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Mapping oil palm expansion in the Eastern Amazon using optical and radar imagery

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ABSTRACT

Palm oil, the world's most widely consumed vegetable oil, plays a pivotal role in the food, biodiesel, and pharmaceutical industries. However, its rapid expansion in tropical regions has led to critical environmental challenges, including deforestation and biodiversity loss. This study maps oil palm plantations in the Eastern Amazon, Brazil's largest producer, for 2014, 2017, and 2020, employing machine learning algorithms such as K-Nearest Neighbors (KNN), Artificial Neural Networks (ANN), Decision Trees (DT), Support Vector Machines (SVM), and Random Forests (RF). This study integrate Landsat-8 optical spectral bands (blue, green, red, and near-infrared) with Sentinel-1 radar backscatter values (VV and VH polarizations) to map the expansion of oil palm in the Brazilian Amazon, a combination that has not been previously implemented in this region. Vegetation indices, including NDVI (Normalized Difference Vegetation Index), EVI (Enhanced Vegetation Index), SAVI (Soil-Adjusted Vegetation Index), DVI (Difference Vegetation Index), RVI (Ratio Vegetation Index), GI (Green Index), and texture indices derived from the gray-level co-occurrence matrix (GLCM), such as contrast, angular second moment (ASM), correlation, and entropy, were used to improve classification accuracy. A linear spectral mixing model was also applied to distinguish the spectral signatures, with the resulting end members subsequently incorporated. The RF achieved the highest classification accuracy, with overall accuracies of 94.53%, 94.28%, and 95.53% for 2014, 2017, and 2020, respectively. A land use and land cover (LULC) transition analysis revealed a substantial expansion of 72.16%, with the area growing from 1,074 km^2 in 2014 to 1,849 km^2 in 2020. Notably, 156.88 km^2 (20.24%) of this expansion occurred directly at the expense of vegetation cover, underscoring areas of significant environmental concern. This study offers valuable insights to guide the development of public and market-driven policies aimed at promoting sustainable and environmentally responsible oil palm expansion.

1. Introduction

Palm oil is the most widely consumed and exported vegetable oil globally, playing a pivotal role in the food, biodiesel, and pharmaceutical industries (Villela et al., 2014; Chong et al., 2017). The increasing global demand for this commodity is driven by its

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high production potential, low costs, and incentives to replace fossil fuels with biofuels, leading to a rapid expansion in cultivation areas (Xu et al., 2021). Oil palm cultivation is primarily concentrated in tropical Asian countries, with Indonesia and Malaysia leading as the top producers globally, accounting for approximately 85% of the world's total production (Peteru and Komarudin, 2022).

While the oil palm industry contributes to economic growth and provides income for both large- and small-scale growers, it is also linked to negative environmental impacts, such as tropical deforestation and biodiversity loss (Englund et al., 2015). With area and market restrictions on major producers, the expansion of oil palm cultivation poses a significant environmental threat to other tropical countries, particularly in the Amazon, where nearly half of the region is suitable for cultivation, with Brazil possessing the largest tracts of suitable land (Pirker and Mosnier, 2015; Englund et al., 2015; Furumo and Aide, 2017; Zhao et al., 2024).

Even though Brazil is the 10th largest producer of oil palm in the world, the cultivated area is still small compared to the country's productive potential. Economic challenges, such as high production costs, limited knowledge about oil palm cultivation, and issues within the sector's governance model, hinder its expansion (Englund et al., 2015; Benami et al., 2018; Brandão et al., 2021). Recognizing these challenges, Brazil implemented several programs between 2004 and 2010 to promote oil palm production. These include the National Program for the Production and Use of Biodiesel (PNPB) in 2004, the Agroecological Zoning of Palm Oil Cultivation (ZAE) in 2010, the Sustainable Palm Oil Production Program (PPSP) in 2010, and Pronaf Eco Palm Oil in 2010 (Villela et al., 2014; Carvalho et al., 2015; Benami et al., 2018; Nahum et al., 2020; Almeida et al., 2020).

Since then, Brazil has experienced significant growth in oil palm plantations, particularly in the state of Pará, which accounts for 95% of the national production. Between 2004 and 2014, Pará's cultivated area increased by over 200%, reaching 2190 km^2 and 900,000 tons of palm oil per year (Villela et al., 2014; Carvalho et al., 2015; Benami et al., 2018; Nahum et al., 2020; Almeida et al., 2020). After 2010, this growth accelerated even further, with plantations expanding by 11.9% annually (Silva et al., 2023).

While this expansion has delivered beneficial economic returns (Ferreira et al., 2023), it has also led to deforestation and biodiversity loss (Carvalho et al., 2015; Lameira et al., 2016; Furumo and Aide, 2017; Benami et al., 2018; Almeida et al., 2020; Silva et al., 2023). Considering the presence of highly biodiverse forests and the rapid expansion the region is experiencing, the potential ongoing conversion of forests to plantation areas raises significant environmental concerns (Carvalho et al., 2015).

This scenario reinforces the need to detect and monitor the oil palm expansion, particularly through remote sensing techniques, which offers an excellent cost-benefit ratio (Holloway and Mengersen, 2018; Weiss et al., 2020). Satellite imagery, especially when classified with machine learning algorithms, has emerged as a valuable tool for monitoring oil palm plantations, offering a cost-effective means of assessing land use changes, plantation expansion, and potential environmental impacts (Srestasathiern and Rakwatin, 2014; Chong et al., 2017; Almeida et al., 2020; Shaharum et al., 2020; Xu et al., 2021).

This study applies advance machine learning algorithms such as K-Nearest Neighbors (KNN), Artificial Neural Networks (ANN), Decision Trees (DT), Support Vector Machines (SVM), and Random Forests (RF) to optical and radar satellite imagery to map oil palm areas in the Eastern Amazon. While recent studies have demonstrated the effectiveness of combining optical and radar satellite data for mapping plantations in Southeast Asia because it overcomes the limitations of cloud cover in tropical regions and improves classification accuracy compared to using optical or radar data alone (Chong et al., 2017; Poortinga et al., 2019; Najib et al., 2020; Sarzynski et al., 2020; Xu et al., 2021; Sari et al., 2022; Zeng et al., 2022; Abramowitz et al., 2023), this approach has not yet been adopted for the Brazilian Amazon. This study aims to fill this gap in the literature by combining optical spectral bands from Landsat −8 and radar backscatter values from Sentinel-1, using a 30-meter pixel spatial resolution, to map oil palm expansion in the Eastern Amazon for the years 2014, 2017, and 2020. This effort are crucial for supporting public policies on oil palm that promote the expansion of production while mitigating environmental impacts.

To achieve the proposed objectives, the paper is structured into four sections, in addition to this introduction. In section two, we present the material and methods. Section three details the results, while sections four and five are dedicated to presenting the discussion and the conclusion, respectively.

2. Materials and methods

2.1. Oil palm mapping: an overview

Remote sensing provides an effective, low-cost tool for regional-scale mapping with repetitive observations (Chong et al., 2017; Najib et al., 2020). Indeed, various techniques have been developed to map oil palm plantations using remote sensing data, which can be manually digitized or fully automated based on spectral and texture analysis of the images (Sarzynski et al., 2020). In recent years, advancements in high spatial resolution imagery and automatic mapping techniques, such as machine learning algorithms, have significantly enhanced the accuracy and efficiency of these processes (Li et al., 2017; Chong et al., 2017).

High-resolution satellite images can accurately detect oil palm trees in plantations, providing a 90% detection rate compared to manual labeling (Srestasathiern and Rakwatin, 2014). In this context, the near-infrared spectral band is the most crucial for classifying oil palm plantations in optical images (Chong et al., 2017). Additionally, the red band is important for distinguishing this crop from other classes (Nooni et al., 2014). These bands are vital in practice, as they reflect the strong absorption of chlorophyll in the red spectrum and water absorption in the infrared. Vegetation indices, particularly those derived from these bands, are also essential for oil palm classification, as they allow for the extraction of phenological information. Moreover, image texture indicators are widely used as they help identify significant geometric features of oil palm plantations (Srestasathiern and Rakwatin, 2014; Xu et al., 2021).

Although the use of optical images to map oil palm plantations is common, their spectral and structural similarity with forested areas makes distinguishing between these classes challenging (Abramowitz et al., 2023). Additionally, optical satellites are limited by cloud cover and shadows, which are prevalent in tropical areas where most oil palm plantations are located. Radar images help overcome these challenges, as they are not affected by weather conditions and provide additional structural information about the plantations. The signals from radar satellites can penetrate through clouds, the canopy and trunks, and are sensitive to the geometry and structure of the plantations (Najib et al., 2020; Sarzynski et al., 2020; Xu et al., 2021).

The information obtained from the polarization of radar signals, specifically the horizontal–horizontal (HH), horizontal–vertical (HV), vertical–horizontal (VH) and vertical–vertical (VV) polarization, has been used successfully in oil palm mapping (Li et al., 2017). Consequently, the combination of optical and radar images, especially when integrated with vegetation and texture indices and feature selection algorithms, has demonstrated superior results and enhanced classification performance (Xu et al., 2021).

Multiple studies have demonstrated that integrating optical data with synthetic aperture radar (SAR) data yields higher classification accuracies compared to using either data type alone (Chong et al., 2017; Poortinga et al., 2019; Najib et al., 2020; Sarzynski et al., 2020; Xu et al., 2021; Sari et al., 2022; Zeng et al., 2022; Abramowitz et al., 2023). This approach have achieved overall accuracies ranging from 84% to 97%, demonstrating their potential for monitoring oil palm expansion and supporting sustainable plantation management. In other words, the integration of optical and radar imagery has shown significant promise in accurately mapping plantations, which is crucial for monitoring deforestation and managing agricultural expansion in tropical regions.

The literature has consistently demonstrated that combining optical and radar images significantly improves classification performance for mapping land use in tropical countries like Indonesia, Malaysia, Myanmar and Ghana. For example, Descals et al. (2019), Sarzynski et al. (2020) demonstrated that this combination improves the Random Forest algorithm performance for mapping oil palm plantations in Sumatra, Indonesia, achieving an overall accuracy of 90.2% and 84%, respectively. Similarly, Xu et al. (2021) applied this approach in Riau Province, Indonesia, achieving a 96.08% accuracy with a Kappa index of 0.9462. Supporting these findings, Sari et al. (2022) reported an overall map accuracy of 92% in Indonesia. In Malaysia, Najib et al. (2020) reported a 98.36% accuracy and a Kappa coefficient of 0.78, further validating this methodology. Additionally, Zeng et al. (2022) found that land use and land cover (LULC) maps generated from combined images in the Muda River Basin, Malaysia, had accuracies ranging from 95% to 97%. Poortinga et al. (2019) demonstrated that this combination produced a good overall accuracy of 84% in Myanmar for the years 2017 and 2018, which could be improved to 91% with filtering methods. Lastly, Abramowitz et al. (2023) showed that the combination of Sentinel-1 and Sentinel-2 bands outperformed using either satellite alone for mapping oil palm in Ghana, Africa, achieving a 90.3% accuracy.

2.2. Study area

We selected the Acará, Moju, Tailândia and Tomé-Açu municipalities (Fig. 1), known as the oil palm pole in Brazil, as the spatial units of analysis. Together, they cover an area of 23,014.36 km^2, a significant portion of which is located in the ZAE. These areas are the leading producers of oil palm in Brazil, noted for their socioeconomic dynamism in the Northeast of Pará (IBGE, 2020).

The region generally receives an average annual rainfall of 2500 mm, with a minimum of 60 mm per month—adequate for oil palm cultivation without the need for irrigation. The terrain is relatively flat, with an altitude ranging from 50 to 100 m, and an average temperature of 26 °C. Historically, the area was occupied by cattle ranching, which began in the 1960s following the completion of the BR-010 (Belém-Brasília) highway. Other economically significant agricultural activities include the cultivation of black pepper, açaí, and eucalyptus for timber, cassava, and rice (Almeida et al., 2020). The region is also near the Belém Endemism Center, an area characterized by high levels of endemism, fragmentation, and fire risk, making it one of the most deforested and ecologically threatened zones in the Amazon.

2.3. Data processing

Fig. 2 presents a schematic flowchart of the methods and procedures adopted in this article, adapted from Xu et al. (2021), for mapping oil palm areas.

In short, we combined optical images from Landsat −8 and radar images from Sentinel-1, from which we extracted features to perform the classification. We selected optical imagery from the Landsat program over Sentinel-2 because the literature has extensively used Landsat data for oil palm mapping, particularly in the Brazilian Amazon, facilitating comparisons with other studies. In addition, we began our study in 2014 to coincide with the operational launch of Sentinel-1, which started on April 3, 2014. We then collected training and testing samples, selecting the most relevant variables during the training stage. Finally, we validated the model on the test sample and used it for classification and mapping. In the following paragraphs, we describe each methodological step used to map oil palm cultivation.

Initially, we selected Landsat −8 and Sentinel-1 images to compose the database, masking clouds using the "pixel_qa" quality band, quality band, where pixel value 322 indicates no cloud interference. Next, we created annual composites for 2014, 2017 and 2020 using the median pixels from the image collection on Google Earth Engine (GEE) (Gorelick et al., 2017; GEE, 2025). We chose the median over the mean because it offers greater robustness against outliers, minimizes artifacts from clouds and shadows, retains critical image details, and ensures more reliable data for classification algorithms in regions with frequent cloud cover.

With the annual composite and cloud-free images, we combined the Landsat −8 and Sentinel-1 data. Despite the spatial resolution difference – 30 m for Landsat −8 and 10 m for Sentinel-1 – we chose to harmonize the images at 30 m resolution to avoid

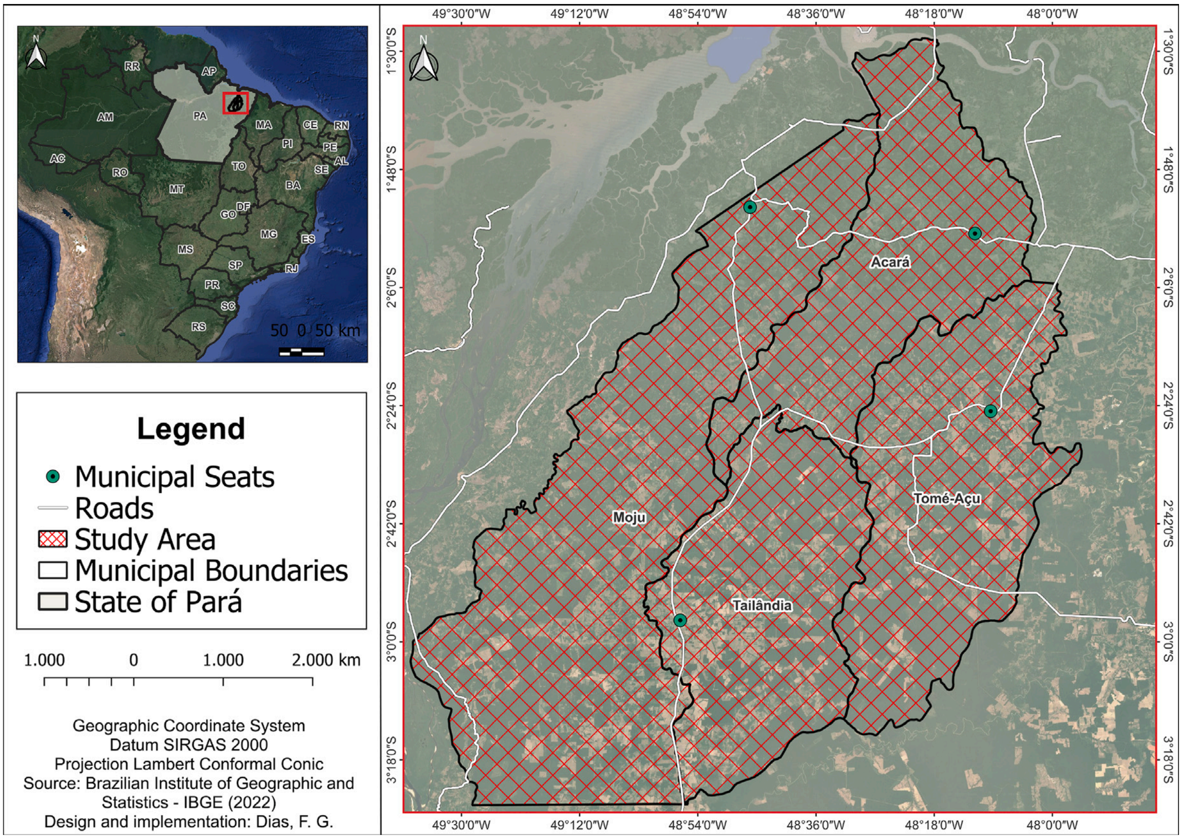

Fig. 1. Map of Study Area: illustrating Pará's municipalities in the Eastern Amazon analyzed for oil palm expansion from 2014 to 2020.

artificially introducing spatial autocorrelation. It is worth noting that the images GEE were properly pre-processed by their respective repositories, making them suitable for final use (Gorelick et al., 2017).

This study used the blue, green, red, and near-infrared spectral bands from Landsat –8, along with VV co-polarization (vertical transmit/vertical receive) and VH cross-polarization (vertical transmit/horizontal receive) data from Sentinel-1's dual-polarized C-band. For more information about the state of the art on radar images and their applications, see Sano et al. (2020). The Landsat images were then used to develop a linear spectral mixing model, which deconstructs the spectral signatures of different materials within each pixel. In this study, the model specifically quantified the bare soil and oil palm fractions, effectively reducing classification confusion between these two classes and minimizing misclassification of oil palm and forested areas. The resulting components are known as *end-members*, which are essentially pure pixels representing specific targets on the Earth's surface (Somers et al., 2011).

Next, we calculated several vegetation and texture indices, as specified below, for the Landsat –8 image bands using R software (R, 2025), specifically employing the Rtoolbox and the gray-level co-occurrence matrix (GLCM) packages. Vegetation indices are derived from arithmetic operations between different bands of remote sensing images, capturing vegetation growth and structure, soil characteristics, and other factors related to vegetation development and health. We included the Difference Vegetation Index (DVI) (Richardson and Everitt, 1992), Ratio Vegetation Index (RVI) (Jordan, 1969), Greenness Index (GI) (Xu et al., 2021), Normalized Difference Vegetation Index (NDVI) (Srestasathiern and Rakwatin, 2014), Enhanced Vegetation Index (EVI) (De Petris et al., 2019), and Soil-Adjusted Vegetation Index (SAVI) (Huete, 1988). These vegetation indices enhances the accuracy of mapping oil palm plantations by capturing diverse aspects of vegetation health, structure, and density.

Texture indices, in turn, capture important geometric features crucial for accurate class discrimination and are crucial for distinguishing oil palm plantations from other land covers, as they capture variations in pixel intensity, spatial patterns, and surface heterogeneity, providing detailed insights into the structural and compositional characteristics of vegetation. In this study, we derived the median of various texture characteristics from the Landsat –8 spectral bands, based on the GLCM. Specifically, we calculated the following GLCM characteristics using a 7×7 moving window: Contrast, Angular Second Moment (ASM), Correlation, and Entropy. According to Xu et al. (2021), this information is vital for improving the classification of oil palm, particularly due to its distinctive geometric properties. Additionally, we used Sentinel-1 images to calculate three indicators from the SAR backscatter values: ratio (VV/VH), difference (VV-VH), and normalized difference index (NDI), (VV-VH)/(VV+VH).

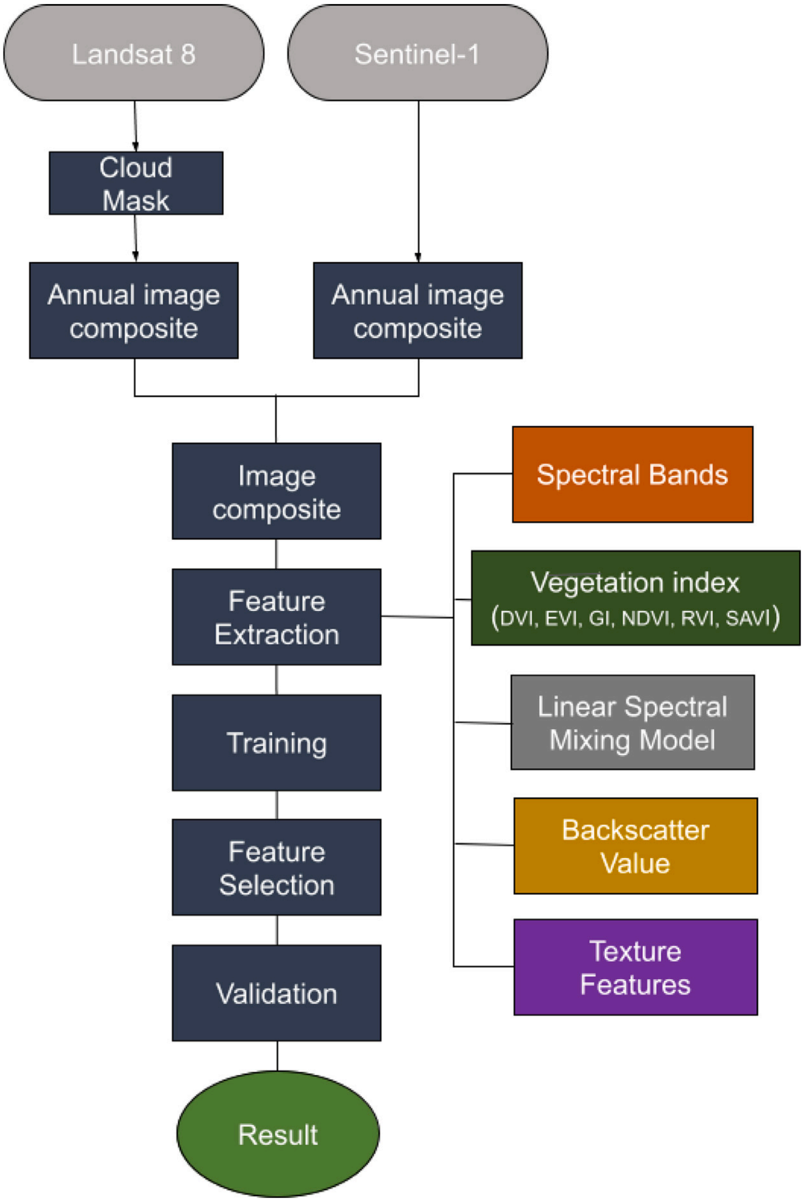

Fig. 2. Schematic flowchart of methods and procedures, adapted from Xu et al. (2021).

We collected a training sample of 6194 observations through the visual interpretation of Landsat –8 images for the supervised classification aimed at detecting and mapping oil palm plantations in Northeast Pará. The samples were categorized into three classes: Vegetal Formation, Bare Soil, and Oil Palm. The Vegetal Formation class includes areas of primary forests and secondary vegetation. Bare Soil represents a land use class that encompasses various human-induced transformations, such as urban infrastructure, agricultural areas, and roads. Although oil palm has an arboreal stratum, it is classified as a land-use class due to its economic and environmental significance.

We used a random sampling criterion for data collection, resulting in the following distribution across classes (in pixels): Vegetal Formation (3330), Oil Palm (1564), and Bare Soil (1300). The sample was then validated through visual interpretation of high-resolution images from Google Earth. Finally, we randomly subdivided the sample, allocating 80% for training and 20% for testing.

2.4. Classification

The main goal of machine learning is to construct a statistical model that predicts or classifies an outcome or class of interest. In fact, statistical models form the foundation of machine learning algorithms, particularly regression, classification, and mixed models.

Table 1
Machine learning algorithms results.

	Overall Accuracy		
	2014 (1)	2017 (2)	2020 (3)
K-Nearest Neighbor	92,54%	94,61%	93,87%
Artificial Neural Network	89,84%	83,51%	78,44%
Decision Tree	86,50%	84,34%	86,74%
Support Vector Machine	94,03%	94,20%	93,29%
Random Forest	94,53%	94,28%	95,53%
	Kappa Coefficient		
	2014 (1)	2017 (2)	2020 (3)
K-Nearest Neighbor	0,8737	0,9088	0,8956
Artificial Neural Network	0,8284	0,7201	0,6313
Decision Tree	0,7678	0,7305	0,7707
Support Vector Machine	0,8993	0,9022	0,8867
Random Forest	0,9075	0,9031	0,9239

Unlike traditional statistics, which focus on asymptotic theory and causal relationships, machine learning literature emphasizes the model's predictive or classification power. Practically, machine learning algorithms are divided into two basic categories: supervised and unsupervised (Burger, 2018; Holloway and Mengersen, 2018; Kamusoko, 2019). In this paper, we employ various supervised algorithms to classify remote sensing information, assigning a class to each pixel in the images, to choose the most effective machine learning algorithm among five complementary methods: K-Nearest Neighbors (KNN), Artificial Neural Networks (ANN), Decision Trees (DT), Support Vector Machines (SVM), and Random Forests (RF).

To implement this approach, the first step is to train the model to minimize misclassification and avoid overfitting. In practice, this requires splitting our data sample into two parts: one for training and the other for testing. This process is essential for validating the model, as the testing sample is used to assess the classification power of the estimated model. To minimize potential bias, we applied sampling techniques to construct the training and test samples, comprising 80% and 20% of the total sample, respectively (Burger, 2018; Kamusoko, 2019).

To check the robustness of the results, we employed a 5-fold cross-validation method to ensure that the testing data accurately represents our sample. This technique divides the data sample into k chunks, creates a training and testing set for each chunk, and then estimates the model. The average of the k predicted errors from each chunk is calculated, allowing us to assess potential classification variation due to sampling. Additionally, we used a recursive feature elimination method, an optimization algorithm that selects the best combination of variables for model training. This method reduces high data dimensionality and minimizes redundancy by iteratively training the model with subsamples of variables, retaining only those that significantly improve classification performance. Finally, we compared the classification results by applying the trained model to the test sample to evaluate the estimations' performance on data not used in training. The best classification algorithm was selected based on overall accuracy and the Kappa coefficient (Kamusoko, 2019).

After classification, we applied a spatial mode filter to the images, as suggested by Sarzynski et al. (2020), to minimize the salt-and-pepper effect common in pixel-based classifications. This effect occurs because pixel-based classification does not account for spatial dependence, leading to the independent classification of each pixel without considering neighborhood relationships (Liang et al., 2021). The spatial mode filter, implemented using the *raster* package in R software, aims to reduce this effect and improve the final classification. Finally, we performed a manual reclassification of oil palm areas based on the visual interpretation of their geometric characteristics, color, texture, and other features. Subsequently, we identified the transitions between LULC classes.

With the final oil palm mapping completed, we analyzed LULC transitions at the pixel level. This analysis is crucial for understanding the dynamics of oil palm expansion in the region, allowing us to determine whether it is occurring over previously deforested areas or through the deforestation of natural landscapes. In other words, the transition results enable us to assess whether the advancement of oil palm in the Eastern Amazon is sustainable. Finally, it is worth noting that all analyses were performed using R software with the OpenLand package (OpenLand, 2025)

3. Results

To obtain the best results, we compared each machine learning algorithm using its overall accuracy and Kappa coefficient, estimated from the test sample. Additionally, we validated all models with the 5-fold cross-validation method, applied during both feature selection and final classification (Kamusoko, 2019). The results, presented in Table 1, reflect the statistics after applying the recursive feature elimination method.

In 2014, the RF algorithm was the top performer, with an accuracy of 94.45% and a Kappa coefficient of 0.9075, followed by the SVM with an accuracy of 94.03% and a Kappa of 0.8993. In 2017, the KNN algorithm performed best, achieving an accuracy of 94.61% and a Kappa of 0.9088, followed closely by RF with an accuracy of 94.28% and a Kappa of 0.9031. Finally, in 2020, RF again emerged as the best algorithm, with an accuracy of 95.53% and a Kappa of 0.9239, followed by KNN with an accuracy

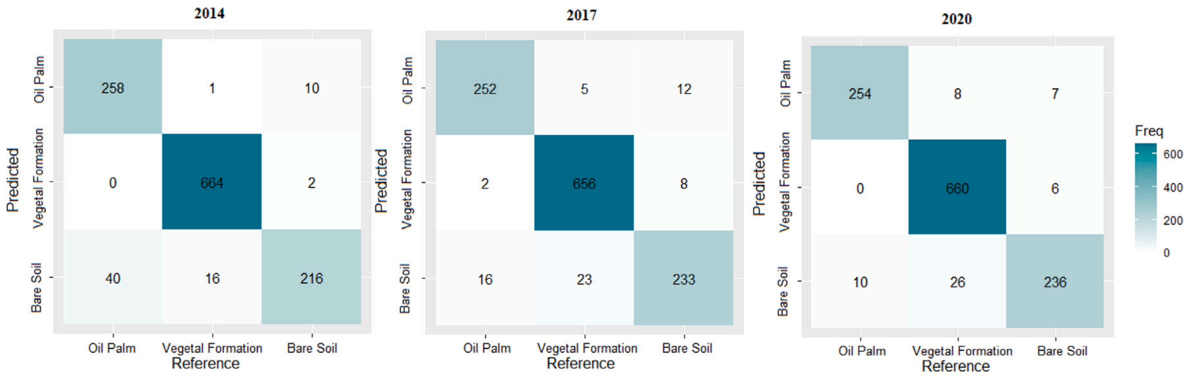

Fig. 3. Confusion matrices for the test sample.

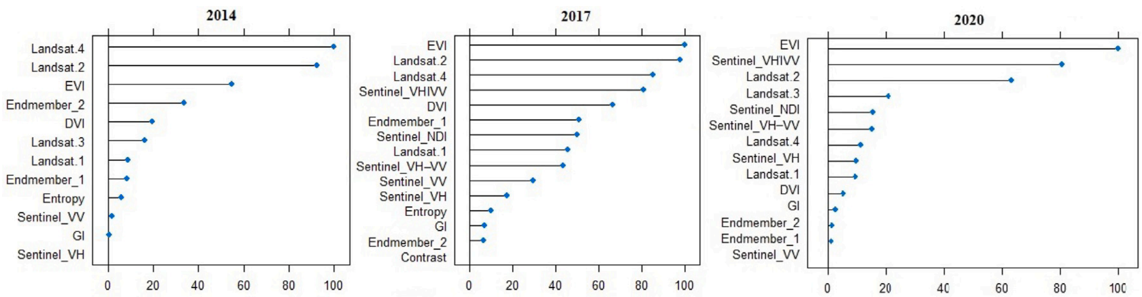

Fig. 4. Features importance for the RF classification.

of 93.87% and a Kappa of 0.8956. In summary, RF consistently showed the best performance for mapping oil palm in the selected region and period. However, it is worth noting that KNN and SVM also produced strong classification results, with KNN showing the best performance for 2017.

This empirical evidence aligns with the findings of Xu et al. (2021), who also compared several algorithms and identified RF as having the best classification performance. Conversely, Shaharum et al. (2020) reported higher overall accuracy and Kappa for the SVM, but they emphasized that RF was the most effective in delineating oil palm areas. Specifically for the Eastern Amazon, Almeida et al. (2020) performed a classification using RF and achieved an overall accuracy of 88.06% and a Kappa of 0.85, using Landsat images. Radar images provide additional geometric information, enhancing the discrimination of targets with unique geometric characteristics, such as oil palm. In this context, we present only the classification results for the RF algorithm due to its superior performance and to maintain consistency in the subsequent analyses. Finally, we calculated the confusion matrices based on the test samples, with the results shown in Fig. 3.

Fig. 4 presents the features selected using the recursive feature elimination method for the RF algorithm. This method identifies the optimal combination of features for final classification. The relevant characteristics for oil palm mapping vary by year, likely reflecting differences in climatic conditions, phenological stages, and maturation phases. In 2014, 12 features were selected: Landsat.4, Landsat.2, EVI, Endmember_2, DVI, Landsat.3, Landsat.1, Entropy, Setinel_VV, GI e Sentinel_VH. For 2017, 15 features: EVI, Landsat.2, Landsat.4, Sentinel_VH|VV, DVI, Endmember_1, Sentinel_NDI, Landsat.1, Sentinel_VH-VV, Sentinel_VV, Sentinel_VH, Entropy, GI, Endmember_2, Contrast. Finally, for 2020, 14 features were selected: EVI, Sentinel_VH|VV, Landsat.2, Landsat.3, Sentinel_NDI, Sentinel_VH-VV, Landsat.4, Sentinel_VH, Landsat.1, DVI, GI, Endmember_2, Endmember_1, Sentinel_VV.

Features derived from Landsat −8 surface reflectance proved particularly effective for classifying oil palm areas, with the Enhanced Vegetation Index (EVI) standing out as especially significant. This finding aligns with previous empirical evidence highlighting EVI's ability to accurately capture vegetation macro-phenology and dynamic changes (De Petris et al., 2019). Sentinel-1 features also proved to be highly influential, particularly the difference and ratio between VV and VH polarizations. This aligns with the findings of Xu et al. (2021), which demonstrated that radar satellite-derived information is essential for the accurate detection of oil palm plantations.

Fig. 5 presents LULC maps for the study area in the years 2014, 2017, and 2020, classified using the RF algorithm. The maps reveal that oil palm areas are primarily concentrated along highways and in the north-central region of the Tailândia municipality.

On the other hand, oil palm expansion is primarily occurring within the administrative boundaries of Tomé-Açu, particularly in the southeastern region of the municipality. Fig. 6 shows the total area of each LULC class within the study area. The Vegetation Formation class covered 17,529.57 km^2 (76.37% of the total area) in 2014, decreasing to 16,436.8 km^2 (71.61%) in 2017 and 16,289.13 km^2 (70.96%) in 2020. In contrast, the oil palm class expanded from 1,074.93 km^2 (4.68%) in 2014 to 1,703.27 km^2

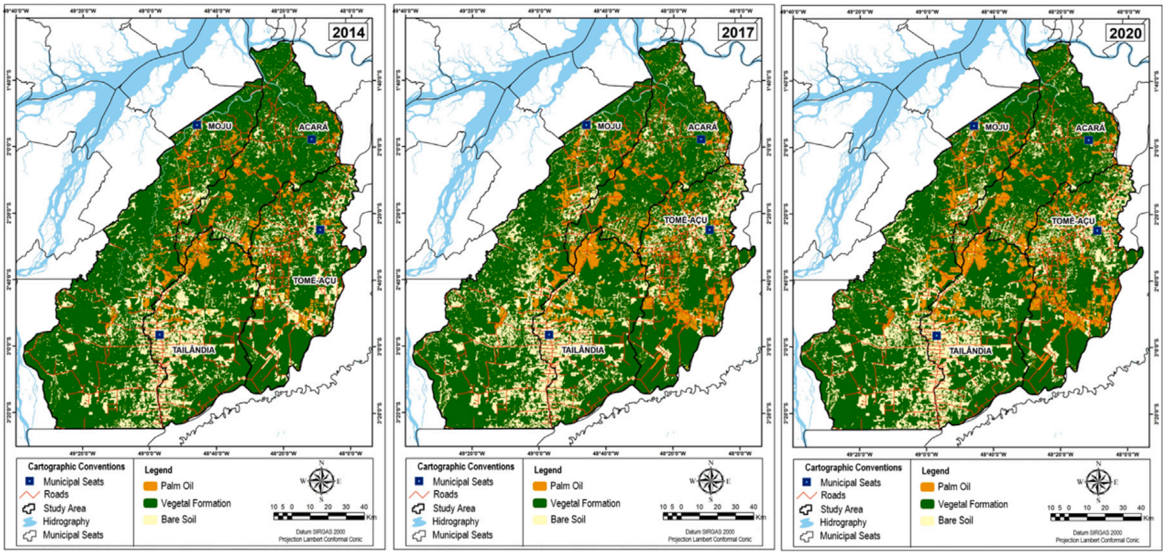

Fig. 5. Land Use and Land Cover (LULC) maps for 2014, 2017, and 2020. Expansion of oil palm plantations in the Eastern Amazon, classified by the Random Forest algorithm.

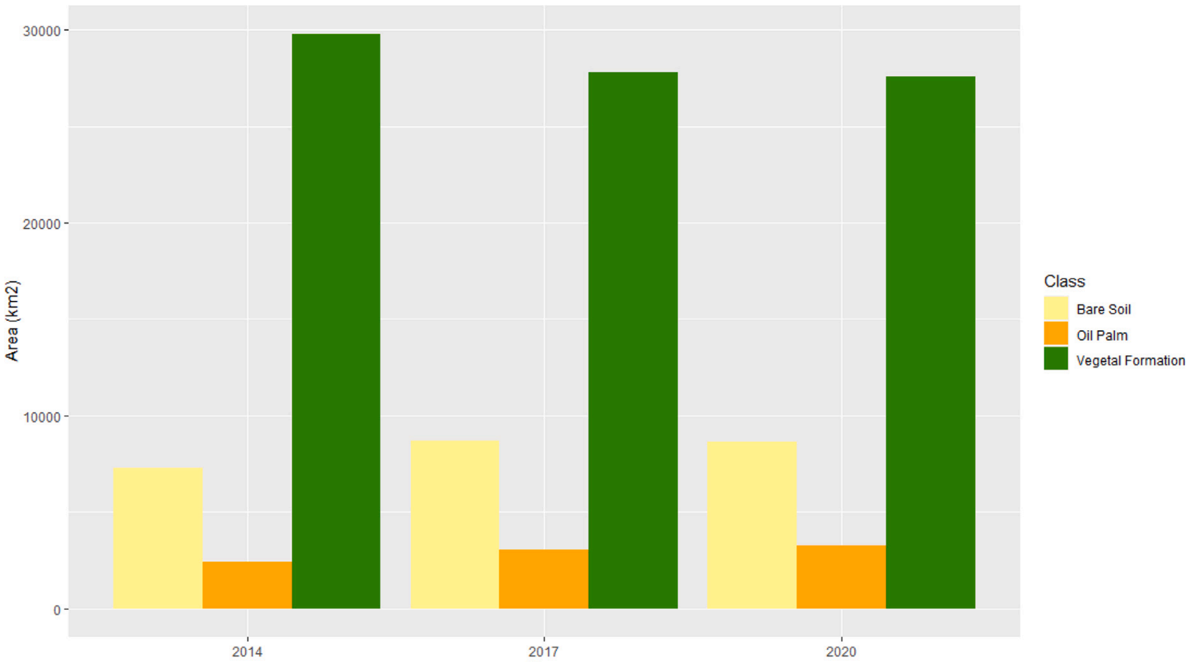

Fig. 6. Classes total area in km^2.

(7.42%) in 2017, reaching 1,849.89 km^2 (8.06%) in 2020. Meanwhile, the Bare Soil class increased from 4,349.72 km^2 (18.95%) in 2014 to 4,814.15 km^2 (20.97%) in 2017, and further to 4,815.2 km^2 (20.98%) in 2020.

The land use class growth was more pronounced between 2014–2017 than between 2017–2020. For instance, during the 2014–2017 period, oil palm and bare soil areas increased by 628.34 km^2 and 464.43 km^2, respectively, reflecting growth rates of 58.45% and 10.68%. Conversely, vegetation formation areas decreased by 1,092.77 km^2, a decline of 6.23%. In the 2017–2020 period, the transitions continued in the same direction but at a slower pace, with oil palm and bare soil areas expanding by 146.62 km^2 and 1.05 km^2 (growth rates of 8.61% and 0.02%), respectively, while vegetation formation decreased by 147.67 km^2, a decline of 0.90%. Therefore, the empirical evidence indicates gains in land use classes and losses in the vegetation cover class.

It is important to note that the results reflect net gains and losses, which can obscure significant transitions in LULC change. Understanding these transitions is crucial for developing strategies to curb illegal deforestation and optimize public policies for land

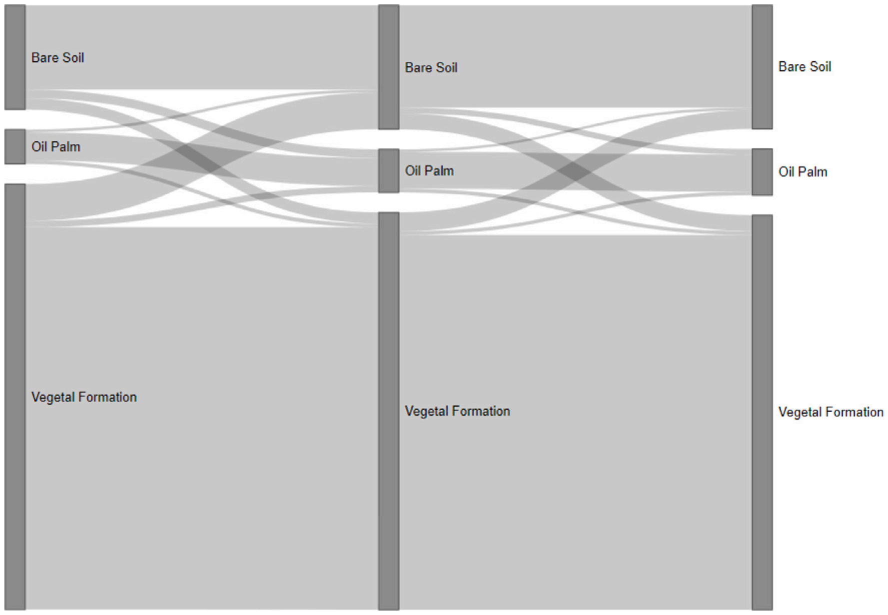

Fig. 7. LULC transitions between 2014–2017 and 2017–2020.

use planning. In this context, Fig. 7 presents the LULC transitions for the years 2014, 2017, and 2020. The results generally show that the most significant transitions occur between the vegetation formation and bare soil classes. This scenario likely reflects the influence of major deforestation drivers in the Amazon, which are often associated with the bare soil class, particularly agricultural activities.

4. Discussion

This study demonstrated the effectiveness of using a combination of Landsat −8 and Sentinel-1 images along with machine learning algorithms for mapping oil palm in the Eastern Amazon. The results generally show an expansion of oil palm cultivation alongside a significant reduction in vegetation cover, with a portion of this loss directly linked to the expansion of oil palm, despite efforts aimed at sustainable development. This reduction in vegetation cover represents a significant environmental impact for the region, as it includes the deforestation of forests that are crucial for carbon storage, biodiversity, and ecosystem services.

The expansion of oil palm directly reduced vegetation cover by 156.88 km^2 between 2014 and 2020, contradicting the goals of public policies such as the PPSP, which aimed to promote its sustainable growth. These empirical findings align with existing literature, which indicates that part of the oil palm expansion in Pará occurs at the expense of forested areas (Carvalho et al., 2015; Lameira et al., 2016; Furumo and Aide, 2017; Benami et al., 2018; Almeida et al., 2020; Dias and Lima, 2021; Silva et al., 2023). Overall, this demonstrates the fragility of environmental policies and institutions in Brazil, which have been unable to prevent the reduction of vegetation cover in the Eastern Amazon. The following paragraphs will highlight some of the key policies and institutions involved.

In 2009, the government of Pará introduced the Plan for Prevention, Control, and Alternatives to Deforestation in the State of Pará (PPCAD-PA), followed by the “Green Municipalities” Program in 2011, both aimed at curbing deforestation in the state (Dias and Lima, 2021). These initiatives complement broader federal policies, such as: (i) the Action Plan for the Prevention and Control of Deforestation in the Legal Amazon (PPCDAm) launched in 2004; (ii) the 2008 mandate for environmental compliance as a condition for rural credit; and (iii) the List of Priority Municipalities also established in 2008. Additionally, specific public policies targeting oil palm cultivation were implemented, including the ZAE and the PPSP in 2010, both designed to promote sustainable expansion of oil palm and prevent deforestation of forested areas. In general, these policies were not sufficient to curb environmental impacts due to oil palm expansion,

However, it is important to note that during the analyzed period, particularly after 2019, the federal government significantly scaled back its environmental preservation efforts, which has undermined the country’s environmental policies (Barbosa et al., 2021). This shift raises concerns that the reduction in vegetation cover in the Eastern Amazon may continue or even worsen, exacerbating existing environmental challenges. This region, already characterized by a history of occupation and human activity, has a fragmented and ecologically threatened landscape. Therefore, despite the initiatives at both national and state levels to curb deforestation and promote the sustainable expansion of oil palm, the increasing fragility of institutions necessitates additional efforts to monitor and manage this expansion (Lameira et al., 2016; Brandão et al., 2021).

Despite the negative environmental impacts, it is important to note that most of the oil palm expansion occurs on bare soil, including previously deforested areas (Carvalho et al., 2015; Benami et al., 2018; Almeida et al., 2020). However, as Benami et al. (2018) highlights, much of this expansion takes place close to forests, which may encourage future deforestation. Additionally, some pasture areas converted to oil palm were recently deforested, casting doubt on the environmental sustainability of oil palm expansion even in deforested regions. In other words, the definition of deforestation-free oil palm expansion depends heavily on the reference year used. Moreover, the expansion of oil palm over pasture areas can lead to Indirect Land Use Changes (ILUC), which occur when higher-value agricultural activities like oil palm displace cattle ranching, pushing it into agricultural frontier regions and increasing pressure on forest areas (Richards et al., 2014).

Finally, the European Union (EU) deforestation-free supply chain legislation, which came into force on June 29, 2023, with a phased implementation over 18 to 24 months, and the United Kingdom's (UK) related measures under Schedule 17 of the Environment Act 2021, establish stringent regulations on forest-risk commodities in commercial activities. These policies aim to address global environmental challenges associated with agricultural expansion by promoting sustainable trade in key commodities, including cattle, soybeans, coffee, and oil palm. For oil palm, compliance with these regulations will require robust monitoring frameworks, traceability systems, and alignment with international standards (Cesar de Oliveira et al., 2024). The methodology and findings of this study can provide valuable tools to support these requirements, offering data-driven insights that can facilitate the implementation of effective monitoring strategies and governance mechanisms, thereby helping to satisfy the demands of the legislation and mitigate environmental impacts.

5. Conclusion

This study employed an innovative methodology by combining optical images from Landsat −8 and radar images from Sentinel-1, along with machine learning algorithms, to map oil palm in the Eastern Amazon for the years 2014, 2017, and 2020. The classification of oil palm areas achieved accuracies of 94.53%, 94.28%, and 95.53%, with Kappa coefficients of 0.9075, 0.9031, and 0.9239 for 2014, 2017, and 2020, respectively. Notably, these results surpass those reported in previous studies that also aimed to map oil palm in the Eastern Amazon, confirming the superior classification power of the methodology adopted in this study.

We then conducted a pixel-level analysis of LULC changes to map the expansion of oil palm between 2014 and 2020. Although this effort confirmed that the expansion predominantly occurred over deforested areas, a significant portion still took place directly over vegetation cover, raising concerns about the sustainability of this growth. Notably, this expansion occurred despite public policies aimed at curbing deforestation and promoting the sustainable development of oil palm. Additionally, expansion into arable areas can lead to indirect effects, such as the displacement of replaced activities to agricultural frontier regions, where deforestation pressures may increase.

In this context, the expansion of oil palm in the Eastern Amazon continues to raise important questions that should be addressed in future research, such as: (i) To what extent have the adopted environmental and sectoral policies inhibited deforestation and/or encouraged the expansion of oil palm? (ii) Will future oil palm expansion lead to further deforestation? (iii) Has the advancement of oil palm in deforested areas displaced other activities to agricultural frontier regions, thereby indirectly contributing to increased deforestation?

The first issue can be addressed through the construction of a counterfactual scenario, where a control group shares the same characteristics as the treatment group (those benefiting from the policy) but is not subject to the policy. In other words, the only systematic difference between the two groups is participation in public policy, enabling the use of inferential statistics to measure the causal effect of the policy. The second question, in turn, could be approached using machine learning methods to predict the future expansion of oil palm, including models such as RF, SVM, Gradient Boosting Machines (e.g., XGBoost), Deep Learning models (e.g., Convolutional Neural Networks, CNNs), Long Short-Term Memory (LSTM) networks, and Ensemble Methods. Finally, the third question can be tackled with conventional and spatial econometrics, exploring spatial leakages, spillovers, and interactions between variables.

In summary, significant issues remain to be addressed to better understand the expansion of oil palm in the Eastern Amazon and to identify its impacts and causes. The evidence that this expansion is occurring over both vegetation cover and deforested areas raises concerns about the sustainability of this crop due to its potential direct and indirect impacts on deforestation. Therefore, gaining a deeper understanding of these effects and developing appropriate public policies are crucial to ensuring the sustainable expansion of oil palm in the Amazon region. Practically, the oil palm mapping and the pixel-level LULC change analysis conducted in this paper can be utilized to identify areas of highest environmental risk, thereby supporting the design of public policies and improving governance within the oil palm production chain.

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CRediT authorship contribution statement

Pedro Henrique Batista de Barros: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Filipe Gomes Dias:** Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **José Alberto Quintanilha:** Writing – review & editing, Supervision, Project administration, Conceptualization. **Carlos Henrique Grohmann:** Supervision, Conceptualization.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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