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Mapping low-intensity selective logging across the Peruvian Amazon

Christopher G Bousfield[1,*], David P Edwards[2,3], Matthew G Hethcoat[4], Luis Enrique Campos Zumaeta[5], Edwin Allccahuaman Mañuico[5], Anabella Minhuey[5] and Robert G Bryant[6]

[1] Ecology and Evolutionary Biology, School of Biosciences, University of Sheffield, Sheffield, United Kingdom
[2] Department of Plant Sciences and Centre for Global Wood Security, University of Cambridge, Cambridge, United Kingdom
[3] Conservation Research Institute, University of Cambridge, Cambridge, United Kingdom
[4] Canadian Forest Service, Edmonton, AB, Canada
[5] Organismo de Supervisión de los Recursos Forestales y de Fauna Silvestre, Magdalena del Mar, Lima, Peru
[6] School of Geography and Planning, University of Sheffield, Sheffield, United Kingdom
[*] Author to whom any correspondence should be addressed.

E-mail: c.bousfield@sheffield.ac.uk

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Supplementary material for this article is available online

Abstract

Selective logging is a major driver of tropical forest degradation and is estimated to span over 400 million hectares of tropical forest. Despite widely available forest monitoring tools that effectively map deforestation, accurate and scalable remote sensing methods to detect selective logging are less advanced. Previous efforts are largely unable to reliably detect the low-intensity selective logging (<10 m^3 ha^{-1}) that dominates across much of the Amazon rainforest, the world's largest remaining stock of tropical timber. Utilising a unique training dataset of high-resolution uninhabited aerial vehicle imagery from logged forests across the Peruvian Amazon, we build random forest models trained to detect selective logging using freely available optical satellite images from Sentinel-2 and Landsat. We find the Sentinel-2 model to be highly accurate (F1 score: 0.88, kappa: 0.85, false detection rate: 6.3%), outperforming the Landsat model (F1 score: 0.77, kappa: 0.74, false detection rate: 21.7%). Both models accurately detected 3- to 20-fold more selective logging activity in our validation data than widely available forest monitoring tools (TMF, GLAD-S2, RADD). We demonstrate novel uses for these logging-detection models in the monitoring of legal timber harvesting inside forest concessions and illegal harvesting of wood inside Protected Areas. These results have the potential to transform our understanding of low-intensity, logging-induced forest degradation at broad scales, demonstrating the clear potential of remote sensing methods to effectively monitor both legal and illegal selective logging in tropical forests.

1. Introduction

Tropical forests cover ∼15% of the world's terrestrial surface [1]. They play a crucial role in global carbon cycling [2], sustain the majority of the world's terrestrial biodiversity [3] and provide a host of vital ecosystem services [4] that support the livelihoods of up to 1.5 billion people [5]. Despite their ecological importance, widespread deforestation and degradation of tropical forests is ongoing, with 219 million hectares (Mha) converted and a further 106 Mha degraded between 1990 and 2020 [6]. One of the major drivers of tropical forest degradation is selective logging [7]. Tropical forests are a key source of timber, with more than 400 Mha of tropical forest having either been previously logged or set aside for future timber harvest [8], notwithstanding the large areas of tropical forest that have been illegally logged [9, 10]. So pervasive is timber harvest across the tropics that the area of logged forest likely exceeds that of primary forest in all major forested tropical regions except the Amazon [11].

Selective logging has substantial impacts on forest carbon stocking, biodiversity and functioning. Loss of tree biomass through removal of trees, road construction, and residual damage during harvesting reduces carbon stocks by 24% [12], with selective logging accounting for 6% of all greenhouse gas emissions from tropical regions [13]. Despite retaining high species richness [14], significant species turnover and loss of forest specialists occurs after logging [15, 16]. Selectively logged forests also have simpler forest structure and reduced ability to provide additional ecosystem services [17], whilst road creation facilitates hunting [18] and gaps increase temperatures and potentially susceptibility to fire [19].

Understanding the extent of selective logging is vital for predicting the spatial footprint of its impacts. This is essential for monitoring and enforcement of illegal forest harvesting, which can represent 50%–90% of timber harvests in tropical countries [20]. It also underpins modelling of the global carbon budget to account for logging impacts [21] and for assessing the performance of REDD+ and other conservation measures seeking to avoid forest degradation [22]. Remote sensing techniques have the potential to provide automated, large-scale forest monitoring for signs of selective logging, allowing for remote identification of specific areas requiring further on-the-ground efforts, thus reducing the time and cost of investigation. However, whilst remote sensing has been effectively implemented to monitor deforestation at scale [6, 23, 24], detecting selective logging has proven substantially more difficult because of the far more subtle spectral signal, given that two or fewer trees are often removed per hectare of forest [25]. Improving detection capabilities to monitor and track the spatial and temporal extent of selective logging at the pan-tropical scale thus remains a critical challenge.

Previous attempts to map selective logging in tropical forests using remote sensing have taken several approaches. In the Brazilian Amazon, Hethcoat *et al* [26] used forest inventory data and Landsat images to detect selective logging, but the 30 m resolution Landsat-based model was too coarse to capture small-scale disturbances associated with lower-intensity selective logging (e.g. $<10\ \mathrm{m}^{-3}\ \mathrm{ha}^{-1}$), whilst efforts using radar-based methods proved less effective [27]. In the Congo Basin, change-detection models using Sentinel-1 radar data have detected logging roads [28] and larger logging gaps with high accuracy [29, 30], but have struggled to maintain accuracy when detecting small gaps typical of selective logging (i.e.$<300\ \mathrm{m}^{-2}$). In the Amazon, where logging intensities are some of the lowest in the tropics [16], recent efforts have demonstrated correlation between optical satellite metrics and logging biomass removal [31], but only over a very small test area (4 one-hectare plots). There currently remains no scalable tool directly trained to detect selective logging using supervised methods across large expanses of tropical forest at high resolution.

Here we address this critical gap by combining machine learning techniques with freely available high-resolution satellite imagery (10 m) to build a model that accurately detects low-intensity selective logging ($\sim$6 $\mathrm{m}^3\ \mathrm{ha}^{-1}$). We use the Peruvian Amazon as a test area, which covers 71 Mha and has >7 Mha of legal logging concessions and considerable rates of illegal harvesting [32]. The models were trained using a database of logged and unlogged forest locations obtained from high-resolution uninhabited aerial vehicle (UAV) imagery taken from $\sim$3600 hectares across seven different logging concessions located throughout the Peruvian Amazon. We have four key objectives: (1) build and validate Sentinel-2 and Landsat based models for detecting selective logging in the Peruvian Amazon; (2) compare model performance against widely available forest monitoring tools; (3) test the model's ability to track logging activity through time in timber concessions; and (4) test the model's ability to monitor selective logging within Protected Areas.

2. Methodology

The methodology overview for this study is presented in figure 1. First, we used UAV imagery from logged concessions across the Peruvian Amazon to create a training dataset of logged and unlogged point locations. For these locations we then collected satellite data from two sources (Sentinel-2 and Landsat) and used these data to train and validate random forest models to detect selective logging in Amazonian forests. The models were compared to other available forest monitoring tools and applied to use cases in the form of monitoring legal forest concessions and illegal harvesting in Protected Areas.

2.1. Study area

We used data from seven different sites across six logging concessions that span 234 000 hectares of tropical forest in Peru, spread across the three key Amazonian Departments of Loreto, Ucayali, and Madre de Dios (figure 2). We focused specifically on detecting low-intensity selective logging. Harvesting activities in the logging concessions were conducted between 2022 and 2023, at an average harvest intensity of $\sim$6 $\mathrm{m}^{-3}\ \mathrm{ha}^{-1}$ (range: 1.4–13.4 $\mathrm{m}^{-3}\ \mathrm{ha}^{-1}$; Table S1).

2.2. Fieldwork—UAV data collection

To create an accurate and time-referenced point location dataset that reflects the disturbance to the forest observed after selective logging, we collected a large number of RGB orthomosaics taken from UAV flights within logging concessions across Peru. In total, we

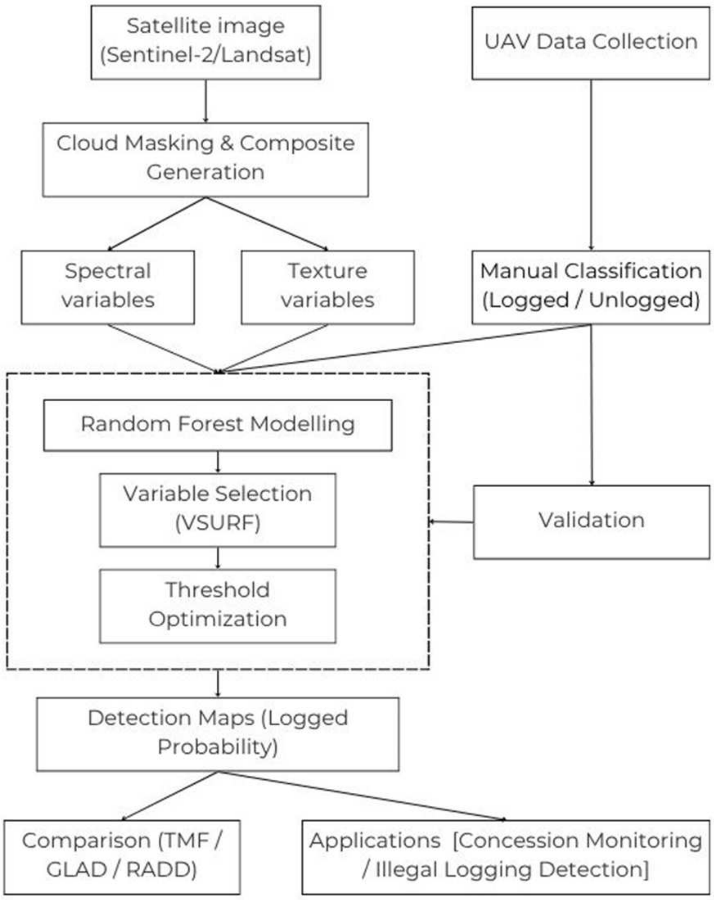

Figure 1. Methodology overview of this study that used machine learning and satellite data to remotely monitor selective logging in the Peruvian Amazon.

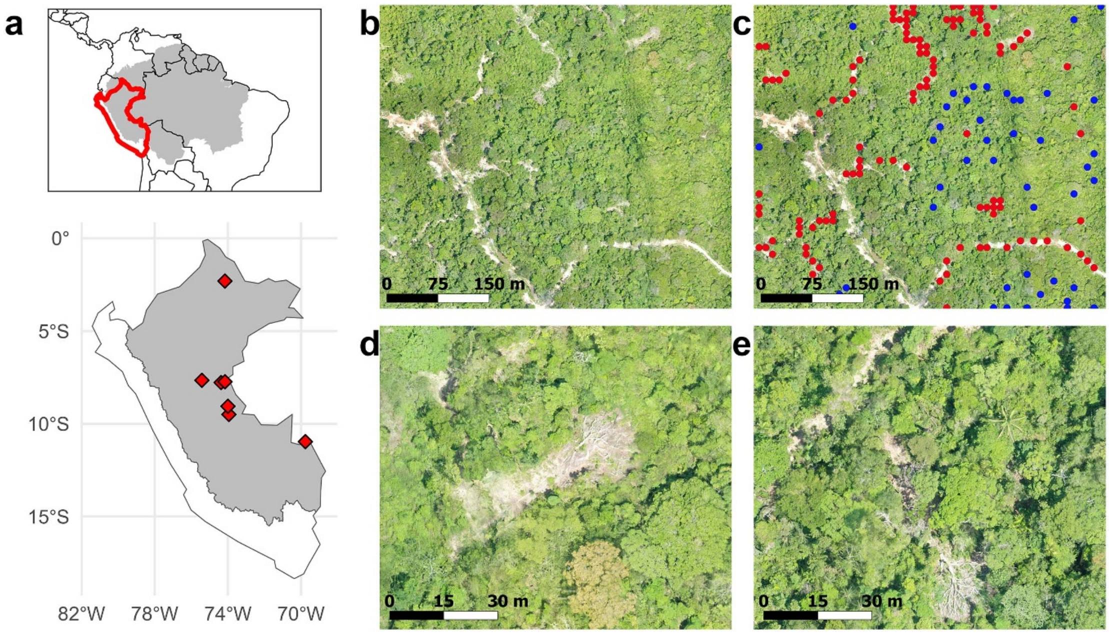

Figure 2. Study sites and UAV imagery. This study used seven different sample sites (red diamonds) in logging concessions located throughout the Peruvian Amazon (a). For each site, UAV imagery was collected after selective logging had taken place (b), and training data locations (c) were generated based on logged forest patches (red) and unlogged forest patches (blue) as visible in the UAV imagery. Zoomed images demonstrate clear logging gaps from felled trees (d) as well as logging gaps and accompanying skid trails (e). The grey in (a) represents the Amazon Biome.

utilised 72 UAV orthomosaics from across our seven study sites, spanning the major Amazonian departments of Loreto, Ucayali and Madre de Dios, and covering ∼3600 hectares of logged tropical forest (table S1). All UAV flights were undertaken using DJII Mavic 02 pro UAVs, within 3 months of logging having occurred. Orthomosaics were generated using the Pix4Dmapper software.

We manually processed the UAV orthomosaics and converted them into grids of non-overlapping point locations showing: (1) clear signs of logging disturbance, which we defined as canopy gaps from tree felling, skid trails, and small logging roads; and (2) points showing no signs of logging disturbance, i.e. unbroken forest canopy (figure 2). Since we were interested in detecting the subtle signs of selective logging that current tree cover disturbance products miss (e.g. canopy gaps, skid trails), we opted not to include the main logging roads in our training data, which are already detected with current techniques [6, 23, 28] and might bias the model towards more intense disturbances making it less able to detect smaller logging-related disturbances.

2.3. Satellite data

Our goal was to build models that could detect even low-intensity selective logging using freely available satellite data. We therefore focused on two satellite datasets: Sentinel-2 Harmonised Level 2 A Surface Reflectance imagery (at 10 m resolution); and Landsat 8 and 9 Surface Reflectance products (at 30 m resolution). Using Google Earth Engine [33], for each satellite dataset we created a cloud-free composite for each test site using images taken in the 2–3 month period after the initial UAV images were taken. For Sentinel-2, we used the Cloud-Score+ algorithm [34] to retain only pixels with a cloud free score of >0.6 (whereby a score of 0 indicates full cloud, and 1 indicates completely clear), before then creating a cloud-free composite by selecting each pixel with the highest cloud-free score across the time period. For Landsat, we constructed cloud-free mosaics from the latest cloud-free pixel within the same time period, with clouds masked using the QA band and a 300 m buffer to remove cloud shadows missed by the QA mask. We also created cloud-free composites in the years preceding harvest to expand the size of our training data and provide more 'unlogged forest' points. For each concession, we went back 2, 3, and 4 years prior to the logging taking place (ignoring one year prior to avoid capturing pre-harvest exploration and road building) and built another cloud-free composite representing images of the unlogged forest prior to logging activity.

To generate our dataset for training and testing the model, we then extracted and calculated for every pixel in the cloud-free composites the following values: RED, GREEN, BLUE, NIR, Shortwave Infrared 1 (SWIR1), and Shortwave Infrared 2 (SWIR2). For each of these values, we also calculated a suite of texture metrics using 3 different window sizes (3 × 3, 5 × 5, 7 × 7). In addition, we calculated the normalised difference vegetation index (NDVI) and the normalised burn ratio (NBR), as well as two additional measures of 'texture' for each of these metrics: (1) standard deviation of the values; and (2) a 'normalised difference' for each value (calculated as the pixel value minus the standard deviation of the 50 m focal median). Again, these texture metrics were calculated for three different window sizes (3 × 3, 5 × 5, 7 × 7). In sum, this left us with 338 satellite-derived metrics for every pixel in the cloud-free composite (figure 3), with these metrics then assigned to logged and unlogged pixels. Points were spatially separated to ensure no overlap at the native resolution of the satellite being used (i.e. no points within the same 10 m cell for Sentinel-2, and none within the same 30 m cell for Landsat, see figure S1). The final dataset consisted of 6765 logged pixels and 35 061 unlogged pixels for the Sentinel-2 dataset, and 2716 logged pixels and 18 845 unlogged pixels for the Landsat dataset.

2.4. Random forest modelling for detection of selective logging

We created Random Forest [35] classifiers to detect selective logging in areas of tropical forest. To train and then independently validate the models, we followed previous methods [26, 29] by splitting the dataset into separate training and test datasets that were spatially independent from one another. To generate the test dataset, we randomly selected several individual UAV orthomosaics from each concession, which ensured spatial independence between training and test data (since each orthomosaic covers a non-overlapping ∼50 hectare area of forest), meaning the model would be tested on parts of the forest it had no prior knowledge of. This resulted in a training to testing data split of roughly 85%:15%.

Given our dataset contained a large number of potential predictor variables (338), many of which could prove to be redundant in predicting logging activity, we first implemented the VSURF workflow [36] to remove redundant variables and retain only those variables that are most effective in predicting the outcome. This variable selection process was carried out on the training dataset, using the final set of 'prediction' variables, reducing the total number of input variables into our models from 338 to 18 for Sentinel-2 and 14 Landsat. After variable selection, we then trained a random forest classifier using the *caret* [37] package and the *ranger* [38] implementation of the random forest algorithm. We tuned the random forest model to optimise the number of trees (*ntree*) and the number of randomly selected variables used in each decision tree (*mtry*), under five-fold cross validation. We then used the held back test

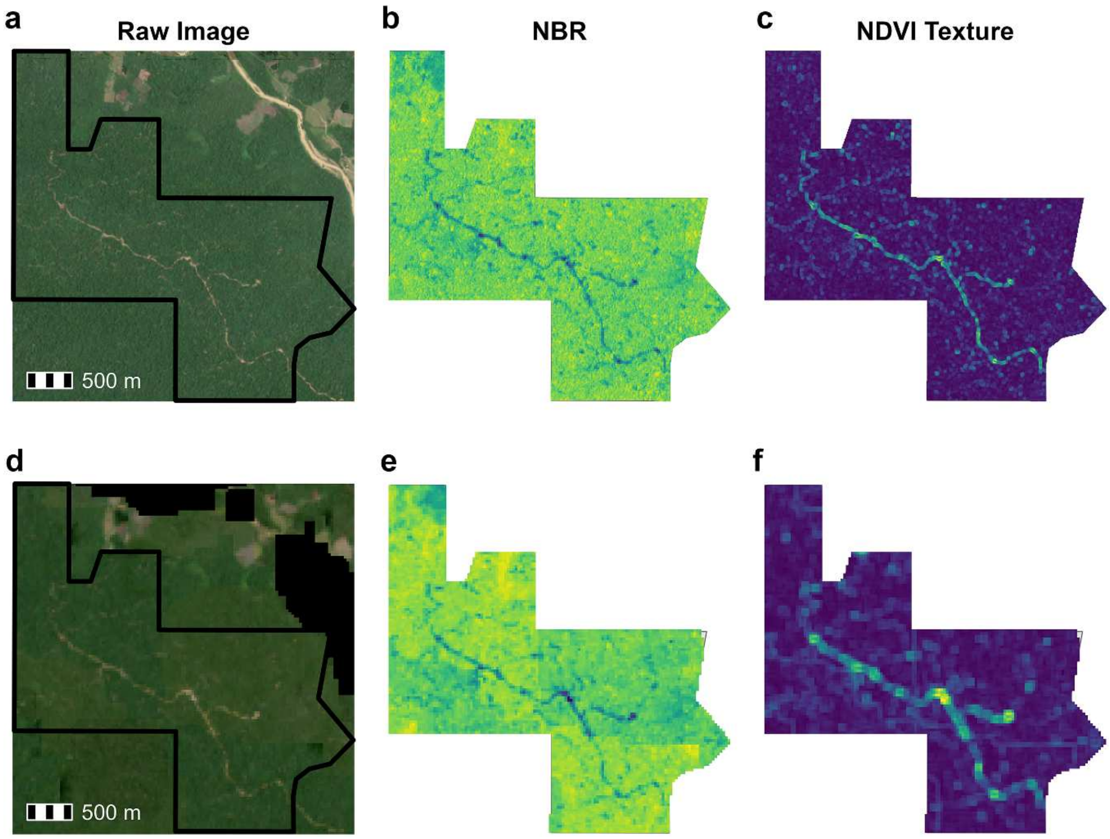

Figure 3. Example imagery and inputs for Sentinel-2 (a)–(c) and Landsat (d)–(f) models Shown is an example of the satellite imagery from Sentinel-2 (a) and Landsat (d) used for obtaining input variables for model construction. Two example input variables, NBR (b,e) and an NDVI texture metric (Standard Deviation across a 3 × 3 pixel kernel) (c),(f) are also shown. Black squares in (d) represent areas where no cloud free Landsat images were available. Data source credit = Sentinel-2 data courtesy of Copernicus/ESA (European Space Agency), data credit = Copernicus Sentinel-2 data, 2025, Sentinel-2 Harmonised Level 2A surface reflectance imagery acquired from the European Space Agency (ESA) via the Google Earth Engine repository. Landsat-8 image courtesy of the U.S. Geological Survey. Data credit: USGS Landsat 8 Level 2, Collection 2, Tier 1, acquired from the USGS via the Google Earth Engine repository.

dataset to independently validate the models and generate a confusion matrix to calculate the F1-Score, Cohen's Kappa, and errors of omission and commission associated with each model, and compared these results between models.

2.5. Comparison with other forest monitoring tools

We compared the performance of the final Sentinel-2 and Landsat models with three widely available tools for pan-tropical forest monitoring that include selective logging within their detections. (1) Joint Research Centre's Tropical Moist Forest (TMF) dataset, which monitors annual changes in the TMF extent using Landsat (30 m resolution) imagery [6]. The product monitors deforestation and degradation (which are short term disturbances and include selective logging). We combined the deforestation and degradation layers into one set of predictions and included observations in both the year of logging and the following year to account for lag effects in the dataset. (2) Global Analysis and Discovery (GLAD)-Sentinel-2 alerts (GLAD-S2), which detects canopy gaps indicative of selective logging at 10 m resolution and is available from the global forest watch website [39]. (3) RAdar for detecting deforestation (RADD) alert [24], a 10 m resolution Sentinel-1 radar-based alert system that maps forest disturbances including selective logging. For both alert systems, we obtained for comparison all disturbance alerts in the year of harvesting and the following six months.

We compared the performance (F1-Score, logged detection rate—defined as 1 minus the omission error, and false detection rate—the commission error) of each monitoring tool and the models developed in this study in correctly predicting the outcome (logging disturbance or no disturbance) of points in the test dataset against which we validated our models. Restricting the assessment to just the test dataset means that we were not biasing results towards our models, since these models had no prior knowledge or training on the points in the test dataset.

2.6. Use cases: tracking logging activity in legal concessions and protected areas

We tested two different use cases for the logging-detection algorithms. The first was its ability to track harvesting activity through time in a legally designated logging concession. Such concessions occur across >7 Mha of the Peruvian Amazon, typically on 40 year leases [32] and in some cases have previously been accused of enabling illegal timber harvesting and laundering [40]. The second use case was to monitor the levels of logging disturbance across an entire protected area (IUCN Category VI 'Comunal Alto Tamaya—Abujao' Regional Conservation Area in Ucayali, Peru). In each test case, we gathered one cloud-free composite per year during the dry season (July–September), and used the Sentinel-2 model to make predictions of logging activity for this composite. Prior to applying the model, we masked out areas that had <90% tree cover in 2000 or had undergone tree cover loss events during the period [23] and areas that were within 100 m of a river [41]. Our logging predictions were therefore restricted only to areas of previously undisturbed forest with high canopy cover and no history of tree cover loss.

3. Results

3.1. Detection of selective logging: model accuracy

We found that both models performed well, but overall, the Sentinel-2 model exceeded the Landsat model in its detection capabilities (table 1). The F1 score for the Sentinel-2 model was 0.88 compared to 0.77 for Landsat, whilst the detection rate of logged points using Sentinel-2 was 82% (95% CI: 79.8%–84.4%) compared to 75% (69.5%–80.1%) for Landsat. Significantly, the Sentinel-2 model achieved a false detection rate (commission error) of only 6.3% (4.8%–8.0%) compared to the much higher false detection rate of 21.7% (16.8%–27.2%) using Landsat (see figure S2 for the impact of altering classification thresholds). For the logged class, the Sentinel-2 model tended towards omission rather than commission. These results demonstrate the superior capabilities of Sentinel-2 at mapping fine-scale logging disturbance (figure 4, see figures S3 and S4 for results from each test concession).

3.2. Comparison with other forest monitoring tools

Overall, the Sentinel-2 and Landsat models presented in this study, which detected 82% (79.8%–84.4%) and 75% (69.5%–80.1%) of all logging activity, respectively, were considerably more accurate at detecting logging disturbance than currently available forest monitoring tools. The TMF data (deforestation and degradation combined) detected 23.8% (21.4%–26.4%) of logging disturbances and the GLAD-S2 and RADD alerts detected only 8.9% (7.3%–10.7%) and 4.2% (3.1%–5.6%), respectively (figure 5(a)). In addition, our Sentinel-2 based model had similar false detection rates (6.3%, 4.8%–8.0%) compared to the TMF data (7.3%, 4.6%–11.0%) and GLAD-S2 alerts (3.8%, 1.1%–9.6%), and lower false detection rates than the RADD alerts (25.4%, 15.2%–37.9%), despite successfully detecting >3 times greater logging disturbance than TMF and >20 times compared to RADD. In the example logged concession (figures 5(b)–(g), see figure S5 for alternative colour scheme), all other monitoring tools were largely restricted to mapping the sizeable roads created to facilitate logging operations, and a small number of the largest canopy gaps associated with logging (see figures S6 and S7 for areas of agreement between the detections).

3.3. Tracking harvest activity through time in selective logging concessions

As the best-performing logging detection model, we applied the Sentinel-2 model to two potential use cases. The first was to monitor and track the development of logging activities over time across a legally designated timber concession. Applying the algorithm to an unseen logging concession (one the model was not trained on) ∼8000 hectares in size over a period of six years (figure 6, see figure S8 for satellite images), we find that logging activity demonstrates a distinctive spatio-temporal pattern. Harvesting activity remains relatively constant throughout (mean annual area of detection of 378 hectares) but is concentrated on certain areas of forest each year before changing location and is typically preceded by road construction to facilitate access, all of which is detected using the Sentinel-2 model.

3.4. Monitoring illegal logging at the protected area scale

Given the widespread extent of illegal logging across the Amazon [9, 10], the model can also be used to monitor illegal harvesting within protected areas. Here we used the IUCN Category VI 'Comunal Alto Tamaya—Abujao' Regional Conservation Area in Ucayali as a case study. We found little evidence of logging within the boundary of the Protected Area (figure 7), with a low-intensity of disturbance detections likely caused by natural processes (e.g. windthrow). The only notable examples of logging were small incursions along the eastern border of the PA in 2019 (figure 7(a)) and 2022 (figure 7(d)). By contrast, disturbance levels were higher in the 5 km buffer zone surrounding the park (table S2), with clear timber harvesting occurring on the southern edge of the park throughout the period. These results demonstrate the ability of the model to be scaled and used as a monitoring tool to prevent illegal harvesting of timber within protected areas or indigenous lands, for example.

4. Discussion

Unsustainable and illegal harvesting of timber in tropical forests is one of the most powerful forces of tropical forest degradation [7], and there is an

Table 1. Confusion matrix for each model (Sentinel-2 and Landsat) detailing the errors of omission and commission, overall accuracy (OA), balanced accuracy (BA), F1-score and Cohen's Kappa associated with each model in predicting areas of logged forest based on unseen test data.

Sentinel-2				
OA = 0.96 **F1-Score = 0.88**	**BA = 0.90** **Kappa = 0.85**			
		Reference class		
Predicted Class		Unlogged	Logged	**Commission error** (%)
	Unlogged	4904	198	**3.9** **(3.4–4.5%)**
	Logged	61	914	**6.3** **(4.8–8.0%)**
	Omission error (%)	**1.2** **(0.9–1.6%)**	**17.8** **(15.6–20.2%)**	
Landsat				
OA = 0.95 **F1-Score = 0.77**	**BA = 0.86** **Kappa = 0.74**			
		Reference class		
Predicted class		Unlogged	Logged	**Commission error** (%)
	Unlogged	2200	67	**3.0** **(2.3–3.7%)**
	Logged	56	202	**21.7** **(16.8–27.2%)**
	Omission error (%)	**2.5** **(1.9–3.2%)**	**24.9** **(19.9–30.5%)**	

urgent need for effective monitoring of selective logging across vast areas of tropical forest. Here we present a new model that combines UAV imagery, freely available high-resolution Sentinel-2 imagery, and machine learning techniques to effectively detect selective logging throughout the Peruvian Amazon. The model is highly accurate (F1-Score = 0.88), capable of detecting selective logging at intensities as low as 2–3 m^3 ha^{-1}, and represents a significant advancement on previous detection methods for low-intensity selective logging [26, 29, 30, 42].

Previous efforts to detect selective logging using remote sensing in the Amazon have relied on Landsat imagery, which we found to be less accurate than using Sentinel-2 data, likely because the improved resolution allows detection of subtle canopy changes that occur during low-intensity selective logging [26, 43]. This remained the case even when controlling for the smaller training dataset in the Landsat model (a Sentinel-2 model trained on the same number of points achieved an F1-Score of 0.87). Our Sentinel-2 model was also more effective at detecting selective logging than previous efforts using Landsat in the Brazilian Amazon [26], achieving a higher accuracy (Cohen's Kappa of 0.85 compared to 0.77) and lower false detection rates (6.3% vs 20%) despite significantly less available training data. In addition, our Landsat-based model achieved similar accuracy scores to the Hethcoat *et al* [26] model, despite our model being trained on ∼5 times less data. This suggests that UAV-based training data generation offers significant advances for developing accurate detection models compared to tree inventory data.

Radar-based change-detection methods can effectively detect selective logging in the Congo, but have higher false detection rates (>20% for gaps <300 m^{-2} in size) despite the higher intensity harvests (16 m^{-3} ha^{-1}) compared to this study (∼ 6 m^3 ha^{-1}) [29, 30, 44]. In addition, change detection methods require large volumes of data before a disturbance can be accurately mapped (e.g. 3–10 months) [27, 30, 44]. An advantage of our optical-based method is that the model is trained specifically to detect logging gaps and does so with a single cloud-free image, making near real-time monitoring of selective logging possible. Like Hethcoat *et al* [26], we used cloud free composites from the same dry season as logging activities where canopy gaps were still clearly visible. Whilst evidence of logging roads and skid trails can remain for >5 years, canopy gaps from tree felling can close rapidly [45]. How long after logging has occurred before disturbances can no longer be detected from space is therefore a key future question for forest monitoring purposes.

The model also proved to be far more effective than widely available tools that monitor forest degradation, such as the TMF data [6], GLAD-S2 [39] and RADD alerts [24]. Whilst we might expect alert systems that are used to inform on-the-ground efforts to prioritise lower false detections at the expense of missing true disturbances, they detected <25% of the logging activity in our test area and often had a similar or higher false detection rate than the Sentinel-2 model. This suggests that current monitoring tools for selective logging in the Amazon and wider tropics

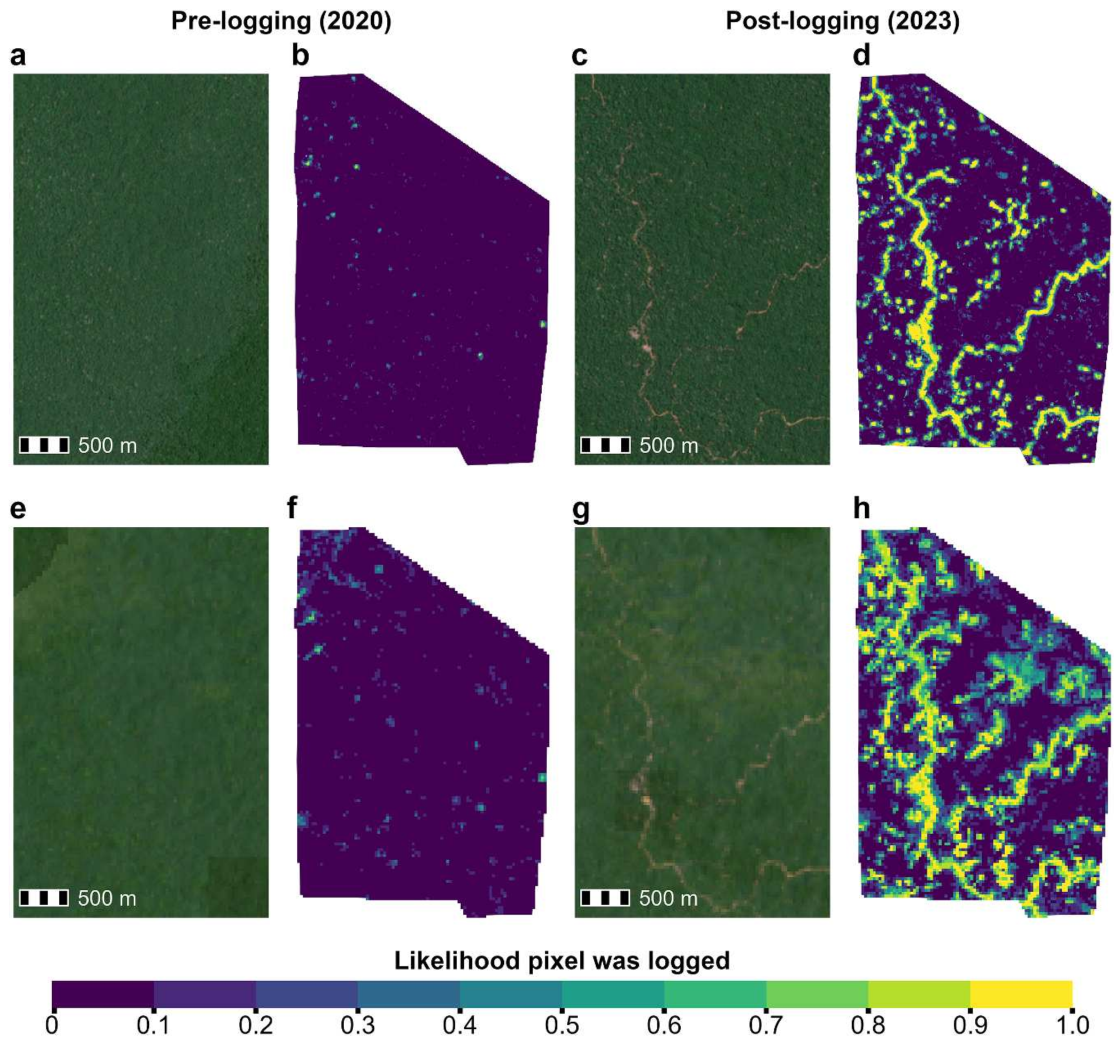

Figure 4. Logging detections from the Sentinel-2 and Landsat models in an active forest concession. Shown are the raw satellite images from Sentinel-2 (a), (c) and model logging predictions (b), (d) both before (a), (b) and after (c), (d) the logging operations, and the same for the Landsat imagery (e), (g) and predictions (f), (h). Increasingly green-yellow colours in (b), (d), (f), (h) represent increased likelihood the pixel was logged according to the model. Data source credit = Sentinel-2 data courtesy of Copernicus/ESA (European Space Agency), data credit = Copernicus Sentinel-2 data, 2025, Sentinel-2 Harmonised Level 2A surface reflectance imagery acquired from the European Space Agency (ESA) via the Google Earth Engine repository. Landsat-8 image courtesy of the U.S. Geological Survey. Data Credit: USGS Landsat 8 Level 2, Collection 2, Tier 1, acquired from the USGS via the Google Earth Engine repository. Data Source Credit = Sentinel-2 data courtesy of Copernicus/ESA (European Space Agency), Data Credit = Copernicus Sentinel-2 data, 2025, Sentinel-2 Harmonised Level 2A Surface Reflectance imagery acquired from the European Space Agency (ESA) via the Google Earth Engine repository. Landsat-8 image courtesy of the U.S. Geological Survey. Data Credit: USGS Landsat 8 Level 2, Collection 2, Tier 1, acquired from the USGS via the Google Earth Engine repository.

are inadequate, particularly where logging intensity is low, and satellite-based estimates of total forest degradation across the tropical forest biome (and its impact on carbon stocks) are likely to be significantly underestimating logging-related disturbances [6, 46, 47].

We tested the ability of the model for two use cases that demonstrate its potential to transform forest monitoring for illegal logging across the tropics (3.3, 3.4). The first is for monitoring logging activities within legally designated logging concessions, where areas and volumes of timber to be harvested are agreed in official forest management plans. In Peru, concessions are subject to inspections by the Supervisory Body of Forest Resources & Wildlife (OSINFOR) in the form of field visits, and levels of illegality are extremely high—around 60% of the timber inspected is thought to be illegal [32]. Given limited resources available to visit individual concessions in the field, our selective logging detection model demonstrates the potential to monitor concessions remotely (figure 6). This type of agile and efficient remote monitoring enables verification that forest operations are being conducted in accordance with approved management plans. Furthermore, it allows for the early detection of potentially unauthorized activities within forest concessions without the immediate need for field visits, thereby providing timely alerts to environmental prosecutors for appropriate enforcement actions. Remote monitoring thus

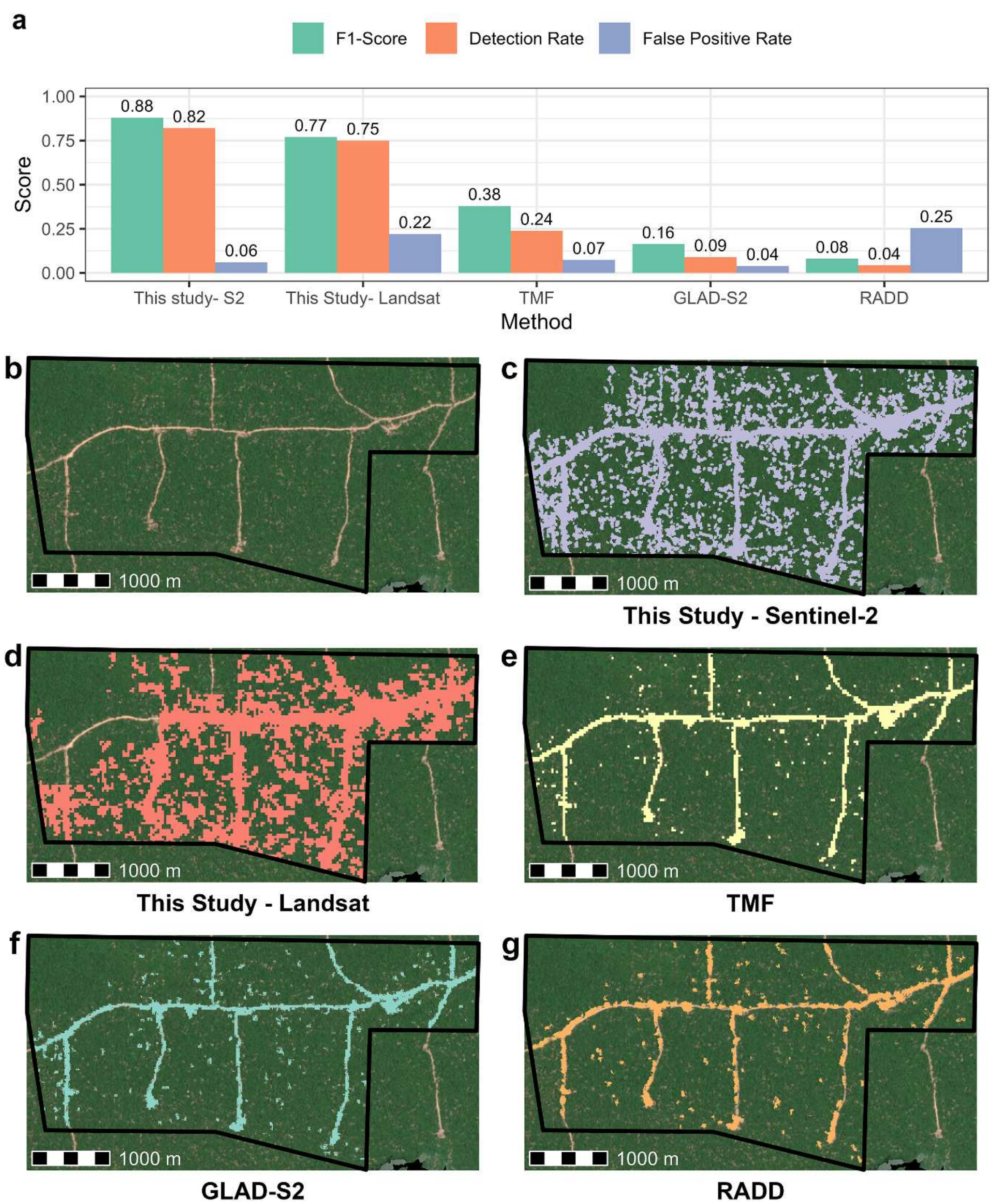

Figure 5. Accuracy metrics and visual comparison of the logging detections from this study with other widely available forest monitoring tools. Accuracy metrics based on the unseen test data are shown in (a). Detection visualisations in (b–f) are shown for an example concession that was logged between June and August 2023 at an intensity of 13.4 m^{-3} ha^{-1}. Sentinel-2 cloud free composite of the study area in 2023 is shown in (b), whilst comparisons are made between logging predictions in this study using Sentinel-2 (c), logging predictions in this study using Landsat (d), the combined deforestation and degradation detections from the TMF dataset (e), and GLAD-S2 (f) and RADD alerts (g). Black outline in (b)–(g) represents the bounds of the analysis, coloured areas in each plots represent disturbance detections. Data source credit = Sentinel-2 data courtesy of Copernicus/ESA (European Space Agency), data credit = Copernicus Sentinel-2 data, 2025, Sentinel-2 harmonised Level 2A Surface Reflectance imagery acquired from the European Space Agency (ESA) via the Google Earth Engine repository. Data source credit = Sentinel-2 data courtesy of Copernicus/ESA (European Space Agency), Data credit = Copernicus Sentinel-2 data, 2025, Sentinel-2 harmonised Level 2A surface reflectance imagery acquired from the European Space Agency (ESA) via the Google Earth Engine repository.

provides significant opportunities to improve tropical forest management and reduce illegality, but fulfilling such opportunities requires engagement with the relevant stakeholders, ensuring they are adequately trained to use remote monitoring tools in the most effective way.

The second use case is to monitor areas where selective logging is not permitted (e.g. Protected Areas, Indigenous Lands), and take preventative actions where illegal logging is detected. Such remote technologies are already being used to monitor and prevent illegal deforestation within PAs [48], but no

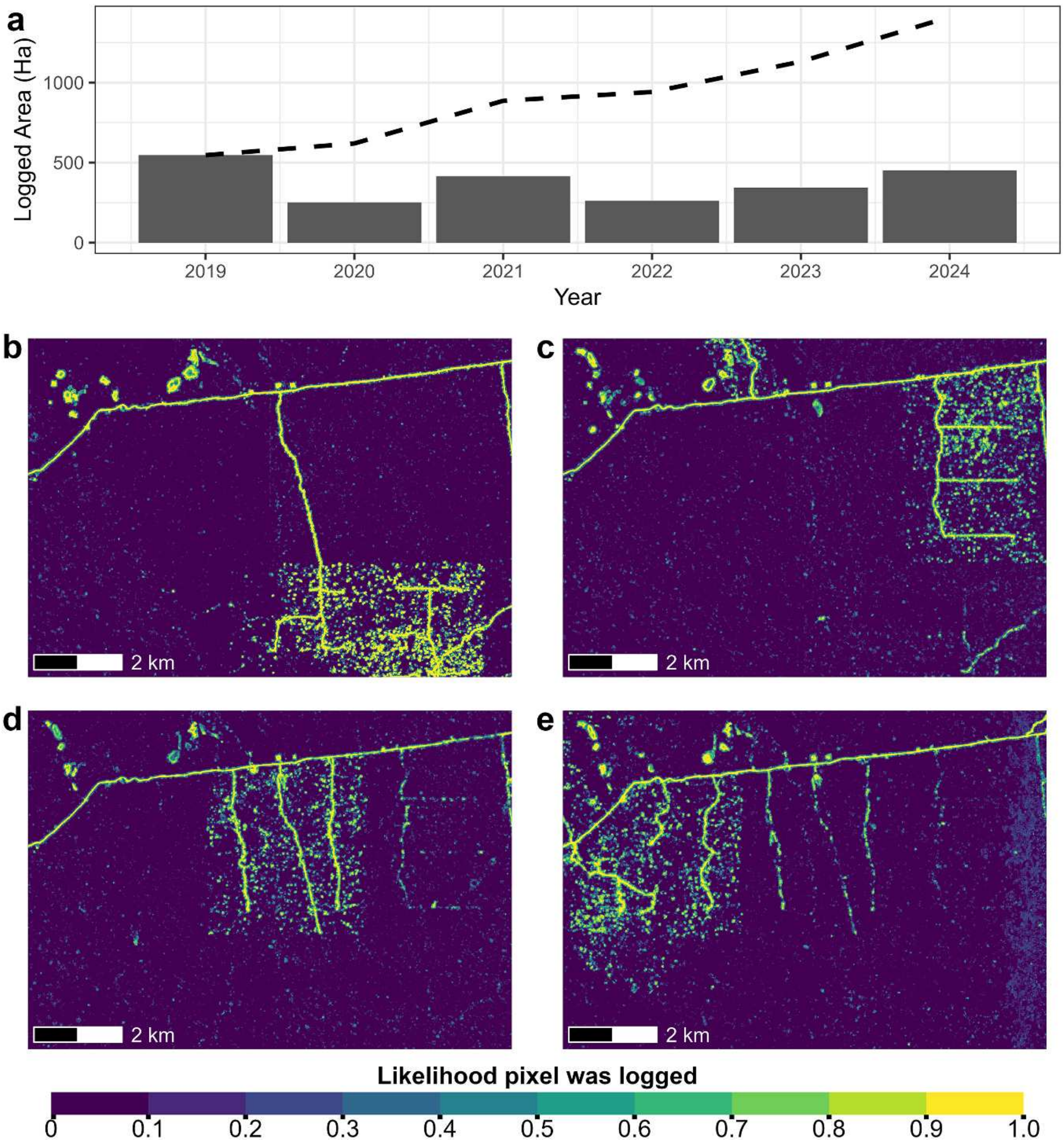

Figure 6. Tracking logging activity in a concession over time. The Sentinel-2 model was applied to a timber harvesting concession on an annual basis between the years 2019–2024. The total annual area of logging detections (hectares) is displayed in panel (a), and logging likelihood predictions per 10 m pixel are displayed for 2019 (b), 2021(c), 2023 (d) and 2024 (e), where increasing green-yellow colour demonstrates increased probability of logging.

system to prevent and detect selective logging (which is missed by widely available forest monitoring tools, 3.2) is currently in place. Furthermore, the model could also be used to monitor areas for forest degradation that are protected under carbon payments (e.g. through REDD+ projects) [49], and aid in estimating avoided emissions through prevention of illegal timber harvest. Beyond the scale of individual projects or PAs, an accurate understanding of the spatial footprint of timber harvesting at the pan-tropical scale across both space and time is severely lacking. Upscaling the models developed here by incorporating additional training data from areas undergoing significant timber harvesting (e.g. Brazilian Amazon, Congo Basin, Borneo) to develop a pan-tropical logging detection model is a vital future application.

4.1. Limitations

This study has three core limitations. First, the models developed focus entirely on optical imagery, and we do not incorporate radar-based approaches. Frequent cloud cover in the tropics can be problematic [28] and was a clear issue when using the Landsat models, though we found the shorter return interval for Sentinel-2 and advances in cloud screening [34] negated cloud cover issues. Whilst radar-based methods avoid the problem of cloud cover [24, 30], radar data can suffer from higher signal-to-noise ratios which can hamper classification efforts [50]. Second, whilst we relied on Sentinel-2 imagery with 10 m spatial resolution, higher-resolution commercial satellites (e.g. PlanetScope) [51] might prove more accurate in detecting selective logging [31].

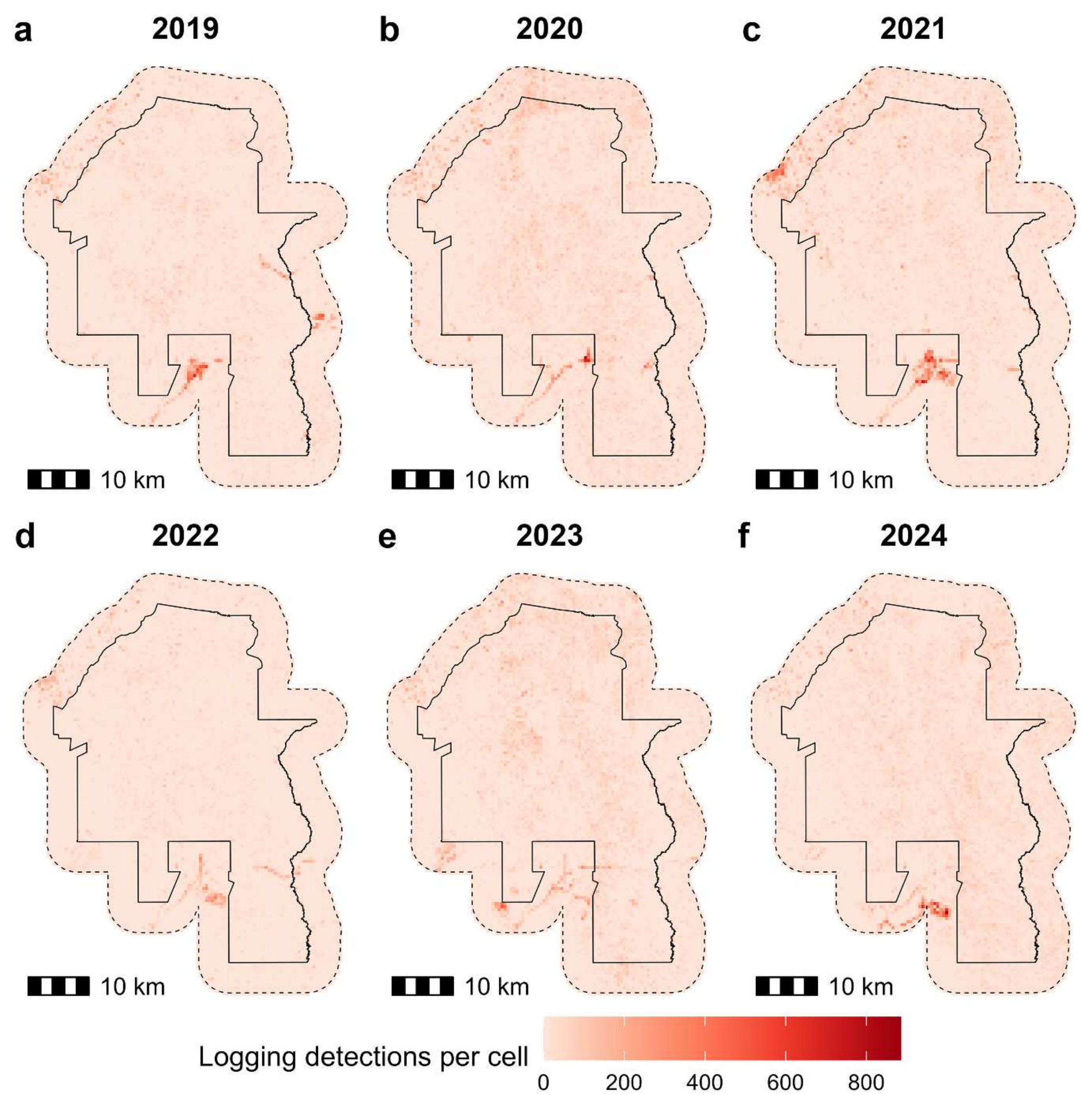

Figure 7. Aggregated annual logging detections across a protected area. Shown are the aggregated annual logging detections per cell (500 m resolution) for the 'Comunal Alto Tamaya—Abujao' Regional Conservation Area in Ucayali, Peru. PA boundaries are represented as a solid black line whilst the dashed black line represents a 5 km buffer zone. Model predictions are based on cloud free composites for the period July–September each year between 2019 and 2024. Predictions are restricted to areas of >90% tree cover with no detected deforestation [23].

However, given critical applications for these models in monitoring tropical forests and preventing illegal logging, algorithms that are effective whilst relying on freely available satellite imagery (e.g. Sentinel-2) are likely preferable to monitoring and enforcement agencies in tropical countries with limited resources. Recent advances in AI-driven multi-source datasets are promising (e.g. Google Satellite Embedding) [52] but the annual data availability limits the capacity to detect short-term disturbances such as canopy gaps that can regrow within the space of a few months. Third, our model represents a binary classification of logged and unlogged forest which, whilst useful in monitoring areas of forest for logging activities, cannot provide insight into how intensively forests are logged [53]. Such information would be of high value for estimating carbon losses and biodiversity impacts associated with logging, or monitoring concessions to ensure legal harvest limits (e.g. 30 m^{-3} ha^{-1} limit in Brazil) [9] are not being exceeded. Utilising detailed harvest records to quantify the relationship between the detection intensity of the model (i.e. logged cells per hectare) and the volume of timber removed would represent an important first step towards a remote sensing-based approach to mapping timber harvest intensity.

5. Conclusion

Given the range of negative impacts selective logging has on forest carbon [12], biodiversity [16] and functioning [17], understanding its spatial footprint is vital for effective forest management that balances economic production with environmental sustainability, whilst preventing widespread illegality. We demonstrate the potential of combining UAV imagery, freely available satellite data, and machine learning to map and monitor selective logging of tropical forests with high accuracy. We have developed a highly accurate Sentinel-2 based model that significantly outperforms current forest monitoring tools and can be used to track timber harvests across concessions through time and monitor Protected Areas for illegal logging. Such methods demonstrate the largely untapped potential of remote sensing in effectively monitoring tropical forests for selective logging, providing the basis for the monitoring and prevention of illegal harvesting, and improving our understanding of the spatial extent of logging-induced forest degradation at the pan-tropical scale.

Data availability statement

The data cannot be made publicly available upon publication because they are owned by a third party and the terms of use prevent public distribution. The data that support the findings of this study are available upon reasonable request from the authors

Supporting data 1 available at https://doi.org/10.1088/1748-9326/ae3787/data1.

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CRediT authorship contribution statement

Christopher G Bousfield: Writing—original draft, Visualisation, Validation, Methodology, Investigation, Formal analysis, Conceptualisation, Funding acquisition. David P. Edwards: Writing—review and editing, Investigation, Conceptualisation. Matthew G. Hethcoat: Writing—review and editing, Methodology, Investigation, Conceptualisation. Luis Enrique Campos Zumaeta: Writing—review and editing, Validation, Resources, Data curation. Edwin Allccahuaman Mañuico: Writing—review and editing, Validation, Resources, Data curation. Anabella Minhuey: Writing—review and editing, Validation, Resources, Data curation. Robert G. Bryant: Writing—review and editing, Investigation, Data curation, Conceptualisation, Funding acquisition.

Conflict of interest

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

ORCID iDs

Christopher G Bousfield 0000-0003-3576-9779
David P Edwards 0000-0001-8562-3853
Luis Enrique Campos Zumaeta 0000-0003-1478-6596
Edwin Allccahuaman Mañuico 0009-0002-0305-7718
Anabella Minhuey 0000-0002-2471-3043
Robert G Bryant 0000-0001-7943-4781

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