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Uncovering Shifting Cultivation Dynamics in the Amazon: the Synergy Between Field Data and Remote Sensing Image Time Series Classification

Revelando Dinâmicas da Agricultura Itinerante na Amazônia: a Sinergia entre Dados de Campo e Classificação de Séries Temporais de Imagens de Sensoriamento Remoto

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Abstract: This study evaluates the Compound Maximum *a posteriori* (CMAP) classification of Landsat imagery to reconstruct the land-use history of shifting cultivation areas across the Amazon. We estimated agricultural cycles and secondary forest age near the Juruá, Tefé, and Tapajós rivers using annual Landsat composites (1984–2024) classified with CMAP and a generalized training strategy. Comparison with local landowner interviews showed that CMAP effectively estimates these parameters (55% within ±1 for cycles and 93% within ±3 years for age). These results demonstrate CMAP's potential for land-use history reconstruction, with field data integration likely improving the detailing of information.
Keywords: Compound Maximum *a posteriori*. Land-use history. Secondary forest. Landsat.

Resumo: Este estudo avalia a classificação de Máximo *a posteriori* Composto (CMAP) de imagens Landsat para reconstruir o histórico de uso da terra de áreas de agricultura itinerante na Amazônia. Foram estimados os ciclos agrícolas e a idade das florestas secundárias próximas aos rios Juruá, Tefé e Tapajós, utilizando composições anuais de imagens Landsat (1984–2024) classificadas pelo CMAP com uma estratégia de treinamento generalizado. A comparação com entrevistas de proprietários locais mostra que o CMAP estima de forma eficaz esses parâmetros (55% em ±1 para ciclos e 93% em ±3 anos para idade). Esses resultados demonstram o potencial do CMAP para a reconstrução do histórico de uso da terra. A integração com dados de campo pode aprimorar o detalhamento das informações.
Palavras-chave: Máximo *a posteriori* Composto. Histórico de uso da terra. Floresta secundária. Landsat.

1 INTRODUCTION

Shifting cultivation, also known as swidden-fallow or swidden agriculture, is the primary agricultural system supporting people's livelihoods in the Amazon (Padoch & Pinedo-Vasquez, 2010). Besides supporting food production, it also promotes crop genetic diversity, biodiversity, and the conservation of local traditional knowledge (Denevan et al., 1988; Padoch & Pinedo-Vasquez, 2010). This system is characterized by the rotation of crops with fallow periods. During these fallow periods, the vegetation regenerates due to secondary succession processes. This dynamic creates heterogeneous landscape mosaics that include agricultural fields, successional forests, agroforestry systems, and mature forests (Lawrence et al., 1998; Padoch & Pinedo-Vasquez, 2010). These are also very dynamic systems that can be affected by local or regional environmental variables (such as soil quality and climate) and management practices. As such, related studies demand accurate and detailed information about the localization and land-use history of shifting cultivation areas.

Shifting cultivation systems can occur in rather small patches (ca. 1 ha) (Jakovac et al., 2016b) within relatively heterogeneous and dynamic landscapes. These complex spatial-temporal dynamics can hinder adequate information acquisition. For many regions in the Amazon, this traditional practice predates the 1970s occupation boom. Fallow and regeneration periods can vary between less than four and more than 15 years in riverside regions (Affonso et al., 2016; Jakovac et al., 2017; Steininger, 2000) and over 40 years in indigenous lands (Schmidt et al., 2021). The frequency of cultivation also may vary among regions and due to cultural and socio-economic pressures. For instance, Abrell et al. (2024) mapped one to seven cultivation cycles within 10 years in shifting cultivation fields in the Brazilian Eastern Amazon region.

Usually, the land use history of a given area on the Earth's surface can be acquired using field data or based on land cover information derived from Remote Sensing (RS) imagery. Since field campaigns can demand many resources, they are rarely frequent enough for accurate information retrieval in shifting cultivation areas. The data is usually acquired at isolated times via interviews with local people. As such, its accuracy is subject to the person's memory or personal notes. RS analyses, in turn, often require higher spatial resolution products (Rufin et al., 2025) and/or more refined classification approaches than the trivial land cover classification tasks that consider mono-temporal RS data. Historic (30+ years) RS analyses rely almost exclusively on medium-spatial resolution Landsat imagery, which can be challenging considering the size of some shifting cultivation patches. As proof of complexity, we highlight that shifting cultivation systems are currently invisible in wall-to-wall Brazilian Land Cover and Land Use RS products, such as the Systematic Monitoring of Land Cover and Use (TerraClass) (Almeida et al., 2025) or the Annual Mapping of Land Cover and Use in Brazil (MapBiomas) (Souza et al., 2020).

Estimating land use-history from RS data can be done either by mapping specific types of changes in the RS time series or by classifying those into land cover time series, i.e., labeling observations at each time as a land cover class of interest, and then retrieving the information from this new set (Reis et al., 2020a; Zhu, 2017). When the classification is done independently, this last approach is known as Post-Classification Comparison (PCC). PCC is largely regarded as the most commonly used method for this type of analysis, and has the advantage of allowing for the acquisition of different types of information about land use-history, as it provides the complete information on time and type of changes (Lu et al., 2004). However, this method is subject to the classification of invalid transitions (i.e., those that could never happen in the field) that should be corrected in a post-processing step (Reis et al., 2020a). This can be a very challenging task for complex areas, such as those involving shifting cultivation practices.

Nonetheless, methods that can incorporate multitemporal information to solve the classification of a given time, such as the Compound Maximum *a Posteriori* (CMAP) classifier (Reis et al., 2020b), can offer a viable alternative in using Landsat imagery to help complement field data information. CMAP is a supervised classification approach that considers individual probabilities of observations at each time to generate valid classification time series. When applied to RS data for the land cover problem, CMAP's formulation incorporates the *a priori* knowledge about land cover class dynamics into a Bayesian framework to weight the classification of RS time series. This ensures that only plausible land use and land cover transitions are allowed, without the need for post-classification filters and/or extensive/complex sample collection in space or time.

Based on the above, this study aims to evaluate the use of CMAP to classify Landsat imagery to retrieve land-use history in areas located across the Brazilian Amazon. Here, the estimated attributes of land-use history were the number of agricultural cycles and the age of secondary forests associated with shifting cultivation dynamics. To this end, we compared CMAP results to field information obtained through landowners' interviews, from 88 areas located across the Amazon in three selected sites near the Rivers Tapajós, Tefé, and Juruá. This paper is an extended version of Reis et al. (2025), presented in the XXV Brazilian Symposium on Geoinformatics (GEOINFO 2025).

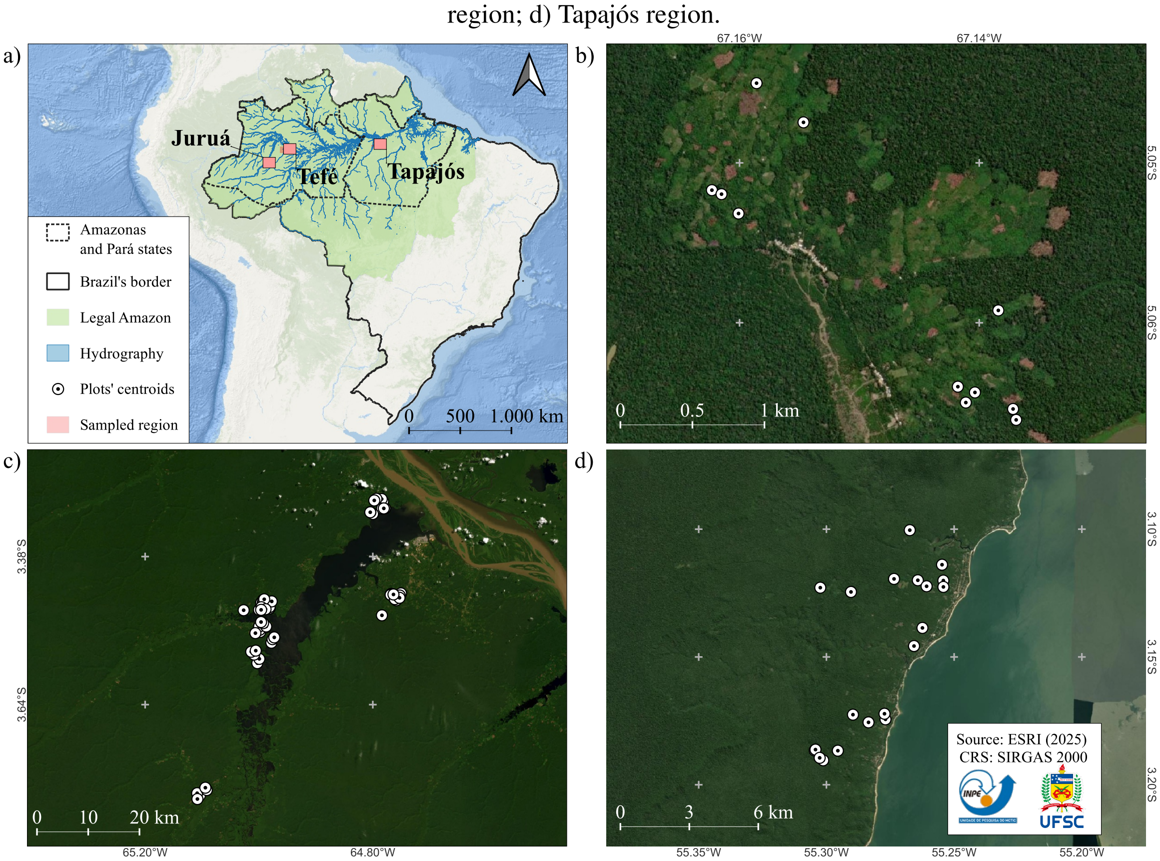
2 MATERIAL

This section describes the study area, classes of interest, and field data, as well as Landsat imagery used in this study. For the Tapajós site, we analyzed the land cover trajectory previously classified by Reis (2022).

2.1 Study area

This study was conducted in the Brazilian Amazon, in riverine communities located at the margins of the Rivers Juruá, Tefé, and Tapajós (Figure 1.a). These areas present slightly different environmental conditions, detailed as follows.

Figure 1 – Location of the study areas: a) in relation to natural and political Brazilian limits; b) Juruá region; c) Tefé region; d) Tapajós region.



Source: The authors (2025).

Juruá is situated in the western Amazon (Figure 1.b), with a mean annual rainfall of around 2,200 mm and a mean annual temperature of about 27 °C. It experiences a short dry season lasting fewer than two months, during which each month receives less than 100 mm of rainfall.

Tefé is located in the central Amazon (Figure 1.c), with a mean annual rainfall of about 2,300 mm and a mean annual temperature of approximately 27 °C. Dry season patterns are very similar to Juruá.

Tapajós is located in the eastern Amazon (Figure 1.d), where both climate and soil conditions differ somewhat from those in the central and western Amazon. This region experiences a pronounced dry season that can last for up to five consecutive months, with each month receiving less than 100 mm of rainfall. The mean annual rainfall is about 2,000 mm (Restrepo-Coupe et al., 2013), and the mean annual air temperature is approximately 25.3 °C.

2.2 Field data

Field data were collected on a total of 88 secondary forest patches (11 in Juruá, 57 samples in Tefé, and 20 in Tapajós, as shown in Figure 1), sampled along gradients of previous land use intensity, in different years: 2023 in Juruá; 2012, 2013, and 2022 in Tefé; and 2024 in Tapajós. The data used in this study correspond to the coordinates of the center point of 20 m × 50 m plots and the information provided by landowners' interviews regarding the land-use history since the mature forest in each patch was cut for the first time. In the interviews, we specifically asked (i) the age of the current secondary forest and (ii) how many times cassava had been planted in that spot. These questions were asked multiple times in different ways and to different family members, in an attempt to filter inaccurate answers.

2.3 Imagery

As previously stated, this study is based on the classification of Landsat time series. We used all Landsat images covering the plots assessed in the field data, from Tier 1 and Collection 2, acquired between August 1 and November 30 of the years 1984 to 2024, hosted in the Google Earth Engine (GEE) platform. We used data from sensors Thematic Mapper (TM), Enhanced Thematic Mapper (ETM+), and Operational Land Imager (OLI) onboard satellites Landsat 5, Landsat 7, and Landsat 8, respectively. This data was used in Surface Reflectance format, without additional processing. The main characteristics of these images are summarized in Box 1.

Box 1 – Landsat imagery description.

Characteristics	**TM**	**ETM+**	**OLI**
Spectral bands (μm)	7 bands:	8 bands:	9 bands:
Coastal/Aerosol	-	-	0.435-0.451
Blue	0.45-0.52	0.45 -0.515	0.452-0.512
Green	0.52-0.60	0.525-0.605	0.533-0.590
Red	0.63-0.69	0.63-0.69	0.363-0.673
NIR	0.76-0.90	0.775-0.90	0.851-0.878
SWIR1	1.55-1.75	1.55-1.75	1.566-1.651
TIR	10.41-12.5	10.4-12.5	-
SWIR2	2.08-2.35	2.08-2.35	2.107-2.294
PAN	-	0.52-0.9	0.503-0.676
Cirrus	-	-	1.363-1.384
Acquisition window (launch to end of the nominal mission)	from July 1982 to January 2013	from April 1999 to April 2022	from February 2013 operating (July 2025)
Spatial resolution (m)	30 (120 in TIR)	30 (60 in TIR, 15 in PAN)	30 (15 in PAN)
Revisit time (days)	16	16	16

Source: NASA (2023), arranged by Reis et al. (2024).

2.4 Classes of interest

For the three regions, we studied the dynamics between four classes of interest:

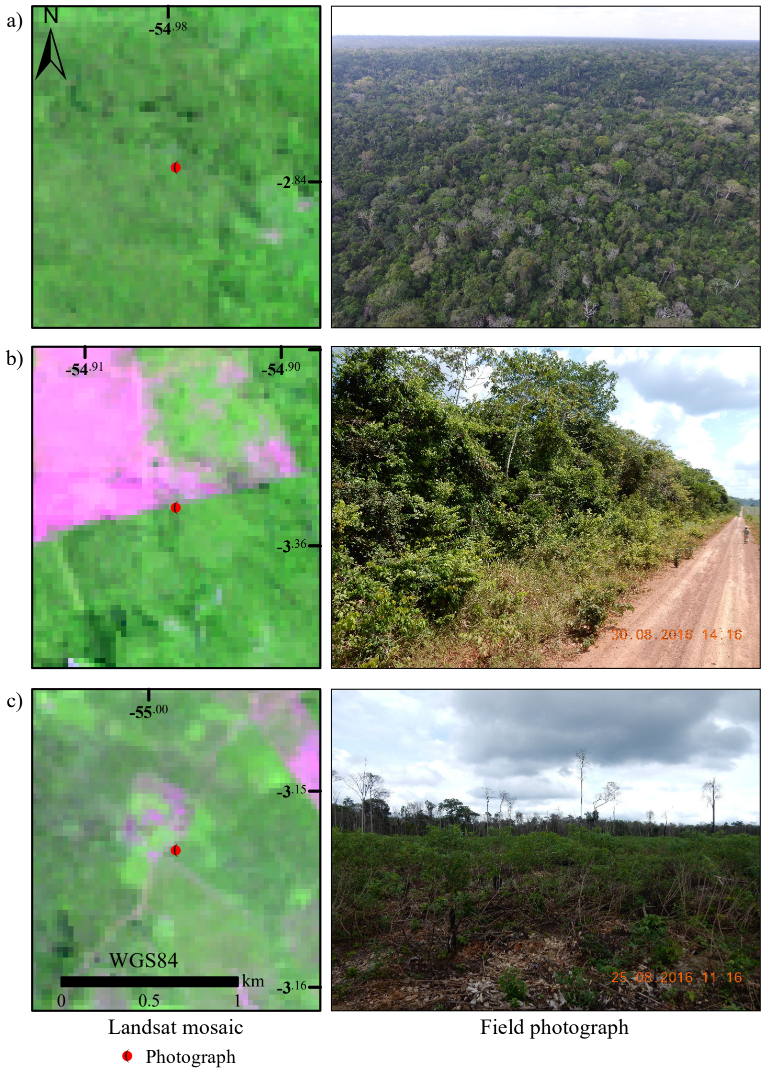
1. Old-growth forest (Figure 2.a) - mature forests, subjected or not to forest degradation events, with no evidence of previous deforestation;
2. Secondary forest (Figure 2.b) - previously deforested areas occupied by structured vegetation not planted by humans;

3. Managed area (Figure 2.c) - agricultural areas used mainly for crop/cattle production, including areas of small-scale agriculture;

4. Other natural areas - areas covered by other natural features, such as rivers, naturally flooded areas, and natural non-forest vegetation.

Figure 2 shows examples of classes of interest. This figure is based on the Landsat mosaics calculated by Reis et al. (2024) and field data collected by Sant'Anna et al. (2016), in August-September of 2016, near the Tapajós region.

Figure 2 – Example of classes of interest as seen in the Landsat mosaic (left) and in the field (right): a) Old-growth forest; b) Secondary forest; c) Managed area. The Landsat mosaic corresponds to the median of Landsat imagery from August to November of 2016, in color composition SWIR1(R) NIR(G) SWIR2 (B) with applied contrast.



Source: Sant'Anna et al. (2016) and Reis et al. (2024).

2.5 Land cover time series for the Tapajós region

This data set encompasses one land cover classification per year in the Tapajós region, from 1984 to 2020, with similar land cover classes and methodology used in the present study. These are fully described in Reis (2022).

3 METHODS

Figure 3 synthesizes the methodology used in this study. Each step is explained in the following subsections.

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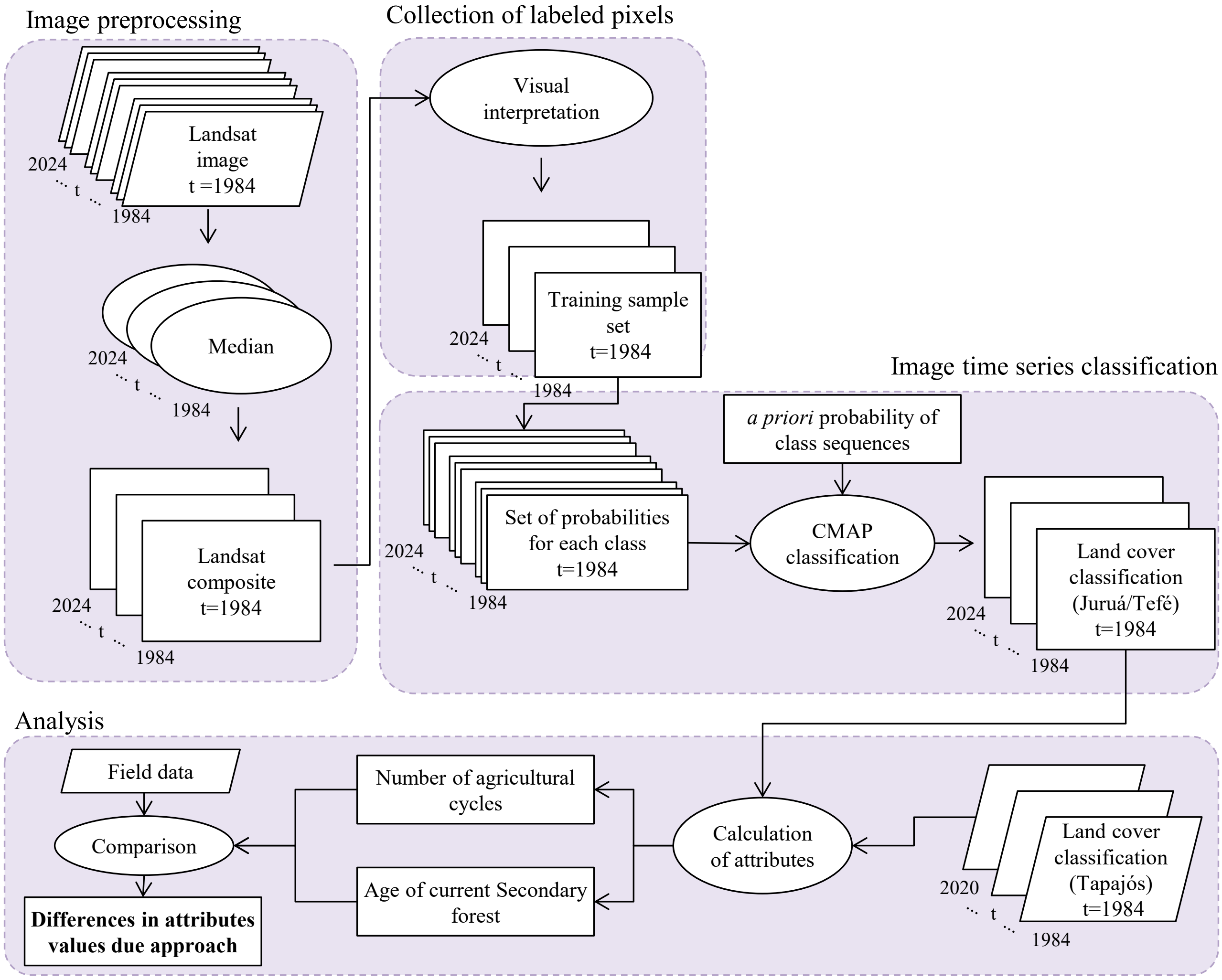
Figure 3 – Methodology flowchart, in which t is the time of the data set.



Source: The authors (2025).

3.1 Image preprocessing

We derived Landsat image composites for each year and set of sensors (TM/ETM+ or OLI) by calculating the median value, per band, of pixels not flagged as invalid or not observed (e.g., clouds/cloud shadow, snow, or with negative reflectance values). We only processed the bands NIR, SWIR1, and SWIR2, both to avoid including uncalibrated or noisy data from the visible bands (Wulder et al., 2018) and to use the same bands for all sensors. Particularly for this study, we noticed that bands Blue, Green, and/or Red present enough spectral variation along time as to not be adequate within our classification design, in which we train CMAP based on labeled pixels collected in different images in the time series. Whereas including these bands returned grave classification errors in our tests, classifying only bands NIR, SWIR1, and SWIR2 returned much more robust results. After the calculation of the median value, remaining areas without valid information were considered as *Not observed*.

3.2 Collection of labeled pixels of the classes of interest

We collected pixels labeled as the classes of interest based on the visual interpretation of the Landsat image composites. In total, we delimited 440 polygons depicting the classes of interest for the Juruá region and 400 for Tefé between 1984 and 2024.

3.3 Image time series classification

The image composites from Juruá and Tefé were classified using a similar approach to the one previously used for the Tapajós region (Reis, 2022): classifying the Landsat image composites for each sensor using a CMAP model trained with generalized samples (meaning that one or more images were classified using training samples collected for another image). CMAP needs two main inputs to calculate the classification time series: (i) the probability of each observation in time given a set of classes, and (ii) the *a priori* probability of a sequence of classes. These are explained as follows.

First, we calculated the probability of each observation in time using the Probability Density Function for the Gaussian distribution (Theodoridis & Koutroumbas, 2009) and labeled pixels transferred from one set of image composites to the other. This process treats each instance of a class in time like a different class, and all of them compete for the maximum value within the CMAP algorithm. We did not use labeled samples collected over OLI image composites to train the model applied to TM/ETM+ composites or vice-versa, and Tefé and Juruá data sets were processed separately.

For the calculation of the *a priori* probability of sequences, we adopted the simplified approach proposed by Reis et al. (2020b) in which invalid class sequences receive a probability equal to 0.0 and all valid sequences have the same probability value, which sums to 1.0. A class sequence is considered invalid if it has an invalid transition. Box 2 presents the validity of transitions considered in this study. Note that a *Not observed* class was not included in this definition, because valid transitions to such a class can cause invalid sequences (as seen in Quevedo et al. (2024)). To avoid this problem, we assumed a constant probability value for all classes in pixels masked as *Not observed*. CMAP then attributed the class it finds most probable due to the *a priori* probability of the sequence to these pixels. As a constant value does not alter the calculation of the maximum, this process does not privilege a class over another for times without observations. Masked pixels automatically received the class *Not observed* at the end of the classification step.

Box 2 – Validity of transitions between land cover classes of interest.

		Time t + 1		
		F+O	S	M
Time t	Old-growth forest (F) + Other natural areas (O)	Valid	Valid	Valid
	Secondary forest (S)	Invalid	Valid	Valid
	Managed area (M)	Invalid	Valid	Valid

Source: The authors (2025).

3.4 Analysis

From the year-by-year classification performed by the CMAP algorithm, we extracted the following information for the pixels corresponding to each one of the 88 plot centers:

1. Number of agricultural cycles - number of times the class *Old-growth forest* or *Secondary forest* changed to a *Managed area* from 1984 to the year of the field campaign;

2. Age of the current secondary forest - the number of consecutive times a pixel was classified as *Secondary forest*, counting backwards from the year fieldwork was conducted for a given area. This attribute could not be computed for pixels not classified as *Secondary vegetation* in the year of the field campaign.

Note that the field campaign in the Tapajós region was conducted in 2024, whereas the last classified image corresponds to the dry period of 2020. We extended the land cover time series of this region, considering that years 2021 to 2024 would be classified as *Secondary forests* for all plots. This extrapolation relies on the field information that none of the plots were younger than four years in 2024. To avoid artifacts generated by *No Observed* pixels (e.g., halving the age of a *Secondary forest* due to cloud cover in the middle of a regeneration cycle), we also applied a post-processing filter that: (i) identifies single instances of *Not Observed* in time and (ii)

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assigns the class of the previous observation for these instances. This choice is made based on the conservative supposition of no-change in the unobserved time. In this study, we did not have problems associated with multiple years without clear observations.

Values of *number of agricultural cycles* and *age of the current secondary forest* were then compared, plot by plot, to the ones acquired through interviews with landowners. We then calculated the difference between the two sources by subtracting the interview value from the CMAP value for each descriptor. A difference of zero indicates complete agreement between the two approaches. Positive differences indicate higher values in CMAP, whereas negative differences indicate higher values in the interviews.

When there was a large disagreement between the two information sources, we further checked the CMAP classification of pixels encompassed by the plot geometry, which provided the classification for up to seven pixels depending on the size of the original plot. We compared these results to the Landsat composite to identify possible sources of classification errors/uncertainty.

4 RESULTS

Figure 4 presents the estimated *number of agricultural cycles*, per region and data source, as well as the calculated differences. Considering all regions jointly, the average ± standard deviation of the number of agricultural cycles was 3.8 ± 2.3 for the interviews and 3.0 ± 1.7 for CMAP. On average, the calculated difference between data from the two information sources was -0.8 ± 1.9. Differences calculated per region correspond to 0.1 ± 2.0, -1.2 ± 1.8, and -0.8 ± 1.7, respectively, for Juruá, Tefé, and Tapajós. Furthermore, the difference between values from the two information sources showed a total agreement (zero difference) of 30% of the samples. This value increases to 55% considering values within ± 1 cycle difference.

From the 88 analyzed plots, 12 were not classified as *Secondary forest* by CMAP at the year of field data collection and were removed from this analysis. As such, the results for *age of the current secondary forest* presented in Figure 5 refer to the remaining 76 plots. We estimated an average age of 5.4 ± 1.0 and 5.7 ± 2.9 years across all sites, using interview records and CMAP classifications, respectively. The mean difference between results from interviews and CMAP was very low, with an average of 0.4 ± 3.0 years. Per region, the average and standard deviation of values were estimated at 0.6 ± 2.2 (Juruá), 0.3 ± 2.3 (Tefé), and 0.4 ± 4.6 years (Tapajós). Sources agree within ± 1 year for 53% of the 76 valid values, and in ± 3 years for 93%.

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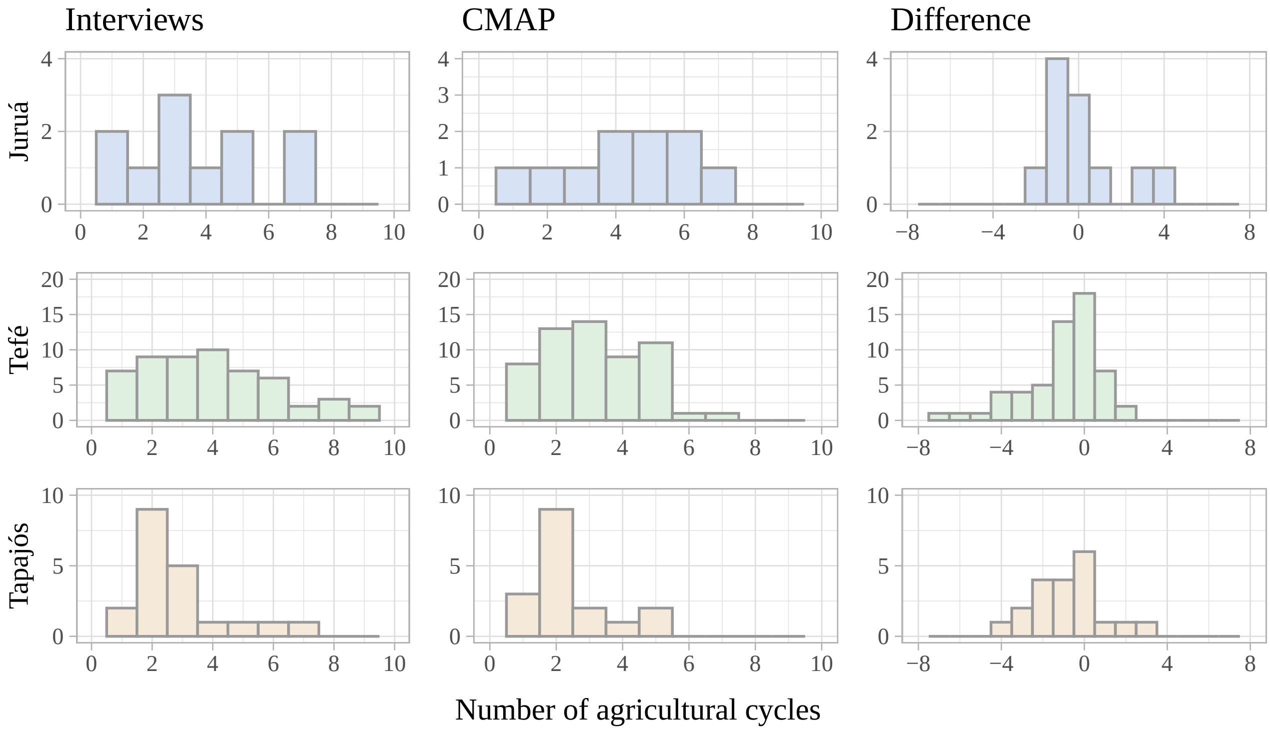
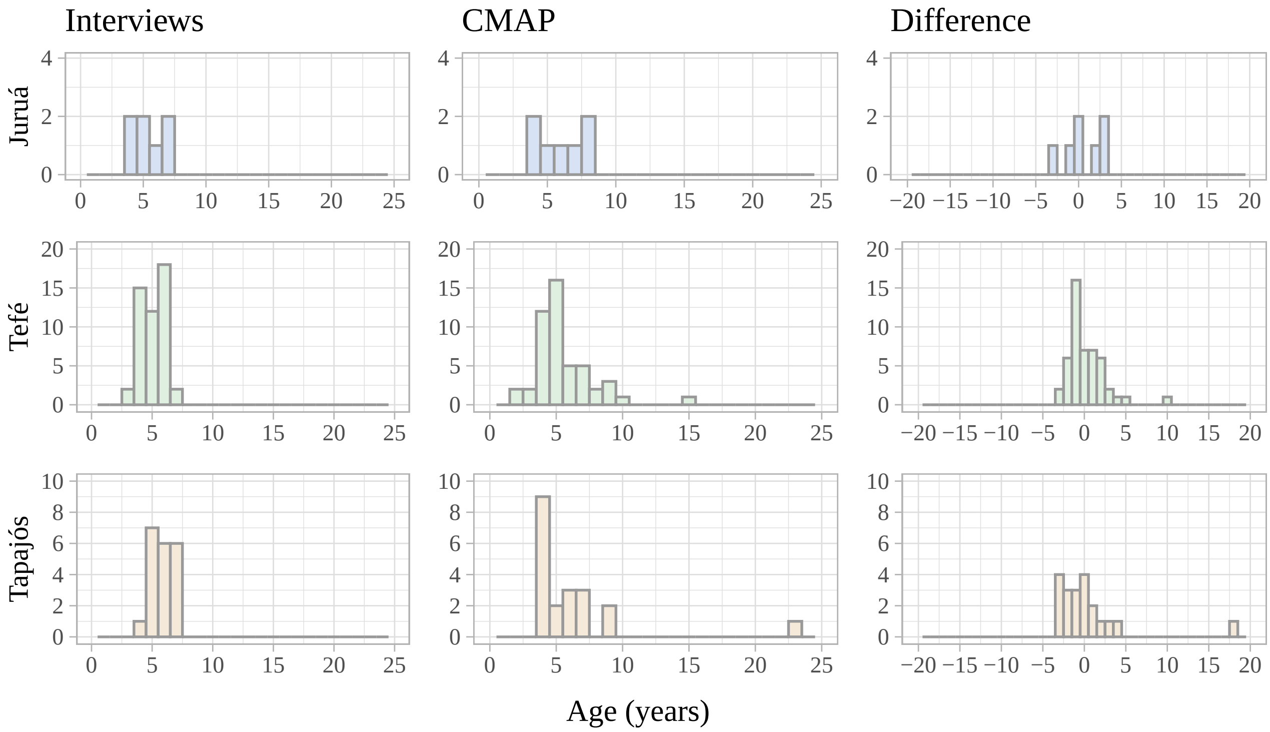
Figure 4 – Frequency of values of *number of agricultural cycles*, extracted from interviews, CMAP classified time series (plots centroids), and difference in values (CMAP - Interviews).



Source: The authors (2025).

Figure 5 – Frequency of values of *age of the current secondary forest*, extracted from interviews, CMAP classified time series (plot centroids), and difference in values (CMAP - Interviews).



Source: The authors (2025).

To better understand these differences, Figure 6 shows a spatial and temporal subset of the Landsat composites for plot 19 in the Tapajós region, which presents the highest absolute difference between the interviews and CMAP results for *age of the current secondary forest*. This age was estimated as 23 years by CMAP, and five years in interviews. To account for the value observed in the interviews, we would expect to see

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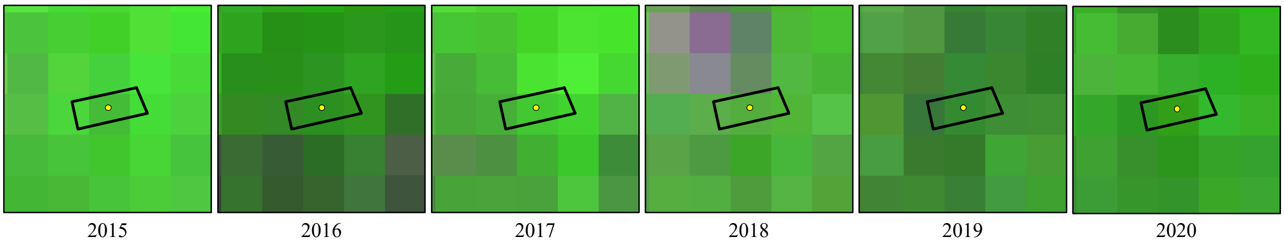
a transition from a forested class to *Managed area* in the 2018 and 2019 Landsat composites. This transition would also equalize the values of *number of agricultural cycles* in this plot. However, all composites from 2015 to 2020 presented spectral values befitting forested areas. We can only see evidence of managing in the magenta pixels in 2018, which (albeit close) do not intersect the plot's limits.

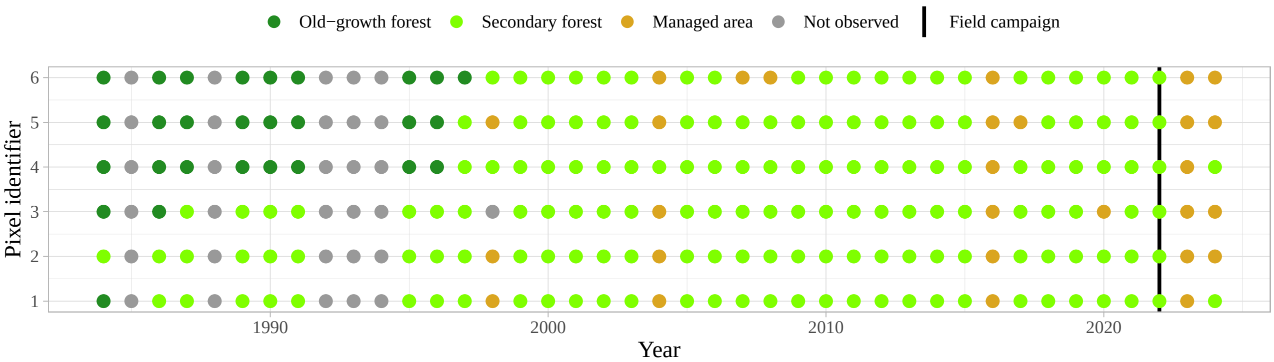
Figure 6 – Spatial and temporal subset of Landsat composites for the Tapajós region (color composition SWIR1(R) NIR(G) SWiR2(B) with applied contrast). The polygon of plot Tapajós-19 is delimited in black. The polygon center is depicted by the yellow point.



Source: The authors (2025).

In this sense, a given plot can present pixels with very different class sequences. Figure 7, for instance, illustrates the classification results for the six Landsat pixels intercepted by plot 43 in Tefé. The centroid corresponds to the pixel identified as 5 in this figure. The interviews recorded two agricultural cycles and a secondary forest of six years for this plot in 2022. Although we cannot make any inferences about classification accuracy based on these values alone, it is possible to see that changing plots' geometries could easily shift the central pixel, resulting in the classification of a different land-use history.

Figure 7 – CMAP classification results for the six pixels intercepted by plot Tefé-43, without interpolating single events of *Not Observed*.



Source: The authors (2025).

5 DISCUSSIONS

Field data and interview records are often treated as the gold standard of land-use history in the Amazon. However, acquiring this type of information depends on (i) the presence of long-term residents who can recall the full history, (ii) people having a good memory of the used management, (iii) the need to interview multiple people to increase accuracy, and (iv) the interviewer being able to facilitate the information without biasing it. In general, the shorter the land-use history, i.e., the more recent the deforestation of mature forest and the start of the cultivation cycles, the better the memory of people. For estimating the age of the secondary forests, interviews were reliable because all plots contained secondary forests younger than eight years, with apparent height and structure attributes that facilitated estimates (Jakovac et al., 2015, 2016a). However, all questions must be defined *a priori* in field interviews, and information about very old or dynamic systems can be uncertain (Dutrieux et al., 2016). Performing fieldwork in the three locations was also time-consuming and economically expensive, involving at least four field expeditions of around 30 days each.

CMAP has the advantage of providing data at lower costs than the interviews in an objective and reproducible way. Our CMAP classification processes used freely available data and software (a version of CMAP in R is available in *https://github.com/marianesreis/CMAP*). Processing time is also relatively short (all preprocessing of images and CMAP classifications could be done in less than a day using local machines and standard GEE capabilities). For CMAP, the most time-consuming task is still the collection of labeled pixels of land cover classes of interest in a few points in time, which is expected for any supervised classification approach.

Nonetheless, a target can only be identified in an RS image, with any classification method, if it can be seen in that image. A great challenge for estimating the number of cycles and the age of secondary forests with CMAP is that both depend on the detection of burned fields within a short time window. Fields are usually cut down and burned in the dry season from August to October (depending on the climatic conditions of each year and region). After fields are burned, manioc is planted from stem cuttings that rapidly sprout and cover the fields. In case manioc is not planted for any reason, forest natural regeneration can take over immediately. Both processes can occur within one to two months (Jakovac et al., 2016c). Therefore, the time window for the detection of an agricultural cycle can be shorter than our proposed one-year interval. This problem can also be exacerbated during years of high rainfall, due to faster vegetation recovery (Poorter et al., 2016) and higher cloud coverage.

For multi-temporal analyses, we further need to guarantee that the images cover the complete analysis period, with adequate temporal resolution to record individual events and spatial resolution to identify small targets. This is not the case with the available Landsat time series. For instance, 28% of the sampled plots analyzed in this study have already been deforested before 1984, so it was not possible to derive the full land-use history of these areas. Interviews and CMAP are not mapping the same time interval at these sampled plots, so the variance in estimates is expected. A plot could also have been converted to manioc after field campaigns, which would explain areas not classified as secondary forests in the last year of analysis. Besides land changes that occurred outside of the dry period and/or were not visible in the Landsat composites, differences in the estimated values could also be related to geometric inconsistencies between the data sets, regarding either the plot centroid definition or the Landsat data alignment over time.

Classification errors on a given date have the potential to greatly impact the land-use history retrieved data, which can or cannot be translated into accuracy metrics of one land cover classification over time. In particular, it is worth noting that cassava crops, abandoned pastures, and young secondary forests can have very similar spectral patterns in Landsat imagery (Reis et al., 2024). The same can be said for old-growth and more mature secondary forests (Carreiras et al., 2017; Reis et al., 2018). CMAP, a pixel-based supervised classifier, operated considering only one rather large pixel for the analysis of possibly very small patches of shifting cultivation. It is expected that this pixel presents a mixture of different types of land cover, which could lead to classification errors derived from the spatial resolution of the used Landsat images. We also considered only one observation per year in a highly dynamic environment, meaning we could have missed the specific images in which land cover changes of interest were visible.

Future studies using CMAP for the classification of the land cover classes associated with shifting cultivation processes could benefit from classifying sets of images with higher spatial resolution (such as Sentinel-1 and 2) in smaller time intervals, even if at a loss of the older years of the analysis. Particularly, it would be interesting to study variations in the Sentinel-1 signal due to burn events, as these Synthetic Aperture Radar images are particularly sensitive to changes in vegetation caused by fires (Doblas et al., 2024). Furthermore, we highlight that our analyses were focused on areas known to be used for shifting cultivation. In these cases, it is also possible to fix known errors of CMAP, such as setting the class of a given pixel in the year of the field campaign as *Secondary vegetation* and limiting transitions to other classes in previous years, to guarantee a minimum sequence that respects what was seen in the field. Such a process is possible by defining appropriate *a priori* probabilities of sequences in CMAP, or by the use of post-processing filters – the latter was organically used by the interpreters when estimating the results presented in Reis et al. (2025). Furthermore, expanding our methodology for unknown areas may result in the misclassification of other types of targets, such as sand banks and mining activities along rivers, which may imply additional data processing and should be evaluated per case.

6 CONCLUSIONS

In this study, we evaluated the potential to use CMAP for the classification of Landsat time series to estimate two attributes used to characterize shifting cultivation dynamics in the Amazon: the number of agricultural cycles and the age of secondary forests. These values were estimated for 88 shifting cultivation systems, distributed along three regions in the Amazon with different environmental and socio-economic characteristics, and validated in comparison to results obtained through field interviews.

Overall, we identified a good agreement between the interviews and CMAP results on the estimates of both attributes. We could not identify clear biases associated with increased or decreased estimations on a given method, although Juruá must be evaluated with caution, due to the very small number of analyzed plots. In general, our results indicate that CMAP has the potential to efficiently retrieve the land-use history and secondary forest age of shifting cultivation patches in the Amazon, with a relatively low error rate when compared to field interviews. As interviews with landowners provide richer information on land use dynamics that cannot be retrieved from imagery, we argue that the use of both methods in a complementary way should be the way forward for campaigns.

The use of CMAP also allows to (i) map out areas of shifting agriculture outside the sampled plots, (ii) map out the intensity of previous land use history, which can be used as a proxy for agricultural productivity and for forest recovery capacity, (iii) describe the temporal dynamics of shifting cultivation systems and evaluate possible changes in this dynamics over time, (iv) estimate the age of secondary forests and (v) estimate the permanence time of secondary forests. All these applications are valuable for understanding drivers of change, the development of land use models, and for the planning and implementation of public policies on forest restoration and ecosystem services provision.

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Authors' Contributions

All authors contributed to the conceptualization, data collection, methodology, analysis, and writing of this paper.

Conflicts of Interest

There are no conflicts of interest.

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