



Integrating remote sensing and in-situ data to determine climate diversity and variability in cocoa systems in the provinces of Jaén and San Ignacio, Cajamarca (NW Perú)

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ABSTRACT

The lack of information on the geographic distribution of cocoa systems, along with species diversity and the influence of climatic factors on yields, presents challenges for the agronomic management of these plantations and the implementation of more effective agricultural policies. The objective of this study was to map cocoa area, species diversity and their response to historical climate variability in the provinces of Jaén and San Ignacio, Cajamarca, Peru.

For this purpose, PlanetScope and Sentinel-1 data, chosen for their high spatial resolution, were processed in Google Earth Engine using the Random Forest (RF) classification algorithm. Species diversity was determined by selecting 15 cocoa plots distributed in three altitudinal ranges. In each plot, all individuals with a diameter at breast height greater than 2.5 cm were registered within four 10 m x 20 m transects. A total of 4,338.6 ha of cocoa monocultures and agroforestry systems (AFS) distributed in valleys and in the proximity of water networks were mapped; overall thematic precision was 0.85 and a kappa index of 0.81. On the other hand, *Musa sp.* predominates at lower altitudes, while *Inga edulis* showed greater dominance at higher altitudes. The application of climatic and cocoa yield data allowed the calculation of the standardized anomaly index, which showed a remarkable impact of rainfall on cocoa yield, especially in 2021 and 2022, when it reached values above 0.94 MT/ha. Consequently, this integrated approach provides a deeper understanding of cocoa AFS, establishing a solid basis for decision-making aimed at optimizing yield through agricultural practices adapted to specific climatic conditions and promoting biodiversity by incorporating native species. Additionally, the findings have practical implications for agricultural policies, such as improving productivity, enhancing biodiversity, and adapting cocoa systems to climate change, promoting their sustainability and resilience.

1. Introduction

In 2022, the global production of cocoa (*Theobroma cacao* L.) reached 5047,000 t (MT), of which 73.6% came from Africa and 20% from America (International Cocoa Organization [ICCO], 2024). Peru, recognized as one of the top 10 producers of coffee and cocoa worldwide (Raihan and Tuspekova, 2022), and distinguished in the international market for its fine or flavor cocoa, with 75% of its exports classified in

this premium category (ICCO, 2024), produced 150,701 MT of cocoa that same year, representing 2.98% of the total. Of this amount, 1072 MT were cultivated in the Cajamarca region, specifically in the provinces of Jaén and San Ignacio (Ministerio de Desarrollo Agrario y Riego [MIDAGRI], 2024).

Cocoa-centered AFS are among the most important terrestrial ecosystems due to the wide range of ecosystem services they provide. Previous studies have documented these benefits, such as soil fertility

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improvement (Arévalo et al., 2020; Blaser et al., 2017), carbon storage of up to 42 MT per hectare (Somarriba et al., 2013; Tinoco et al., 2024), genetic diversity conservation, promotion of biological control (Mortimer et al., 2018), and regulation of climate, water, and nutrients (Ellison et al., 2017; Sauvadet et al., 2020). These benefits make cocoa AFS essential for local communities, increasing cocoa yields by up to 96.6 kg per hectare per year compared to cocoa monocultures (Boeckx et al., 2020; Tinoco et al., 2024).

However, while these benefits are well-documented, challenges remain in understanding the spatial distribution of cocoa systems (Ashiagbor et al., 2023). Satellite remote sensing is commonly used for this purpose, but most sensors, such as the Advanced Very High-Resolution Radiometer (AVHRR) (McGinnis and Tarpley, 1985) and the Moderate-Resolution Imaging Spectroradiometer (MODIS) (National Aeronautics and Space Administration [NASA], 2024), fail to meet the demands for high spatial resolution (Prabhakar et al., 2012), as their resolution exceeds 250 m, making the assessment of small areas difficult (Peng et al., 2017). However, medium-resolution sensors such as Landsat, Sentinel, and PlanetScope have proven fundamental for land use mapping and the development of monitoring strategies in cocoa landscapes (Ashiagbor et al., 2020; Dada and Hahn, 2020; Vizzari, 2022).

Although these medium-resolution sensors represent a significant advancement, they still face limitations in accurately identifying vegetation cover in small and heterogeneous areas. To address these challenges, this study utilizes Google Earth Engine (GEE), which has the capability to efficiently process large volumes of data and perform complex spatial analyses. It also offers a wide range of free datasets (Gorelick et al., 2017) and supports both supervised and unsupervised classification algorithms, such as Random Forest (RF) (Moraiti et al., 2024), K-means clustering (Tutu et al., 2018), Support Vector Machine (SVM) (Kanmegne et al., 2023), Classification and Regression Trees (CART) (Breiman et al., 2017), Spectral Correlation Mapper (SCM) (Carvalho and Meneses, 2000), and Spectral Information Divergence (SID) (Chang, 1999), among others. These tools enable the identification of vegetation cover. Several studies have applied these methods to identify cocoa (Abu et al., 2021; Ashiagbor et al., 2020, 2023; Numbisi et al., 2019; Tutu et al., 2018). However, the high spectral similarity between vegetation classes complicates their separation, which can lead to reduced classification accuracy (Ashiagbor et al., 2020).

Understanding the diversity of timber and/or non-timber forest species in a cocoa AFS is also crucial for ensuring the long-term sustainability of production (Raneri et al., 2021). Several studies have evaluated the structural composition and quantified the diversity of forest species (Sonwa et al., 2010; Storch et al., 2018), while others have measured species diversity in cocoa plots using inventory data (Blaser et al., 2017; López-Cruz et al., 2021; Oke and Odebiyi, 2007; Raneri et al., 2021; Ruiz et al., 2023; Salvador et al., 2019; Sauvadet et al., 2020; Sonwa et al., 2010). However, alternative methods for rapid biodiversity assessments, such as using in situ cameras (Alberton et al., 2017), environmental DNA barcoding (Rey and Capdevielle, 2020) and remote sensing techniques (Peng et al., 2018). Despite their effectiveness, the implementation of these methods is limited by the need for specialized technical knowledge (Raneri et al., 2021). Recently, a new approach has emerged involving the voluntary participation of the local population in species recording and inventory, as well as conducting surveys for large-scale biodiversity monitoring (Kelling et al., 2019). This approach not only improves the quality and quantity of the data collected but also empowers local communities, promoting capacity building and fostering greater environmental awareness (Danielsen et al., 2009).

Finally, climate variability plays a crucial role in the productivity and yield of cocoa AFS (Bunn et al., 2017). Studies have shown that fluctuations in rainfall and unusually high or low temperatures can significantly affect the phenological cycle of cocoa, reducing production and altering bean quality (Rufus and Sekumade, 2016). To predict the

impacts, regression models and other predictive tools have been applied. For example, Adejuwon et al. (2023), used a multiple regression model to predict yield and calculated the Standardized Anomaly Index (SAI) to identify values above and below the mean, finding that precipitation variability significantly influences productivity. Lamos et al. (2020), used machine learning techniques combined with LASSO (Least Absolute Shrinkage and Selection Operator) linear regression analysis to improve prediction accuracy. However, some studies consider including farmers perceptions, as their local knowledge can provide valuable insights for adapting to these climatic variations (Adejuwon, 2018).

In this sense, it is essential to conduct a comprehensive analysis of cocoa AFS that considers not only the sustainability and resilience of the system, but also its geographic location, species diversity, and response to historical climate variability. Unlike previous studies, this study fills existing information gaps by focusing on integrating the mapping of cocoa cultivation areas, evaluating species diversity in relation to elevation, and analyzing the impact of climate variability on cocoa yields in the provinces of Jaén and San Ignacio, Cajamarca region, for better understanding and management of the territory.

2. Material and methods

2.1. Study area

The study area comprises the provinces of Jaén and San Ignacio, in the region of Cajamarca, northwestern Peru (Fig. 1). The study area was selected due to its productive leadership and as an area of intervention for the implementing organization of the research (MIDAGRI, 2024).

The province of Jaén has a legal area of 506,385.65 ha, with an altitudinal range of 333–3963 m.a.s.l (Agencia de Exploración Aeroespacial de Japón [JAXA], 2014). It stands out for its agricultural activity, with a rainy, temperate, and very humid climate throughout the year, an annual average temperature ranging from 11 °C to 33 °C, and an average annual precipitation ranging from 350 mm to 1000 mm (Servicio Nacional de Meteorología e Hidrología del Perú (SENAMHI), 2020). Its population totals 185,532 inhabitants (Gobierno Regional de Cajamarca [GRC], 2012; Instituto Nacional de Estadística e Informática [INEI], 2018), of which 809 are dedicated to cocoa production (MIDAGRI, 2024).

For its part, the province of San Ignacio covers an area of 480,670.8 ha with an altitudinal range of 352–3799 m.a.s.l. (JAXA, 2014). It is characterized by a minimum temperature of 11 °C and a maximum of 29 °C (SENAMHI, 2020). Of its 130,620 inhabitants (INEI, 2018), most are involved in agriculture, with 855 registered cocoa producers (MIDAGRI, 2024).

2.2. Methodological flow

Fig. 2 shows the methodological framework applied to map the cocoa-growing area, determine species diversity, and identify how climate variability impacts the production of cocoa systems in the study area.

2.2.1. Mapping and cartography of cocoa AFS

The processing was conducted on the Google Earth Engine (GEE) platform (Gorelick et al., 2017); for this, the importation and pre-processing of optical and synthetic aperture radar satellite image collections were carried out, which was complemented with a supervised classification using training data and machine learning algorithms, as shown in first section of Fig. 2.

2.1.1.1. Source of satellite data. In this study, a normalized mosaic for February 2024 was acquired, provided by the Satellite Data Program of the Norwegian International Climate and Forest Initiative (NICFI) in collaboration with Planet Labs (Planet Team, 2017). These data were

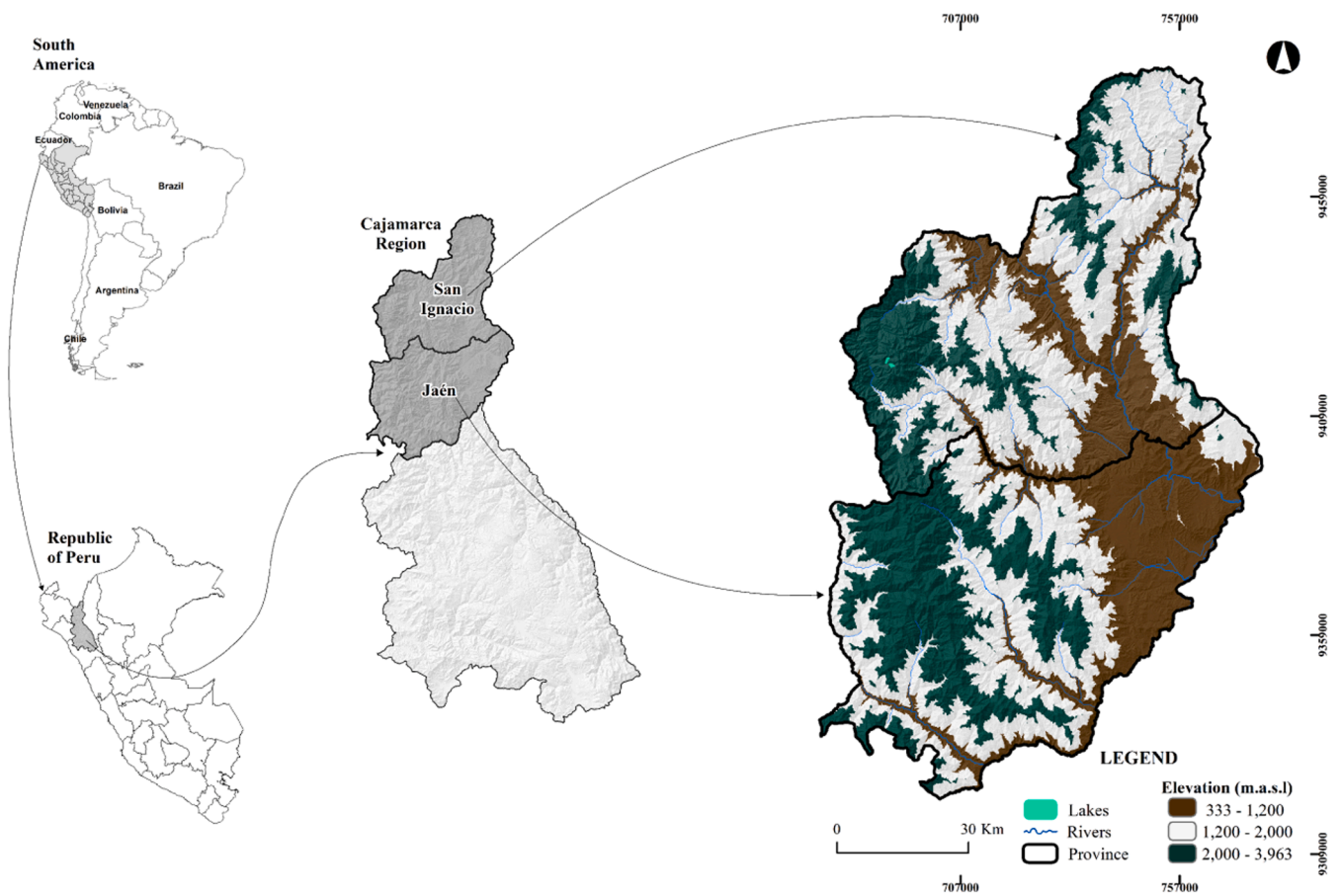


Fig. 1. Geographic location of the provinces of Jaén and San Ignacio in the region of Cajamarca, Northwestern Peru.

selected for their high spatial resolution (4.77 m), and only the February mosaic was chosen, as it met the quality criteria by being cloud-free and exhibiting low noise, which was crucial for the precision of the analysis.

Additionally, Synthetic Aperture Radar (SAR) images from Sentinel-1 were accessed, acquired with dual polarization (VV (vertical transmission, vertical reception) and VH (vertical transmission, horizontal reception)) in Interferometric Wide Swath mode (European Space Agency [ESA], 2023). The spatial resolution of Sentinel-1 was 10 m, which facilitated effective discrimination of land use. The inclusion of these images was carried out to complement the optical information, thus improving the robustness of the results. Finally, information from the Shuttle Radar Topography Mission (SRTM) (Farr et al., 2007) was used to enrich the data.

2.2.1.2. Preprocessing and dataset generation. In GEE, the normalized mosaic with the identifier “projects/planet-nicfi/assets/basemaps/americas”, was imported. The monthly mosaic for February was selected due to its low cloud coverage, ensuring the availability of high-quality data for further analysis.

Similarly, the SAR data in Ground Range Detected (GRD) format was imported using the identifier “COPERNICUS/S1_GRD”. These data allowed for the generation of a radar image mosaic for February 2024. The imported images underwent a smoothing and noise reduction process, where the median was applied as a morphological reducer to the VV and VH bands, using a 30-meter radius kernel and a single iteration (Gómez-Fernández et al., 2022). Then, potential cocoa areas were masked. Using the SRTM, areas with altitudes lower than 1600 m above sea level and an NDVI greater than 0.3 were extracted. This selection is based on previous studies that classify an NDVI less than 0.2 as bare soil and an NDVI between 0.2 and 0.4 as sparse vegetation (Chuvieco et al.,

1999). Additionally, Anyimah et al. (2021) mention that it is unlikely for cocoa plots to have NDVI values lower than 0.32 or to be located at altitudes above 1600 m.a.s.l. (Rojas et al., 2022). This process aimed to reduce dimensionality and focus the analysis on areas of interest.

Subsequently, vegetation indices were calculated (Table 1) to identify the different vegetation covers and improve the supervised classification.

Finally, to compose the multiband image, topographic variables were added using the functions ee.Terrain.slope and ee.Terrain.aspect, considering the SRTM DEM as input data. Textural variables were also calculated through the gray level co-occurrence matrix using the ee.Image.glmTexture function from Sentinel-1 data. Additionally, amplitude and polarization statistical variables were included, forming a mosaic comprising 37 bands, as shown in Table 2.

2.2.1.3. Dataset classification and accuracy assessment. For the classification, field training data for all vegetation covers were collected using a Global Navigation Satellite System (GNSS) receiver and photographic records (Fig. 3).

The Random Forest algorithm was used due to its effectiveness in classifying cocoa plots, as demonstrated by Ashiagbor et al. (2023), where this algorithm outperformed other classifiers, such as k-Nearest Neighbors (kNN), Support Vector Machines (SVM), and Artificial Neural Networks (ANN). Additionally, 100 decision trees were employed, following the recommendation of (Gómez-Fernández et al., 2024), which contributed to improving the accuracy of the results. Then, in ArcGIS Pro v 3.1, areas smaller than 0.01 ha were generalized using the *Eliminate* tool to improve and smooth the classification.

The mapping accuracy was based on 456 validation points, which were randomly and evenly distributed across the different types of land

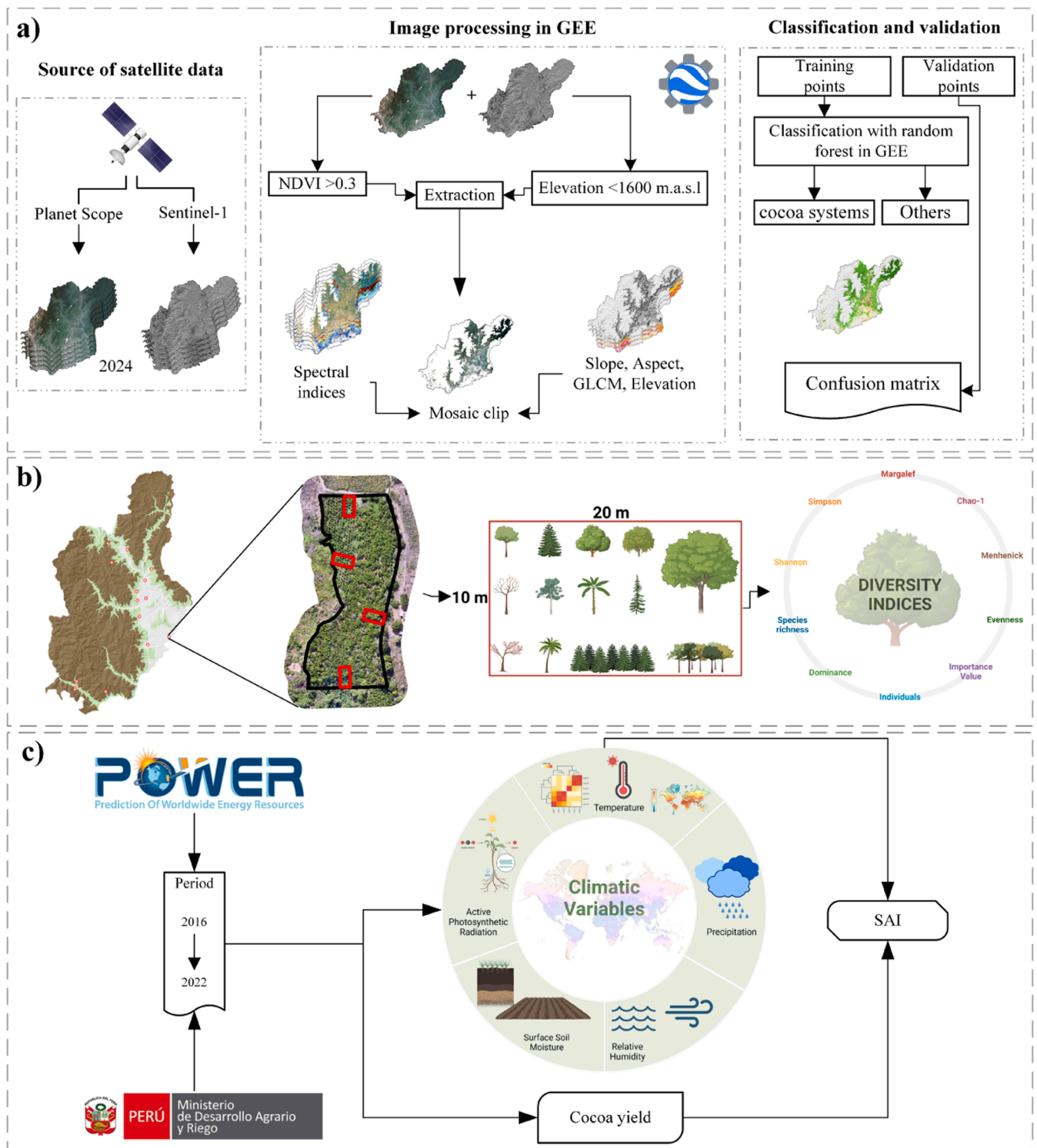


Fig. 2. Methodological framework followed in the research.

cover. These points were determined using the following sample size formula, as used by Atalaya-Marin et al. (2022)

$$n = \frac{Z^2_{(\alpha/2)} * p * q}{e^2}$$

Where:

n = Total number of points needed to obtain reliable results.
 Z^2 = Critical value for the desired confidence level.

p = Percentage of the population that has the desired attribute.
 q = Probability of failure ($1 - p$).
 e = Tolerable margin of error in the estimate.

In this context, Z was 1.96 for a 96% confidence level, p was the expected 95% of the population, q was the complementary probability (5%), and e was the tolerable margin of error (2%). The points were visually inspected and verified through field visits using Qfield. The use of these points allowed for the calculation of overall accuracy and the

Table 1
Spectral indices derived from optical products.

Indices	Formula	References
Normalized Difference Vegetation Index	$NDVI = \frac{(NIR - Red)}{(NIR + Red)}$	(Tucker, 1979)
Soil Adjusted Vegetation Index	$SAVI = \frac{(NIR - Red) * 1.5}{(NIR + Red + 0.5)}$	(Huete, 1988)
Enhanced Vegetation Index	$EVI = \frac{2.5 * (NIR - Red * 1.5)}{(NIR - 6 * Red + 7.5 * Blue) + 1}$	(Huete et al., 1999)
The two-band Enhanced Vegetation Index	$EVI2 = 2.5 * \frac{(NIR - Red)}{(NIR + 2.4 * Red + 1)}$	(Jiang et al., 2008)
Normalized Difference Water Index	$NDWI = \frac{(Green - NIR)}{(Green + NIR)}$	(Mcfeeters, 1996)
Green Normalized difference vegetation index	$GNDVI = \frac{(NIR - Green)}{(NIR + Green)}$	(Gitelson et al., 1995)
Visible atmospherically resistant index	$VARI = \frac{(Green - Red)}{(Green + Red - Blue)}$	(Gitelson et al., 2002)
Green Chlorophyll Index	$GCVI = \frac{((NIR + 0.1) - (Green - 0.1))}{((NIR + 0.1) + (Green - 0.1))}$	(Gitelson et al., 2002)
Triangular Vegetation Index	$TVI = 0.5 * (120 * (NIR - Red) - 200 * (Blue - Red))$	(Haboudane et al., 2004)
Modified Chlorophyll Absorption Ratio Index	$MCRC = \frac{1.2 * ((Red - Green))}{(Red + Green)}$	(Yang et al., 2006)

Table 2
List of variables/bands that comprised the multiband image.

Mission and derivatives	Bands	N° bands
Planet Scope	Red, Green, Blue, NIR.	4
Sentinel 1	VH, VV (ascending and descending)	4
SRTM	Elevation	1
Derived spectral variables	NDVI, NDWI, SAVI, EVI, EVI2, GNDVI, VARI, GCVI, TVI, MCRC	10
SRTM derived variables	Slope, Aspect	2
Sentinel-1 texture	Gray Level Co-occurrence Matrix (Inverse Difference Moment, Contrast, Correlation, Variance, Entropy, Sum Variance, Sum Entropy, Angular Second Moment)	8
Amplitude and polarization statistics	VH, VV Ratios (2), VH and VV Standard Deviation (2)	8

kappa index, resulting in the determination of thematic accuracy.

2.2.2. Estimation of diversity, richness, and abundance of species associated with cocoa AFS

To ensure representativeness of the mapped cocoa systems, 15 plots larger than 1 ha were strategically distributed, as Goñas et al. (2022). 5 plots were considered for each altitudinal range, according to the suitability for cocoa cultivation (Rojas et al., 2022): 1200 m.a.s.l. (elevation 3), as shown in Fig. 4, 2022), these were: lower than 800 m.a.s.l. (elevation 1), 800 to 1200 m.a.s.l. (elevation 2) and higher than 1200 m.a.s.l. (elevation 3), as shown in Fig. 4. This subdivision allowed a detailed analysis of how altitude influences species composition in AFS cocoa.

Additionally, photogrammetric flights were conducted in all the plots using a wide-angle camera: 4/3" CMOS, 20 MP, and a telephoto camera: 1/2" CMOS, 7–56x zoom, onboard the Mavic 3 Enterprise RTK, at a flight altitude of 70 m. Subsequently, these images were processed in the DJI Terra software, resulting in 15 orthophotos with a spatial resolution of 2.5 cm, which served as the basis for delineating the plot boundaries and applying the methodology proposed by Raneri et al. (2021). In each identified plot, 4 transects of 10m x 20m were distributed, separated from each other by a minimum of 30 linear meters. In each transect, all species with a diameter at breast height (DBH) greater

than 2.5 cm were recorded using the Qfield application, as shown in Fig. 5.

Tree species were identified in the field by technicians and plot owners, based on the recognition of known fruit and timber species.

Finally, in the Past 4 software, species dominance, species richness index (S), diversity indices (Shannon-Wiener, Simpson, Margalef, Chao-1, Menhinick, and Evenness), and the structural importance value index were calculated by altitude, following the mathematical basis shown in Table 3.

Where:

Pi is the proportion of individuals found in the i-th species, S is the number of species in the sample, N is the total number of individuals in the sample, S1 is the number of singleton species, S2 is the number of doubleton species, and Si is the total number of individuals of the i-th species.

2.2.3. Analysis of the relationship between the yield of cocoa systems and climate variation

To analyze yield and its relationship with historical climate variation, climatological data per province were downloaded from the Power Data Access Viewer. Meanwhile, yield data were obtained from the Ministry of Agrarian Development and Irrigation (MIDAGRI) from 2016 to 2022, excluding the year 2020 due to the lack of cocoa yield data in the area.

The data were also analyzed by calculating the Standardized Anomaly Index (SAI) to examine the annual deviation of climatic variables and yield relative to normal values. SAI values near zero indicated normal conditions, while values above or below zero indicated unusual conditions. This methodology allows for a more accurate assessment of climatic anomalies, as the SAI provides information on the magnitude of these anomalies by removing dispersion influences, as detailed in the study by Adejuwon et al. (2023).

$$SAI7 = \frac{(r_{ij} - r_i)}{\sigma_i}$$

where

- r_i = Temperature, relative humidity, wind speed, surface soil moisture, precipitation, photosynthetically active radiation, and average annual cocoa yield at station i throughout the entire record.
- r_{ij} = Temperature, relative humidity, wind speed, surface soil moisture, precipitation, photosynthetically active radiation, and annual cocoa yield for station i in year j.
- σ_i = Standard deviation of temperature, relative humidity, wind speed, surface soil moisture, precipitation, photosynthetically active radiation, and annual cocoa yield at station i.

3. Results

3.1. Mapping and cartography of cocoa systems

Five types of vegetation covers were found below 1600 m.a.s.l among which the forest class covers 173,053.2 ha, while grasslands comprise 90,864.4 ha. Additionally, 76,543.7 ha of sparse vegetation, 14,497.9 ha of other crops, and 4338.6 ha of cocoa systems are present, most of them located in the valley of the provinces, in proximity to water networks (Fig. 6).

The statistical evaluation of the generated map was performed using a confusion matrix, where the accuracy for each land use and land cover (LULC) class was determined. It is noteworthy that the class corresponding to cocoa systems achieved an accuracy of 0.82, although in 9% of the cases, it was confused with the forest class. Additionally, the producer's accuracy, which indicates the model's ability to correctly identify the elements of a class in relation to the total actual elements of that class, and the user's accuracy, which measures the reliability of the



Fig. 3. Collection of training data using a GNSS receiver in the provinces of Jaén and San Ignacio. Images (a–d) illustrate cocoa systems at various stages of development, while images (e–h) show areas with forests, grasslands, sparsely vegetated areas, and other crop types, respectively.

model when predicting that an element belongs to a given class, were calculated. For the cocoa systems, both accuracies were 0.82. In summary, the model presented an overall accuracy of 0.85 and a Kappa index of 0.81. This means that 85% of the model's predictions were correct, indicating a high level of reliability in classifying cocoa systems. The Kappa index of 0.81 suggests that the model's predictions are not only correct but also show excellent agreement with the actual data, accounting for the possibility of chance agreements. Together, these

metrics demonstrate that the model is effective and reliable for identifying and classifying cocoa systems (Fig. 7).

In summary, 4338.6 ha of cocoa systems were mapped, achieving an overall model accuracy of 0.85 and a kappa index of 0.81. These results highlight the effectiveness of the methodology used for identifying and classifying cocoa systems in the study area.

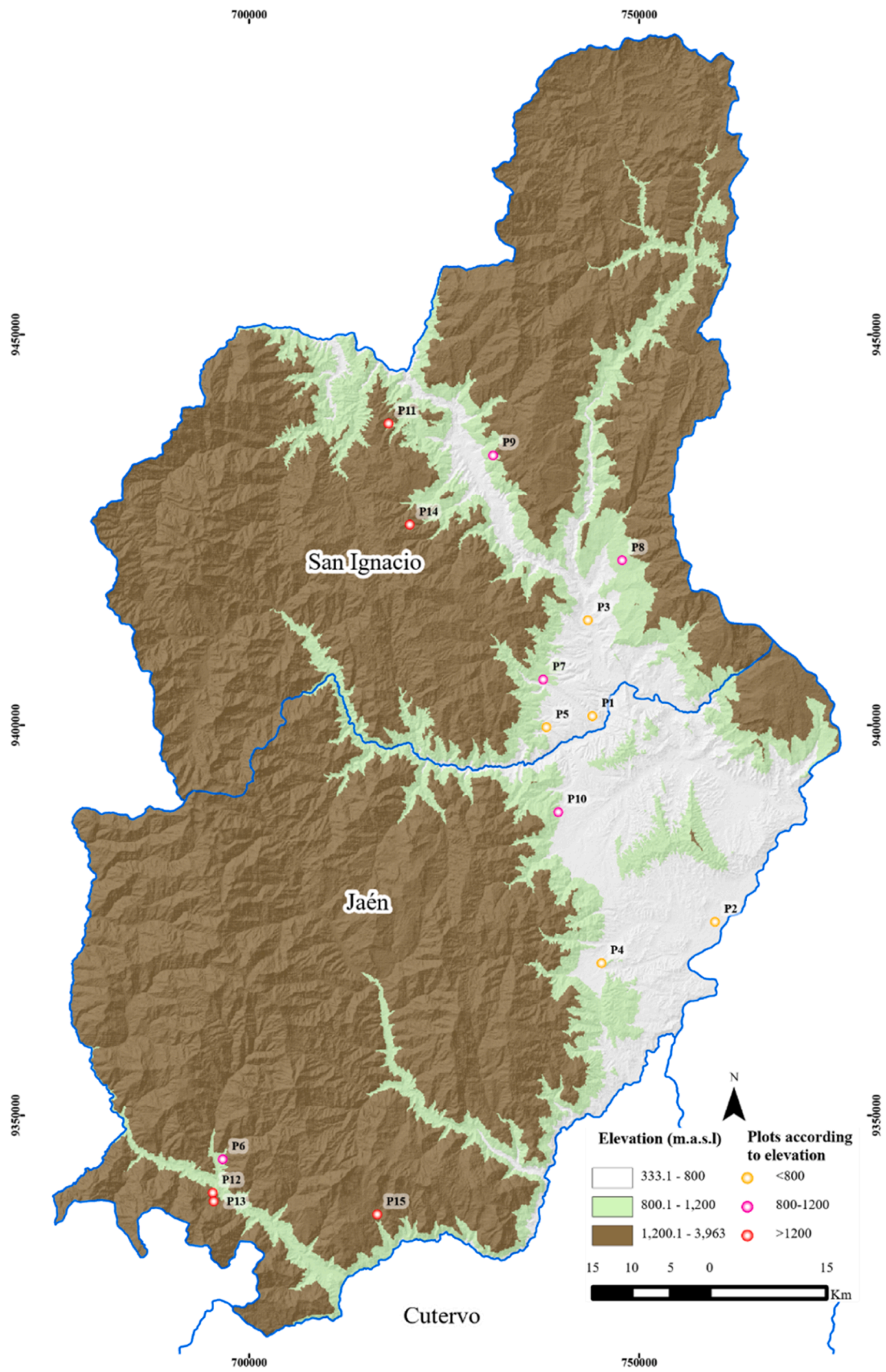


Fig. 4. Distribution of cocoa AFS plots by altitude.

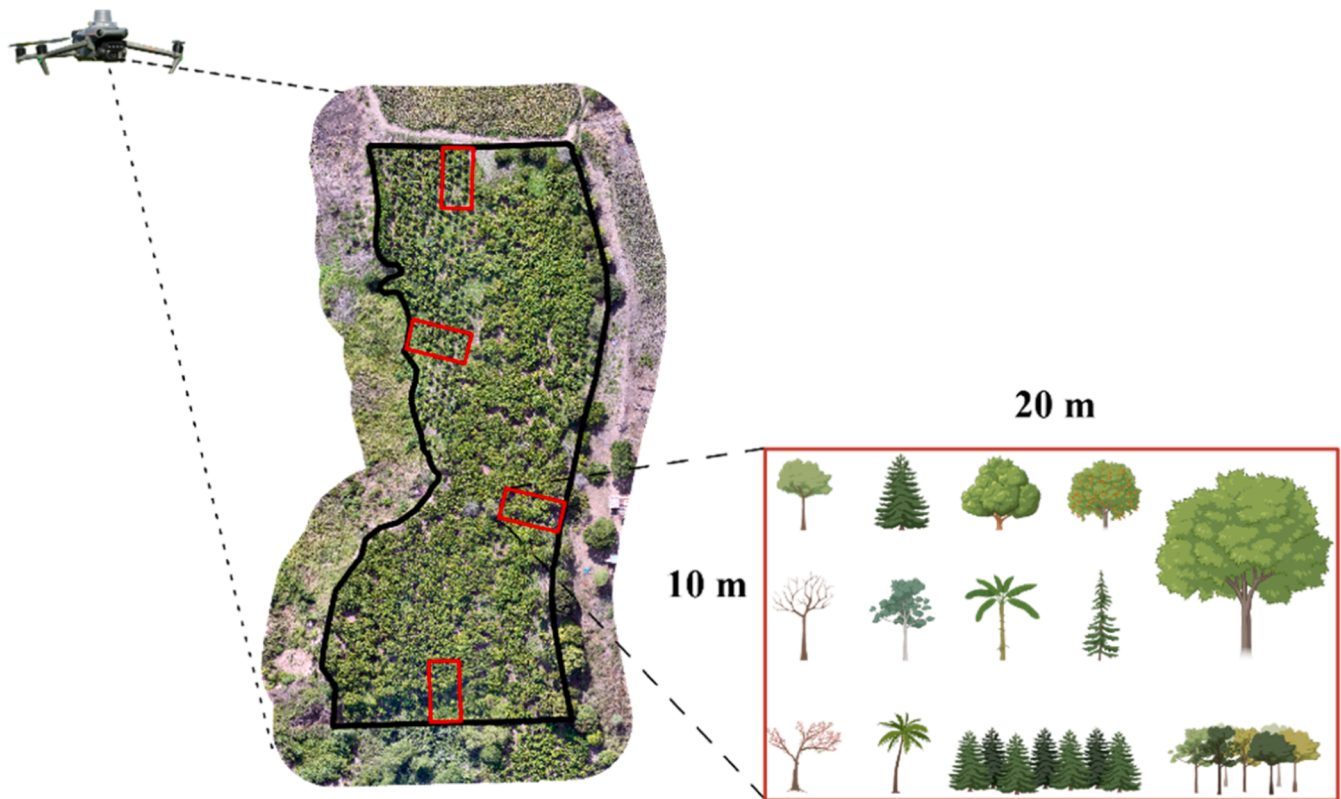


Fig. 5. Distribution of transects in plot 1 for species recording.

Table 3
Structural and diversity indices of trees used in this study.

Indice	Formula	References
Dominance	$D = \sum (Pi \log Pi)$	(Shannon, 1948)
Species richness	S	(Kempston, 1979)
Shannon-Wiener heterogeneity	$H' = \sum_{i=1}^n (Pi)(\log_2 Pi)$	(Shannon, 1948)
Simpson heterogeneity	$1 - D = 1 - \sum_{i=1}^N (Pi)^2$	(Simpson, 1949)
Margalef	$R_{Mg} = \frac{S - 1}{\ln N}$	(Margalef, 1973)
Chao-1	$C = S \frac{(S1)^2}{2(S2)}$	(Chao, 1984)
Menhénick	$R_{Mn} = \frac{S}{\sqrt{N}}$	(Menhinick, 1964)
Evenness	$E = \frac{e^{H'}}{\log(s)}$	(Pielou, 1966)
Importance value	$IVI = \frac{Pi + \frac{Si}{S} + (1 - D)}{3}$	(Curtis and McIntosh, 1951)

3.2. Diversity, richness, and abundance of species associated with cocoa AFS

A total of 404 individuals were inventoried, distributed across 27 families and 49 species. The most abundant families were Musaceae, Fabaceae, and Rutaceae, with 124, 59, and 38 individuals, respectively. When analyzing the three elevation levels, it was found that the Musaceae family predominated at all elevations, with 69, 29, and 32 individuals at elevations 1, 2, and 3, respectively (Fig. 8).

Additionally, Fig. 9 shows the distribution of species found in the three elevation ranges associated with *T. cacao* L. At elevation 1, a total of 30 species were identified with varying proportions. The predominant species was *Musa* sp., belonging to the Musaceae family, with 69

individuals. This species is key for its function as a shade plant for the main crop and provides economic benefits from the sale of its fruits. Other notable species include *Citrus sinensis* (Rutaceae) and *Cocos nucifera* (Arecaceae), each with 10 individuals, and *Swietenia macrophylla* (Meliaceae) with 7 individuals. Additionally, species such as *Citrus limon* (Rutaceae), *Inga edulis* (Fabaceae), *Cordia alliodora* (Boraginaceae), and *Mangifera indica* (Anacardiaceae) were recorded with four individuals each, while the least abundant species, such as *Carica papaya* (Caricaceae) and *Cedrela odorata* (Meliaceae), had only three individuals.

At elevation 2, 24 species associated with *T. cacao* L. were recorded. The most abundant species was *Musa* sp., belonging to the Musaceae family, with a significant number of individuals, indicating a dominant presence in this ecosystem. Other notable species include *Calycophyllum spruceanum* (Rubiaceae) and *C. papaya* (Caricaceae), each with four individuals, reflecting moderate diversity. Additionally, species such as *Citrus limetta* Risso (Rutaceae) and *C. odorata* (Meliaceae) were recorded with three and two individuals, respectively. In contrast, several species were found in very low numbers, such as *Acrocarpus fraxinifolius* (Fabaceae) and *Pouteria caimito* (Sapotaceae), each with only one individual.

At elevation 3, 26 species associated with *T. cacao* L. were recorded. The most abundant species was *Musa* sp. (Musaceae), with 33 individuals, followed by *I. edulis* (Fabaceae) with 29 individuals, both indicating a dominant presence in this ecosystem. *C. alliodora* (Boraginaceae) also showed notable abundance with 15 individuals. Other significant species include *Persea americana* (Lauraceae) with 13 individuals and *C. odorata* (Meliaceae) with nine individuals, indicating considerable representation. Species such as *Myrsine oligophylla* (Myrsinaceae) and *C. sinensis* (Rutaceae) had 5 and 4 individuals, respectively, reflecting moderate diversity. Several species were found in very low numbers, with some recording only one individual, such as *Averrhoa carambola* (Oxalidaceae), *Bactris gasipaes* (Arecaceae), and *P. caimito* (Sapotaceae), among others.

On the other hand, at elevation 1, *T. cacao* L. showed significant co-

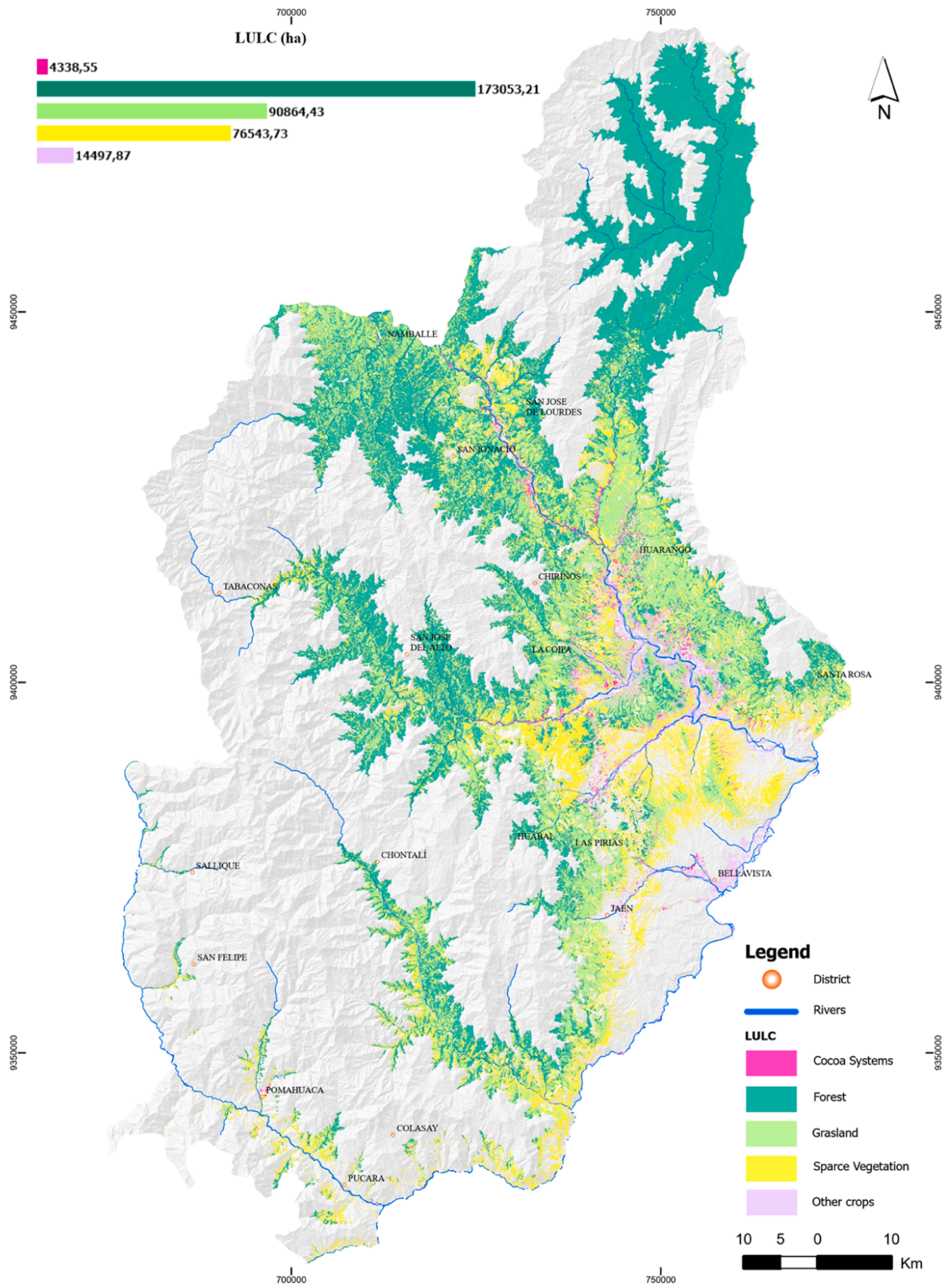


Fig. 6. Distribution map of cocoa systems in the provinces of Jaén and San Ignacio.

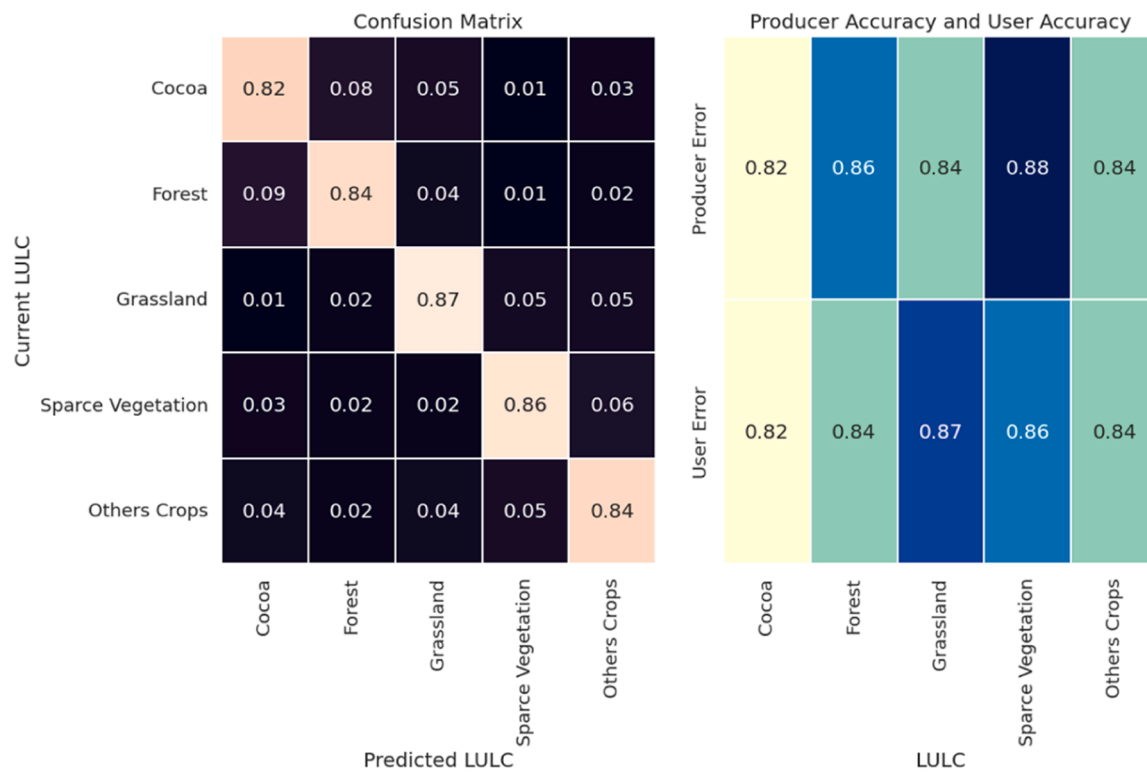


Fig. 7. Map accuracy assessment using a confusion matrix and user and producer metrics.

occurrences with various species. Specifically, a 41.7% coexistence was observed with *Musa* sp., 6.4% with *C. sinensis*, 5.9% with *C. nucifera*, and 4.1% with *S. macrophylla*. These figures represent the highest co-occurrences of *T. cacao* L. with other species at this elevation (Fig. 10). At elevation 2, a co-occurrence of 16.3% was recorded with *Musa* sp., 9.6% with *I. edulis*, 7.4% with *C. nucifera*, and 6.4% with *Erythrina edulis*. Compared to elevation 1, the co-occurrence with *Musa* sp. decreased significantly. Moreover, at elevation 2, the co-occurrence percentages among the remaining species were more evenly distributed, without the marked variation observed at elevation 1.

Additionally, according to Fig. 10, at elevation 3, *T. cacao* L. continued to show significant co-occurrences with various species. Specifically, a 22.6% co-occurrence was observed with *Musa* sp., 18.1% with *I. edulis*, 8.7% with *P. americana*, 6.0% with *C. alliodora*, and 4.5% with *C. odorata*. These figures reflect a high frequency of coexistence between *T. cacao* L. and these species at this elevation.

In the study, species were classified according to their potential use for producers, identifying 21 species with fruit-bearing potential, among which *Musa* sp. (Musaceae), *P. americana* (Lauraceae), *C. sinensis* (Rutaceae), and *M. indica* (Anacardiaceae) were the most abundant. As for timber species, 20 were identified, with *C. alliodora* (Boraginaceae), *C. odorata* (Meliaceae), *S. macrophylla* (Meliaceae), and *Guazuma crinita* (Sterculiaceae) being the most abundant (Fig. 11).

Likewise, four species with both fruit-bearing and timber potential were identified, including *I. edulis* (Fabaceae) and *C. nucifera* (Arecaceae). Additionally, three species were documented for exclusive medicinal use: *Bixa orellana* (Bixaceae), *Croton lechleri* (Euphorbiaceae), and *Morinda citrifolia* (Rubiaceae), as shown in Fig. 11.

When comparing the different diversity indices, the results show that elevation 1 has the highest species richness (30 species) and the greatest number of individuals (148). Additionally, this elevation also shows the highest dominance (0.23) and the lowest evenness (0.38), indicating that a few species significantly dominate. On the other hand, elevation 2 shows the lowest dominance (0.07) and the highest evenness (0.74), along with the highest values for Shannon (2.88) and Simpson (0.93)

diversity indices, indicating a more equitable and diverse community. Finally, elevation 3 presents intermediate values, with a species richness of 26, moderate dominance (0.12), and reasonable Shannon (2.59) and Simpson (0.88) diversity indices.

These results reflect that, although elevation 1 has the highest species diversity, the dominance of some species over others limits the ecological balance in these systems. On the contrary, elevations 2 and 3 present low and moderate dominance with greater species uniformity, thus generating more balanced ecosystems in which the stability and resilience of the system does not depend on a few species. In addition, interactions between species such as nitrogen fixation, physical support and low competitiveness for resources make these systems more productive and sustainable (Fig. 12).

The analysis of the Importance Value Index (IVI) shows that *Musa* sp. is the most dominant species at elevation 1, with an IVI of 23.46. However, its dominance decreases at elevations 2 and 3, with IVIs of 11.58 and 14.49, respectively. In contrast, *I. edulis* becomes the most dominant species at elevation 3, with an IVI of 17.43, indicating a better adaptation to higher altitude conditions compared to *Musa* sp.

C. nucifera maintains significant importance at elevations 1 and 2, with IVIs of 10.69 and 10.33, but its relevance drops drastically at elevation 3 (IVI of 1.35), suggesting lower adaptability to higher altitudes. *M. indica* shows a more stable presence across the three elevations, with IVIs of 6.39, 9.24, and 5.22, indicating moderate adaptability to different altitude levels. Among the timber species, *C. odorata* is significant at elevation 3, with an IVI of 8.01. In contrast, at elevation 2, its IVI is 3.28 and at elevation 1, it is 1.66. These results suggest that *C. odorata* plays a more prominent role at higher altitudes. Additionally, *S. macrophylla* exhibits notable importance at elevation 2, with an IVI of 3.41. However, it does not appear as one of the most important species at the other altitudes. On the other hand, *C. alliodora* stands out particularly at elevation 3, with an IVI of 6.78, highlighting its relevance at this altitude, as well as at elevation 2, where it reaches an IVI of 4.12 (Fig. 13).

In summary, a total of 404 individuals belonging to 49 species and 27

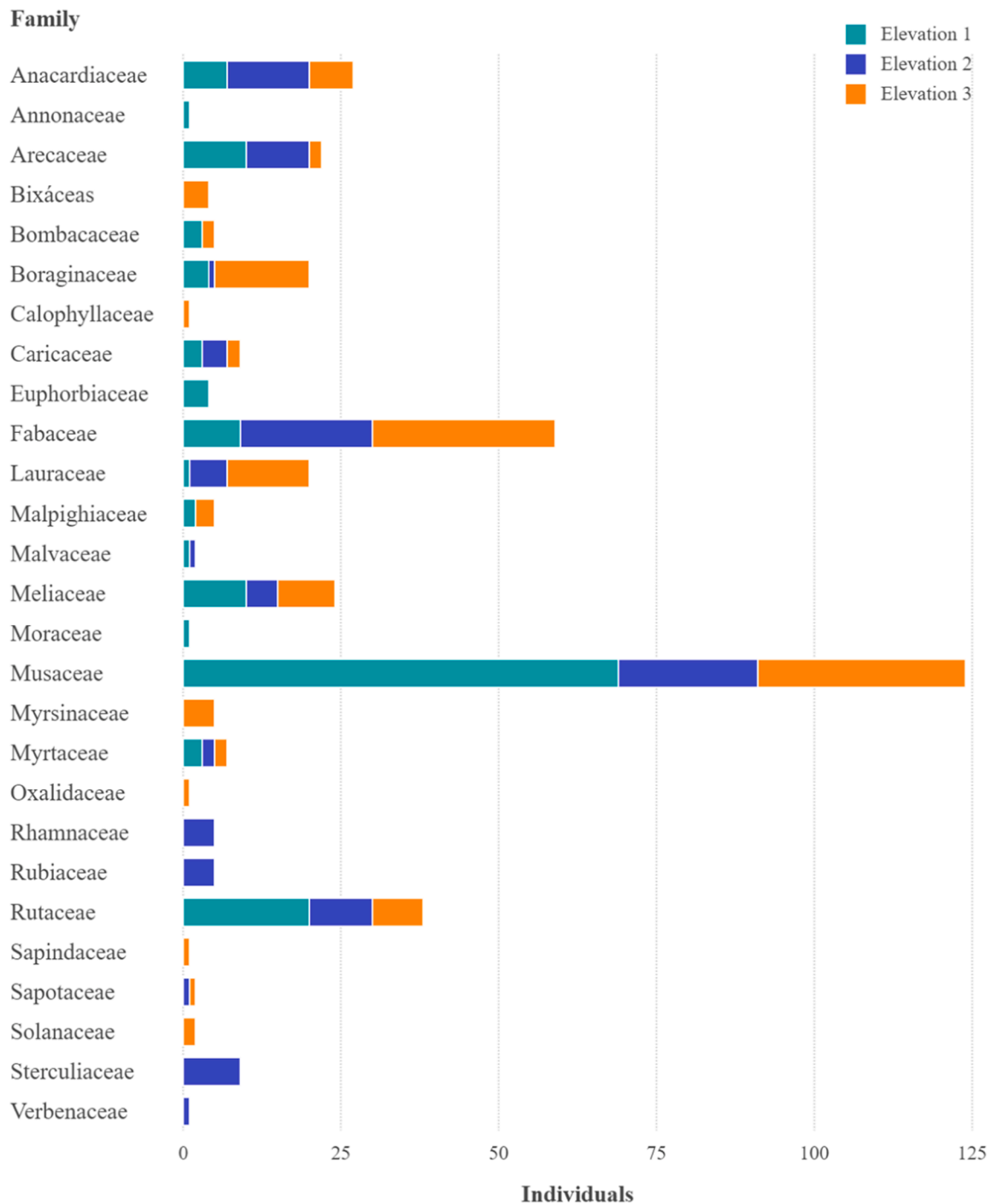


Fig. 8. Distribution of individuals by family and elevation in the 15 research plots.

families were recorded in the systems of *T. cacao* L. The most abundant families were Musaceae, Fabaceae, and Rutaceae. In the three analyzed elevations, *Musa* sp. dominated, with 69, 29, and 33 individuals at elevations 1, 2, and 3, respectively, achieving a co-occurrence of 41.7% with *T. cacao* L. at elevation 1 and 22.6% at elevation 3. Additionally, 21 species with fruit-bearing potential, 20 with timber potential, and 3 medicinal species were identified. Diversity indices revealed that elevation 1 had the highest species richness, while elevation 2 stood out for its greater evenness. The Importance Value Index (IVI) showed that *Musa* sp. was the most dominant species at elevation 1, while *I. edulis* excelled at elevation 3, suggesting a favorable adaptation to higher altitudes.

These findings underscore the importance of maintaining a high diversity of species in cocoa AFS, as this diversity contributes to the resilience of the ecosystem against climate change and pest outbreaks (Mortimer et al., 2018). The identification of fruit-bearing and timber species not only optimizes crop yield and sustainability but also provides valuable information for decision-making in the management of AFS (Tinoco et al., 2024). Furthermore, diversifying the agroecosystem with shade trees enhances overall performance by fulfilling essential functions in nutrient cycling, pest control, biomass production, and carbon reserves (Andreotti et al., 2018).

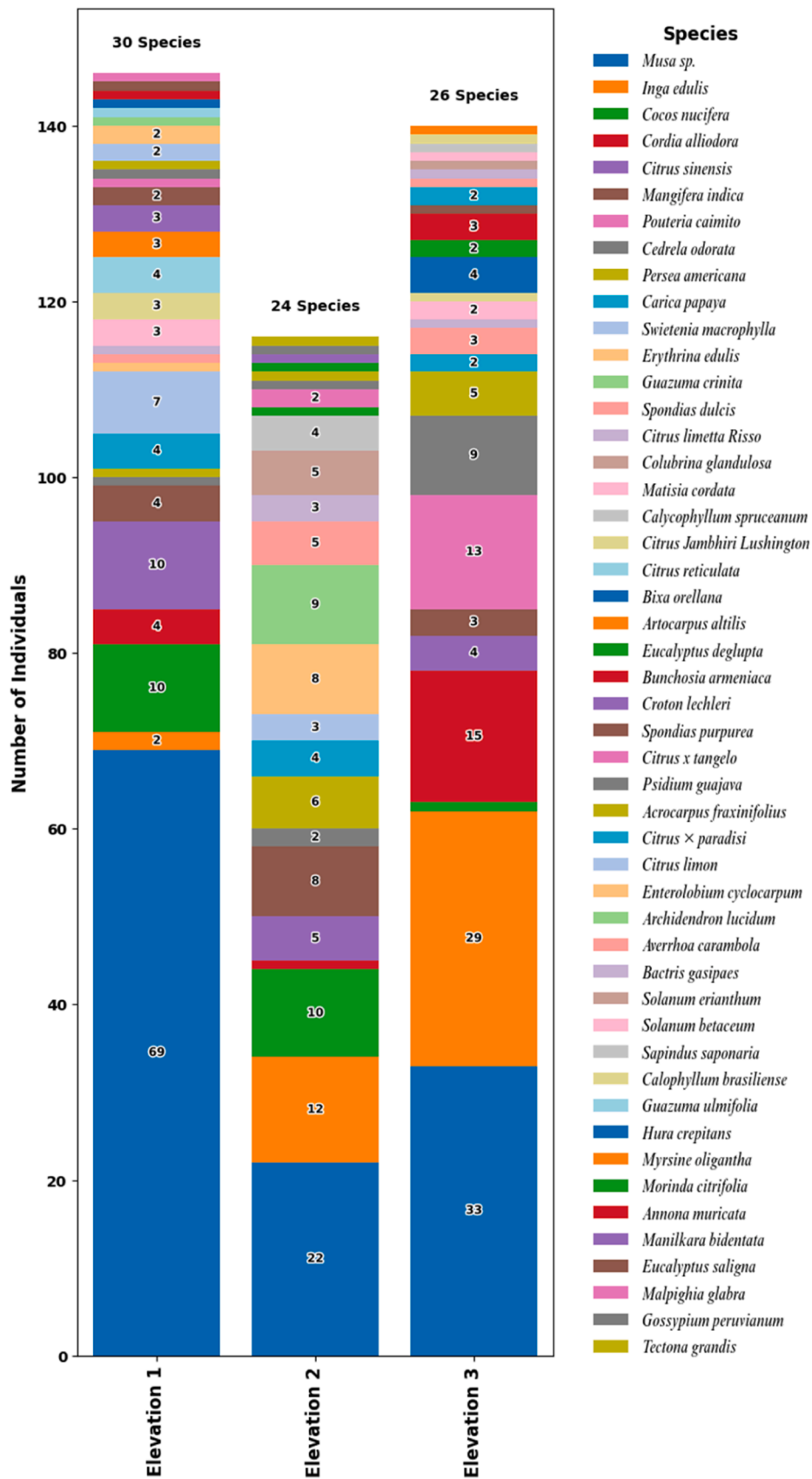


Fig. 9. Distribution of species and individuals associated with *Theobroma cacao* L. across the three elevation ranges.

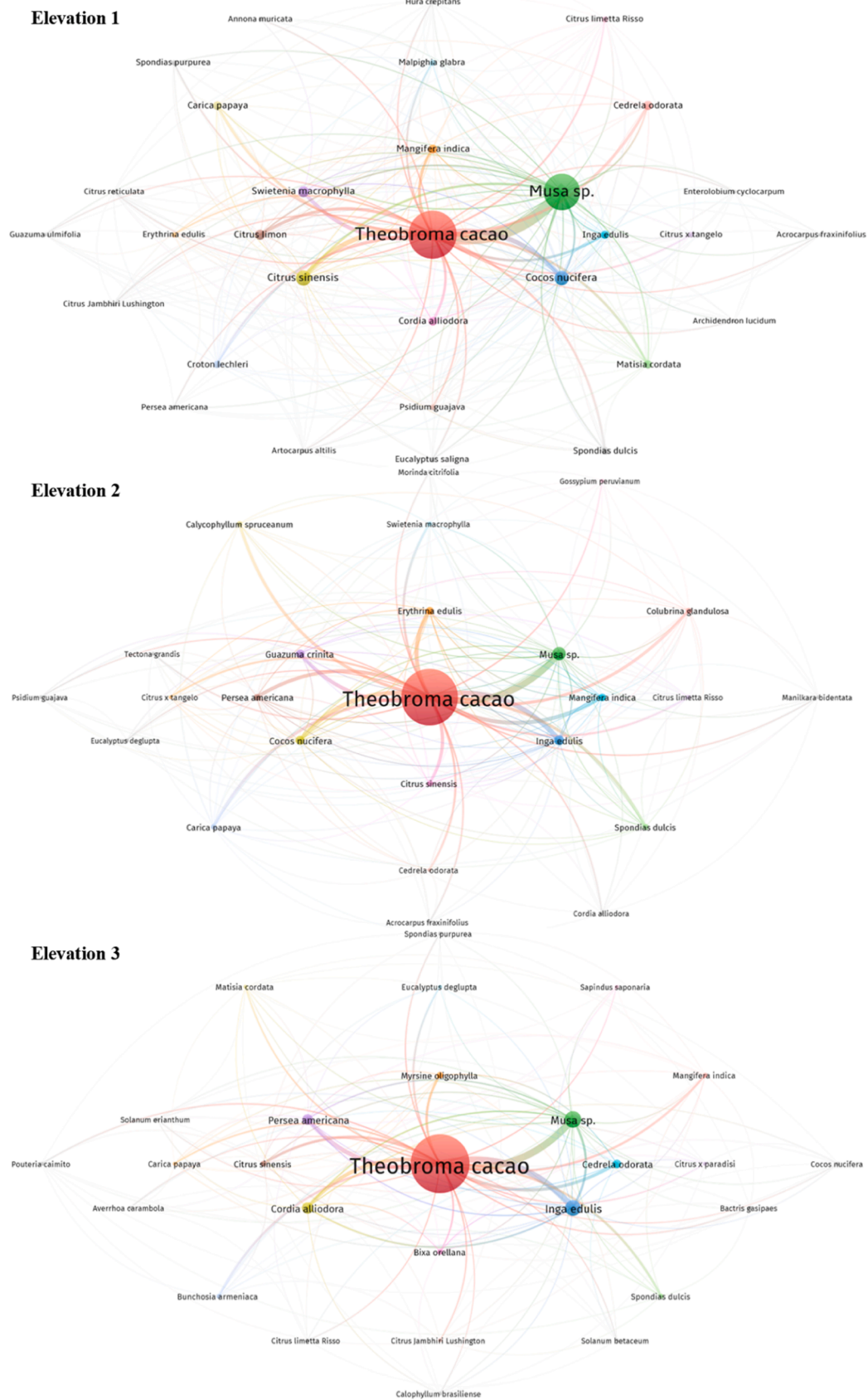


Fig. 10. Species co-occurrence and degree of coexistence within the same plot and elevation range.

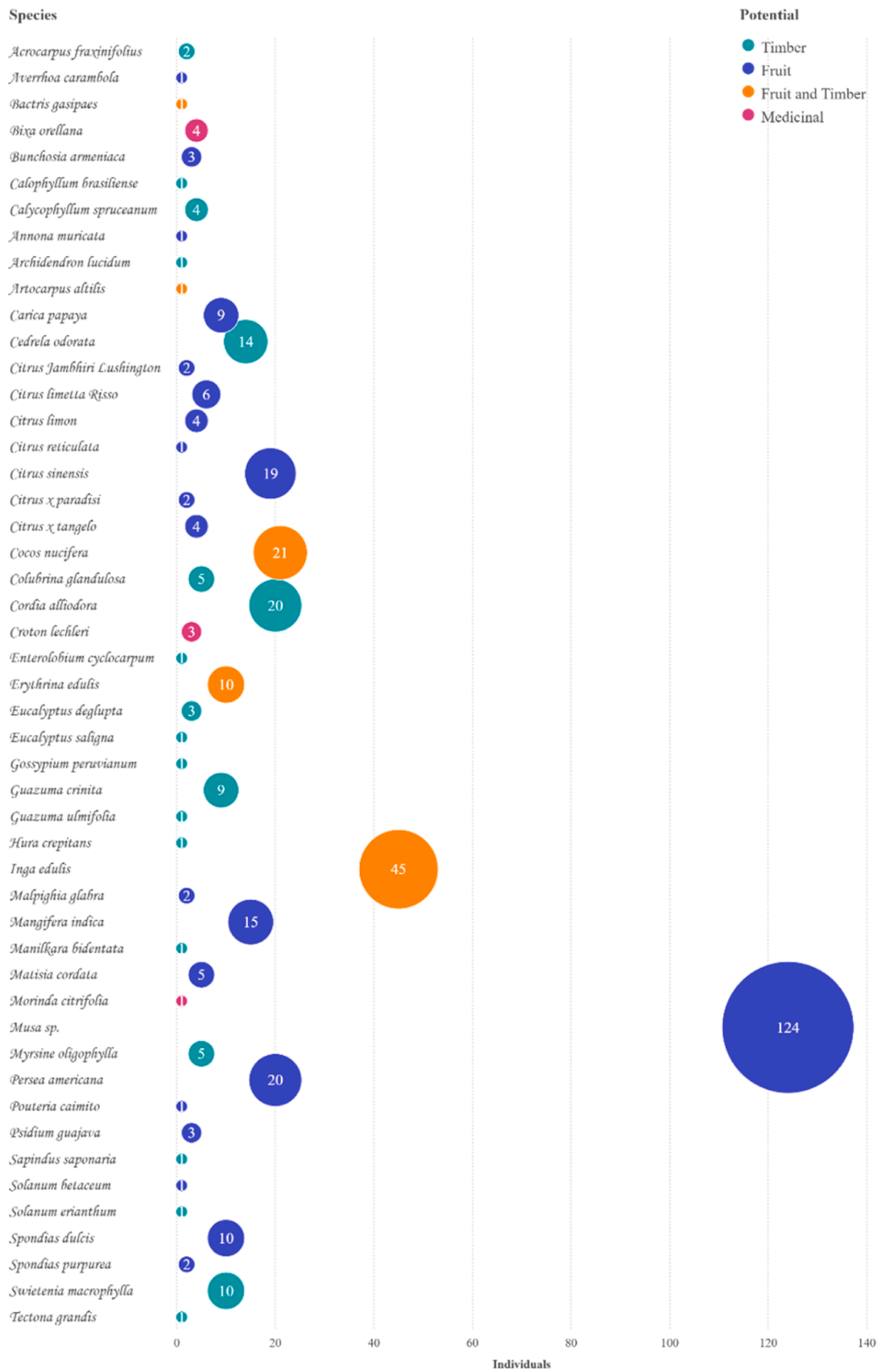
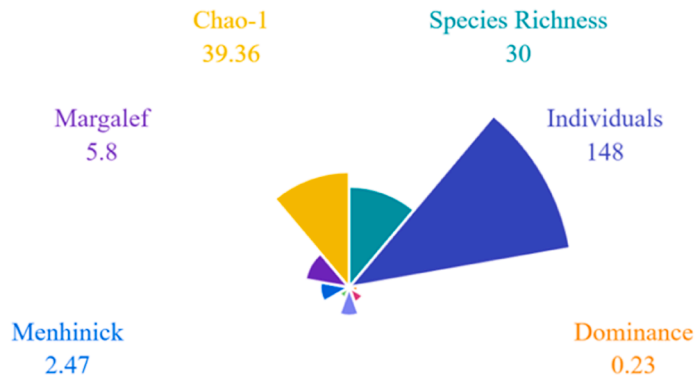
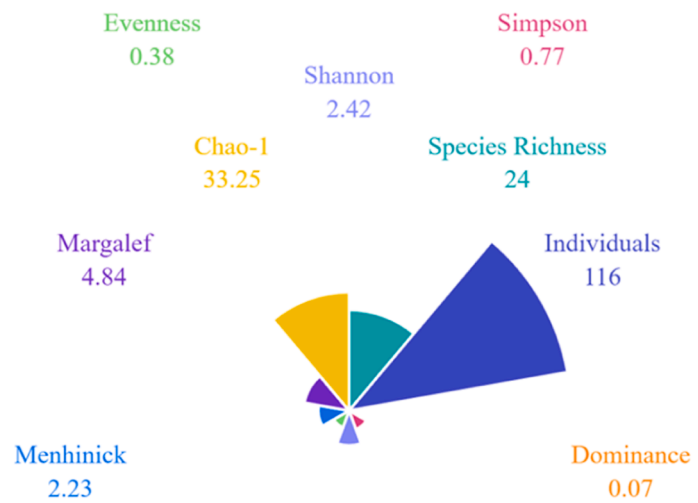


Fig. 11. Classification of tree species according to fruit-bearing, timber, and medicinal potential.

Elevation 1



Elevation 2



Elevation 3

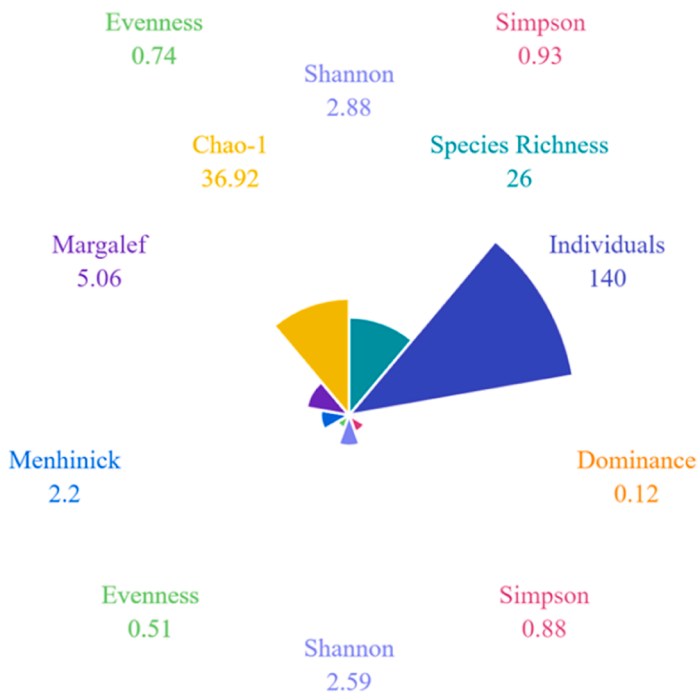


Fig. 12. Comparison of diversity indices at the 3 elevation levels.

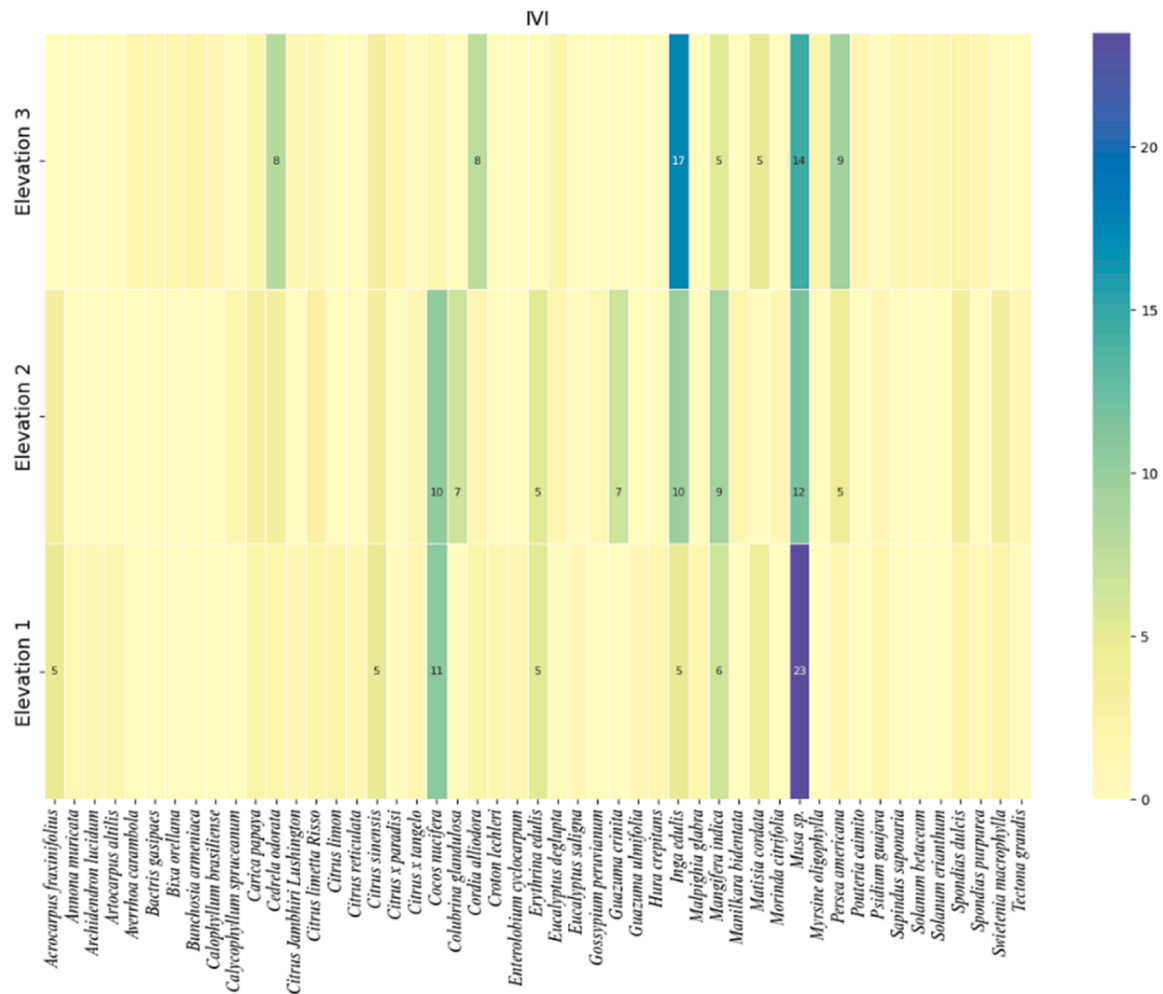


Fig. 13. Importance Value Index (IVI) of tree species at the three elevation levels.

3.3. Climate variability and cocoa yield

The SAI analysis of climate variables and cocoa yield in the province of Jaén showed that annual precipitation levels were below the average (281.65 mm) between 2017 and 2019, reaching their minimum value in 2019 with 208 mm. This coincided with an extreme drought in the area. It is also noteworthy that precipitation levels increased significantly in 2021 and 2022. In contrast, the annual average temperature followed a different pattern. It remained above the average (22.2 °C) only in the years 2016, 2019, and 2022, while in the other years it experienced a sharp decline, reaching its lowest point in 2018 (21.89 °C). On the other hand, relative humidity and surface soil moisture showed a similar pattern, reaching a minimum below the average in 2022 and 2016, respectively, while peaking in 2017. Additionally, photosynthetically active radiation was highly variable, reaching its lowest point in 2019 and its highest in 2022. Regarding cocoa yield, it showed values below the average (0.85 Tm/ha) in 2016, 2017, and 2018. However, these data showed a gradual improvement in the following years, reaching a peak in 2021 (0.94 Tm/ha), a year characterized by above-average precipitation (Fig. 14).

Similarly, in the province of San Ignacio, precipitation patterns were comparable to those observed in the province of Jaén, with drought conditions prevailing in 2019 (1012.44 mm) and abundant rainfall in 2021 (1254 mm). Regarding temperature, it also followed similar patterns, remaining above the average (20.49 °C) in the years 2016, 2019, and 2022, while showing a decline in the other years. Relative humidity and surface soil moisture showed a similar trend, reaching their

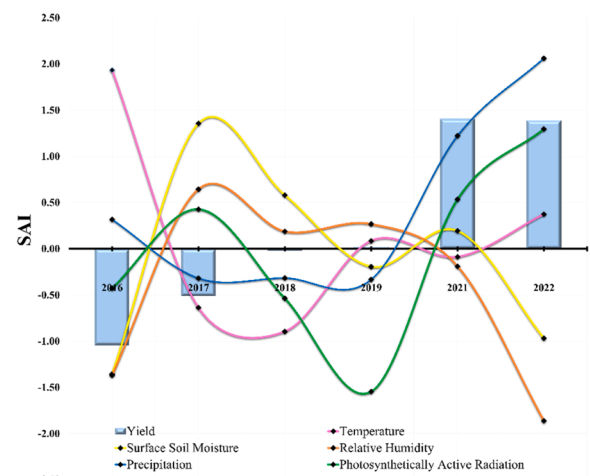


Fig. 14. Standardized Anomaly Index of temperature, precipitation, relative humidity, photosynthetically active radiation, surface soil moisture, and cocoa yield in the province of Jaén.

maximum values above the average in 2017 and 2021, respectively. Photosynthetically active radiation was highly variable, reaching its lowest point in 2019 and its highest in 2022. Finally, regarding cocoa yield, values were below the average (0.91 Tm/ha) in 2016, 2018, and

2019, but improved in 2017, 2021, and 2022, reaching its peak in 2021 (1.05 Tm/ha), when climatic conditions were more favorable, especially in terms of precipitation (Fig. 15).

In summary, in the province of Jaén, the SAI revealed that annual precipitation was below the average (281.65 mm) between 2017 and 2019, reaching a minimum in 2019 with only 208 mm. Cocoa yield remained below the average (0.85 Tm/ha) in 2016–2018 but improved notably in 2021 (0.94 Tm/ha), coinciding with a significant increase in precipitation, which totaled 336.6 mm that year. In San Ignacio, precipitation was also low in 2019 (1012.44 mm) and high in 2021 (1254 mm). Despite temperatures remaining above 20.49 °C in 2016, 2019, and 2022, cocoa yield was low (0.91 Tm/ha) in 2016, 2018, and 2019, reaching its maximum in 2021 (1.05 Tm/ha), coinciding with more favorable climatic conditions.

4. Discussion

This study prioritized the use of optical data from PlanetScope due to its spatial and temporal resolution and availability in GEE. The decision not to use MODIS, AVHRR, and Landsat data was based on their limited spatial resolution, which makes the evaluation of small areas difficult (Zhang et al., 2024). Instead, Sentinel-1 SAR images were used, showing significant improvements in land use/land cover (LULC) classification, especially in cloudy environments (Ashiagbor et al., 2020; Numbisi et al., 2019), using advanced algorithms such as Random Forest (Gómez-Fernández et al., 2024).

To increase the thematic accuracy of cocoa area mapping, auxiliary variables were added, such as those derived from the gray-level co-occurrence matrix (GLCM) of Sentinel-1 (Table 2). These variables have been validated by studies that achieved overall accuracies greater than 0.80 (Strzelecki et al., 2019; Tutu et al., 2018). In our case, contrast and correlation improved classification by capturing spatial patterns in texture, facilitating the discrimination of land covers, especially in forest and cocoa areas, where the model showed higher levels of confusion. While the methodology produces reliable maps (Fig. 7), it could benefit from higher-resolution UAV images and other machine learning techniques, such as the K-Nearest Neighbor (KNN) algorithm, which, when combined with these images, achieved an accuracy of up to 99% (Tariku et al., 2023).

However, Moraiti et al. (2024), consider that quantitative accuracy values alone are not sufficient to determine the reliability of the results. These authors suggest a thorough visual inspection of the classification map overlaid on very high spatial resolution images. In our case, we only used validation points to obtain accuracy (Atalaya-Marin et al., 2022), and we applied polygon generalization for areas smaller than 0.01 ha to

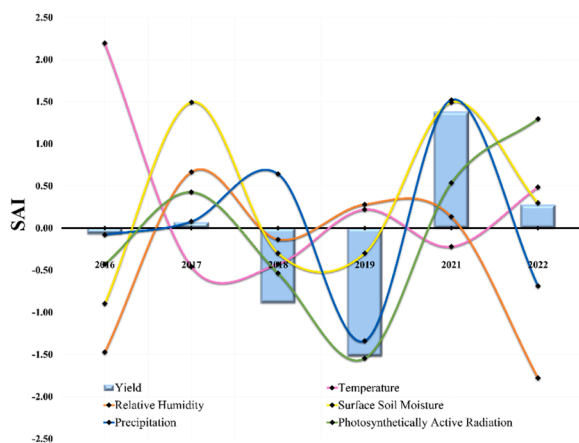


Fig. 15. Standardized Anomaly Index of temperature, precipitation, relative humidity, photosynthetically active radiation, surface soil moisture, and cocoa yield in the province of San Ignacio.

eliminate misclassified pixels (asato, 2017).

The cocoa-growing area for the year 2024 covers a total of 4338.6 ha, mainly distributed in the lower areas and close to water sources (Fig. 7). This strategic location is supported by the water requirements of the crop, which needs between 0.0 and -0.4 MPa (megapascals) of water potential (Olwig et al., 2023). Additionally, the ideal conditions for the crop include temperatures between 20 and 35 °C, terrain slopes below 30%, and fertile soils (Rojas et al., 2022). Reinforcing the location of these areas at altitudes below 1600 m.a.s.l., typically in valleys with low erosion and high nutrient content.

The agroforestry systems of *T. cacao* L. harbor a large number of plant species. Studies in other countries have reported up to 237 different species within cocoa AFS (Abada et al., 2016; Asase et al., 2010; Sambuichi et al., 2012; Tondoh et al., 2015). In this study, we identified 49 species, surpassing the 17 recorded in the neighboring region of Amazonas, Peru (Goñas et al., 2022). This reinforces the idea that the methodology used is highly effective, as mentioned by Raneri et al. (2021), but it can be improved by using new methods that include optical and LiDAR data derived from aerial and terrestrial sensors, allowing for more detailed information (Sun et al., 2021; Tamburlin et al., 2021; Torresani et al., 2020).

The high species richness within a cocoa AFS is associated with altitude; in the Amazonas region, 14 out of the 17 species were found at the first 235 m.a.s.l. (Goñas et al., 2022), while in Jaén and San Ignacio, 30 out of the 49 species were found below 800 m.a.s.l. (Fig. 12), confirming that, in general, species diversity tends to decrease with altitude (Zhang et al., 2016). This decrease in diversity has significant implications for the cocoa AFS, as lower diversity reduces ecosystem resilience to pest-disease and climate change, which negatively affects cocoa production. However, at higher altitudes, the composition becomes more uniform and balanced (Figs. 8 and 9), especially at elevation 2, this generates an ideal zone for sustainable cocoa production, where interactions between species provide mutual benefits, such as *Inga edulis* fixing nitrogen and *Cocos nucifera* providing shade demonstrating that diversity and balanced species distribution can be harnessed to design more resilient and productive AFS (Thompson et al., 2014).

At low altitude, *Musa* sp. co-occurs at 41.7% with *T. cacao* L. (Fig. 10), due to its preference for altitudes below 1000 m.a.s.l. (Vu et al., 2023). This association is strategic, as *Musa* sp. is a highly marketable and economically valuable crop for producers in developing countries (Petsakos et al., 2019). Moreover, this combination shows the lowest rates of pest and disease infection (Vera-Velez et al., 2024). However, as altitude increases, other species such as *I. edulis*, *C. nucifera*, and *P. americana* coexist more evenly with *T. cacao* L.

This coexistence can bring significant benefits, such as the provision of timber, shade, additional income from the sale of fruits and greater functional diversity in cocoa agroforestry systems, thus improving the resilience of these systems to environmental changes (Iglesias et al., 2011; Osei et al., 2002). However, it can also pose problems if proper integrated management (planting density, fertilization and pest-disease control) is not applied, as it could generate competition for key resources such as water and nutrients, affecting cocoa production at these altitudes.

The species identified in the study have potential food, timber, and medicinal uses (Fig. 11). However, several timber species are listed in the IUCN Red List of Threatened Species due to the deforestation process in cocoa plots, driven by the belief that removing trees improves yields and reduces diseases (López-Cruz et al., 2021). The presence of medicinal species suggests an untapped potential for the development of pharmaceutical products, given their antimicrobial, antioxidant, anti-inflammatory, and antitumor properties (Alonso et al., 2012; Ashraf et al., 2023; Zhao et al., 2023). This highlights the importance of balancing conservation and production in cocoa AFS. Future research should investigate the bioactivity of these species and explore partnerships with pharmaceutical companies and local communities to develop sustainable products.

The inclusion of trees in cocoa plots improves soil health, water infiltration, and reduces erosion (Lojka et al., 2017). Specifically, trees such as *I. edulis* and *C. alliodora* provide shade, regulate soil temperature, and mitigate heat stress, which is an advantage in the context of climate change, where extreme temperatures and variations in precipitation affect yields (Allen et al., 2024).

Studies such as Hernández et al. (2015), show that in some areas of Mexico, farmers achieved yields of up to 800 kg/ha throughout the year. In the provinces of Jaén and San Ignacio, these values were surpassed in 2021, with reported yields of 944 and 1050 kg/ha, respectively. Additionally, farmers diversify their income through the production of timber, fruits, and medicinal products such as those derived from *B. orellana*, reducing dependence on cocoa and financial risks (Somarriba and Beer, 2011), enabling more stable agricultural production (Lojka et al., 2017).

The average cocoa yield in the provinces of Jaén and San Ignacio was 847 and 910 kg/ha, respectively. In the last 2 years, these values were above the average in both provinces, which reinforces the relationship between precipitation deficit and yield reduction. This crop requires at least 100 mm of water per month (Motato and Cedeño, 2010), to prevent the reduction of floral buds due to soil moisture deficit (Adejuwon et al., 2023). In both provinces, when precipitation reached its highest values, yield increased significantly (Figs. 14, 15), highlighting the importance of monitoring weather conditions to mitigate the effects of water deficit and improve cocoa production in the region.

It is worth noting that the Intergovernmental Panel on Climate Change (IPCC) projects that by the end of the 21st century, cocoa yield will decrease by 40% due to climatic factors. However, other key factors should not be underestimated, such as soil type and fertility, the incidence of pests and diseases, and agronomic practices (Altieri and Nicholls, 2003; Tandzi and Mutengwa, 2020). Therefore, proper farm maintenance and management, including the appropriate use of control products, the removal of dead plants and diseased fruits, weed control, and proper pruning (Adejuwon et al., 2023; Ríos, 2017), will contribute to more efficient production.

This study addressed important limitations. Although 49 species were identified in 15 plots, this may not be sufficient for a comprehensive assessment of species diversity in the cocoa AFS. Previous research used a larger number of plots, such as the 20 plots of Abada et al. (2016) and the 60 by Tondoh et al. (2015), suggesting that an increase in the number of plots could provide a more complete understanding of biodiversity. However, the 15 plots in the present study were strategically distributed along the altitudinal gradient of the study area (see Fig. 4). This allowed us to obtain more representative information on species diversity in cocoa systems.

In addition, regarding climate variability and its impact on cocoa yield, some studies have used data from more than 20 years (Adejuwon et al., 2023), which highlights the importance of having ample information for more robust analyses (Waqas et al., 2025). For the study area, only official yield data for the period 2016–2022 were available, which is why yield prediction was not addressed, and only SAI was used to analyze anomalies of climatic variables and their impact on cocoa yield. Therefore, it is essential that future research focus on collecting broader and more diverse data to effectively address these issues.

In this context, this research fills an important gap by providing key information on the geographical distribution of cocoa systems in the provinces of Jaén and San Ignacio, the species diversity within these systems, considering altitude, and the climatic factors influencing their yields. These findings offer valuable insights for the sustainable management of cocoa, providing practical applications for policymakers and agricultural professionals, such as strategies to optimize productivity, improve biodiversity conservation, and adapt to climate variability. Furthermore, this research lays the foundation for future studies, such as the use of advanced remote sensing and UAV technologies, artificial intelligence, and machine learning to predict yields and monitor crop health, and ecophysiological modeling to assess the response of cocoa

AFS to future climate scenarios.

5. Conclusions

This study used PlanetScope and Sentinel-1 data, classified with Random Forest in GEE, to estimate the area dedicated to cocoa cultivation in the provinces of Jaén and San Ignacio. A total of 4338.6 ha were reported, with an overall thematic accuracy above 85%. The potential of merging optical and radar data enabled effective discrimination of these land covers, especially in cloud-prone areas.

The cocoa agroforestry systems in the provinces of Jaén and San Ignacio host considerable species diversity, with *Musa* sp., *I. edulis*, and *C. nucifera* being the most prevalent. These species show notable variations in their distribution depending on altitude. *Musa* sp. displays a greater affinity for lower altitudes, while *I. edulis* shows a preference for higher altitudes.

The calculation of the SAI shows that precipitation is a particularly key factor related to cocoa yield. Anomalies such as the 2019 drought negatively impacted productivity, highlighting the urgency of developing climate adaptation strategies. Therefore, it is important to consider altitudinal gradients in agroforestry management due to their impact on composition and resilience, indicating that future studies should integrate climate projections and advanced remote sensing, such as the use of UAV, to model the viability of cocoa agroforestry systems in the face of climate change.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author used Chat GPT in order to improve readability and language. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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CRedit authorship contribution statement

Nilton Atalaya-Marin: Writing – original draft, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Malluri Goñas:** Writing – original draft, Validation, Supervision, Resources, Data curation. **Daniel Tineo:** Validation, Supervision, Resources, Project administration, Data curation. **Beimer Chuquibala-Checan:** Validation, Formal analysis, Data curation. **Marielita Arce-Inga:** Validation, Formal analysis, Data curation. **Ever Tarrillo:** Validation, Formal analysis, Data curation. **Yeltsin A. Alvarez-Robledo:** Validation, Formal analysis, Data curation. **Josué Tafur-Culqui:** Validation, Formal analysis, Supervision, Data curation. **Héctor Cabrera-Hoyos:** Visualization, Validation, Supervision, Data curation. **Darwin Gómez-Fernández:** Writing – review & editing, Validation, Software, Data curation.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Nilton Atalaya-Marin reports administrative support, article publishing charges, equipment, drugs, or supplies, statistical analysis, and travel were provided by Instituto Nacional de Innovación Agraria. Nilton Atalaya-Marin reports a relationship with Instituto Nacional de

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Data availability

Upon reasonable request, the corresponding author will provide access to the data used to support the study’s findings.

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