

Mapping palm-tree cover using drone orthomosaics and AI-based methods in the Tiputini region of the Ecuadorian Amazon

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Abstract

This study evaluates the capacity of PalmsCNN, using its default model, to map palm crown cover from UAV orthomosaics at the Tiputini Biodiversity Station (ca. 7 km²) in the Ecuadorian Amazon. We assessed the model performance across three different forest types using clips from two UAV-derived orthomosaics. *Mauritia flexuosa*, the dominant species in the area, was reliably mapped with very few false positives, and its predicted distribution closely matched the existing reference point dataset, although crown cover was underestimated. In contrast, model performance was limited for *Euterpe precatoria* and *Oenocarpus bataua*, the other two species that PalmsCNN was trained to identify. Predictions labeled as *O. bataua* consistently corresponded to *Attalea butyracea*, requiring reinterpretation of the outputs. Additionally, *Iriartea deltoidea*, which is not included in the current PalmsCNN model, was found to be relatively common across all forest types. PalmsCNN performed slightly better on one orthomosaic set despite the other having higher image quality scores. In conclusion, while PalmsCNN effectively generates reliable crown cover maps for *M. flexuosa* across the Tiputini Biodiversity Station, its current model is not suitable for accurately mapping other palm species. Future efforts should focus on fine-tuning PalmsCNN's current model, and/or developing and applying new approaches adapted to the forest composition of the region.

Key words: UAV imagery, palm crown mapping, deep learning, remote sensing, *Mauritia flexuosa*

1. Introduction

Tropical rainforests constitute one of the most complex ecosystems on Earth, providing essential services for global climate regulation, biodiversity conservation, and human livelihoods (Brandon, 2015; Bockerhoff et al., 2017; Belcher, 2005; Pan et al., 2011; Barlow et al., 2016). Within these ecosystems, palm species (family *Arecaceae*) play a central role, contributing to forest structure and offering key resources for local communities through the sustainable extraction of fruits, fibers, and other non-timber forest products (NTFPs) (Ribeiro et al., 2020; Tagle et al., 2025). Among Amazonian palms, species such as *Mauritia flexuosa*, *Oenocarpus bataua*, and *Euterpe precatoria* have attracted increasing attention due to their high ecological and socio-economic importance, particularly in floodplain and swamp forests (Horn et al., 2012; Tagle et al., 2025).

Accurately quantifying palm population distributions, densities, and crown characteristics is useful for

sustainable resource management and conservation. Traditional forest inventory methods in remote Amazonian landscapes are labor-intensive, spatially limited, and logistically challenging (Thaker, 2024; Tagle et al., 2025). While satellite-based remote sensing has transformed large-scale forest monitoring, its spatial resolution remains insufficient to resolve individual palm crowns, especially in dense multi-strata canopies where target species often occupy heterogeneous upper canopy layers (Tagle et al., 2020; Tagle et al., 2025). The advent of unmanned aerial vehicles (UAVs) equipped with conventional RGB sensors and/or more sophisticated multi-spectral, thermal or lidar sensors, has led to the production of cm-resolution orthomosaics, in which individual tree crowns can be visually identified (Csillik et al., 2018; Schiefer et al., 2020). Current advances in deep learning techniques are now enabling crown-level mapping of individual trees across broad spatial extents (Birdal et al., 2017; Csillik et al., 2018; Tagle et al., 2025). Deep convolutional neural networks (CNNs) trained on UAV imagery are demonstrating high accuracy in segmenting and classifying palm crowns, thus providing detailed information on palm density and spatial distribution at spatial extents useful for forest

management and conservation planning (Tagle et al., 2025).

PalmsCNN represents one of the first operational deep learning frameworks specifically developed for palm crown detection in the Amazon, integrating UAV mosaics with extensive ground reference datasets collected in Loreto and Madre de Dios regions of the Peruvian Amazon (Tagle et al., 2025). Such high-resolution maps have significant potential for supporting sustainable harvesting assessments (Hidalgo et al., 2022), monitoring over-extraction pressures (Gilmore et al., 2023), habitat suitability modeling for threatened species (He et al., 2015), restoration planning and land-use decision-making (Cordell et al., 2016; Rochon et al., 2003), and broader forest governance applications across the Amazon basin (Tagle et al., 2025).

However, a key challenge remains in evaluating model transferability across different geographic regions. Variations in crown morphology, palm aggregation, and community composition across Amazonian subregions may affect model performance when applied beyond its original training domain (Dalagnol et al., 2022; Abre-Dias et al., 2025). Therefore, testing PalmsCNN under a wide range of forest types is important to assess its robustness across regions.

In this study, we test the combined use of drone orthomosaics and PalmsCNN to map palm cover in the geographic extent of the Tiputini Biological Station (TBS) (Yasuní Biosphere Reserve, Ecuadorian Amazon), contributing to evaluate in the passing the spatial transferability of PalmsCNN to a sector not included in the training. We thus proceeded without additional fine tuning, which we defer for an ulterior study. We have analyzed 9 clips of UAV surveys across three major forest types: *terra firme*, seasonally flooded plain forest, and swamp forest, capturing key habitat variability known to influence palm distribution.

2. Materials and methods

2.1. Study area

We conducted our research at the Tiputini Biodiversity Station (TBS), Orellana Province, eastern Ecuador (ca. 0°37' S, 76°10' W; 190–270 m a.s.l., Figure 1). TBS spans approximately 7 km² on the left bank of the Tiputini River, adjacent to Yasuní National Park, within one of the most biologically diverse regions on Earth (Bass et al., 2010). The study site encompasses a mosaic of forest types characteristic of the western Amazon basin, including not flooded upland forest ("*terra firme*"), seasonally inundated plain forest (*várzea*, "*inundated*") and permanently flooded palm swamps ("*pantano*"), which host diverse palm assemblages of

both ecological and economic importance (Tagle et al., 2025; Pitman et al., 2017). The region experiences a perhumid tropical climate with high annual precipitation ranging between 2800 mm and 3500 mm, distributed relatively evenly throughout the year with a peak between April and August (Bass et al., 2010; Cisneras, 2003). Mean daily temperatures typically remain between 24 °C and 26 °C, with minimal seasonal variation, and relative humidity often exceeds 80% (Bass et al., 2010).

2.2 UAV Surveys

2.2.1 TBS Imagery

One set of UAV orthomosaics was produced by Gonzalo Rivas in 2023 from photograms acquired using a DJI Mavic 3E platform equipped with a high-resolution RGB sensor (5280×3956 px, 12.29 mm focal length, 3.36×3.36 µm pixel size). Three independent UAV missions were performed across the different forest types: *pantano*, *inundated*, and *terra firme* (Figure 1). All flights were conducted at low altitudes between 82.6 m and 91.2 m above ground to ensure sufficient spatial resolution for detecting individual palm crowns (Table 1).

2.2.2 Purdue University Imagery

A second dataset covering the entire extent of the TBS (Figure 1) was obtained by Purdue University on 9-11/June/2024 using a DJI Mavic 3 Multispectral UAV platform. Flights were conducted at a constant altitude of 150 m above ground with 80 % forward and 80 % side overlap (Table 2).

2.3 Photogrammetric Processing

TBS datasets were processed by Gonzalo Rivas using Agisoft Metashape Professional v.1.8.3 (build 14331) (Agisoft LLC, 2022). The photogrammetric workflow applied identical processing steps for all sites. Dense clouds were generated under high quality settings without filtering. Orthomosaics were created using the DEM as a surface reference, applying mosaic blending mode.

The Purdue flights were processed using Agisoft Metashape Professional v.2.1.0 (build 17526) under default parameters (Agisoft LLC, 2023). Post-processed kinematic (PPK) correction was applied to improve geolocation accuracy, although its final performance is still under evaluation.

In both cases, the coordinate system used was UTM zone 18S with datum WGS 84 (EPSG:32718).

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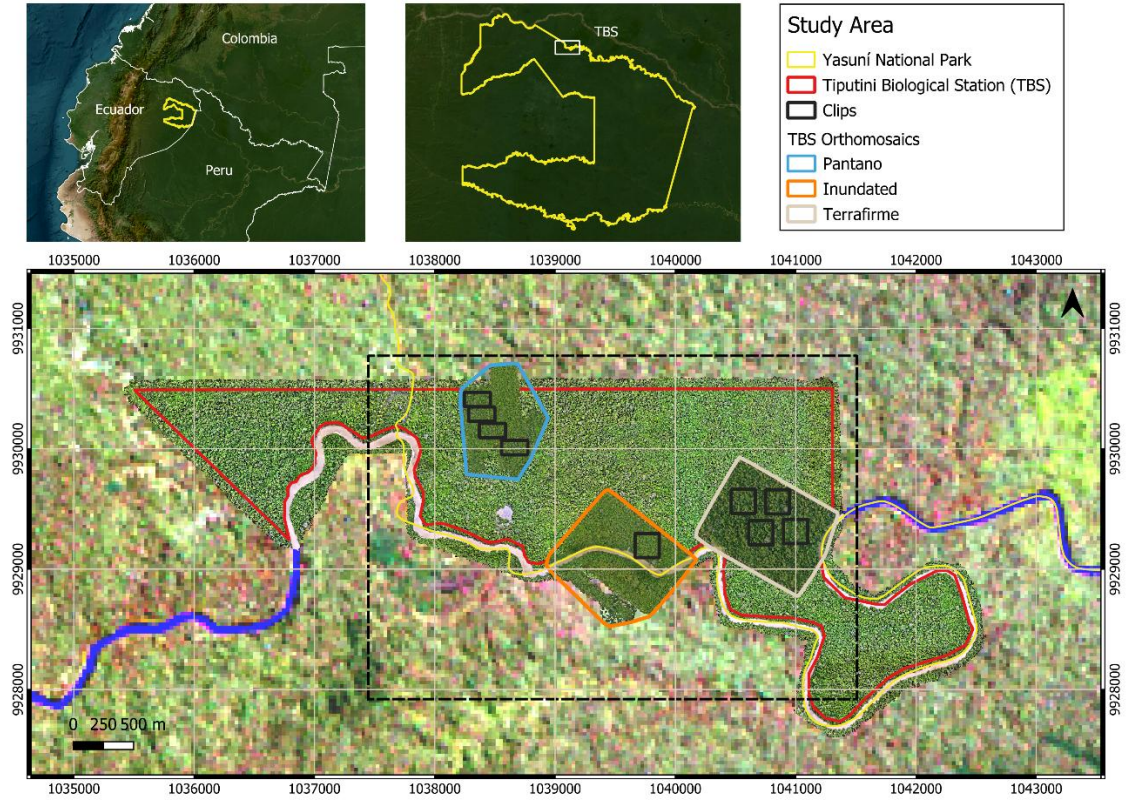


Figure 1. Study area within the Tiputini Biological Station, located in the Yasuní Biosphere Reserve, eastern Ecuador. The main map (UTM zone 18S with datum WGS 84; EPSG:32718) displays UAV orthomosaics and the boundaries of the analyzed clips covering three forest types: permanently flooded palm swamp (*pantano*), seasonally inundated forest and *terra firme*. The first inset map shows the location of Tiputini bordering Yasuní National Park, while the second one places the area within the broader context of Ecuador and the Amazon Basin. The dashed black line outlines the region displayed in Figure 9.

Table 1. TBS UAV Flight Acquisition Parameters

Forest Type	Height (m)	Image Size (px)	Focal (mm)	Pixel (μm)	Images	Area (ha)	Resolution (cm/pix)	Date	Camera Angle
Pantano	85	5280x3956	12.29	3.36	1168	42.8	1.96	Nov 2023	Nadir
Terra firme	91.2	5280x3956	12.29	3.36	725	74.2	2.41	Nov 2023	Nadir
Inundated	82.6	5280x3956	12.29	3.36	653	110	2.19	Nov 2023	Nadir

Table 2. Purdue UAV Flight Acquisition Parameters

Location	Height (m)	Image Size (px)	Focal (mm)	Pixel (μm)	Images	Area (ha)	Resolution (cm/pix)	Date	Camera Angle
Tiputini	150	5280x3956	24	3.3	10243	1011	5	Jun 2024	Nadir

2.4 Clips

In order to keep computing and human efforts within reasonable limits, we defined a set of clips. A total of 9 clips were cropped in each of the two mosaics, the Purdue University and the TBS, covering the same 9 subscenes. Due to minor geometric discrepancies between the two orthomosaics, a slight spatial displacement was observed.

The clips span the three main forest types present in the study area. In both mosaics, four clips were selected in pantano, four in terra firme, and one in the inundated forest. This stratified selection allowed us to assess model performance across varying ecological conditions and canopy structures.

2.5 Orthomosaics Quality Assessment

2.5.1 Distortion

The quality of the UAV orthomosaics was systematically assessed following a distortion-based visual evaluation adapted from the methodology proposed by Tian et al. (2024) for no-reference image quality assessment (NR-IQA) in UAV hyperspectral imagery. While Tian et al. established five quality grades ranging from *Very Bad* to *Excellent*, our dataset did not include severely degraded mosaics corresponding to the lowest category. Therefore, the scale was adjusted with the same number of grades, ranging from 1 (*Poor*) to 5 (*Excellent*), to better describe our data (Table 3).

Before evaluation, a grid of 50 m × 50 m was overlaid on each subscene in QGIS (QGIS.org, 2009) to ensure a systematic and spatially balanced assessment. Each cell was labeled using a row-column system (e.g., 1.1 for row 1, column 1; 2.4 for row 2, column 4 and so on). This labeling helped to organize the data and to easily reference each cell during the analysis. The visual

inspection was then conducted at a fixed scale of 1:250, allowing for detailed observation of image sharpness, crown visibility, and potential distortions within each grid cell. This approach allowed us to identify potential sources of error that may affect model performance across orthomosaics.

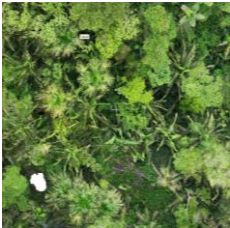
2.6 Interactive crown identification

Gonzalo Rivas (pers. comm.) provided the reference dataset (named here as the *Gonzalo Rivas Point Data-GRPD*), which consists of 6685 tree crown points manually marked on TBS orthomosaics. GRPD includes individuals from 28 species, of which 10 are palm species (Table A1). Each observed palm species was assigned a code (1–10). GRPD was reprojected from its original CRS (EPSG:4326) to that of the orthomosaics (EPSG:32718). As TBS and Purdue mosaics are slightly shifted to each other, I created a second version of GRPD for the clips of the Purdue mosaic by adjusting the points to its correct crown.

For validation of PalmsCNN results, I generated 100 random points within each sub-scene and assigned each point to 0 (no palm crown) or 1 (palm crown). In few cases, the point laid on a dubious position and was recorded as “invalid” (code 200). I recorded the palm species in an additional column: wherever the same palm crown was identified in the GRPD, I kept the corresponding identification. In case the point laid on a palm crown that was not identified in the GRPD, I recorded the point as “unknown” species (code 100), except for *M. flexuosa* and *Attalea butyracea* crowns, which I was able to reliably identify myself.

PalmsCNN predictions were compared against the observations in the validation dataset to compute confusion matrices and calculate evaluation metrics (See Sec. 2.9).

Table 3. Visual examples of UAV image quality across five QA scores (1 = Bad, 5 = Excellent) for datasets TBS and Purdue. Images represent RGB mosaics from forested regions in the Tiputini area, selected across different clips. All images were analyzed at a scale of 1:250.

Quality Score	TBS	Purdue
1= Bad		None
2= Poor		
3= Fair		
4= Good		
5= Excellent		

2.7 PalmsCNN

As fully described in Tagle et al. (2025), PalmsCNN assigns each pixel to class 0 (background) or one of three palm tree species of ecological and economic importance: *M. flexuosa*, *O. bataua* and *E. precatoria*. PalmsCNN is a two-stage deep learning model that combines semantic and instance segmentation. The semantic module is based on DeepLabV3+ architecture with MobileNet-v2 as backbone and Atrous Spatial Pyramid Pooling (ASPP), which allows capturing multi-scale contextual information while maintaining localization accuracy. This semantic module assigns each pixel to either background or one of the target palm species. The instance segmentation module applies the DeepWatershed Transform (Bai and Urtasun, 2017) to delineate individual crowns, using distance-to-boundary information to separate overlapping crowns. Post-processing steps include hole filling, morphological erosion adjusted by species, removal of small segments, and final hole corrections to ensure realistic crown shapes. Full model development, training procedures, and data augmentation strategies are described in Tagle et al. (2025).

Tagle et al. 2025 trained the model using a dataset of 5,089 georeferenced palm individuals with UAV imagery collected across 55 sites in the Loreto region of northern Peru, encompassing diverse forest types including upland terra firme, seasonally flooded forests, palm swamps, and community-managed areas. Extensive data augmentation was applied to enhance generalization, including geometric, radiometric, and distortion-based transformations simulating variability in flight and environmental conditions.

Tagle et al. 2025 evaluated model performance in their imagery through internal validation and external testing on UAV mosaics from Madre de Dios (southern Peru). The final model achieved high detection performance for *M. flexuosa* (F1-score 81 %), and moderate performance for *O. bataua* (F1-score 65 %) and *E. precatoria* (F1-score 64 %).

2.8 PalmsCNN runs

Agustín Lobo (pers. comm.) run PalmsCNN for the selected clips using slightly modified versions of python scripts provided by Ximena Tagle, on GEO3BCN-CSIC high-performance computing facility. PalmsCNN output consists on geotiff raster files with the same geometry of the input clips, in which 0 codes for no palm and integers 1-3 code for each palm species considered by the model: *M. flexuosa*, *O. bataua*, and *E. precatoria* respectively.

2.9 Evaluation of PalmsCNN results

We evaluated PalmsCNN results using the aforementioned dataset of 100 random points for each subscene (See Sec. 2.6). For each point, the model prediction (SPpred) was automatically extracted from the PalmsCNN output raster, while the validation class (SPobsv) was manually assigned based on visual interpretation of the high-resolution imagery with the help of GRPD. As the GRPD had been positioned on TBS orthomosaics and those by Purdue have a slightly different geometry, we made a second version of GRPD for those clips by interactively shifting GRPD points to their corresponding crown in Purdue clips. In addition to the species code, we introduced a column for palm/non palm. We also recorded whether a given random point was on a palm crown that had been marked in GRPD. PalmsCNN results were evaluated from the confusion matrices, both for palm/non-palm and at species level. We calculated precision (user's accuracy), recall (producer's accuracy), F1 score and overall accuracy. All processing in this section was performed using R Statistical Software (v4.1.2; R Core Team 2021). The overall accuracy (OA) is the total number of correctly classified pixels (tp), divided by the total number of samples (N_c):

$$OA = \frac{\sum_{class}^i tp}{N_c}$$

where i is the number of classes.

The precision- user's accuracy (UA)- is the number of correctly classified objects (true positives, tp) in a class divided by the total number of points that were predicted by the model:

$$UA_{class} = \frac{tp_{class}}{N_{classified}}$$

The recall- producer's accuracy (PA)- is derived by dividing the number of correctly classified objects per class (tp) by the total number of polygons according to the ground reference:

$$PA_{class} = \frac{tp_{class}}{N_{groundreferenceclass}}$$

The F1 score is the harmonic mean of recall and precision to provide a comprehensive assessment of a model's performance and thus expresses the balance between recall and precision:

$$F1score = 2 \times \frac{precision \times recall}{precision + recall}$$

The F1 score was used to assess overall performance, instead of the overall accuracy, because *M. flexuosa* was more abundant in most plots compared to other palm species.

2.10 Crown cover

2.10.1 From PalmsCNN results

In order to produce a map at an operational scale for the TBS region and to keep a similar scale to that of most common satellite products, we estimated palm crown cover by calculating the percentage of crown area within a 400 m² circular neighborhood (radius= 11.3 m) centered on each pixel. We applied a two-step process. First, we aggregated crown cover from high-resolution rasters to a 1 m² resolution to keep computing requirements within the limits of a desktop computer. Then, we used a circular moving window to compute the percentage of palm crown cover in each pixel neighborhood ($r= 11.3$ m). For both sets of clips, we generated two maps: one showing *M. flexuosa* only (the dominant species in swamp forests), and another including all three target species of PalmsCNN. We carried out all processing in R using custom scripts built with the *terra* package.

2.10.2 From GRPD

To mimic crown results as those from PalmsCNN, we assumed GRPD points to be the center of constant circular palm crowns of 4 m radio, and rasterized at 0.05 m resolution. We then proceeded as with PalmsCNN results to generate maps of (i) all palm species, (ii) the 3 palm species resulting from PalmsCNN, and (iii) *M. flexuosa*.

2.11 Software

Computing was performed with R (R Core Team, 2025), with particular use of packages *terra* (Hijmans, 2025) for geoprocessing, *lmodel2* (Legendre, 2024) for model II regression, *ggplot2* (Wickham, 2016) for graphics, and *plyr* (Wickham, 2011) for data handling. Visualization and interactive analysis were conducted with QGIS (GIS Development Team, 2024).

3. Results

3.1 Orthomosaics Quality Assessment

The orthomosaic quality assessment indicated overall fair image quality for both UAV datasets, with localized distortions commonly observed. In the TBS dataset ($n= 140$), the mean quality score was 3.10, while the

Purdue dataset (n= 140) achieved a slightly higher mean of 3.25 (Figures 2 and A1). In both datasets, the modal score was 3 (Fair), accounting for 59 % of cells in TBS and 69 % in Purdue. Comparison between results in Figure 2 highlights the higher central tendency and narrower score distribution in the Purdue dataset, with no bad quality grids.

Quality Score	TBS % (n=140)	Purdue % (n=140)
1	2.9	0
2	12.9	5.0
3	58.6	67.9
4	22.9	24.3
5	2.9	2.9

(a)

3.2 Evaluation of PalmsCNN results

Figure 3 shows an example of the crown segmentation resulting from PalmsCNN overlaid on both TBS and Purdue mosaics, alongside the GRPD for the same area. Although we did not formally evaluate the geometric quality of PalmsCNN crown segmentation, PalmsCNN crowns were in general better delineated in the TBS mosaic, in particular in the case of *A. butyracea*.



(b)

Figure 2. UAV orthomosaic image quality scores for TBS and Purdue datasets. (a) Distribution of quality scores in percentage across all grid cells. (b) Plot showing individual points representing evaluated grid cells of 50 m x 50 m. While both datasets show similar central tendencies (mode= 3, or Fair), Purdue exhibits fewer cells with Poor and Bad quality.

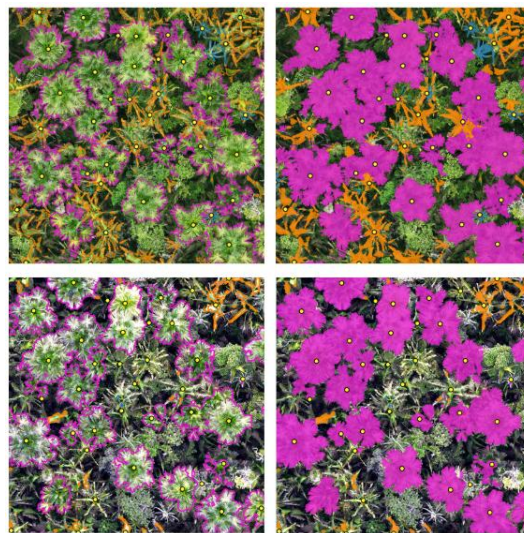


Figure 3. Crown segmentation results from PalmsCNN: *M. flexuosa* (purple), *E. precatoria* (blue) and *A. butyracea* (orange). Validation points from GRPD reference data (yellow) over orthomosaics from TBS (up) and Purdue (down).

3.2.1 Palm/non-palm classification

In the TBS clips, 0.009 % of the random validation points (n=8) were excluded due to dubious positioning (class= 200), and 0.03 % (n=25) were labeled as unknown species (class= 100). In the Purdue clips, all points were valid, though 0.035 % (n= 31) were labeled as unknown (class= 100). Palm vs. non-palm identification was always possible, even in the cases of unknown species. The confusion matrices for TBS and Purdue clips (Table 5) summarize the total number of correctly and

incorrectly classified palm and non-palm instances for each dataset. PalmsCNN consistently shows a conservative behavior, with a strong tendency to avoid false positives- only one was recorded in the TBS dataset and none in Purdue (Table 6). However, PalmsCNN tends to underestimate palm abundance, particularly in the Purdue clips (Figure 4, Table A2).

Table 5. Global confusion matrices for palm/non-palm classification

		Observed	
		Palm	Non-palm
Predicted	Mosaic		
	TBS	Palm (1)	64
		Non-palm (0)	80
	Purdue	Palm (1)	37
		Non-palm (0)	91

Table 6. False positive and false negative rates for palm classification in TBS and Purdue UAV clips. The total number of observed palms corresponds to the sum of true positives and false negatives in each confusion matrix.

Mosaic	Total Palm Observed	False Positives (%)	False Negatives (%)
TBS	145	0.13	55.6
Purdue	128	0	71.1

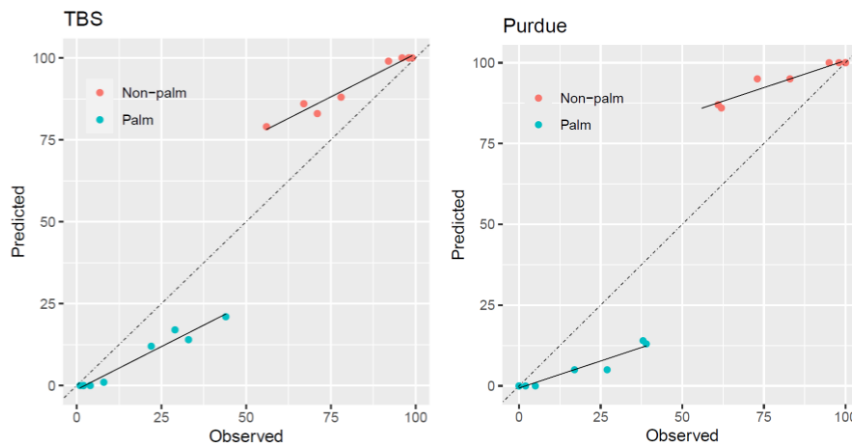


Figure 4. Observed vs. predicted values for palm and non-palm classes in TBS and Purdue UAV datasets. Each point represents a validation subscene, with blue indicating palm and red indicating non-palm classifications. The dashed line represents the 1:1 reference. See Table A2 for regression statistics.

The model achieved high overall accuracy in both datasets, 91.0 % in TBS and 89.9 % in Purdue. User's accuracy (precision) was excellent: 0.985 in TBS and 1.000 in Purdue, reflecting its remarkably few false positive predictions. However, producer's accuracy (sensitivity) was considerably lower, especially in Purdue (0.289), due to the high number of missed palm instances. The F1-score, which balances precision and recall, was higher in TBS (0.612) than in Purdue (0.448), indicating a better balance of detection performance in the TBS mosaic (Table 7).

Table 7. Summary of model classification metrics on TBS and Purdue UAV mosaics across 9 clips: Overall Accuracy (OA), Producer's Accuracy (PA), User's Accuracy (UA), F1-score.

Dataset	OA	PA	UA	F1
TBS	0.910	0.444	0.985	0.612
Purdue	0.899	0.289	1.000	0.448

3.2.2 Species identification

3.2.2.1 TBS

Excluding points labeled as “unknown” (n=25; 0.03 %) and as “invalid” (n=8; 0.009 %), PalmsCNN achieved an overall accuracy of 91.8 %. Notoriously, none of the predictions for *O. bataua* (class=3) were correct. Instead, 16 of the predictions for *O. bataua* corresponded to *A. butyracea* and 3 were classified as “unknown”. We can thus consider that, in this region, PalmsCNN code “3” stands for *A. butyracea* rather than for *O. bataua*. When reinterpreting the results with this adjustment, the overall accuracy of the revised confusion matrix raises to 93.6 % (Table A3). No crowns of *E. precatória* were identified by PalmsCNN at the positions of the validation points, but this species was also very rare in the random validation points (n=1; 0.001 %). Because of their low density in the GRPD, none of the random validation points coincided with individuals of *Wettinia maynensis* and *Bactris riparia*.

Non-palm and *M. flexuosa* were the only classes with consistent detection: *Non-palm* achieved excellent performance across all metrics (PA= 0.999, UA= 0.926, F1= 0.961), while *M. flexuosa* showed good results (F1 = 0.845), despite a lower producer's accuracy (0.759), indicating omission errors (Table 8). PalmsCNN produced only one false positive out of 892 validation points across all TBS clips, which corresponds to an individual of *Cecropia herthae*, a non-palm species (Fig. 5).



Figure 5. *Cecropia herthae* detected by PalmsCNN as a palm tree species.

3.2.2.2 Purdue University

In the Purdue clips, 31 points (0.035 %) were labeled as unknown species, with no invalid records. Species-level classification results are shown in Table A4. PalmsCNN run on clips of the Purdue mosaic detected *M. flexuosa* at the positions of the random validation points only, despite 33 crowns of *A. bataua* being actually observed in the validation dataset. The “no palm” class achieved the highest performance (PA= 1.000, UA= 0.928, F1= 0.963), and *M. flexuosa* obtained a reasonable balance (PA= 0.648, UA= 0.946, and F1= 0.769). After excluding “unknown” points, PalmsCNN achieved an overall accuracy of 92.9 % (Table 9).

3.3 Palm crown cover

Figure A2 displays palm crown cover (%) by species and for each subscene, stratified by forest type (*inundated*, *pantano* and *terrafirme*) and by dataset: interactive point data (GRPD), PalmsCNN on TBS orthomosaics, and PalmsCNN on Purdue orthomosaic. Note that, beyond the species identified by PalmsCNN (*M. flexuosa*, *E. precatória* and *A. butyracea*), 6 more species are recorded in GRPD. Among those, *Iriartea deltoidea* occurs in appreciable crown cover.

While PalmsCNN results of palm crown cover from TBS and Purdue orthomosaics are linearly related (Fig. 7a, Table A5), results from the Purdue mosaic are clearly under those of TBS, particularly so for *E. precatória* and *A. butyracea*.

Compared to results from GRPD, crown cover from PalmsCNN is underestimated (Fig. 7b, Fig. 9, Table A6), although with a very linear relationship for *M. flexuosa*, in particular for the case of clips from TBS orthomosaics (Fig. 10). As *M. flexuosa* largely dominates, results from PalmsCNN for total palm cover are very linear as well (Fig. 8). Results for *E. precatória* and *A. butyracea* severely depart from results derived from GRPD observations.

Table 8. Evaluation metrics for species-level results of PalmsCNN on TBS UAV mosaics: Producer's Accuracy (PA), User's Accuracy (UA) and F1-score. Note: PalmsCNN code 3 revised to be *A. butyracea* (see text). OA=0.933.

Species	PA	UA	F1
No palm	0.999	0.926	0.961
<i>M. flexuosa</i>	0.759	0.953	0.845
<i>E. precatoria</i>	0	NA	NA
<i>O. bataua</i>	0	0	NA
<i>A. butyracea</i>	0.485	0.842	0.615

Table 9. Evaluation metrics for species-level classification in Purdue University UAV mosaics: Producer's Accuracy (PA), User's Accuracy (UA) and F1-score. OA= 0.929.

Species	PA	UA	F1
No palm	1	0.928	0.963
<i>M. flexuosa</i>	0.648	0.946	0.769
<i>E. precatoria</i>	NA	NA	NA
<i>O. bataua</i>	0	NA	NA
<i>A. butyracea</i>	0	0	0

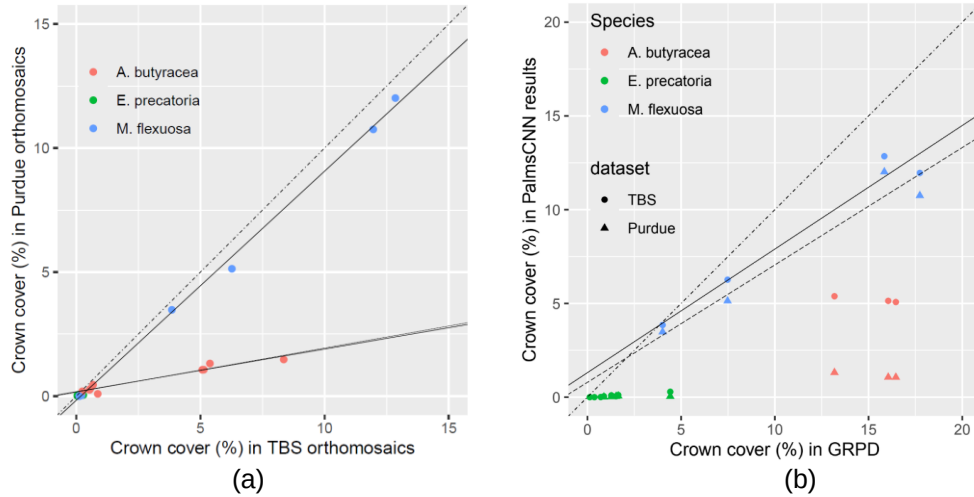


Figure 7. Scatterplot of (a) Palm crown cover by species and for each subsene, as predicted by PalmsCNN in TBS and Purdue orthomosaics and (b) Palm crown cover for each subsene: PalmsCNN results vs. GRPD results by species (See Table A5 and A6 respectively for regression statistics).

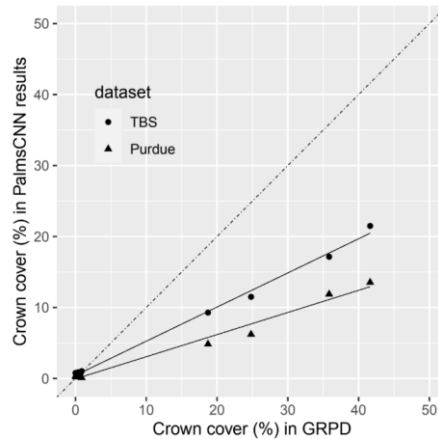


Figure 8. Palm crown cover for each subsene: PalmsCNN results vs. GRPD results of total palm crown cover. Dotted line is the 1:1 relationship for reference.

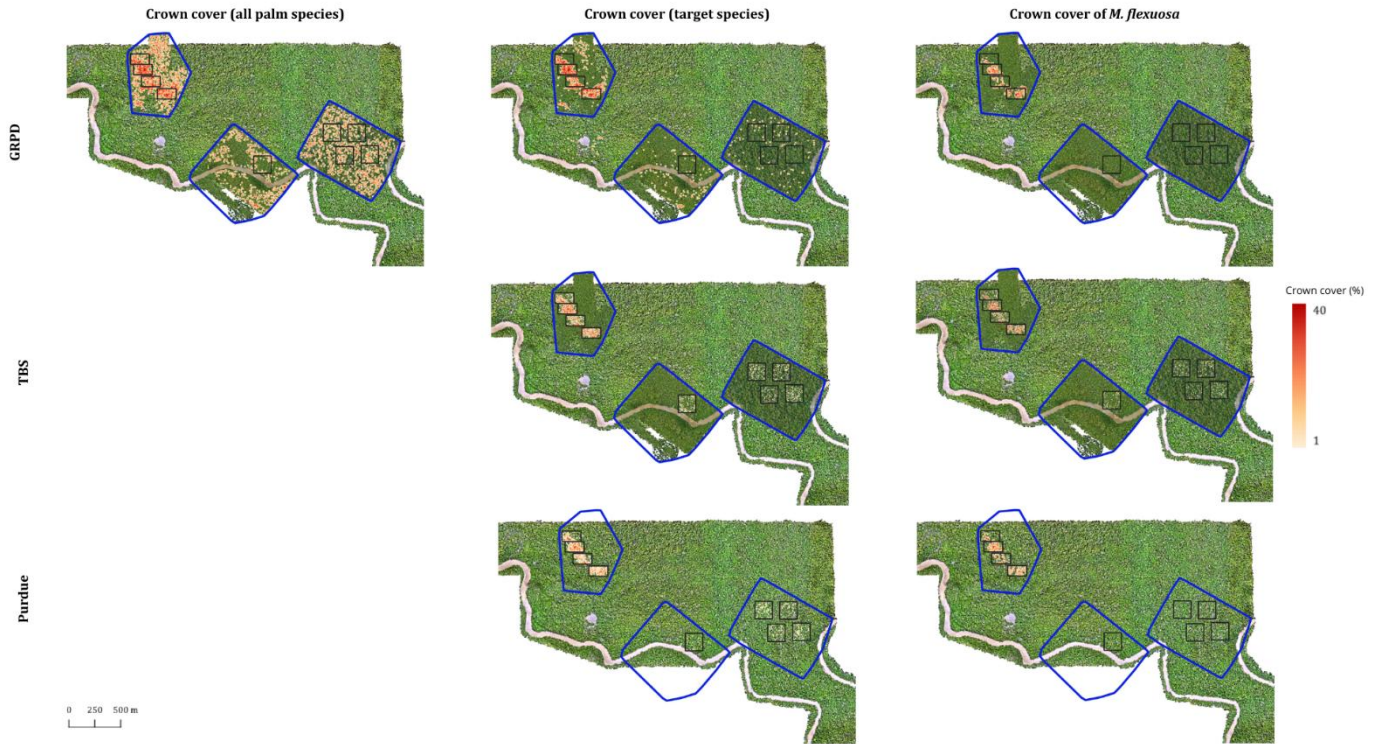


Figure 9. Palm crown cover derived from the three datasets: GRPD (interactive points), TBS (PalmsCNN results with clips of TBS orthomosaics), and Purdue (PalmsCNN results with clips of Purdue orthomosaic). "All palm species" refers to the 10 species identified in GRPD; "target species" refers to *M. flexuosa*, *E. precatoria*, and *A. butyracea*. The represented area matches the dashed black polygon highlighted in Figure 1.

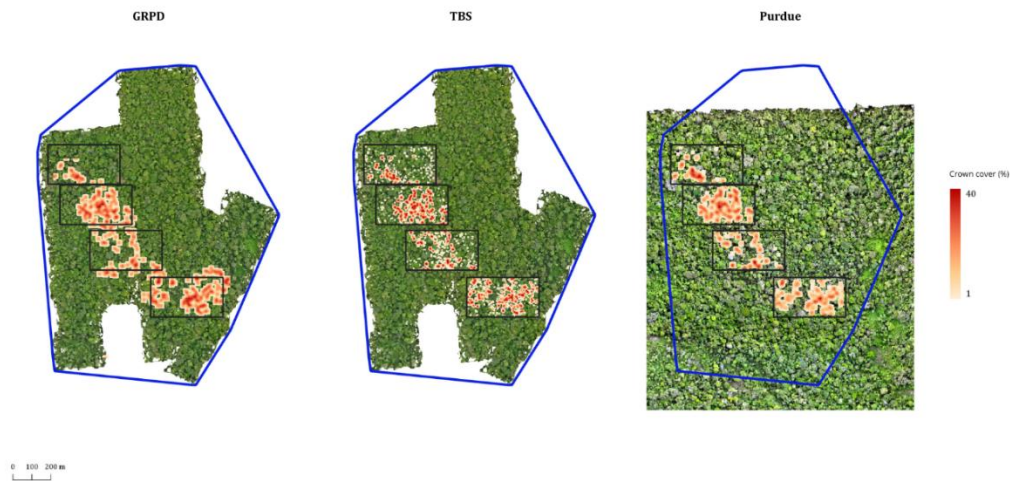


Figure 10. Crown cover of *M. flexuosa* in the *pantano* area as derived from the three datasets: GRPD (interactive points), TBS (PalmsCNN results with clips of TBS orthomosaics), and Purdue (PalmsCNN results with clips of Purdue orthomosaic). The blue polygon corresponds to the one situated at the NW of Figure 1.

4. Discussion

Previous studies have successfully combined UAV imagery with convolutional neural networks to detect and classify individual palm trees and generate species-specific crown density maps in Amazonian forests (Ferreira et al., 2020; Tagle et al., 2025). However, although individual tree classification methods tend to achieve high accuracy in controlled settings, their applicability in environments that differ from their training conditions remains uncertain (Abre-Dias et al., 2025). Our results confirm that *M. flexuosa*, the dominant species in our study area, can be reliably mapped using PalmsCNN with its default model. Its predicted spatial distribution closely matched that of the GRPD reference data, although palm crown cover was generally underestimated. Nevertheless, its current configuration is not adequate for other species present in the region. Since *M. flexuosa* is the dominant species, it might appear sufficient to characterize total palm cover. However, this would lead to misinterpretations, as GRPD clearly shows that the spatial distribution of *M. flexuosa* differs from that of other palm species. In areas where *M. flexuosa* is absent, relying on the model's predictions would result in inaccurate estimates of total palm cover.

At a species level, PalmsCNN obtained high classification accuracy for *M. flexuosa*, with better metrics in TBS (precision 75.9 %; recall 95.3 % and F1 score of 84.5 %) than Purdue (precision 64.8 %; recall 94.6 % and F1 score of 76.9 %). These findings are consistent with Tagle et al. (2025), who reported a F1 score of 81 % for *M. flexuosa* in Peruvian peatlands applying PalmsCNN. In contrast, performance for *E. precatoria* and *O. bataua* was limited. *E. precatoria* was not detected in either dataset. This species had the fewest training samples in the original model (282), which may partly explain its poor detection. *O. bataua* was only detected in the TBS dataset, but all predictions under this label corresponded to *A. butyracea*, requiring reinterpretation of PalmsCNN's output in this region. Previous studies mapping *A. butyracea* reported misclassification rates exceeding 18%, likely due to canopy structural similarities with other palm species (Ferreira et al., 2020). The limited number of *O. bataua* samples (n=310) in the training data, compare to other species such as *M. flexuosa* (n= 4497), may have limited the model's ability to extract species-specific characteristics. Consistent with the findings of Tagle et al. (2025), we observed that detection was lower in subscenes where palm crowns were partially obscured by taller non-palm trees, contributing to underestimation of abundance, particularly in the *terra firme* subscenes. Interestingly, PalmsCNN's performance was better in the TBS than in Purdue mosaics, despite Purdue receiving slightly higher quality score in our image

quality assessment (3.25 vs 3.10 on a 5-point scale). TBS had higher producer's accuracy (0.44 vs. 0.29) and better delineation of palm crowns, particularly for *A. butyracea*. A likely conjecture is the higher spatial resolution of TBS imagery (2.5 cm/pixel, captured at 82 m- 91 m altitude) compared to Purdue (5 cm/pixel, captured at 150 m), since ground sampling distance has been shown to strongly influence crown segmentation and detection (Ferreira et al., 2020). Although we did not perform a formal crown segmentation analysis, we qualitatively observed clearer crown delineation in TBS mosaics. Nevertheless, we must specifically address this issue in the future.

When generating density maps derived from the GRPD reference data, we used a uniform 8 m crown diameter for all species, which is obviously a first, crude approach. While this allowed a first comparison of PalmsCNN outputs with the currently best available data (the GRPD dataset), it ignores species and eventually site differences in crown size. Palm crown size of *M. flexuosa* can exceed 8-10 m in diameter, while *I. deltoidea* or *E. precatoria* crowns are often smaller. Future analyses must estimate this error by incorporating species-specific crown dimensions in a subsample.

Our accuracy assessment relied on a random sample of 900 points, which was a required first step but implied a relatively small number of validation points on palm crowns other than *M. flexuosa*. Despite using the F1 metric, the short number of palm crowns other than *M. flexuosa* recorded in the confusion matrices limited the statistical relevance of user's and producer's accuracies. We obviously must include additional validation points in a future analysis.

All things considered, fine-tuning the current PalmsCNN model to the Tiputini region should be a priority for future work. Incorporating palm crown data from the study area into the training process would help the model to adjust to regional variations. Fine-tuning could improve detection for underrepresented or locally abundant species, making PalmsCNN more effective for palm crown mapping in the Tiputini Biological Station beyond *M. flexuosa*.

5. Conclusions

Our study evaluated the capacity of PalmsCNN with its current model to map palm crown cover from UAV orthomosaics across three forest types in the Tiputini region. The default model showed useful and reliable results for *M. flexuosa*, the dominant species in the study area, with very few false positives. The predicted spatial distribution of *M. flexuosa* closely followed the observed one in the GRPD dataset, although crown cover was underestimated.

By contrast, model performance for the other species contemplated by the model (*E. precatoria* and *O. bataua*) was limited. Although PalmsCNN was originally trained to identify *O. bataua*, predictions under this label consistently corresponded to *A. butyracea* in our study area, requiring reinterpretation of the outputs. Additionally, the analysis of GRPD indicated that *I. deltoidea*, which is not contemplated by the current model of PalmsCNN, is a relatively common species in Tiputini across all three forest types.

PalmsCNN results were slightly better in runs with subscenes of the TBS orthomosaics than in those of the Purdue orthomosaic, despite our orthomosaic quality assessment indicated slightly higher image quality scores in the Purdue orthomosaic.

In summary, PalmsCNN with its current model can be applied to generate reliable crown cover maps of *M. flexuosa* in the entire region of the Tiputini Biological Station (~7 km²), but it is not suitable for other species. Future efforts should focus on fine-tuning the model and/or testing other approaches adapted to the forest composition of the region.

Acknowledgments

This work has been possible thanks to the kind collaboration of outstanding scientists who have shared their knowledge, data and software, for which I am grateful and feel privileged. Gonzalo Rivas facilitated his awesome dataset of identified tree crowns and the TBS drone orthomosaics. Jinha Jung and his team shared his amazing orthomosaic covering the entire area of Tiputini Biological Station. Ximena Tagle provided the PalmsCNN code and default mode, along with advices for running it. I would also like to express my deepest gratitude to Agustín Lobo, my thesis advisor, whose unwavering support has been a driving force throughout this work. His guidance extended far beyond remote sensing, helping me navigate a wide range of tools and methodologies essential to this research. I am especially thankful for his patience, insightful feedback, and contagious enthusiasm, which greatly enriched my learning experience and the outcome of this thesis.

Appendix

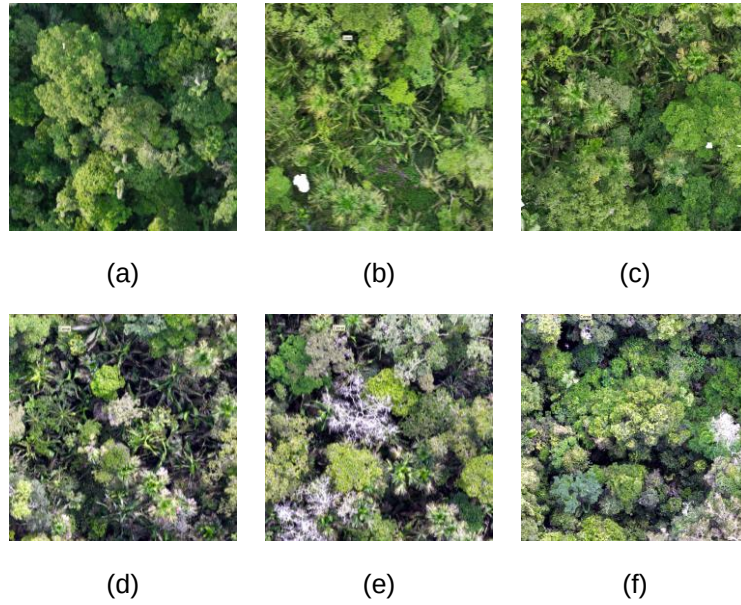


Figure A1. Representative grid cells assessed as "Fair" (score=3) from the TBS dataset (a–c) and the Purdue dataset (d–f).

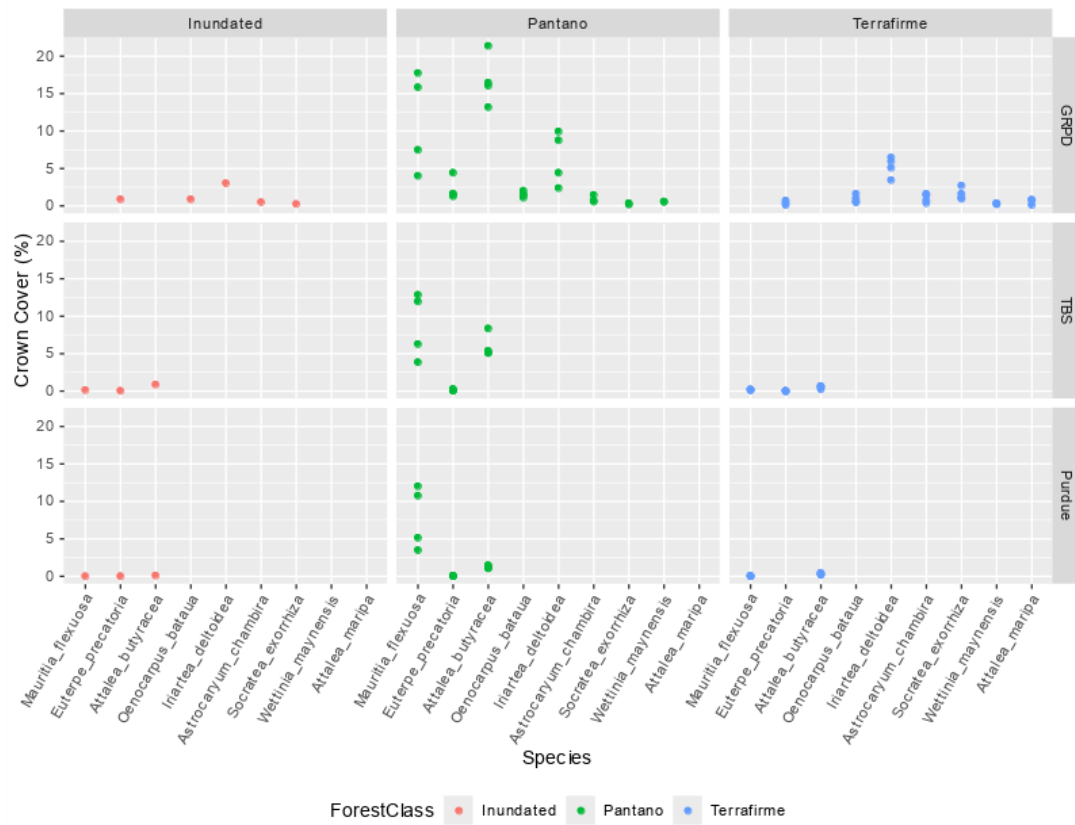


Figure A2. Palm crown cover (%) by species and for each subszene, stratified by forest type and dataset.

Table A1. List of palm and non-palm species recorded in the reference dataset Gonzalo Rivas Point Data (GRPD).

Palms species	Non palm species
<i>Astrocaryum chambira</i>	<i>Brownea grandiceps</i>
<i>Attalea butyracea</i>	<i>Cecropia ficifolia</i>
<i>Attalea maripa</i>	<i>Cecropia herthae</i>
<i>Bactris riparia</i>	<i>Cecropia membranacea</i>
<i>Euterpe precatoria</i>	<i>Cecropia sciadophylla</i>
<i>Iriarte deltoideia</i>	<i>Cecropia sp.</i>
<i>Mauritia flexuosa</i>	<i>Cedrela odorata</i>
<i>Oenocarpus bataua</i>	<i>Ceiba pentandra</i>
<i>Socratea exorrhiza</i>	<i>Erythrina sp.</i>
<i>Wettinia maynensis</i>	<i>Ficus sp.</i>
	<i>Gustavia longifolia</i>
	<i>Inga sp.</i>
	<i>Parkia sp.</i>
	<i>Pentagonia subauriculifolia</i>
	<i>Sloanea sp.</i>
	<i>Triplaris cumingiana</i>
	<i>Virola sp.</i>
	<i>Zygia sp.</i>

Table A2. Results of OLS regressions of the number of PalmsCNN predictions against the number of observations for both TBS and Purdue validation datasets. See Fig. 4.

Dataset	Intercept	Slope	R ²	p	Class
TBS	48.746	0.525	0.963	<0.001	Non-palm
TBS	-1.234	0.525	0.963	0.195	Palm
Purdue	67.208	0.334	0.932	<0.001	Non-palm
Purdue	-0.644	0.334	0.932	0.401	Palm

Table A3. Confusion matrix for species-level PalmsCNN predictions across 9 clips from the TBS UAV mosaics. Rows represent predicted classes and columns represent observed classes. Species are abbreviated as follows: *No. p* = No palm, *Mf* = *M. flexuosa*, *Ep* = *E. precatoria*, *Ob* = *O. bataua*, *Ab* = *A. butyracea*, *Id* = *Iriartea deltoidea*, *Ac* = *Astrocaryum chambira*, *Am* = *Attalea maripa*, *Se* = *Socratea exorrhiza*. Code 100 indicates unknown palm species (*Unk.*) and 200 denotes invalid observations (*Inv.*). (*) Indicates revised version in which PalmsCNN code 3 stands for *A. butyracea* (see text). See Appendix 1 for the complete list of species.

			Observed										
			<i>No palm</i>	<i>Mf</i>	<i>Ep</i>	<i>Ob</i>	<i>Ab</i>	<i>Id</i>	<i>Ac</i>	<i>Am</i>	<i>Se</i>	<i>Unk.</i>	<i>Inv.</i>
			0	1	2	3	4	5	6	7	8	100	200
Palms CNN Predicted	<i>No palm</i>	0	755	13	1	4	17	9	3	1	2	22	8
	<i>Mf</i>	1	1	41	0	0	0	0	1	0	0	0	0
	<i>Ep</i>	2	0	0	0	0	0	0	0	0	0	0	0
	<i>Ob</i>	3	0	0	0	0	16	0	2	0	1	3	0
	<i>Ab</i>	3 (*)	0	0	0	0	16	0	2	0	1	3	0
	<i>Unk.</i>	100	0	0	0	0	0	0	0	0	0	0	0
	<i>Inv.</i>	200	0	0	0	0	0	0	0	0	0	0	0

Table A4. Global confusion matrix for species-level classification across 9 clips from Purdue University UAV mosaics. Species are represented by name, 100 indicates unknown palm species, and 200 denotes invalid observations. *Mf*, *M. flexuosa*; *Ep*, *E. precatoria*; *Ob*, *O. bataua*; *Ab*, *A. butyracea*.

		Observed									
		<i>No palm</i>	<i>Mf</i>	<i>Ep</i>	<i>Ob</i>	<i>Ab</i>	<i>Id</i>	<i>Ac</i>	<i>Unk.</i>	<i>Inv.</i>	
		0	1	2	3	4	5	6	100	200	
Palms CNN Predicted	<i>No palm</i>	0	772	19	0	2	31	7	1	31	0
	<i>Mf</i>	1	0	35	0	0	2	0	0	0	0
	<i>Unk.</i>	100	0	0	0	0	0	0	0	0	0
	<i>Inv.</i>	200	0	0	0	0	0	0	0	0	0

Table A5. Results of major axis (MA) regression of predicted palm crown cover (TBS vs. Purdue datasets) for each target species and for all palms combined. See Figure 7a.

Intercept	Slope	p	Species
-0.616	0.824	0.01	<i>All</i>
-0.169	0.924	0.01	<i>M. flexuosa</i>
0.026	0.089	0.23	<i>E. precatoria</i>
0.177	0.172	0.01	<i>A. butyracea</i>

Table A6. Results of major axis (MA) regression of predicted palm crown cover (TBS and Purdue datasets) against the ground reference dataset (GRPD), separately for each target species. See Figure 7b.

Intercept	Slope	p	Species	Dataset
1.306	0.659	0.08	<i>M. flexuosa</i>	TBS
0.790	0.626	0.12	<i>A. butyracea</i>	TBS
-1.10	0.423	0.26	<i>E. precatoria</i>	TBS
0.440	0.481	0.01	All species	TBS
0.746	0.029	0.24	<i>M. flexuosa</i>	Purdue
-0.021	0.069	0.01	<i>A. butyracea</i>	Purdue
0.024	0.006	0.21	<i>E. precatoria</i>	Purdue
-0.055	0.312	0.01	All species	Purdue

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