Cat Tien							SH	AC	S/L	SH	F	L									

Agent (targeted)
SH small/medium land holders or communities
LH large land holders
G government

Sector (targeted)
AC agriculture - crops
AP agriculture – pasture
F forest conservation/NTFPs etc
Fi fishery
TP tree plantation
O Other
* all sectors

Implementation level
N National
S Subnational jurisdiction
L local

from the sale of carbon credits (Garrish et al., 2014) – never came through due to expiration of operational funds for the project in 2014.

3.4.3. Indonesia-KCCP

The Ketapang Community Carbon Pool (KCCP) is a forest carbon initiative of Fauna and Flora International (FFI) Indonesia Programme. The lowland and peat swamps in this area in West Kalimantan experienced 4.6 % forest loss in the period 2001–2012, threatening biodiversity and carbon-rich tropical forests (Sunderlin et al., 2014b; Intarini et al., 2014). Started in 2008, the NGO focusses on arranging community forest rights for local villages, aiming to strengthen communities' tenure security and counter threats from large-scale external actors in order to protect biodiversity and reduce DD related emissions (Intarini et al., 2014).

The project's main intervention is attaining a designation for specific forest areas in groups of villages as a Hutan Desa (HD, Village Forest), forming a forest carbon pool. The tenure-based intervention is done in combination with support for village boundary mapping, land use planning, monitoring and control, and reforestation. At the same time, there were existing government reforestation programs and a forest monitoring activity by a separate NGO. By attaining the HD status, the tenure of specific villages over communally-managed forest areas are clarified. This paves the way for getting management rights of the forest. By 2011, six villages[10] in Ketapang district, West Kalimantan, had proposed and attained HD status from the central government. During the same year, the Indonesian Ministry of Forestry initiated a national moratorium on the issuance of new permits for forest utilization and conversion on peatlands and primary forests, partially overlapping our study area in KCCP (Indonesian Ministry of Forestry, 2011). This moratorium became permanent in August 2019, covering 66 million hectares of rainforest (Diela, 2019).

3.4.4. Indonesia-Katingan

The Katingan Peatland Restoration & Conservation Project, currently known as the Katingan Mentaya project, was founded in 2007, and is managed by the private company PT Rimba Makmur Utama (PT. RMU) (Indriatmoko et al., 2014). The villages collaborating in the project are adjacent to Sebangau National Park. The REDD + project site is largely forested and experienced 2.6 % forest loss in the period 2001–2012 (Sunderlin et al., 2014b). The main project strategy is to protect an entire peat hydrological unit (i.e. 'peat dome') by converting the status of the land into a restoration concession and supporting communities with locally suitable and sustainable income-generating activities. Between 2010 and 2018, the project generated 23.3 million Verified Carbon Units (VCUs) equivalent to 23.3 million tons of greenhouse gas emissions removed (VCS, 2015).

The main interventions of this initiative are: (i) prevent large-scale deforestation by attaining an Ecosystem Restoration Concession (ERC) over a carbon-dense peat dome between the Katingan and Mentaya rivers; (ii) provide incentives for communities living in areas surrounding PT RMU's ERC to support the prevention of DD through various alternative livelihood interventions agreed upon with communities; (iii) restore degraded peat forests through forest restoration activities; and (iv) establish fire-fighting teams in communities.

3.4.5. Vietnam-Cat Tien

This project (2009–2012) was initiated by SNV (the Netherlands Development Organisation) as a REDD + readiness project to assess the opportunity for accessing the voluntary carbon market and to establish a forest carbon facility in participation with local villagers. In the project area, 58 %–71 % of villagers interviewed considered agriculture as their primary or secondary occupation (Huynh, 2014). Their largest proportion of land consist of secondary forest, followed by agriculture.

[10] Including the four GCS REDD + intervention villages

Natural forests are owned by the government. The forest cover in this area is high (94.5 % in 2000), with 5.3 % forest loss from 2001 to 2012 (Sunderlin et al., 2014b). The REDD + readiness interventions primarily focused on carbon monitoring and participatory forest monitoring trainings (Huynh, 2014).

Interventions in Vietnam-Cat Tien were implemented by government agencies and non-governmental organizations (NGOs), and mainly focussed on forest protection through trainings (on forest protection, REDD + carbon credits, agroforestry), alternative livelihoods provisions (focussing on cacao and cashew) and participatory monitoring (participatory forest management) activities. Government agencies such as the National Park management and NGOs targeted their activities to communities living in the buffer zone of a national park. In one intervention, an NGO assisted district government agencies, focussing on REDD + policy making.

4. Discussion and conclusion

In this final section, we first return to the three research objectives as stated in the introduction. We also reflect upon our study design and results and conclude with some final remarks.

4.1. Complementarity of different data sources in providing DD drivers information

Each data source and method used has its advantages and disadvantages. Their ability to assess certain driver elements is shown in Table 8. Human interpretation of high resolution remotely sensed imagery provides insights into the activities associated with different conversion types. When a proper sampling design is applied, a sample-based approach like ours allows for estimating the relative share of different conversion types. Increasing the number of DD classes may lead to more informative results but requires increased numbers of samples (Foody, 2009). Further, although going beyond the scope of this research, temporal changes in DD processes can be revealed when the same samples are assessed repeatedly over time. Mapping the different conversion types of the samples reveals within-site spatial patterns (SM2).

Spatial modelling and random forest models in particular can reveal the relative importance of preselected underlying factors and they can deal with non-linear relationships between prediction variables. Spatial models enable ranking of these variables by relative importance, and thus explain to what extent certain topographic, climatic and proximity variables play a role in the land use change and land cover conversions in a specific area. These insights are particularly valuable for detecting risk areas for future forest loss, and thus may be used as information for selecting future REDD + target areas. Yet, the relationships between the prediction variable and spatial factors that turn out to be important may not be easily interpretable. While not part of this particular study, the spatially explicit prediction maps allow for identification of areas at immediate deforestation risk.

Village and household level surveys further complement the previous methods, as they can provide insights in to the agents of specific DD activities. Further, local stakeholders can often help to identify the underlying factors at play. The spatial and temporal information about DD activities are often limited compared to remotely observed methods, but participatory mapping and recurrent surveys can be of added and unique value when combined with the spatial DD information.

4.2. Deforestation and forest degradation drivers

Using the high-resolution imagery, we detected both across- and within-site variability of land patterns following DD. The locally reported drivers showed this diversity too, as a variety of both endogenous and exogenous causes were found in all sites. Agriculture is the dominant DD in the sites of Brazil (mainly pasture) and Vietnam (mainly crops), and as underscored by the RF results, distance to existing agriculture was found to be in the top three important spatial factors for predicting DD. In the South American sites, a greater mixture of endogenous and exogenous causes were reported, including agriculture by smallholders, settlement by migrants, presence of logging companies, agro-industrial firms and mining. In absolute terms, more household level clearing (for annual crops) was reported at the Brazilian site than in other sites, although large differences between households exist.

In the Southeast Asian sites, large-scale conversions were reported and mainly comprised of agro-industrial activities such as oil palm, pulp and food plantations. We did not consider whether these activities took place in- or outside concession areas. Degradation is the main forest change in Peru-MDD (selective logging) and Indonesia-Katingan (near oil palm). This is in line with findings from earlier studies in those four countries (e.g. Soares-Filho et al., 2006; Asner et al., 2013; Gaveau et al., 2018; Khuc et al., 2018).

Most of our sites showed within-site spatial variability in land patterns (SM2). In Peru-MDD, mining was found only close to the main river in the south, pastures mainly close to roads, while selectively logged areas were also observed further away from roads and rivers. The RF model showed that forest loss occurred often close to roads in the two sites in Latin America and in Indonesia-Katingan. In Indonesia-KCCP mining was found in the south west, while other conversion types were found across the site. In Indonesia-Katingan large areas of oil palm plantations were found in the north east, while degraded forest due to fires were mainly found along the two main rivers. In Vietnam-Cat Tien, crops, and tree plantations were each found in particular regions within the site, and deforestation in the east was associated with the establishment of a large hydropower dam.

4.3. Alignment of DD drivers and REDD + interventions

4.3.1. Site specific findings

In Brazil–Transamazon, local interventions generally focus on local small-to-medium sized farmers by promoting sustainable farming practices (incentives), while federal forest restrictive policies (disincentives) do not distinguish between agents and sectors. Both local interventions and federal restrictive policies thus seem to be aligned with the agriculture related DD drivers. Yet, the national policy partially pardons small-scale deforestation, thus somewhat contrasting federal policies.

Table 8
Complementarity of methods and datasets.

	Agent *who*	Activity *what*	Location *where*	Time *when*	Underlying factors *why*	Size (of activity) *how much*
High resolution imagery	✗	✓	✓	✓	✗	✓
Random Forest model	✗	✗	~	✗	✓	~
Socio-economic surveys	✓	✓	~	~	~	✗

✓yes
~to some extent
✗no

In Peru-MDD, we found clear within-site spatial differences in DD drivers, which calls for a locally tailored approach. The REDD + initiative focusses on Brazil nut concession owners north of the river, thus not targeting the large-scale mining near the main river. Further research is needed to verify whether other interventions target mining agents specifically or if indeed this driver is currently not addressed sufficiently. The REDD + initiative indirectly addressed small-scale logging by adding value to Brazil nut concessions via increased prices for producers. Yet, limited logging under forestry regulation in Peru is allowed (Garrish et al., 2014).

In Indonesia-KCCP, the initiative's focus on tenure clarification is aimed as an empowerment tool for local communities, in order to keep exogenous agents out. In that sense, these interventions are in line with the exogenous threats coming from large scale palm oil companies. Mining was found to be a considerable, but very localised driver present in the south west of the area. This again calls for a locally tailored approach of REDD + interventions, as mining was not addressed specifically by any of the interventions in this study.

Part of the initiative's focus in Indonesia-Katingan is fire prevention, to correspondingly reduce the impact of fires and thus prevent forest degradation. This is in line with the major threat we found in the area. Exogenous agents such as palm oil companies play an increasing role in the area's forest change activities, and is correspondingly putting a pressure on local communities. These exogenous drivers are not targeted directly by the interventions.

In Vietnam-Cat Tien, mostly secondary forests are being converted to agriculture and plantations (mainly orchards and cashew plantations). Interventions focused primarily on environmental education and stimulating sustainable livelihood practices through the provision of livelihood enhancements. Yet, reported clearance at household level was minimal, so conversions by other actors may have been addressed insufficiently.

4.3.2. General remarks regarding driver-intervention alignment

While national or subnational policy interventions across the sites mostly comprise of regulations to restrict forest access, the local initiatives often comprise of a mixture of interventions. These 'baskets' are regularly targeted towards individual smallholders or communities, and are often continuations of existing integrated development and conservation projects and programmes, as described in earlier studies based on the GCS REDD + data (Sunderlin et al., 2014a; Duchelle et al., 2017).

The village and household level survey data showed that exogenous agents played an important role in DD and high-resolution imagery revealed most conversion activities to be large-scale, while most REDD + interventions mainly targeted local communities and smallholders. Still, incentives to smallholders are of value as they can compensate for disincentives affecting smallholders and large landholders alike.

Müller et al. (2013) argue that proper driver-intervention alignment does not necessarily mean that REDD + should prioritise its activities on the largest driver at play (mechanized agriculture in that case), but rather should take into account its opportunity costs. In addition, one might argue that for effective and efficient REDD + alone, driver-intervention alignment is not essential as, at least in theory, DD can be addressed by forest use restrictions combined with effective law enforcement. However, this is most likely not equitable in the sense that people who depend on the forest the most for their livelihoods, will most likely be disproportionally affected by restrictive interventions. Reduced DD may then lead to trade-offs in well-being and forest-related income. As Godar et al. (2014, p. 15595) acknowledge: "Beyond the technical difficulties and increased costs, efforts to curb deforestation in areas dominated by smallholders are politically and socially problematic because many smallholders depend on clearing small areas of forest for their livelihoods and subsistence". Therefore, understanding driver-intervention alignment is at the least essential to understand who is most likely to lose out from curtailing deforestation, and where trade-offs between carbon and well-being outcomes can be expected.

4.4. Study reflections

4.4.1. Dynamics of drivers over time

In addition to spatial variability in drivers, drivers can change over time, as a result of interventions or due to other processes. As Godar et al. (2014) argue, the changing (relative) contributions of specific actors to deforestation and degradation need to be examined in order to achieve further reductions in DD. These dynamics should be studied in more detail, and be taken duly into account when designing, implementing or evaluating REDD + interventions.

In our study, the timeframes from our remote sensing and spatial modelling assessment (2001/2004–2014/2015) differ from the timeframe addressed in the socio-economic surveys (conducted in 2010–2011, with reported forest clearing regarding the two years prior to the surveys). Remote sensing requires longer timeframes to detect follow-up land use and other DD patterns, which would complicate year-to-year comparison between remotely sensed patterns and reported drivers. We argue that for the purpose of method complementarity assessment, however, year-to-year alignment is of lesser importance, as the different data sources and corresponding methods focus on different driver elements.

4.4.2. Discrepancies in deforestation magnitudes and deforestation drivers

Although assessing their complementarity was the main reason for using multiple data sources, the results contain some, at least seemingly, discrepant findings regarding deforestation estimates and direct drivers categories.

We only report relative shares (in percentages) of forest change patterns observed by remote sensing, as the area of interests of the remote sensing analysis are based on rectangular buffers around the REDD + initiative areas and therefore comprise most likely of more than the study villages' area of influence. In the absence of spatially explicit household areas, direct comparison of deforestation numbers in absolute terms would therefore be impossible. It is possible that household level clearance was under-, or over-reported, although multiple verification questions in the household survey limited this chance considerably.

In Section 2.4 we already acknowledged that the follow-up land use after deforestation is not always the main driver of deforestation. Findings on 'drivers' from high resolution imagery can therefore seemingly contradict the findings from village and household surveys. In addition to the reasons addressed in the previous section, this would call for a longitudinal study on local land use patterns, in which corresponding DD drivers and changes therein would be repeatedly assessed.

4.4.3. Study limitations and further research

We acknowledge that in this study, we have put limited focus on the underlying forces influencing agents' land use decisions. Here, we limited ourselves to aspects of land tenure, while other potential underlying forces including commodity prices were largely ignored. We do argue however that REDD + interventions may have limited influence on these (global) market prices, whereas strengthening land rights is at the core of many interventions as shown in this study.

In the drivers assessment part of this study, our main focus was to examine the complementarity of different data sources in addressing different driver elements. We therefore simplified the study design for each of the three methods. This means that especially in the spatial modelling part further research is needed. Among other things, future studies could experiment with feeding the Random Forest model with more or other spatial factors that potentially explain or relate to DD, such as distance to cities and markets, distance to palm oil mills, and other microclimate factors. In that way, the Random Forest model could further enhance the understanding of the relative importance of

different spatial factors determining DD, and to further increase the accuracies of the prediction models, so as to identify future deforestation risk areas.

As explained in the introduction, this study is not an impact assessment of REDD + interventions. We present a qualitative assessment of the alignment between drivers and interventions. The number of interventions is often not representative for the level of influence it has on drivers. For example, one overarching restricting intervention can have a bigger influence than ten small-scale livelihood enhancement interventions together. A quantitative analysis would therefore require information on the treatment intensity of interventions, which goes beyond the scope of this study.

4.5. Concluding remarks

DD activities are the result of a complex interplay of agents, underlying forces and the environment. Our study showed that DD patterns differ across and within sites. This calls for a locally tailored approach when designing and implementing REDD + interventions. We show that no single dataset or method can reveal all facets (who, what, where, why, when and how much) of DD drivers, while a combined assessment leads to a better understanding of these facets. Access to transparent information on direct drivers and underlying factors is important in all phases of the policy cycle of REDD + (De Sy et al., 2018). In early phases, this information plays an important role in raising awareness and problem definition. Based on spatially explicit information on deforestation hotspots and drivers of DD coming from earth observation data, spatial modelling and existing socio-economic datasets, policy-makers can decide as to what areas and which agents to prioritise on in the policy option and selection stage, for example as part of the plans written in the national climate change mitigation plans written for the Paris Agreement (i.e. NDCs). In the implementation stage, repeatedly updated forest data allow for continuous progress tracking of interventions. Finally, for evaluation and performance assessment purposes, information on drivers, interventions and the state of the forest using forest observation data play different roles at different scales, varying from local intervention effectiveness and impact evaluation, national-level GHG and NDC progress reporting, to estimating UNFCCC stock-takes at the global level.

Despite the differences between sites, some general lessons can be drawn from our study. The remote sensing analysis on DD classes showed that in most sites the predominant activity was large-scale agriculture or large-scale tree plantations. Household survey results showed that household-level forest clearance was mainly for annual crops. A basket of REDD + interventions were applied in the study areas aiming to prevent forest conversions. Our results show that the local interventions mainly targeted households and small-scale processes, in contrast with the remote sensing findings that drivers were mostly large-scale.

In this interdisciplinary study, we have provided insights into the complexity of DD driver identification and complementarity of different data sources at the local scale. Further, we have assessed the alignment of these identified drivers and REDD + interventions. A better understanding of the alignment between DD drivers and REDD + interventions is vital for practitioners and policy makers to enhance the effectiveness, efficiency, equity and co-benefits of REDD + at the local level.

CRediT authorship contribution statement

Astrid B. Bos: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Visualization, Writing - original draft, Writing - review & editing. **Veronique De Sy:** Conceptualization, Methodology, Writing - original draft, Writing - review & editing, Supervision. **Amy E. Duchelle:** Conceptualization, Methodology, Investigation, Writing - original draft, Writing - review & editing, Supervision. **Stibniati Atmadja:** Methodology, Investigation, Writing - original draft, Writing - review & editing. **Sytze de Bruin:** Methodology, Writing - review & editing. **Sven Wunder:** Methodology, Writing - review & editing. **Martin Herold:** Conceptualization, Methodology, Supervision.

Declaration of Competing Interest

The authors report no declarations of interest.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at https://doi.org/10.1016/j.envsci.2020.08.002.

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