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Assessment of selective logging impacts using UAV, Landsat, and Sentinel data in the Brazilian Amazon rainforest

Guido Vicente Briceño Castillo¹,^a Lucas José Mazzei de Freitas¹,^{a,b}
Victor Almeida Cordeiro¹,^a Jorge Breno Palheta Orellana,^a
Jorge Luis Reategui-Betancourt,^a Laszlo Nagy,^c
and Eraldo Aparecido Trondoli Matricardi¹,^{a,*}

^aUniversity of Brasilia, College of Technology, Forestry Department, Campus Darcy Ribeiro, Brasília, Brazil

^bEMBRAPA Amazônia Oriental, Travessa Dr. Enéas Pinheiro, Bairro Marco, Belém, Brazil

^cUniversity of Campinas, Institute of Biology, Department of Animal Biology, Cidade Universitária, Campinas, Brazil

Abstract. Several studies have assessed forest disturbance in tropical forests using Landsat imagery. However, the spatial resolution (30 m) of Landsat images has often been considered too coarse to accurately detect the extent and impacts of selective logging. The Sentinel-2 satellite launched in 2015 has been providing images at spatial resolutions of 10 to 20 m and those images have shown an improved potential for detecting forest disturbances in tropical regions. We compared Landsat-8 and Sentinel-2 imagery for detecting selective logging in a rain forest site in the Brazilian Amazon. The aerosol-free modified soil adjusted vegetation index (MSAVI_{af}) was retrieved from the satellite images acquired in August 2020 immediately following logging. A robust reference dataset of very-high-resolution imagery (0.5 m) acquired using a complementary metal oxide semiconductor sensor (visible bands) onboard of an unmanned aerial vehicle was used to image the area of interest and a map derived from it was used to assess the classification accuracies made using satellite-derived data. The overall accuracy of the classified Sentinel-2 and Landsat-8 images varied between 54% and 83%, depending on the applied classification parameters for distinguishing undisturbed from disturbed forest canopy. Images acquired using the UAV allowed us to detect subtle impacts of canopy openings by selective logging activities. Images acquired using the UAV allowed the detection of small canopy openings, but not Sentinel-2 or Landsat-8. Sentinel-2 provided more details of canopy disturbances than Landsat image. Our classification approach is fully implementable on the Google Earth Engine platform and is a promising technique to monitor selective logging impacts in tropical forests. © 2022 Society of Photo-Optical Instrumentation Engineers (SPIE) [DOI: [10.1117/1.JRS.16.014526](https://doi.org/10.1117/1.JRS.16.014526)]

Keywords: forest degradation; Landsat-8; selective logging; Sentinel-2; unmanned aerial vehicle.

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1 Introduction

Over the past three decades, increasing deforestation rates have been observed in tropical regions, despite governmental and non-governmental efforts to protect forests and their biodiversity.¹ Selective logging of the rainforests in the Brazilian Amazon has been considered economically important, however, in the meantime, it is acknowledged to be a potential precursor of deforestation. Selective logging, whether legal or illegal, may open the way to land occupation and the conversion of the forest to other land uses such as slash-and-burn agriculture or large-scale clearing for pasture. Forest stands with an opened-up canopy are sensitive to fire

*Address all correspondence to Eraldo Aparecido Trondoli Matricardi, ematricardi@gmail.com

events in the dry season and thus selective logging may be a significant contributor to forest degradation,² i.e., the “the reduction of the capacity of a forest to provide goods and services.”³

Estimating accurately the extent of degraded forests and deforestation are a key component of international climate change initiatives such as reducing emissions from deforestation and forest degradation in developing countries (REDD+), launched within the UN framework convention on climate change. This requires the use of robust and transparent methods to quantify carbon emissions from forest degradation and deforestation.⁴ As selective logging is widespread, it is imperative to develop a national or subnational system that can accurately monitor forest canopy opening caused by selective logging. It is especially important for enforcing harvest regulations regarding established intensities of selective logging in tropical forests.^{5,6} By enforcing harvest regulations, it helps to ensure that well-planned and well-executed selective logging⁷ is based on sustainable forest management principles that contribute to improve recovery of forest biomass (carbon stocks) and reduces the chances of forest degradation.^{8,9} Importantly, illegal logging has been estimated to account for up to 72% of all logging in the Brazilian Amazon,^{10,11} and forest degradation has affected as much of the Amazon forests as deforestation.^{2,12}

In Brazil, much effort has been dedicated to monitoring deforestation (forest clearing) in general (e.g., MapBiomass project¹³) and with special attention to Amazonia (PRODES¹⁴ and DETER¹⁴ projects). Despite the valuable time series data available on detecting and monitoring the dynamics of forest disturbances in Amazonia,^{14–16} there remain gaps of scientific knowledge. For example, the use of Landsat imagery, with its spatial resolution of 30 m and temporal frequency of 15 days, has been criticized for lacking sufficient accuracy^{17,18} for the detection and quantification of forest degradation by selective logging activities. Comparisons between the use of multispectral images of the recently launched Sentinel-2 satellite (13 bands; 5-day recurrence interval) and those of Landsat 8 to assess land use and land cover changes^{19,20} and mapping the extent of burned areas¹⁹ have shown that Sentinel-2 provided maps of higher accuracy than those produced by using Landsat imagery.²⁰ These results suggest that Sentinel-2 data may provide a basis for improved accuracy in identifying selectively logged forest areas and thus improve estimating and monitoring of forest degradation in tropical forests.

In this study, we developed a remote sensing-based approach to classify forests impacted by selective logging at a study site in eastern Amazonia using Landsat-8, Operational Land Imager (OLI) sensor, and Sentinel-2, Multispectral Instrument (MSI) sensor, imagery. We calculated the aerosol-free modified soil adjusted vegetation index (MSAVI_{af}) to detect forest canopy gaps caused by selective logging.¹⁸ For reference, we applied supervised classification (random forest) to high spatial resolution (0.5 m) images acquired using a (CMOS sensor visible bands) onboard of an unmanned aerial vehicle (UAV) during the dry season of 2020, immediately after logging of the study site. The classification accuracies using Landsat-8 and Sentinel-2 were calculated by comparing them with the high-resolution reference map.

2 Materials and Methods

2.1 Study Site

The study site was a logging unit of 50 ha, within the Rio Capim Forest Estate (RCFE), a logging concession in south-western Paragominas municipality, state of Pará, Brazil, 217 km south of the state capital Belém (Fig. 1). The RCFE, owned the Cikel Brasil Verde Madeiras Ltda. logging company, has a total area of 140,658 ha, of which 121,000 ha are under or are earmarked for selective logging. Timber from selective logging at the estate has been certified by the Forest Stewardship Council since 2001,²¹ and the estate has permanent research plots for field measurements and forest monitoring activities established by the Tropical Managed Forests Observatory scientific network.²²

The predominant vegetation type is non-inundated (*terra firme*) lowland evergreen rain forest that grows in a Köppen Aw type climate, with an average annual precipitation of 1800 mm, a well-defined dry season (mean monthly precipitation < 100 mm) from May to October; the annual average temperature is 26.3°C.²³ The predominant soil types include yellow Latosols and Argisols, Plinthosols, and few small patches of Gleisols and Neosols.²⁴

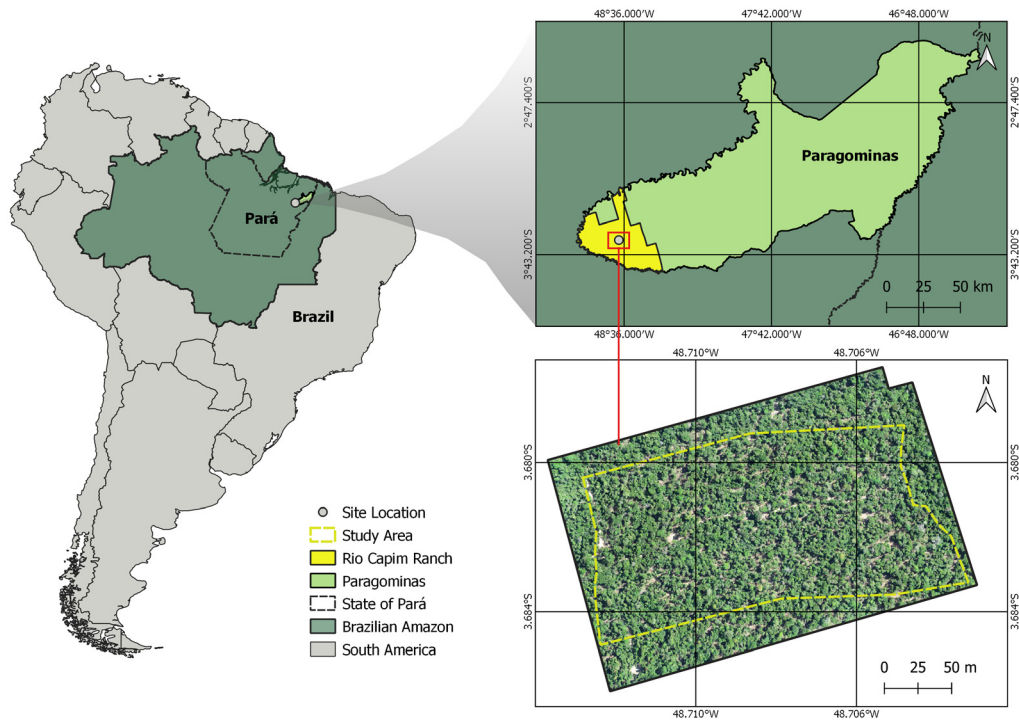


Fig. 1 The location of the study site, a logging unit of 50 ha within the Rio Capim Forest Estate, state of Pará, Brazil. The bottom right-hand image is composed of a mosaic of multispectral images (bands 1 to 3, acquired at a resolution 0.5 m) using a UAV showing the site after logging in August 2020.

2.2 Datasets

The UAV image was acquired using a built-in camera onboard of a DJI Phantom 4 Pro, with a CMOS sensor of 20 MP of mechanical shutter resolution, which eliminates rolling shutter distortions. This sensor and processor captured images in three composite bands (blue, green, and red; 0.5-m spatial resolution) and supplied sufficient detail for a reference data set.

Landsat-8 and Sentinel-2 images (Table 1) available from the Google Earth Engine platform²⁵ were used in this analysis. We used one Landsat-8 scene and one Sentinel-2 scene with <5% of cloud cover, acquired between August 13 and 20, 2020, during the dry season (Table 1). The dry season is the period when most of forest operations including selective logging are carried out in Amazonia.

We used in this analysis the red, green, blue, near-infrared (NIR), and short-wave infrared 1 (SWIR-1) spectral bands, recorded by the sensors (OLI and MSI) of both satellites. The SWIR-1 band by Sentinel-2 is acquired at a spatial resolution of 20 m and, in this study, we pansharpened it to a resolution of 10 m of the visible bands, using nearest-neighbor resampling.

Table 1 The characteristics of the remote sensing and UAV datasets used to detect selective logging in a 50-ha site, Rio Capim Forest Estate, Pará, Brazil.

Satellite/sensor	Acquisition date
Sentinel-2A/MSI ^a	August 13, 2020
Landsat 8/ OLI ^b	August 15, 2020
UAV/CMOS ^c	August 20, 2020

^aMSI, multispectral instrument, level-1C.

^bOLI, operational land imager, C1 level-1.

^cCMOS, complementary metal-oxide-semiconductor sensor.

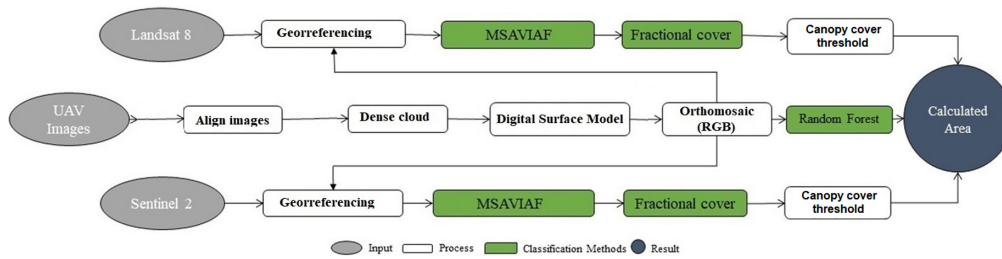


Fig. 2 Flow diagram of geometric corrections of Landsat-8 and Sentinel-2 images used for detecting forest disturbances caused by selective logging activities in the study site, Rio Capim Forest Estate, state of Pará, Brazil, August 2020.

2.3 Methodological Approach

The step-by-step image processing and classification to detect the extent of the areas affected by selective logging using UAV image mosaic and the Landsat-8 and Sentinel-2 imagery is presented in Fig. 2. Images acquired using a CMOS sensor onboard of an UAV, composed of three visible bands (blue, green, and red), were georeferenced and mosaicked using the Agisoft Photoscan Professional® software. We applied the random forest algorithm to the UAV image mosaic to classify it into areas with intact canopy cover versus open areas affected by logging, using the Google Engine Platform. The UAV image mosaic was used as a cartographic reference to geometrically correct the Landsat-8 and Sentinel-2 images. After geometrical correction, we calculated the MSAVI_{af} index from Landsat-8 and Sentinel-2 images and estimated the fractional percentage canopy cover (FC%). The FC% images were binary reclassified into (1) areas disturbed by selective logging activities (<30% of canopy cover) and (2) undisturbed forest areas (≥ 30% of canopy cover). Finally, the areas identified as disturbed by logging using the UAV mosaic were used to estimate the accuracy of the binary classification of satellite images.

2.3.1 Automatic photogrammetric adjustments

Photogrammetric adjustments of the UAV images were made using Agisoft PhotoScan Professional®. This software uses the coordinates of the exposure centers for each image, performs aerial triangulation, and reconstructs the photogrammetric block. The software initially works with the coordinates captured during the flight by the antenna of the UAV. Specific information regarding the spatial location of the camera and image overlays of the UAV image processing is presented in Table 2.

The photogrammetric block was automatically reconstructed using the encrypted metadata that contains the internal orientation and image acquisition angles. Once the photogrammetric

Table 2 Parameters used in the Agisoft PhotoScan® software for image mosaicking and georeferencing the UAV image of the study site, Rio Capim Forest Estate, state of Pará, Brazil, August 2020.

Attribute	Value
Number of images	162
Flying altitude	250 m
Ground resolution	0.50 m pix ⁻¹
Coverage area	0.324 km ⁻²
Camera stations	162
Tie-points	140, 224
Error	1.00 pix

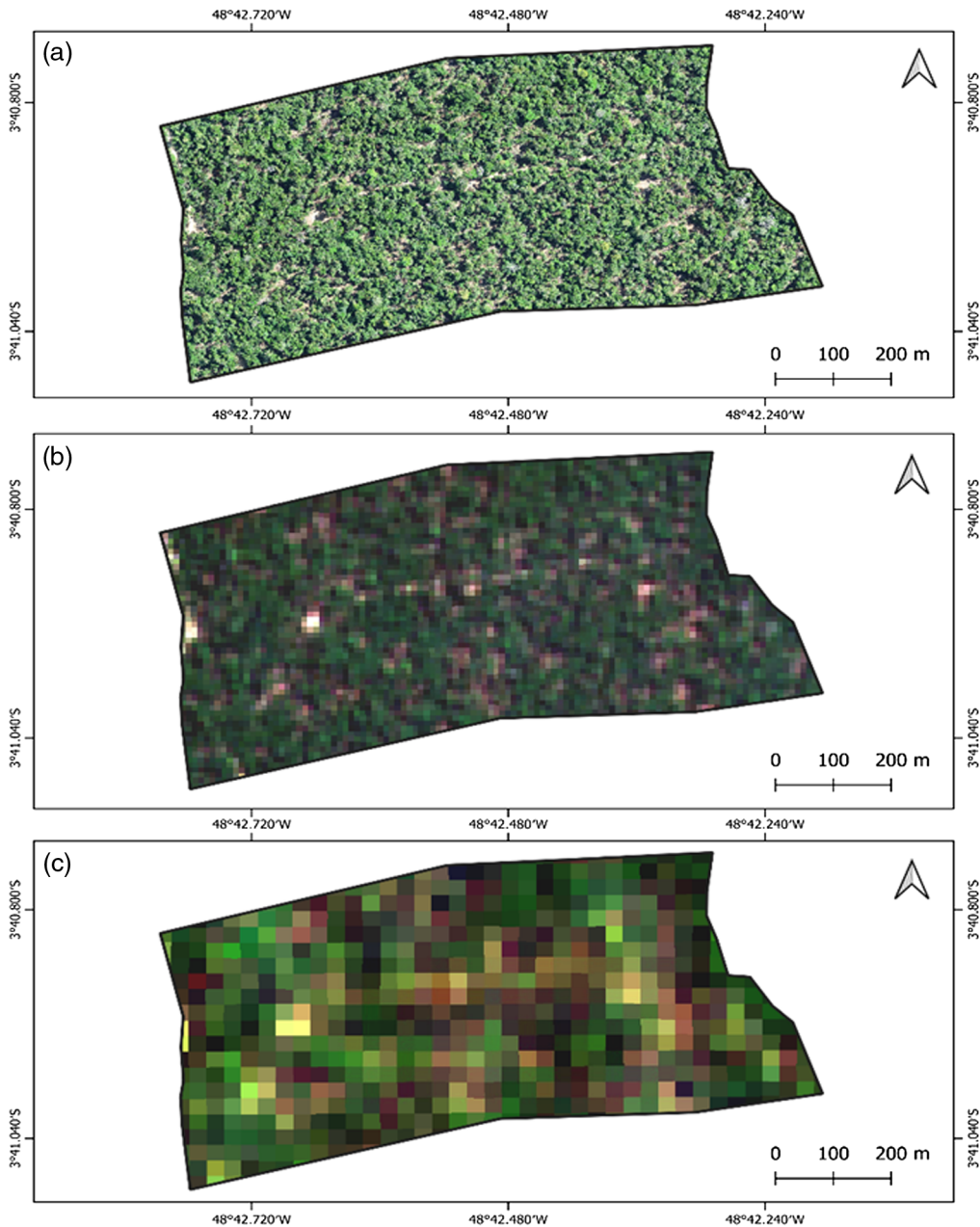


Fig. 3 Remotely sensed images of the study site: a logging unit (50 ha) within the Rio Capim Forest Estate, state of Pará, Brazil, immediately after logging in August 2020. (a) UAV-borne CMOS sensor composite bands (bands 1 to 3; 0.5 m resolution); (b) Sentinel-2 color composite bands (RGB 4/3/2; 10 m resolution); (c) Landsat-8 color composite bands (RGB 4/3/2; 30 m resolution).

block reconstruction was complete, the software automatically generated mooring points to construct the ortho images. The UAV image composite [Fig. 3(a)] allowed us to identify individual trees, while the corresponding image sections derived from Sentinel-2 [Fig. 3(b)] and Landsat-8 [Fig. 3(c)] imagery showed increasingly less details of forest disturbances.

2.3.2 Image capturing and processing using the UAV-borne sensor

The images acquired using the UAV-borne sensor were preprocessed for altitude and image overlap for subsequent photogrammetric adjustments and generating an orthomosaic image in RGB

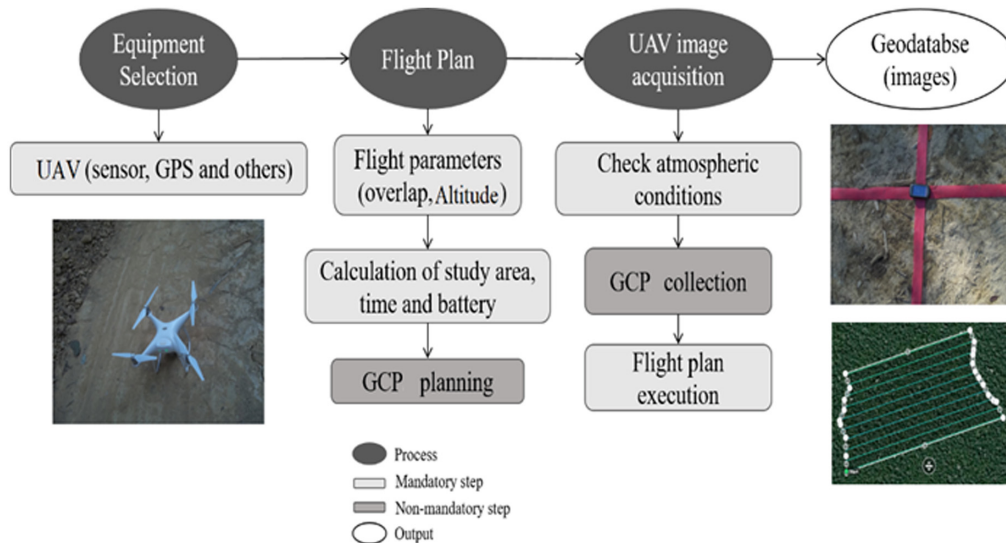


Fig. 4 Flow diagram of the image acquisition process by using the UAV-borne CMOS sensor to produce an RGB color composite image at 0.5 m spatial resolution. In addition, four ground control points (GCP) using a handheld GPS device (Garmin, GPSMAP 86s) were collected, however, as the location error using the handheld GPS was greater than the UAV onboard GPS, handheld GPS data were not used in the analyses.

format (Fig. 4). The UAV images were synchronized using control points acquired by an onboard GPS. The accuracy of georeferencing was limited by the accuracy of the GPS receiver (± 0.5 m vertical and ± 1.5 m horizontal); the total estimated error was 5 m or less. After georeferencing, the UAV images were geoprocessed using the Agisoft Photoscan Professional.²⁶

In addition, four ground control points (GCP) using a handheld global positioning system (GPS) device (Garmin, GPSMAP 86s) were collected in the study site; however, as the total location error using the handheld GPS was greater than the UAV onboard GPS, we did not use the handheld GPS data in the analyses.

2.3.3 UAV image classification

Forests disturbances caused by selective logging activities (logging roads, skid trails, log landings, and canopy gaps caused by tree felling) were detected by applying the random forest algorithm and the RGB orthoimage mosaic acquired using the UAV, on the Google Earth Engine[®] platform. The random forest algorithm combines a large number of decision trees to achieve a best forecast and predictive performance.²⁷ Training areas to represent disturbed and undisturbed forests were selected by visual photo interpretation. The final UAV image classification was used as a reference of canopy openness.

2.3.4 Aerosol free modified soil adjusted vegetation index (MSAVI_{af})

The aerosol free modified soil adjusted vegetation index (MSAVI_{af})¹⁸ was estimated using the Landsat-8 and Sentinel-2 images. The MSAVI_{af} has shown good results to estimate impacts on forest canopies caused by selective logging activities in tropical regions.^{2,18,26} This index was calculated using Eqs. (1) and (2):

$$MSAVI_{af} = \frac{\rho_{NIR} - 0.5\rho_{SWIR}}{\rho_{NIR} + 0.5\rho_{SWIR} + L} (1 + L), \quad (1)$$

where ρ_{NIR} is the surface reflectance in the NIR range, ρ_{SWIR} is the surface reflectance in the SWIR range (2.1 μm), and L is the soil adjustment factor:

$$L = [(\rho_{\text{NIR}} - 0.5\rho_{\text{SWIR}}) * s + 1 + \rho_{\text{NIR}} + 0.5\rho_{\text{SWIR}}]^2 - 8.0 * s * (\rho_{\text{NIR}} - 0.5\rho_{\text{SWIR}}), \quad (2)$$

where $s = 1.2$ is the slope of the soil line calculated from the reflectance of the surface in exposed soil areas at the study site.

Subsequently, we estimated fractional percentage of forest canopy cover derived from MSAVI_{af}.

2.3.5 Fractional percentage of canopy cover

The fractional canopy cover (fc) was originally developed and applied by Ref. 28, and it can be estimated using two spectral end members: forest canopy and bare soil [Eq. (3)]:

$$fc = \frac{VI - VI_{\text{open}}}{VI_{\text{canopy}} - VI_{\text{open}}}, \quad (3)$$

where fc is the fractional coverage retrieved from vegetation index (%), VI is the vegetation index (in this analysis, MSAVI_{af}), VI_{canopy} is the end member with homogenous closed canopy areas acquired from the vegetation index, and VI_{open} is the end member with homogeneous open areas acquired from the vegetation index.

2.4 Accuracy Assessment

The accuracy assessment was conducted for the full extent of the study site using as reference the binary classified image (logged versus undisturbed forests) based on the UAV orthorectified photomosaic by comparing it to the classifications derived from Sentinel-2 and Landsat-8 imagery based on different classification parameters (variable canopy cover threshold from 5% to 50%). The Sentinel-2 and Landsat-8 classified images were resampled to 0.5 m resolution to match the spatial resolution of the UAV image.

The canopy openness classified in the binary maps and their spatial relationships were quantified using Fragstats v. 4.2.²⁹

3 Results

We assessed the classification accuracies of our technique to distinguish areas disturbed by selective logging activities from areas of undisturbed forests (closed canopy) using Sentinel-2 and Landsat-8 imagery by comparing them with a UAV CMOS image classification mosaic (Fig. 4). Our results indicate that the overall accuracies of both classifications (Landsat-8 and Sentinel-2) were similar, varying from 78% to 53%, according to the applied classification canopy cover threshold.

We also observed high accuracies for detecting undisturbed canopies using Sentinel-2 and Landsat-8 images, which varied from 84.6% to 98.5%, according to the applied canopy cover classification threshold. Meanwhile, accuracies for classifying areas disturbed by selective logging were limited for both images (Sentinel-2 and Landsat-8), varying from 22.1% to 35.3%, according to the applied canopy cover classification threshold (Table 3).

Our results indicated high omission (>84%) and commission (>64%) errors in classifying canopy disturbance. The omission error decreased three-fold by increasing the canopy cover classification threshold from 5% to 50% using both Landsat-8 and Sentinel-2 images. Conversely, the average commission errors ($72 \pm 5\%$ and $68 \pm 3\%$) for canopy disturbance did not substantially change by varying the canopy cover classification threshold. The optimum canopy cover classification threshold (30%) resulted in an overall accuracy of >78% and the value of the kappa index >0.72 (Fig. 5). The equilibrium between omission errors of classifying disturbed and undisturbed canopies were observed by applying a 45% canopy cover classification threshold; however, it resulted in overall accuracies <70% for both Landsat-8 and Sentinel-2 images.

Table 3 Classification accuracies for detecting disturbed by selective logging activities and undisturbed areas (closed forest canopy) using (a) Landsat 8 and (b) Sentinel-2 imagery by applying different canopy cover classification thresholds.

(a) Classification using Landsat-8 image and different canopy openness thresholds								
Canopy cover threshold ^a (%)	Accuracy (%)		Omission error (%)		Commission error (%)		Overall accuracy (%)	Kappa index
	Disturbed canopy	Closed canopy	Disturbed canopy	Closed canopy	Disturbed canopy	Closed canopy		
5	23.56	98.51	97.59	1.49	76.44	15.84	83.17	0.78
10	30.91	97.64	94.45	2.36	69.09	15.53	82.94	0.78
15	34.35	96.54	90.47	3.46	65.65	15.12	82.64	0.77
20	34.66	85.35	85.7	5.12	65.34	14.65	82	0.76
25	33.85	86.26	76.51	8.72	66.15	13.74	80.45	0.74
30	32.17	87.13	67.68	12.95	67.83	12.87	78.31	0.72
35	28.36	87.97	57.14	20.57	71.64	12.03	73.59	0.69
40	26.75	88.99	47.22	27.47	73.25	11.01	69.33	0.66
45	24.04	90.18	34.88	39.09	75.96	9.82	61.58	0.59
50	22.15	91.04	26.32	49.21	77.85	8.96	54.45	0.53

(b) Classification using Sentinel-2 image and different canopy openness thresholds								
Canopy openness threshold ^a (%)	Accuracy (%)		Omission error (%)		Commission error (%)		Overall accuracy (%)	Kappa index
	Disturbed canopy	Closed canopy	Disturbed canopy	Closed canopy	Disturbed canopy	Closed canopy		
5	32.55	84.64	92.8	2.83	67.45	15.36	82.79	0.77
10	34.42	84.99	89.3	3.87	65.58	15.01	82.48	0.77
15	35.32	85.42	85.22	5.14	64.68	15.58	82.07	0.76
20	34.64	85.91	80.14	7.12	65.36	14.09	81.22	0.75
25	33.1	86.42	74.61	9.75	66.9	13.58	79.89	0.74
30	32.93	87.31	66.55	12.95	67.07	12.69	78.49	0.72
35	31.91	88.34	57.5	17.23	68.09	11.66	76.34	0.70
40	29.9	89.31	48.57	22.91	70.1	10.69	72.99	0.68
45	28.15	90.42	39.35	29.42	71.85	9.58	68.99	0.65
50	26.18	91.56	30.43	37.28	73.82	8.44	63.82	0.61

^aThe classification thresholds tested to distinguish disturbed canopy from closed canopy.

Based on the supervised classification using the random forest algorithm of the UAV images indicated a total of 8.0 ha of canopy gaps caused by selective logging, which corresponds to 16% of the total studied [Figs. 6(A) and 6(D)]. The corresponding values for Sentinel-2 image was 10.5 ha [Figs. 6(B) and 6(E)] and using Landsat-8 were 11.5 ha [Figs. 6(C) and 6(F)] by applying the 30% canopy cover classification threshold.

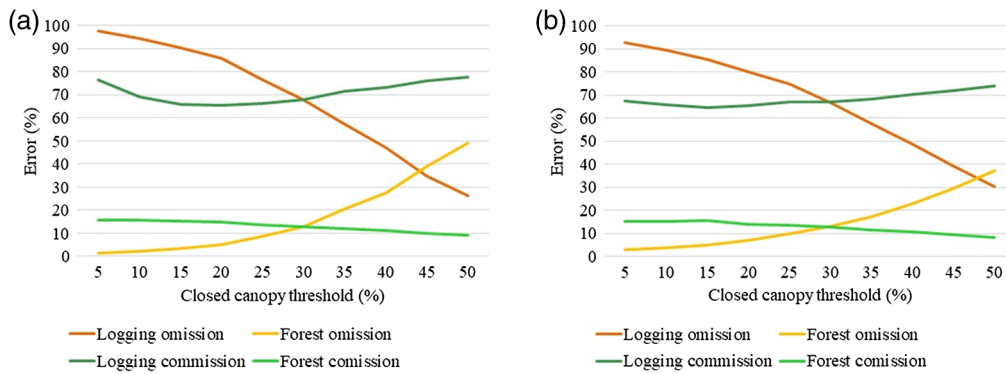


Fig. 5 Omission and commission errors by varying the canopy cover classification thresholds using (a) Landsat-8 and (b) Sentinel-2 images. Logging, disturbed canopy, forest, undisturbed canopy.

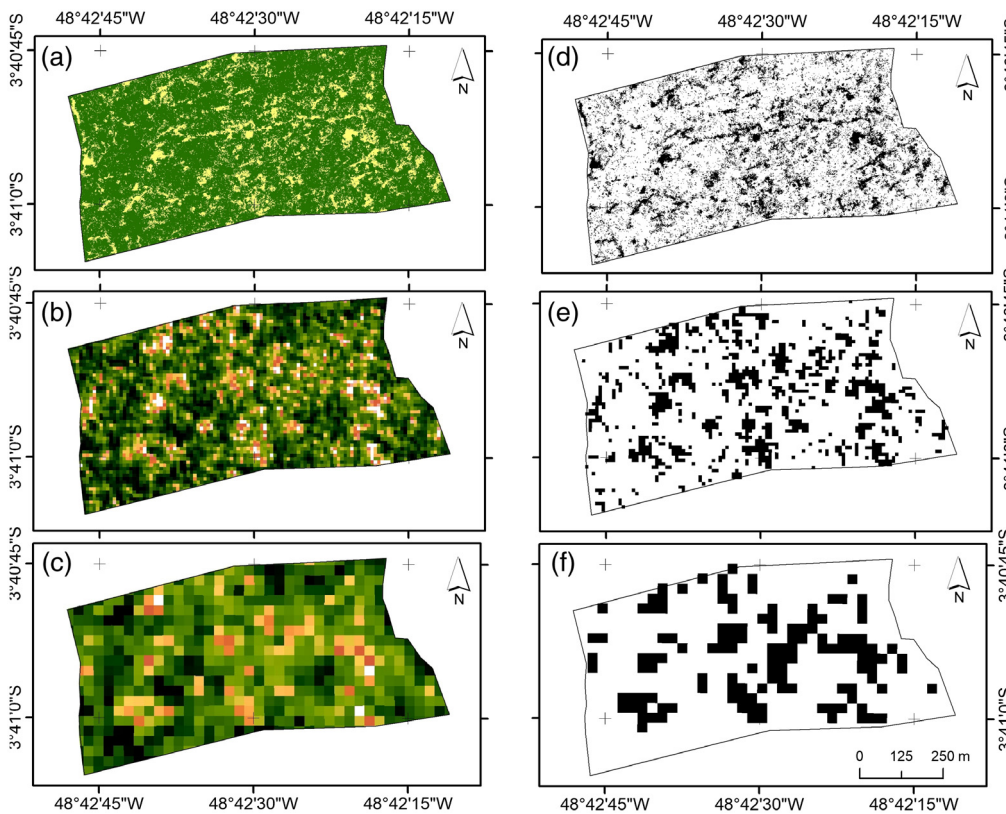


Fig. 6 Classification results for the study site, a logging unit of 50 he within the Rio Capim Forest Estate, state of Pará, Brazil, August 2020. (a) Classified image acquired by the UAV-CMOS, where canopy openings by selective logging are shown in yellow and closed canopy in green. (b) Fractional coverage derived from Sentinel-2 MSI, where closed canopies are in dark green and canopy openings caused by logging are in white, orange, yellow, and light green, varying from heavy to light impacts, accordingly. (c) Fractional coverage derived from Landsat-8 OLI, where closed canopies are in dark green and canopy openings caused by logging are in white, orange, yellow, and light green indicate heavy to light impacts. Binary images derived from UAV-CMOS (d), Sentinel-2 (e), Landsat-8 OLI (f); white, closed canopy; black, canopy opening.

The similar values of estimated overall canopy gaps across the study site were associated with spatial landscape characteristics (Table 4; Fig. 5), largely related to sensor spatial resolution. Regarding canopy gaps, Sentinel-based maps contained seven times more distinct gap areas identified (2.7 ha^{-1}) than those based on Landsat (0.4 ha^{-1}). The largest canopy gap in the

Table 4 Landscape characterization of images resampled to a common resolution of 0.5 m in a selectively logged are of 50 ha, Rio Capim Forest Estate, state of Pará, Brazil, August 2020.

Sensor	Class level (gap)		LSI	LPI (%)
	Patch density (100 ha ⁻¹)	Edge density (m.ha ⁻¹)		
Landsat-8	42	158	4.2	9.3
Sentinel-2	270	372	14.8	1.7
UAV-CMOS	9567	1680	74.6	0.6

Note: LSI, landscape shape index; LPI, largest patch index.

Sentinel map was over five times smaller (1.7% of the total study area) than that in the Landsat-based map (9.3%). The complexity of the shape of the gaps was over three times greater in Sentinel (LSI = 14.8) than in Landsat (4.2).

4 Discussion

Field verification is usually required to assess accuracy of digital image classification. A major drawback of field verification is it being labor and time intensive. Our study showed that by applying an alternative (although not being a substitute) approach using UAV, we were able to produce reference images of very high spatial resolution (0.5 m).

We successfully used UAV images to assess detailed forest impacts caused by selective logging, including tree fall gaps, skid trails, and log landings (patios and forest roads). Our results showed that the number of individual gaps identified by UAV was 228 and 35 times larger than those detected using Landsat-8 and Sentinel-2 imagery, and the maximum gap size was reduced 16- and 3-fold, respectively. This can explain the estimated high omission and commission errors to detect selectively logged forests when using remotely sensed data acquired from Sentinel-2 and Landsat-8. Sensors onboard of the UAV have been applied for several applications (e.g., to detect illegal occupation of urban areas³⁰ and changes in canopy height³¹) given their superior ability to acquire images at a high spatial resolution and suffering from less atmospheric effects compared with satellite-borne sensors. In addition, the built-in GPS of UAV can accurately acquire location coordinates for using for georeferencing the UAV images satellite images. However, in comparison with satellite sensors, UAV-born sensors have the disadvantage of limited extent, which makes their use for large-scale studies limited.

Complementarily, we observed that overall accuracies of detecting canopy opening caused by selective logging and undisturbed canopy were similar using Landsat-8 and Sentinel-2 imagery. The observed low accuracies for detecting canopy disturbances by selective logging were mainly due to the medium spatial resolutions of Landsat-8 and Sentinel-2 images that did not enable capturing subtle disturbances such as tree fall gaps and skid trails. Using Landsat-8 and Sentinel-2 images allowed the detection of heavy forest canopy disturbances and high spectral variations on satellite images caused by log landings/patios and forest roads.

Selective logging has been reported to cause a drier microclimate that makes logged stands susceptible to fire, initiate major changes in stand structure (e.g., Ref. 32) and species composition, and affect animal diversity directly and by increased hunting via improved access (see Ref. 33 for a detailed treatment of edge effects cause by deforestation and in selectively logged forests).

Forest disturbance caused by selective logging in Paragominas municipality has been investigated for decades. The first study by Ref. 34 applied Landsat-5 images acquired in 1986 and 1991 to estimate the extent selectively logged and undisturbed forests. The authors concluded that selective logging disturbed 12% of their study region and that forest canopy impacts were not detectable 3 years after logging activities. Asner et al.³⁵ estimated an average of 4.8% to 8.6% of forest canopy disturbances by reduced impact selective logging in Paragominas municipality

using Landsat imagery acquired between 1996 and 1999. Asner et al.³⁵ also estimated that conventionally logged forests impacted an average of 8.9% to 11.2% of the forest canopy in the same period and study region. These results indicate that canopy openings by selective logging observed in our study site were like those by conventional logging reported by Ref. 35, as a result of the logging intensity currently applied by logging companies in the Amazon region.

5 Conclusions

The image acquired using the UAV for this study allowed us to generate a very high-resolution image mosaic of 0.5 m spatial resolution, which provided a by far more realistic and detailed classification of forest disturbances caused by selective logging activities compared to those based on Landsat-8 and Sentinel-2 imagery. Using the dataset derived from UAV-CMOS sensor, we were able to detect subtle impacts (tree fall gaps, skid trails) as well as heavy impacts (log patios and forest roads) caused by logging. Meanwhile, using remotely sensed imagery (Sentinel-2 and Landsat-8), we were able to detect only the heaviest logging impacts. We observed that spatial resolutions of Sentinel-2 and Landsat-8 were the main constraint to detect detailed canopy disturbances, although we were able to capture more details of forest canopy impacts using the Sentinel-2 than the Landsat-8 image.

We observed that our classification approach using fractional coverage derived from MSAVI_{af} was simple to apply and showed high overall accuracies for detecting disturbed and undisturbed forests. However, it allowed us to better detect undisturbed areas than disturbed ones; for disturbed areas there was a balance between omission and commission errors, which remains a concern as a large number of small-scale canopy openings caused by selective logging go undetected.

Although the overall estimates of selectively logged forests showed good results, we recommend special care in identifying forests impacted by selective logging at local scale using remotely sensed data. Fractional coverage alone showed to be reliable to quantify canopy openings using the Sentinel-2 image, which can be used for monitoring canopy cover impacts and support planning and monitoring of forest management in tropical forests.

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Guido Vicente Briceño Castillo is currently a PhD student at CIRAD (French Agricultural Research Centre and International Development). He was awarded a forest science master's degree in 2021 by University of Brasilia, Brazil. He has been working with remote sensing and geoprocessing applied to forest management in tropical forests.

Lucas José Mazzei de Freitas is a senior scientist at the Brazilian Agricultural Research Corporation (Embrapa) Amazônia Oriental. He was awarded a forest science master's degree in 1999 by the Federal University of Viçosa, Brazil, and his PhD in 2010 by the École Nationale du Génie Rural des Eaux et des Forêts, France. He has been working with forest management in tropical forests and environmental service payments.

Victor Almeida Cordeiro (in memoriam) was an agronomist working with cartography, geoprocessing, and remotely sensed data applied to tropical forest management. He had been admitted to the master's program in forest science, University of Brasilia, Brazil. He tragically died in a car crash in 2021.

Jorge Breno Palheta Orellana is a forest engineer working with forest products. He was awarded a forest science master's degree in 2015 by the University of Brazil, Brazil.

Jorge Luis Reategui-Betancourt is currently a PhD student at the University of Brasilia, Brazil. He was awarded a forest and environmental sciences master's degree in 2017 by Federal University of Mato Grosso, Brazil. He has been working with tropical forest management in the Brazilian Amazon.

Laszlo Nagy is a lecturer in ecology. He leads an integrated Long-term Ecological Research program in the south-eastern Brazilian mountain range.

Eraldo Aparecido Trondoli Matricardi is an associate professor at the University of Brasilia, Brazil. He has been working with forest degradation by selective logging and forest fires in the Brazilian Amazon. His current research interest includes land use and land cover changes, climate changes, and applied remote sensing to environmental issues.