Mapping Perennial Crops in Complex Tropical Landscapes with Harmonized Landsat Sentinel Time Series

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Abstract

Mapping perennial crops in tropical regions remains challenging due to high spectral complexity, frequent cloud cover, and phenological overlap between different types of vegetation. This study evaluated the potential of the Harmonized Landsat-Sentinel (HLS) dataset to identify perennial crops in the municipality of Jacupiranga, São Paulo, Brazil, an area representative of the Atlantic Forest mosaic. A hierarchical classification was applied using the Random Forest (RF) algorithm on temporal compositions of 2024 NDVI, NDWI, and BSI indices, structured into three analytical levels: (1) natural vegetation versus anthropic areas, (2) perennial crops versus other uses, and (3) banana versus peach palm. Accuracies ranged from 0.86 to 0.98 and F1 ranked between 0.86 and 0.95. The most influential variables were concentrated in the transition months between the dry and rainy seasons, highlighting the relevance of canopy moisture and vegetative vigor in class discrimination. The final maps indicate that approximately 25% of Jacupiranga is agricultural land, of which 43 km² corresponds to perennial crops, with 80% occupied by banana plantations. The results demonstrate the potential of HLS open data to generate accurate multiscale mapping of perennial crops in complex tropical landscapes, supporting digital agriculture and sustainable management in family farming regions.

1. Introduction

The Atlantic Forest, a tropical forest biome that stretches across large areas of Brazil, Paraguay, and Argentina, is home to one of the greatest biodiversities on the planet and, at the same time, concentrates a variety of traditional production systems capable of sustaining thousands of farming families (Tubenchlak, 2021; Santos et al., 2020). In Brazil, the Ribeira Valley, located in the south of the state of São Paulo, stands out. The variety of permanent systems, including tropical fruit cultivation, coffee cultivation, and floriculture, reflects the state's climatic and productive amplitude. In this perspective, the Ribeira Valley stands out as one of the most significant regions for the production of tropical perennial crops, serving as a strategic territory that combines rural economic development and environmental conservation.

These productive landscapes coexist with continuous remnants of Atlantic Forest, forming an extremely heterogeneous socio-environmental mosaic. The marked topographical variation, the presence of dense forests, and the transition between successional stages and cultivated areas result in high spectral complexity, making mapping and monitoring by remote sensing difficult (Rodrigues et al., 2020). In humid tropical areas, such as the Ribeira Valley, the constant presence of clouds restricts the acquisition of images without atmospheric interference. In addition, the spectral similarity between the canopies of native forests, pastures, and perennial crops causes confusion between classes. Furthermore, phenological overlap reduces the contrast between spectral signatures, making the mapping of these systems a persistent scientific challenge, even for medium spatial resolution sensors (Tufail et al., 2025).

In this context, digital agriculture and artificial intelligence techniques have become essential tools for improving the monitoring and management of agricultural systems, especially in regions with high spatial heterogeneity. The use of machine learning algorithms has enabled the extraction of complex spatial and temporal patterns from large volumes of remote sensing data, allowing for the automation of crop identification and reducing uncertainties in classifications (Kuikel et al., 2021). However, the advancement of these technologies does not always reach small and medium-sized producers, who constitute the agricultural base of the Ribeira Valley and other tropical regions of Brazil, in an equitable manner. Barriers, including limited access to connectivity, technical training, and high-resolution open data still restrict the full adoption of digital agriculture, reinforcing technological inequalities in rural areas (de Souza et al., 2022; Silva et al., 2024). These limitations emphasize both the scientific and social challenges associated with applying digital innovation in family-based tropical agriculture.

The Harmonized Landsat-Sentinel (HLS) dataset emerges as a promising alternative, still in its infancy in Brazilian agricultural mapping. HLS integrates observations from Landsat 8/9 and Sentinel-2 satellites, harmonizing their surface reflectances and providing images with a spatial resolution of 30 meters. This integration improves radiometric and temporal consistency between sensors, enabling the generation of dense time series in regions frequently affected by persistent cloud cover, which remains one of the main constraints for optical remote sensing in tropical environments, often limiting data availability and reducing the reliability of vegetation monitoring (Claverie et al., 2018). In this regard, multisensor harmonization and dense time series analysis represent innovative methodological advances, capable of improving accuracy and temporal stability in agricultural mapping under challenging atmospheric conditions (Illarionova et al., 2025). In addition to its technical robustness, HLS stands out for being an open-access and free product, which significantly expands its applicability in family farming and public research contexts, where financial and technological resources are often limited. Recent studies demonstrate the novelty and effectiveness of using HLS series in agricultural applications, such as mapping coffee phenological stages (Parreiras et al., 2025) and analyzing agricultural intensification in Cerrado (Bolfe et al., 2023). The high temporal density and multisensor consistency of HLS data also enhance the performance of machine learning approaches, particularly Random Forest, by providing a more complete representation of spectral and phenological variability over time, which is essential for improving class separability and classification accuracy in heterogeneous agricultural landscapes (Parreiras et al., 2025).

Thus, this study aims to evaluate the potential of the HLS dataset in identifying and mapping perennial crops in the municipality of Jacupiranga, São Paulo, Brazil, using hierarchical classification and machine learning techniques. Beyond its empirical results, the research highlights innovative contributions related to harmonized time-series use and addresses ongoing scientific challenges in discriminating perennial crops under the complex biophysical and spectral conditions of tropical environments.

2. Material and Methods

2.1 Study area

The municipality of Jacupiranga, which is situated in the Ribeira Valley in southeast São Paulo State, Brazil, was selected as the study area (Figure 1).

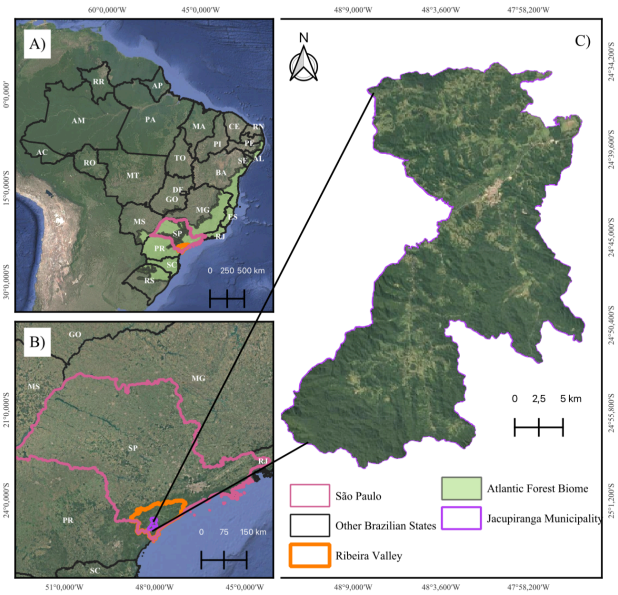

Figure 1. Location map of the study area. A) Map of Brazil highlighting the State of São Paulo. B) São Paulo State showing the Ribeira Valley region in the southern portion of the state. C) Jacupiranga municipality, located within the Atlantic Forest biome, southeastern Brazil.

The Ribeira Valley hosts one of the largest remaining continuous tracts of Atlantic Forest in Brazil, containing nearly 21-23% of the biome's total remnants (SOS Mata Atlântica, 2023). These forests constitute the largest continuous remnant of the Atlantic Forest biome and include not only dense montane rain forest but also about 150.000 hectares (ha) of restinga (coastal forest) and 17.000 ha of mangroves in excellent conservation status (SOS). Therefore, Ribeira Valley conservation is crucial for preserving biodiversity as well as for sustaining low-impact family farming systems and sustainable livelihoods that support regional food security and cultural heritage.

The region is characterized by rugged terrain and a humid tropical–subtropical climate, with an average annual temperature of approximately 21 °C and annual precipitation around 1700 millimeters (mm) (CHC, 2024). The complex geomorphology typical of the Atlantic Forest biome is expressed in elevations ranging from low valleys to over 1200 meters (m), producing high spatial heterogeneity and ecological diversity across the municipality. Jacupiranga's landscape is a mosaic of pastures, diversified agricultural areas, and remnants of native forest. Covering about 704 square kilometers (km²), the perennial crops are largely cultivated on small and medium-sized holdings that account for more than 95% of the local agricultural production (SOS Mata Atlântica, 2023).

Since the coexistence of perennial crops, pastures, and native forest, along with significant topographic gradients, presents difficulties for both spectral discrimination and seasonal signal separation, Jacupiranga's location within the Vale do Ribeira offers an optimal setting for remote-sensing-based land-use and land-cover classification from a geospatial standpoint (Bolfe et al., 2020; MapBiomas, 2023).

2.2 Data Acquisition

The HLS Collection 2.0 products, which integrate Landsat-8/9 and Sentinel-2 surface reflectance at a spatial resolution of 30 m and a temporal frequency of approximately 2-3 days, were the source of the satellite data, downloaded via the Earth Data portal (https://search.earthdata.nasa.gov/). 15-day gap-filled composites were created by acquiring and processing the dataset for 2024, all available images for the period were used, which had undergone pre-processing.

The HLS dataset was chosen because of its distinctive blend of high temporal resolution (2-3 days) and radiometric harmonization between Landsat and Sentinel-2. This is especially beneficial in tropical areas prone to clouds, like the Ribeira Valley. Family-based agriculture in the study region is usually organized in small to medium-sized holdings that are typically larger than a single pixel (900 m²), even though the spatial resolution of 30 m may limit the detection of very small agricultural plots. Furthermore, the use of dense multi-temporal information compensates for spatial limitations by capturing phenological and structural differences over time, which are critical for distinguishing perennial crops in heterogeneous tropical landscapes (Bolfe et al., 2023; Claverie et al., 2018)..

A sequence of preprocessing steps was applied to prepare the HLS images for time-series analysis and land-use classification. First, low-quality or missing pixels were eliminated by removing clouds and shadows using the quality assurance bands found in the HLS dataset. To ensure radiometric consistency across sensors, the optical reflectance bands were then scaled in accordance with surface reflectance standards. After that, each image was spatially harmonized to a resolution of 30 m and clipped to the study area's boundaries. Bilinear interpolation was used to resample the shortwave-infrared bands in order to match the visible and near-infrared bands' spatial resolution.

For every biweekly composite, three vegetation indices, the Normalized Difference Vegetation Index (NDVI) (Rouse, 1973), Normalized Difference Water Index (NDWI) (Gao et al., 1996), and Bare Soil Index (BSI) (Rikimaru et al., 2002), were computed from these harmonized photos. These indices, which stand for vegetation greenness, canopy moisture, and soil exposure, are complementary features of the landscape that offer an effective spectral basis for differentiating between different types of land cover and perennial crops.

To reduce data dimensionality and improve the physical interpretability of the features, this study used three well-known spectral indices (NDVI, NDWI, and BSI) in place of raw spectral bands. Complementary biophysical characteristics of the landscape, such as soil exposure, canopy moisture, and vegetation vigor, are captured by these indices and are especially important for differentiating perennial crops in tropical settings. Additionally, this method increases model robustness and decreases redundancy among spectral bands, particularly in situations where training samples are scarce and spectral similarity between classes is high [Parreiras et al., 2025].

The resulting time-series dataset served as input for the hierarchical Random Forest (RF) classification and contained 25 biweekly layers per index.

2.3 Reference Data and Hierarchical Classification Scheme

The study area's primary land-use gradients were reflected in the classification's hierarchical structure (Figure 2). By enhancing spectral separability and logical consistency across levels, this structure makes it possible to discriminate between vegetation types gradually.

Using visual interpretation of high-resolution imagery, field observations, and supplementary land-cover maps, pixels were first divided into two categories: Natural Vegetation and Anthropogenic Agricultural Areas, considering in the second category also the pasture areas. Then, to differentiate between short-cycle annual crops and long-lived perennial plantations, the Anthropogenic Agricultural Areas were separated into Permanent Crops and Other Uses. Lastly, the classification determined that the two dominant species in the permanent-crop domain are the peach palm (*Bactris gasipaes*) and the banana (*Musa spp.*).

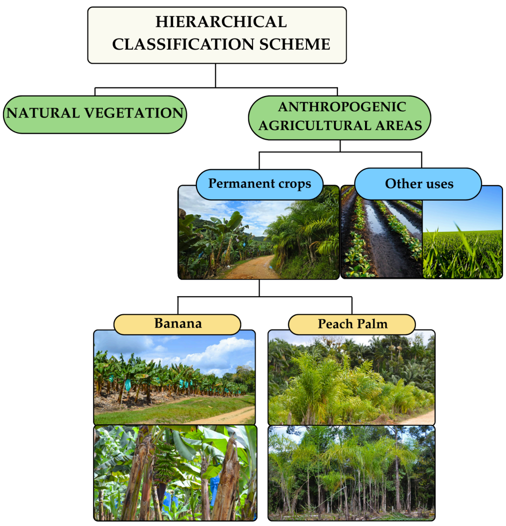

Figure 2. Hierarchical classification scheme showing the progressive separation of classes in this study.

Field data, UAV imagery, and manual photointerpretation of recent high-resolution satellite images were used to create the training and validation samples. To guarantee a balanced number of samples across classes and hierarchical levels, homogeneous areas of each class were first drawn as polygons and subsequently transformed into random points. The conversion from polygons to points was performed by randomly sampling pixels within each homogeneous polygon, ensuring that each point represents a single 30 m pixel compatible with the spatial resolution of the HLS dataset. In total, 959 samples were used for Level 1 (500 natural vegetation, 459 anthropogenic areas), 162 for Level 2 (78 permanent and 66 other uses), and 151 for Level 3 (85 banana and 66 peach palm) (Figure 3).

The high-resolution imagery used for reference data generation includes UAV data and satellite images with spatial resolutions ranging from sub-meter to approximately 5 meters. This level of detail ensured accurate identification of crop types and land-use classes, allowing reliable training and validation of the classification models despite the coarser spatial resolution of the HLS dataset.

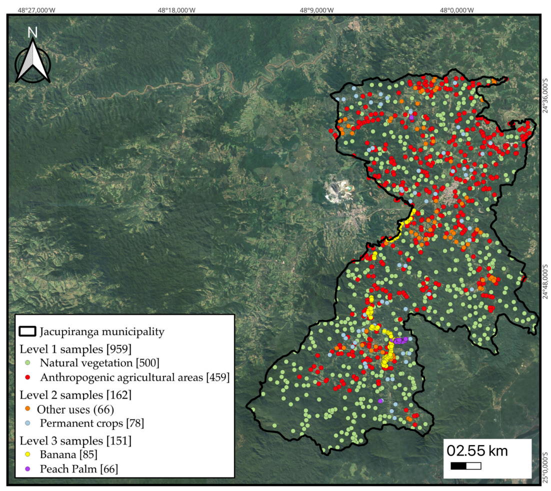

Figure 3. Spatial distribution of training and validation samples used in this study.

Data collection at Level 3 was supported by the AgroTag mobile and WebGIS system, which enabled the geo-referenced recording of field plots, photographs, and attribute forms, streamlining the integration of ground-truth points and high-resolution imagery (Araújo et al., 2019).

2.4 Model Training and Validation

A hierarchical modeling workflow was implemented to classify vegetation and crop types across three levels. Each level used a separate RF model (Breiman, 2001), trained on combinations of temporal metrics from the NDVI, NDWI, and BSI indices derived from HLS data. Temporal information was incorporated by stacking all 15-day composites as independent features in the classification model. For each spectral index (NDVI, NDWI, and BSI), approximately 25 temporal layers were generated for the year 2024, resulting in a multi-temporal feature space in which each time step contributes to the classification. The reference dataset represents a static land-use condition for 2024, assuming that crop classes remain consistent throughout the year. Thus, all temporal features are jointly used to capture the phenological behavior of each class.

Random Forest was selected due to its robustness to noisy data, strong performance in high-dimensional feature spaces, and suitability for relatively small training datasets, which are common in agricultural applications (Breiman, 2001). In contrast, deep learning approaches typically require larger labeled datasets and higher computational resources, which may limit their applicability in data-scarce and resource-constrained contexts such as smallholder farming systems (Zhong et al., 2019). Additionally, Random Forest provides interpretable outputs, such as feature importance, which are valuable for understanding the temporal and spectral drivers of crop discrimination.

Seven feature sets were tested: individual indices (NDVI, NDWI, BSI), all pairwise combinations, and the full integration of the three indices. The reference dataset for each level was split into 70% training and 30% testing, maintaining class balance through stratified random sampling. Hyperparameter tuning was performed via Grid Search combined with Repeated Stratified K-Fold cross-validation (5 folds × 10 repetitions). The tested parameters included the number of trees (n_estimators = 100, 200, 300), maximum tree depth (max_depth = 3–11 and None), and minimum split size (min_samples_split = 2, 3, 5).

Hyperparameter tuning was performed exclusively on the training dataset using Grid Search combined with Repeated Stratified K-Fold cross-validation (5 folds × 10 repetitions), ensuring that model selection was independent from the test set The final evaluation was conducted on a hold-out test set (30% of the samples), which was not used during model training or hyperparameter optimization. This strategy ensures an unbiased assessment of model performance and reduces the risk of overfitting.

Model performance was evaluated using accuracy, Cohen’s Kappa, weighted F1-score, recall, and precision. The best-performing combination of indices for each level was selected based on the highest accuracy and Kappa values. Confusion matrices and feature-importance plots were generated to interpret model behavior and identify the most influential temporal variables. The selected models were then exported and applied to the corresponding multitemporal raster stacks to produce spatial predictions. This validation and application strategy ensured both statistical robustness and spatial consistency across the hierarchical classification levels.

Model performance metrics (accuracy, Kappa, F1-score, precision, and recall) were computed based on the final classification outputs of the multi-temporal model. Since the classifier integrates all temporal features simultaneously, the reported metrics represent the performance of a single multi-temporal classification, rather than an average over individual time steps.

2.5 Accuracy Assessment and Final Map Generation

For every hierarchical level, confusion matrices and feature-importance analyses were used to assess the model's performance. To ensure consistency between model training and map production, the top-performing classifiers were applied to the corresponding multitemporal raster stacks to produce spatial predictions. With class codes ranging from 1 to 2 and a value of 0 assigned to NoData, all predictions were exported as single-band GeoTIFF files in uint8 format. In order to evaluate spatial coherence and class separability, the outputs were compressed using DEFLATE and displayed in false-color composites.

Each level of the map was subjected to a 3×3 modal filter to improve spatial continuity and reduce salt-and-pepper noise. In order to eliminate non-agricultural regions, such as urban and water classes, the filtered maps were then clipped to the municipal boundary and masked using the MapBiomas dataset (24, 25, 26, 30, 31, 33).

The resulting hierarchical maps show the distribution of perennial crops (Level 2), the extent of vegetation (Level 1), and the spatial patterns of peach palm and banana (Level 3). The effectiveness of the hierarchical RF approach was validated by visual inspection against reference data, which verified the spatial and semantic consistency among levels. Because of its scalability, this framework can easily be expanded to multi-year analyses or other areas with comparable tropical landscape complexity.

3. Results and Discussion

3.1 Data Availability and Cloud Cover

The monthly variation of cloud cover in 2024 was examined using all valid HLS acquisitions to more clearly depict the temporal distribution of atmospheric conditions throughout the year (Figure 4). The boxplots summarize the interquartile range and central tendency of cloud coverage for each month, revealing a clear seasonal signal in cloudiness: lower cloud percentages were concentrated between April and September, whereas higher values occurred predominantly from October to March.

In total, 156 valid HLS images were available for 2024, corresponding to a mean revisit interval of approximately 2.35 days and a median of 2 days. Mean cloud coverage reached 66.99 % between October and March and 64.03 % between April and September, with medians of 77 % and 72 %, respectively. Although these patterns suggest periods with relatively reduced cloudiness, it is important to emphasize that the study area does not experience a well-defined dry season. The Ribeira Valley is characterized by a humid subtropical climate with high cloud persistence throughout the year, which poses a considerable challenge for optical remote sensing, particularly for crop mapping and phenology-based analyses. Even so, 20 clearer scenes (cloud coverage < 40 %) were available between October and March and 23 between April and September.

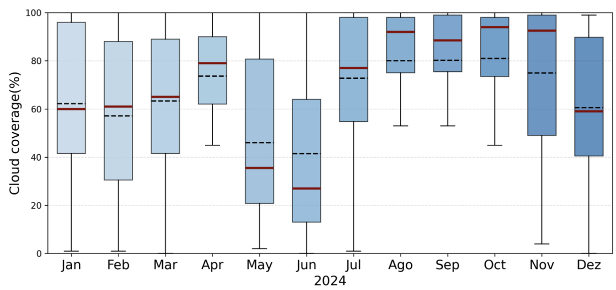

Figure 4. Monthly distribution of cloud cover (%) from HLS images acquired in 2024.

3.2. Accuracy Assessment and Importance of Variables

3.2.1 Overall Performance of Hierarchical Classification: The hierarchical RF models did well at all levels of classification, with overall accuracies between 0.86 and 0.98 (Table 1). The combination of vegetation and moisture indices performed best at Level 1, which distinguishes natural vegetation from areas used for human agriculture. The combination of NDVI and NDWI had the best results (Accuracy = 0.975; Kappa = 0.951; F1 = 0.975), followed closely by NDVI + NDWI + BSI. This shows that greenness and canopy moisture indicators work well together to separate vegetated areas from open or managed areas. At Level 2, which separates permanent and other uses, the accuracies were a little lower but still strong (Accuracy = 0.925; Kappa = 0.847).

Once more, the NDVI + NDWI + BSI feature set outperformed the others, demonstrating the value of spectral data associated with canopy water content, vegetation vigor, and soil exposure in identifying minute structural variations between crop systems. At Level 3, which distinguishes between peach-palm (*Bactris gasipaes*) and banana (*Musa spp.*) (Accuracy ≈ 0.89; Kappa = 0.77). The benefit of integrating vegetation, water, and soil-related data for thorough perennial-crop mapping was reiterated when models combining multiple indices, particularly NDVI + NDWI + BSI, performed better than those based on a single metric.

Level	Model	Accuracy	Kappa	F1
1	NDVI	0.958	0.916	0.958
	NDWI	0.961	0.923	0.961
	BSI	0.965	0.930	0.965
	NDVI+NDWI	0.975	0.951	0.975
	NDVI+BSI	0.982	0.965	0.982
	NDWI+BSI	0.965	0.930	0.965
	NDVI+NDWI+BSI	0.975	0.951	0.975
2	NDVI	0.912	0.819	0.912
	NDWI	0.918	0.834	0.919
	BSI	0.918	0.833	0.918
	NDVI+NDWI	0.912	0.820	0.912
	NDVI+BSI	0.918	0.833	0.918
	NDWI+BSI	0.918	0.834	0.919
	NDVI+NDWI+BSI	0.925	0.847	0.925
3	NDVI	0.913	0.818	0.911
	NDWI	0.913	0.821	0.912
	BSI	0.869	0.728	0.866
	NDVI+NDWI	0.891	0.774	0.889
	NDVI+BSI	0.891	0.774	0.889
	NDWI+BSI	0.869	0.728	0.866
	NDVI+NDWI+BSI	0.891	0.774	0.889

Table 1. Accuracy, Kappa, and F1-score obtained with RF for each hierarchical level and combination of spectral indices (NDVI, NDWI, and BSI) derived from HLS time-series data in this study.

3.2.2 Confusion Matrix Analysis and Error Rates: Tables 2, 3, and 4 present the confusion matrices corresponding to the classification results for Levels 1, 2, and 3, respectively. The classification successfully distinguished between anthropogenic agricultural areas and native vegetation at Level 1 (NDVI + BSI), achieving accuracy levels above 90%. Indicating that spectral indices associated with vegetation vigor and bare soil were adequate to distinguish between natural and cultivated landscapes, commission and omission errors stayed below 10%. At Level 2 (NDVI + NDWI + BSI), the inclusion of the moisture index (NDWI) further enhanced the discrimination between non-perennial and perennial crops, reducing class overlap.CE and OE values (approximately 6–9 %) suggest slight seasonal and phenological similarities among crop types, yet overall model performance remained stable. At Level 3 (NDWI only), the model successfully differentiated banana and peach-palm plantations, maintaining satisfactory accuracy. A slightly higher omission error for peach palm (around 15 %) may be associated with the greater structural variability and smaller canopy size typical of this crop.

The three levels collectively display a consistent and increasing pattern of classification accuracy, demonstrating that the chosen spectral indices effectively captured the physiological and structural traits pertinent to each hierarchical scale.

Level 1	NV	AA	OE %
NV	125	13	9.41
AA	8	142	5.33
CE %	6.02	8.39	---

Table 2. Confusion matrix and error rates (commission and omission errors, CE % and OE %) for Level 1, corresponding to the classification based on NDVI and BSI indices. The RF model accurately distinguishes native vegetation (NV) from anthropogenic agricultural areas (AA).

Level 2	OU	PC	OE %
OU	80	6	6.98
PC	5	57	8.06
CE %	5.88	9.52	---

Table 3. Confusion matrix and error rates (CE % and OE %) of the RF model for Level 2, corresponding to the classification using NDVI, NDWI, and BSI indices. The discrimination is between other uses (OU) and perennial crops (PC).

Level 3	BAN	PAL	OE %
BAN	25	1	3.85
PAL	3	17	15.00
CE %	10.71	5.56	---

Table 4. Confusion matrix and error rates (CE % and OE %) of the RF model for Level 3, corresponding to the classification using only NDWI. The model differentiates banana (BAN) and peach palm (PAL) plantations

Previous studies had already evaluated the performance of classifiers in mapping perennial crops, which reinforced the choice of RF in the present study. Falanga Bolognesi et al. (2020), when applying different algorithms (RF, SVM, Decision Tree, Boosted DT, ANN, and KNN) to detect irrigated areas in southern Italy, including perennial tree crops, observed that RF performed best in almost all preprocessing scenarios, achieving accuracies of 86.3% to 87.8% and Kappa between 0.725 and 0.766. Even when compared to SVM with variable selection, RF maintained more consistent results, especially when the training set was balanced (OA = 87.8%; Kappa = 0.766), demonstrating its robustness in the face of unbalanced classes and spectral variations. This behavior is consistent with the results obtained in Jacupiranga, where RF was also adopted for its stability and superior performance in combining multiple spectral indices. The choice of algorithm was particularly appropriate for the tropical and heterogeneous context, in which intra-class variability is high (Falanga Bolognesi et al., 2020).

Soares et al., (2025), when mapping banana and peach palm with Sentinel-2 data, found that NDWI alone performed best at Level 2, with an overall accuracy of 0.898 and a Kappa of 0.795, reinforcing the role of canopy moisture as a critical variable for distinguishing perennial crops from non-perennial crops. In contrast, in the present study, the difference between Level 1 (NDVI + BSI) and Level 2 (NDVI + NDWI + BSI) shows that the addition of NDWI increased accuracy from 0.912 to 0.925 and Kappa from 0.819 to 0.847, demonstrating that the combination of vegetative vigor, moisture, and soil exposure improves separability between classes with distinct leaf structure. Thus, while Soares et al., (2025) confirm the isolated strength of NDWI in Sentinel-2 data, the results with the HLS series show that integrating multiple indices can better capture the spectral and temporal variability of tropical agricultural systems, resulting in more robust models in heterogeneous mosaics.

3.2.3 Variable Importance and Temporal Patterns: Figure 5 presents the ranking of the most relevant variables used in the best hierarchical classification models for levels. A clear temporal pattern is observed across the three levels, with the most influential variables concentrated in the months corresponding to the main phenological phases of the vegetation and crops. The most significant variables at Level 1 (NDVI + BSI) were primarily derived from mid-year composites (e.g., NDVI_11, BSI_02, NDVI_02), which correspond to the early harvest stage and the dry season, when spectral contrasts between cultivated or exposed-soil areas and natural vegetation become more noticeable.

The most important variables (NDWI_15, NDWI_12, BSI_13, NDWI_13) are concentrated around the dry-wet transition at Level 2 (NDVI + NDWI + BSI), indicating the significance of canopy moisture and vegetation vigor in differentiating perennial from other uses. Lastly, the NDWI composites from the rainy season (e.g., NDWI_21–23) had the highest contributions at Level 3 (NDWI), where variations in water content and leaf density among perennial crops like banana and peach palm are more noticeable.

When discussing the choice of databases used in this study, it is important to consider the practical implications of processing high-resolution images and the balance between spatial detail and computational feasibility. The use of Sentinel-2 at 10 m resolution presents significant limitations when working with large areas, due to the high memory and processing demands. Each 100 x 100 km granule contains approximately 30,000 x 30,000 pixels, and the compressed files can exceed 10 GB per scene, while a single tile reaches approximately 500 MB (GeoSage, 2024). As the sensor provides 13 spectral bands at different resolutions (NASA, 2024), generating complete annual time series can require tens of gigabytes of storage and more than 60 GB of RAM, making processing unfeasible without high-performance infrastructure. In this context, the HLS product emerges as an efficient alternative.

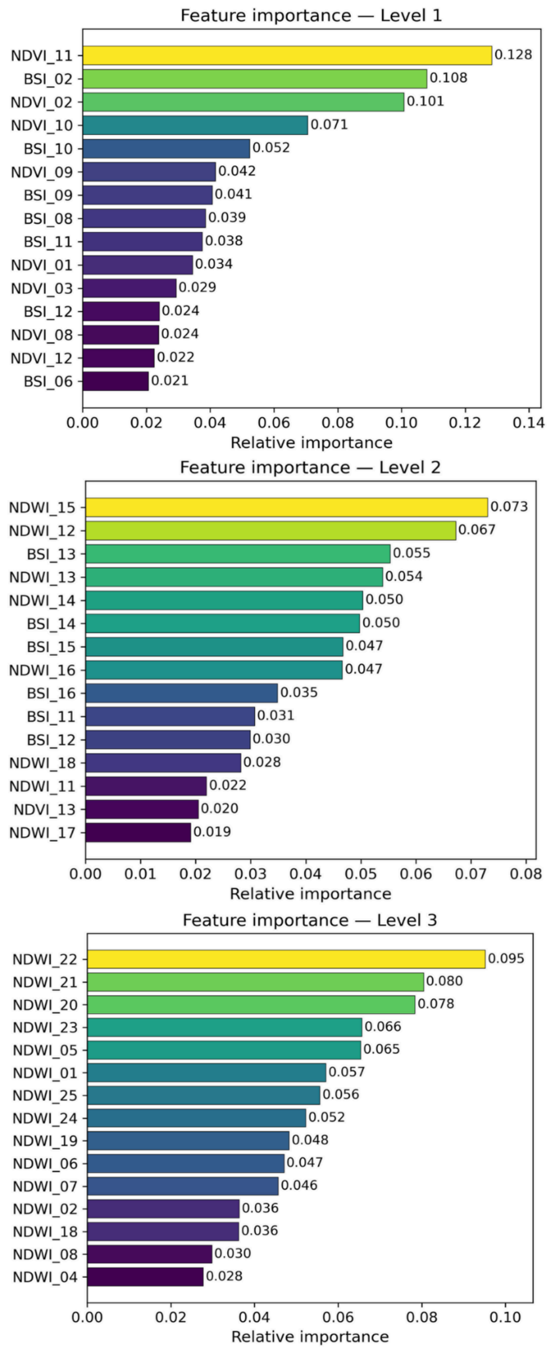

Figure 5. Importance of spectral indices for hierarchical classification models in this study.

3.2.4 Data Efficiency and Methodological Applicability of HLS for Crop Mapping: The HLSS30 product has near-daily global coverage (USGS, 2023), and each band is distributed in COG format, approximately 20 MB per file, which drastically reduces the volume of data to be processed. For municipal or regional scale analyses, HLS allows for an adequate balance between spatial resolution, temporal consistency, and computational feasibility, while Sentinel-2 at 10 m should be reserved for smaller areas or applications that truly require spectral and spatial detail.

Other studies have also mapped banana crops using the RF algorithm and vegetation indices with different sensors, including Sentinel-2, synthetic aperture radar (SAR), and unmanned aerial vehicle (UAV) imagery, reinforcing the strong performance and robustness of RF for perennial crop mapping (Alabi et al., 2022; Kilwenge et al., 2021). In this context, the results presented in this study using free and open HLS data demonstrate an accessible and effective approach for mapping land-use classes and specific perennial crops such as banana and peach palm, reducing the need for field-based UAV surveys and enabling large-scale monitoring without in-situ data collection. Furthermore, the results highlight the potential of combining hierarchical classification, spectral indices, and RF with harmonized satellite imagery.

3.3 Digital Classification Results

3.3.1 Spatial Distribution of Land Use and Land Cover: Land-use and land-cover patterns in Jacupiranga were mapped and spatialized using the outputs from the top-performing classifiers at each hierarchical level (Figure 6). Approximately 25% of the municipality was covered by anthropogenic agricultural areas (17,520 ha) at Level 1, while natural vegetation (53,010 ha) continued to predominate, highlighting the preservation of sizable forest fragments within the Atlantic Forest biome. At Level 2, other uses (12,460 ha) jointly dominated the anthropogenic landscape, whereas permanent crops occupied 4,320 ha. At Level 3, banana plantations covered about 3,460 ha (80% of the permanent-crop area), followed by peach palm (860 ha). The spatial distribution of these classes is consistent with field observations, which show that peach palm and banana are commonly managed or interplanted in adjacent plots, creating intricate agricultural mosaics across the Ribeira Valley landscape.

Bananas (*Musa spp*.) and peach palm (*Bactris gasipaes*) play a central role in the regional economy and food security of local communities in the Ribeira Valley (SMA, 2023). In Jacupiranga, more than 99% of agricultural output is directly associated with banana and peach palm cultivation, underscoring their critical importance for income generation, food security, and cultural identity among local and traditional communities (EMBRAPA, 2025; Coltro et al., 2019; Soares et al., 2025) Moreover, peach palm represents a strategic alternative to native palm species historically explored for palm-heart extraction, offering rapid regrowth in the Atlantic Forest (de Cássia Spacki et al., 2022). Beyond their socioeconomic relevance, perennial crops also contribute to ecosystem services, including soil protection, perennial vegetation cover maintenance, and increased resilience to climatic extremes (Reynolds et al., 2022; Shang et al., 2024).

3.3.2 Implication for Monitoring and Agricultural Planning: Given their environmental, economic, and cultural significance, accurately mapping and monitoring banana and peach palm plantations is essential to support agricultural planning, identify production areas, guide rural extension programs, monitor land-use change, and inform public policies aimed at strengthening sustainable agriculture and territorial management. Scalable geospatial monitoring approaches, grounded in remote sensing and machine learning, are therefore fundamental to providing actionable information for decision-makers, especially in regions dominated by smallholdings and limited field data availability. In this context, studies leveraging open-access satellite imagery and advanced classification strategies play an increasingly strategic role in promoting resilient, inclusive, and sustainable agricultural development in Brazil.

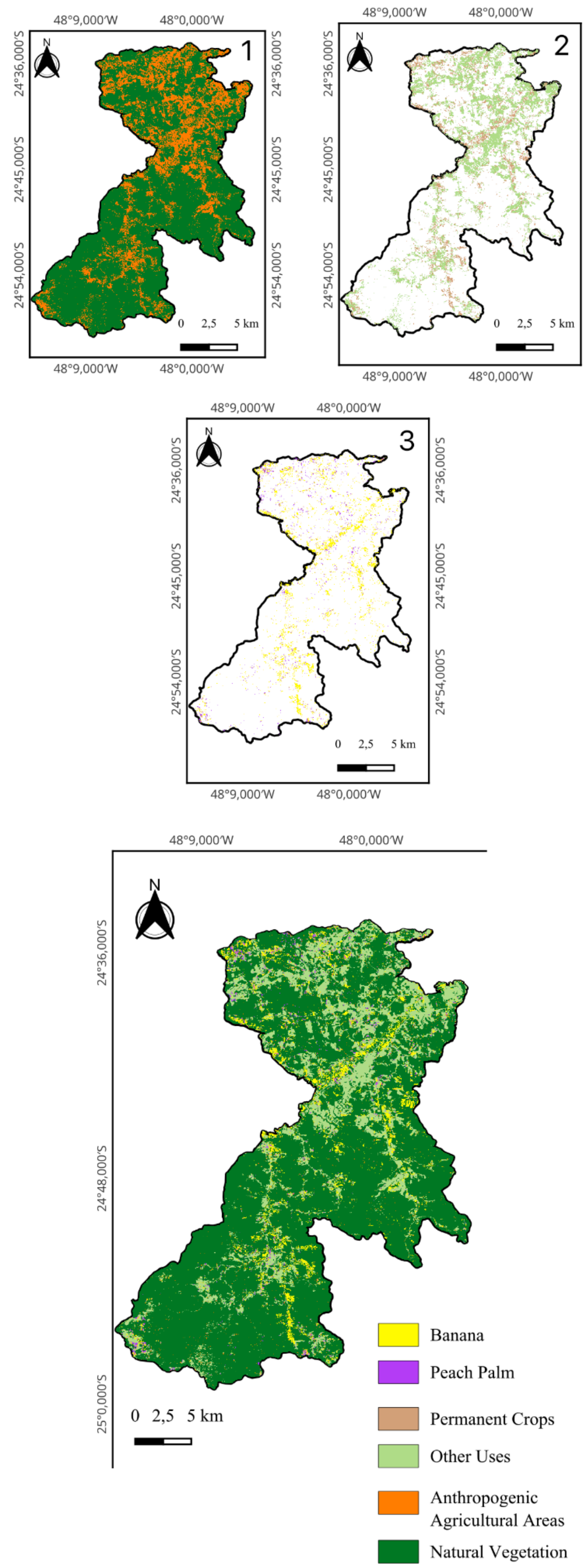

Figure 6. Hierarchical land-use and land-cover classification results for Jacupiranga municipality. Panels 1, 2, and 3 represent the results for classification Levels 1, 2, and 3, respectively.

From a methodological perspective, the accurate discrimination between perennial crops at Level 3 demonstrates the potential of hierarchical classification combined with harmonized multisensor data to capture subtle phenological differences within complex tropical environments. The use of a multi-level structure allowed the classifier to gradually refine distinctions from general vegetation cover (Level 1) to specific crop types (Level 3), improving both interpretability and spatial coherence. These results indicate that integrating dense time-series analysis and hierarchical modeling can overcome some of the limitations traditionally associated with tropical regions, while offering valuable information for territorial management and agricultural planning.

4. Conclusions

This study demonstrated that combining HLS data with a hierarchical classification framework is an effective strategy for mapping perennial crops in tropical heterogeneous landscapes. The approach consistently distinguished natural vegetation, non-perennial crops, and perennial systems, highlighting the value of dense multisensor time series for applications in regions with persistent cloud cover and high spectral similarity among land-use classes. These products support territorial planning, environmental monitoring, and decision-making processes aimed at promoting sustainable agricultural development.

Looking ahead, advances such as deep learning architectures, enriched spectral textural feature sets, and dedicated time-series modeling could further improve the discrimination of perennial systems. Additionally, incorporating UAV-based imagery has strong potential for refining local-scale classifications, validating satellite products, and generating high-resolution information that can directly assist small and medium farmers in crop monitoring, productivity assessment, and management planning.

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