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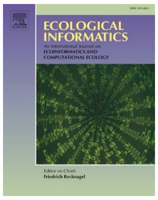

# Territorial zoning as a strategy for sustainable natural resource management in Cajamarca, Northwestern Peru

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## ABSTRACT

Generating agricultural suitability analyses that are objective, consistent, and accessible through digital platforms remains a technical and methodological challenge, creating an information gap for certain stakeholders. To address this issue, we assessed the territorial suitability of the Cajamarca region for coffee and cocoa cultivation using 18 subcriteria grouped into climatic, edaphological, topographic, and socioeconomic categories. To reduce subjectivity and improve consistency in variable comparisons, we applied multicriteria evaluation techniques, including the analytical hierarchy process (AHP) and Shannon entropy method. On the basis of the resulting weights, suitability models were generated using two approaches: one based on threshold reclassification and another using continuous suitability functions. Both approaches were validated using 3886 presence points for coffee and 671 for cocoa. The continuous approach demonstrated a greater ability to capture internal variability and spatial transitions, with greater dispersion and significant differences between classes. The most influential subcriteria for coffee were annual mean temperature, soil texture, elevation, and land use/land cover (LULC); for cocoa, they were annual mean temperature, soil pH, elevation, and LULC. In key districts, up to 59.8 % of the territory was classified as highly suitable, highlighting localized production potential. Finally, the results were integrated into the Suitability Watch Cajamarca application, developed in the Google Earth Engine, enabling interactive inspection of spatial suitability. This tool aims to support evidence-based agricultural planning and is intended for national scaling to other strategic crops.

## 1. Introduction

Coffee and cocoa are globally important products (Pancsira and Lengyel, 2020; Sánchez et al., 2019) and are primarily produced in tropical regions (Ministerio de Agricultura y Riego [MIDAGRI], 2016). These crops represent a significant source of income for families in developing countries, who are also the main producers (Figueroa-Hernández et al., 2019; MIDAGRI, 2019).

Globally, coffee is the most consumed beverage (Boadu et al., 2022) and the second most traded agricultural product (Brenes et al., 2023), cultivated in more than 56 countries (Castro and Carlos, 2020), with an approximate area of 10 million hectares (Centro de Comercio Internacional, 2021). In contrast, among tropical crops, cocoa ranks third in trade volume and fourth in market value (Brenes et al., 2023), with a planted area of approximately 1.8 million hectares (Sánchez et al., 2019).

In Peru, the number of both crops has shown an increasing trend, positioning the country as the eighth-largest exporter of coffee and cocoa worldwide (Food and Agriculture Organization of the United Nations [FAO], 2023), with exports reaching 827 and 219 million USD, respectively (Junta Nacional del Café [JNC], 2023; MIDAGRI, 2024). Cajamarca, in particular, has emerged as the second-largest coffee exporting region and the twelfth for cocoa in Peru (Ministerio de Comercio Exterior y Turismo, 2024). This growth has been supported by

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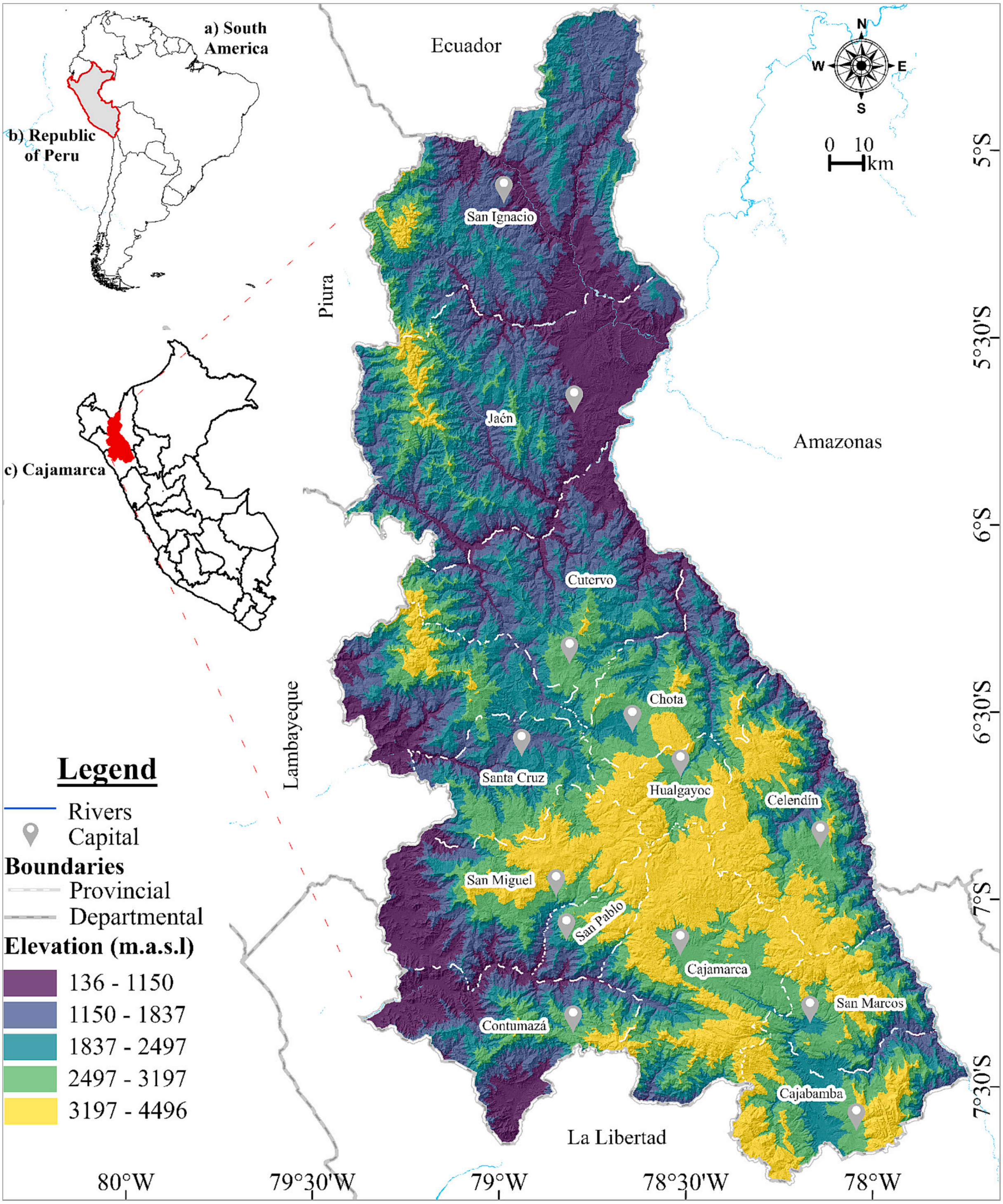


**Fig. 1.** Geographic location of the Cajamarca region in northwestern Peru.

various stakeholders, including the Cajamarca Coffee Multi-Stakeholder Platform, led by regional authorities, cooperatives, NGOs, and private exporters, which promotes the implementation of the National Coffee Action Plan. Notably, the cocoa sector in Cajamarca is emerging because of specific cooperatives and initiatives by the central and local governments.

Although agriculture represents a significant portion of exports in developing countries (Gollin, 2010), contributing to improving the quality of life for producers (Miranda et al., 2024), the expansion of the agricultural frontier does not always yield positive long-term results (Hertel et al., 2019). Furthermore, population growth has led to increases in cultivated areas and production to meet the rising global demand for agricultural products (Pawlak and Kołodziejczak, 2020). This trend is evident for coffee and cocoa crops, for which the harvested area has increased by 23 % and 15 %, respectively, over the past 10 years (FAO, 2023).

The main consequences of agricultural frontier expansion include soil degradation, nutrient loss, and a gradual reduction in crop productivity (Santos et al., 2021), as well as biodiversity loss due to deforestation (Gómez-Fernández et al., 2024; Xiao et al., 2023); climate

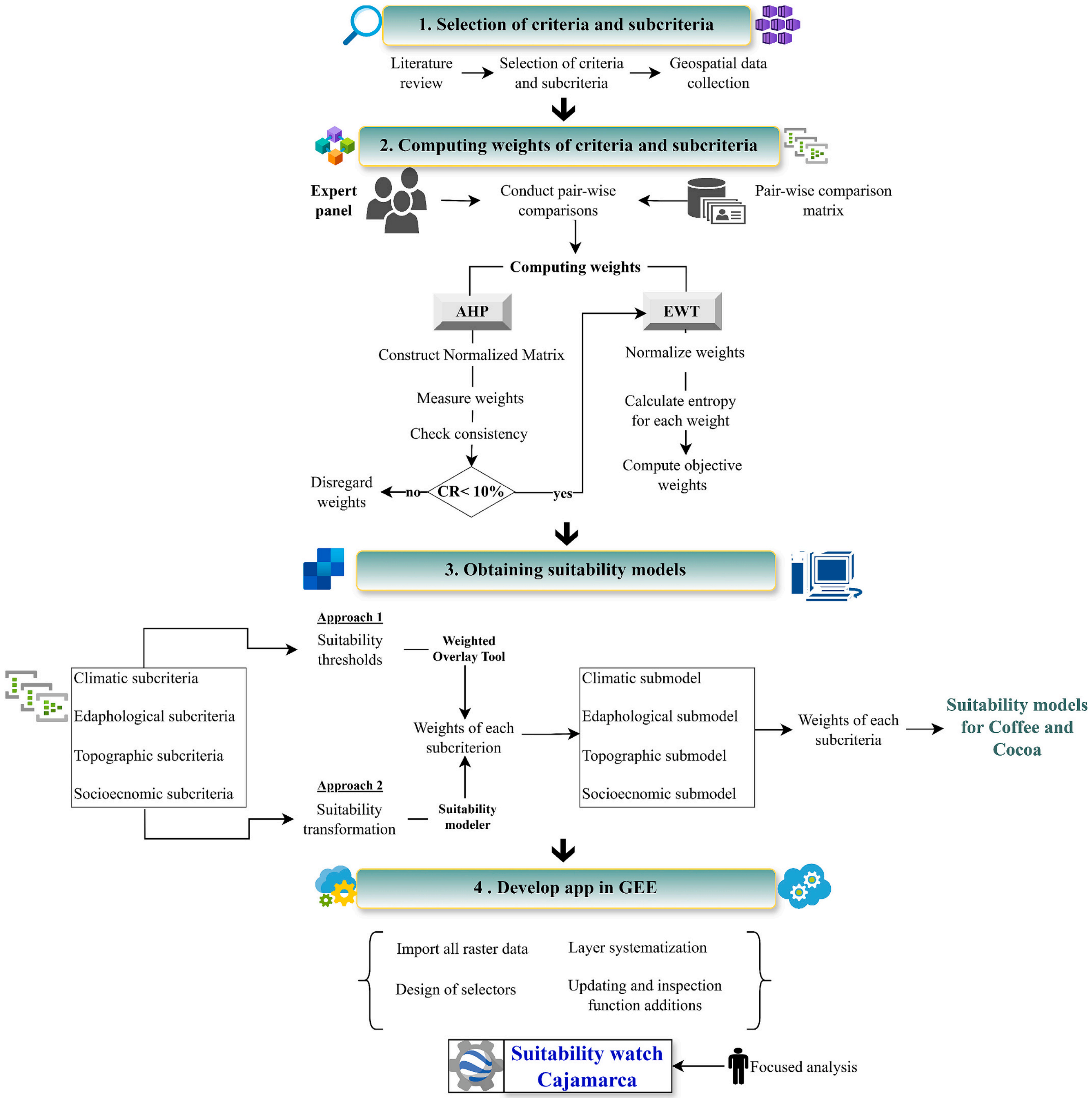


**Fig. 2.** Methodological framework for suitability analysis. Diagram showing the steps followed to assess land suitability for coffee and cocoa in Cajamarca, including criteria selection, weighting using the AHP and EWT, generation of suitability models through two approaches, and app development in the Google Earth Engine.

change driven by greenhouse gas emissions (de Abreu dos Santos et al., 2024); migration (Zarrilli, 2016); and water pollution (Gao et al., 2024), among other issues arising from land cover changes and landscape fragmentation (Gómez-Fernández et al., 2024). These implications underscore the need to implement strategies that promote sustainable agricultural development balanced with environmental conservation (Turner et al., 2021).

Territorial zoning for agricultural purposes involves identifying suitable land for cultivation (Mereu et al., 2024), which, for proper implementation, requires the inclusion of biophysical, climatic, and socioeconomic criteria (FAO, 1997). Inadequate planning can negatively impact the components of a territory (Patra et al., 2018). Therefore, zoning is a key element in sustainable land management (Tan and Cheng, 2024).

An alternative that supports land management is the use of multicriteria evaluation (MCE) techniques combined with geographic information systems (GIS), tools used by planners to make decisions (Barredo Cano, 1998). Notable techniques include the AHP (Aguilar Rivera et al., 2010; Salas-López et al., 2020) and the Decision-Making Trial and Evaluation Laboratory (DEMATEL) (Jayasinghe et al., 2019), which have been applied individually and compared with the Serbian method VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and the maximum entropy method (MaxEnt) (Ljubičić et al., 2023;

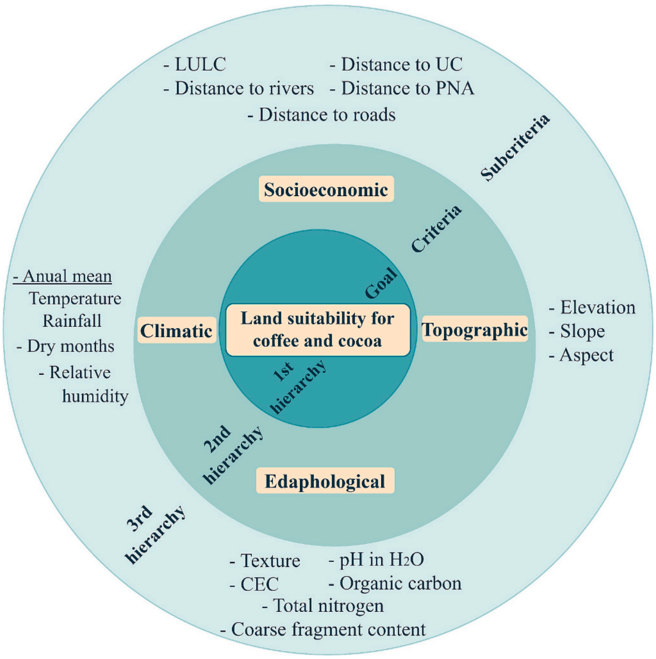


**Fig. 3.** Hierarchical structure for land suitability analysis. Diagram showing the goals, criteria, and subcriteria used to evaluate land suitability for coffee and cocoa. The structure is organized into three levels: overall goal (1st hierarchy), four main criteria (2nd hierarchy), and specific subcriteria (3rd hierarchy).

Rojas-Briceño, 2022; Sari et al., 2020). In addition, machine and deep learning algorithms have been incorporated to estimate soil suitability (Bhat et al., 2023; Huang et al., 2025; Kamga et al., 2025).

A suitability analysis approach based on continuous transformations can enhance the spatial discrimination capacity in heterogeneous environments. For instance, studies in semiarid ecosystems have shown that incorporating continuous functions into analyses increases the accuracy of suitability models by better representing real environmental gradients (Nyimbili and Erden, 2020; Özkan et al., 2020). Recent advancements in the construction rules of suitability functions have also demonstrated that using adaptive weights improves the representation of highly fertile areas.

Similarly, the integration of the AHP with Shannon entropy in GIS-based environments offers clear advantages. By combining expert judgment with objective criteria, the reliability of suitability maps can be significantly improved (Elvis et al., 2022; Nyimbili and Erden, 2020). These findings support the need for methodologically diverse evaluation frameworks to achieve agricultural planning that is sustainable and encompasses territorial variability.

Similarly, implementing suitability analyses through web-based platforms or applications not only improves accessibility and user understanding but also strengthens transparency, model validation, and continuous updating (Carnero, 2021; Razavi et al., 2023). These tools facilitate informed and collaborative decision-making in terms of territorial and natural resource management (Elvis et al., 2022).

The Cajamarca region has territorial management instruments in place (Gobierno Regional de Cajamarca (GRC), 2010), but they fall short for crop zoning. Notably, they do not delineate areas specifically suitable for coffee and cocoa, and there is no public geoportal to facilitate stakeholder access. This lack of precision and accessibility hinders evidence-based decision-making and increases the risk of uncoordinated agricultural expansion. Cajamarca has also topped Peru's specialty-coffee competitions in recent years, positioning the region as a national benchmark for high-quality coffee and providing a strong context for field validation.

**Table 1**
Data sources for the subcriteria considered in this analysis.

| Criteria | Code | Subcriteria | Units | Resource | Resolution |
|---|---|---|---|---|---|
| Climatic | a | Annual mean temperature | °C | World Clim (WC) | 30" |
| | c | Annual mean rainfall | mm | | |
| | d | Dry months | – | Derived from WC | |
| | e | Relative humidity | % | Climatic Research Unit | 10' |
| Edaphological | f | Texture | * | Soil Grids | 250 m |
| | | CEC | Cmol/kg | | |
| | g | pH in $H_2O$ | | | |
| | h | Organic carbon | % | | |
| | i | Total nitrogen | % | | |
| | j | Coarse fragment content | % | | |
| Topographic | k | Elevation | m.a.s.l | SRTM | 30 m |
| | l | Slope | % | | |
| | m | Aspect | ** | | |
| Socioeconomic | n | LULC | *** | Copernicus, MINAM | 100 m |
| | o | Distance to rivers | km | IGN | Feature layer |
| | p | Distance to UC | km | MINEDU | |
| | q | Distance to roads | km | MTC | |
| | r | Distance to PNA | **** | SERNANP | |

[*] Textural classes: Loam (L), Sandy clay loam (SCL), Silty clay loam (SiCL), Clay loam (CL), Sandy loam (SL), Sandy clay (SC), Silt loam (SiL), Silty clay (SiC), Sand (S), Clay (C), Silt (Si), Loamy sand (LS).

[**] Cardinal orientation: North (N), South (S), East (E), West (W), Northeast (NE), Southeast (SE), Southwest (SW) and Northwest (NW).

[***] LULC: Shrubs (20), Herbaceous vegetation (30), Cropland (40), Urban/built up (50), Bare/sparse vegetation (60), water bodies (80), Herbaceous wetland (90), and Forest (>100).

[****] Wildlife refuges, national sanctuaries, protected forests, national parks, game reserves, reserved zones, regional conservation areas, and private conservation areas.

This study addresses these gaps with a replicable, transparent zoning framework tailored to Cajamarca's conditions. Combining methodological rigor with web-based delivery (Suitability Watch Cajamarca), it provides scientifically grounded suitability models and practical tools to support land use regulations, prioritize reforestation in marginal areas, and provide targeted technical assistance on the basis of spatial suitability patterns. Although scaled to Cajamarca to enable in situ validation, the framework and application are designed to be adaptable and scalable to other crops and regions.

Therefore, in this research, the suitability of the Cajamarca region for coffee and cocoa development was investigated. The process involved four main stages: (i) identification and spatial mapping of the criteria and subcriteria influencing the development of both crops; (ii) calculation and adjustment of importance weights using the AHP combined with the Shannon entropy weighting technique; (iii) generation of suitability models and intermediate submodels; and (iv) integration of both the subcriteria data and final suitability outputs into an application developed in the Google Earth Engine.

## 2. Materials and methods

### 2.1. Study area

The Cajamarca region covers a legal area of 32,952.64 km$^2$ and is

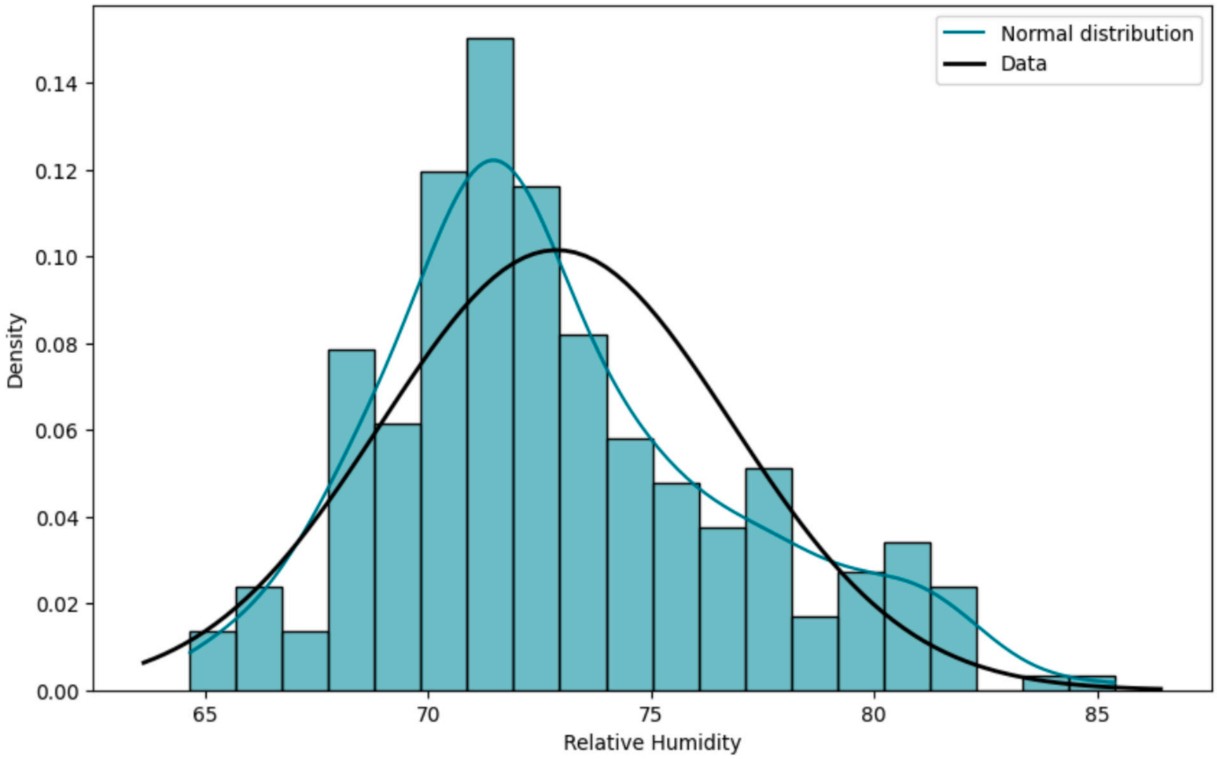


**Fig. 4.** Relative humidity data distribution. Comparison between the empirical distribution (black line) and the normal distribution (cyan line) for annual mean relative humidity in Cajamarca. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

administratively divided into 13 provinces and 127 districts (Gobierno Regional de Cajamarca (GRC), 2010). It extends from 4.62° to 7.76° south latitude and from 79.46° to 77.74° west longitude, with elevations ranging from 136 to 4496 m above sea level (m.a.s.l.), as shown in Fig. 1.

The territory's climate is characterized by two main types: a rainy, temperate climate with dry autumn and winter seasons, featuring maximum temperatures between 19 and 23 °C, minimum temperatures between 3 and 7 °C, and annual precipitation ranging from 700 to 1500 mm. There is also a semiarid, temperate, and humid climate throughout the year, with maximum temperatures between 21 and 25 °C, minimum temperatures between 7 and 11 °C, and annual precipitation ranging from 700 to 2000 mm (SENAMHI, 2020). With respect to agriculture, the Cajamarca region is known for coffee cultivation, with 58,379 registered producers. On the other hand, cocoa cultivation is also of local interest, although it has not been extensively developed, with only 1863 registered producers.

### 2.2. Methodological flow

The methodological framework used to determine the suitability of the Cajamarca region for coffee and cocoa cultivation using multicriteria evaluation techniques within a GIS environment is shown in Fig. 2. A total of 18 subcriteria were selected and grouped into four criteria: climatic, edaphological, topographic, and socioeconomic. Two modeling approaches were applied: a discrete threshold-based method using categorical reclassification (1 to 4) and a continuous suitability function approach using mathematical transformations to normalize values from 1 to 10.

In both approaches, the relative importance of each subcriterion was determined using the AHP and adjusted through the Shannon entropy weighting technique to reduce subjectivity and incorporate data variability. Suitability models were validated using georeferenced presence points (3886 for coffee and 671 for cacao). All subcriteria layers and final suitability maps were integrated into the SWC (Suitability Watch Cajamarca) application developed in the Google Earth Engine, enabling users to visualize and inspect suitability conditions interactively.

### 2.3. Determination and mapping of subcriteria

Through a literature review of the main criteria and subcriteria that influence the development of coffee (*Coffea arabica*) and cocoa (*Theobroma cacao L.*) cultivation, 18 subcriteria common to both crops were identified and selected. These subcriteria were grouped into climatic, edaphological, topographic, and socioeconomic criteria.

The hierarchical structure of the suitability analysis for the Cajamarca region is shown in Fig. 3. Consequently, the climatic subcriteria considered were the annual mean temperature, annual mean precipitation, number of dry months, and relative humidity. Additionally, the edaphological subcriteria included texture, cation exchange capacity (CEC), pH in $H_2O$, organic carbon, total nitrogen, and the coarse fragment content. Additionally, the topographic subcriteria included elevation, slope, and aspect. Finally, the socioeconomic subcriteria were land use and land cover (LULC), distance to rivers, distance to urban centers (UC), distance to roads, and distance to protected natural areas (PNAs).

**Table 2**
Importance scale for pairwise comparison matrices.

| 1/9 | 1/8 | 1/7 | 1/6 | 1/5 | 1/4 | 1/3 | 1/2 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Minimal | | Very weak | | Weak | | Slightly weak | | Equal importance | Moderate | | Strong | | Very strong | | Extreme | |
| Least importance | | | | | | | | | Most importance | | | | | | | |

### 2.3.1. *Data sources*

All the data for subcriteria used in this analysis were extracted from national and international spatial databases. The subcriteria used along with their respective data sources are listed in Table 1.

### 2.3.2. *Mapping and layer generation*

*2.3.2.1. Mapping climatic subcriteria.* Monthly data from World Clim (Fick and Hijmans, 2017) were downloaded to establish the layers for annual mean temperature and precipitation. For temperature, the monthly data were averaged, while for precipitation, the monthly totals were summed, and both processes were performed using the raster calculator in ArcGIS Pro v.3.4.

To generate the layer for the number of dry months, the Martonne aridity index (Im) was calculated monthly:

$$Im = \frac{12*P}{T+10} \tag{1}$$

where **P** is the monthly precipitation (mm) and **T** is the mean monthly temperature (°C).

Next, the conditional function in the raster calculator was used to generate binary maps: cells where $Im < 30$ were assigned a value of 1 (indicating dry conditions), and cells where $Im > 30$ were assigned a value of 0 (indicating wet conditions). Finally, the 12 binary maps were summed to obtain the number of dry months across the year.

To generate the raster layer for relative humidity at a 30-m spatial resolution, the empirical Bayesian kriging (EBK) interpolation method was used in ArcGIS Pro v.3.4, employing point data from the Climatic Research Unit (New et al., 2002) (Fig. S1 and Table S1).

Defining the semivariogram model is a key aspect of interpolation with EBK, which requires understanding the data distribution and evaluating whether transformation is necessary. The results of the Kolmogorov–Smirnov, Shapiro–Wilk, and Anderson–Darling tests were calculated via the SciPy statistics module in Google Colab. The results indicated that the $p$ values were lower or that the test statistic was higher than the critical values at the 5 % significance level, suggesting that the relative humidity data did not fit a normal distribution. This implied the need to use nonparametric techniques to analyze these data or to

**Table 3**
Suitability levels of subcriteria for coffee cultivation (bold font) and cocoa cultivation (regular font).

| Subcriteria | Level of suitability | | | | Adapted from |
|---|---|---|---|---|---|
| | Highly suitable | Moderately suitable | Marginally suitable | Not suitable | |
| Climatic | | | | | |
| AA temperature | **18–21** | **16–18; 21–22** | **14–16; 23–26** | **<14; >26** | (Zhang et al., 2021b) |
| | 25–28 | 22–25; 28–32 | 20–22; 32–35 | <20; >35 | (Ayorinde et al., 2015; Djaenudin et al., 2003; Merchán-Benavides et al., 2018; Ritung et al., 2007; Rojas-Briceño et al., 2022) |
| AA rainfall | **1200–1800** | **1000–1200<br>1800–2000** | **800–1000<br>2000–2400** | **<800<br>>2400** | (Zhang et al., 2021b) |
| | 1600–2500 | 2500–3500<br>1400–1600 | 1200–1400;<br>3500–4400 | <1200;<br>>4400 | (Djaenudin et al., 2003; Ritung et al., 2007; Rojas-Briceño et al., 2022) |
| Dry months | **<4** | **4–5** | **5–6** | **>6** | (Grüter et al., 2022) |
| | <2 | 3 | 4 | >4 | (Buggenhout, 2018; Rojas-Briceño et al., 2022; Sys, 1985) |
| Relative humidity | **40–70** | **70–80; 30–40** | **80–90; 20–30** | **>90; <20** | (Grüter et al., 2022) |
| | 40–65 | 65–75; 35–40 | 75–85; 30–35 | >85; <30 | (Djaenudin et al., 2003; Ritung et al., 2007) |
| **Edaphological** | | | | | |
| Texture | **CL, SiCL, SiL** | **L, SCL, Si** | **SL, SC** | **Si, S, C** | (Grüter et al., 2022) |
| | SiCL, CL, SiL | L, SCL, SC | Si, SL, C | LS, S, SiC | (Djaenudin et al., 2003; Ritung et al., 2007; Rojas-Briceño et al., 2022; Sys, 1985) |
| CEC | **>40** | **25–40** | **15–25** | **<15** | (Verheye, 2017) |
| | >24 | 20–24 | 16–20 | <16 | (Ayorinde et al., 2015; Rojas-Briceño et al., 2022) |
| pH of $H_2O$ | **5.5–6.5** | **5–5.5; 6.5–7** | **4.5–5; 7–7.5** | **<4.5; >7.5** | (Salas-López et al., 2020; Zhang et al., 2021a) |
| | 6–7 | 5–6; 7–7.6 | 4.2–5; 7.6–8.2 | <4.2; >8.2 | (Alabi et al., 2013; Arvelo et al., 2017; Rojas-Briceño et al., 2022) |
| Organic carbon | **>1.2** | **0.8–1.2** | **<0.8** | **–** | (Grüter et al., 2022) |
| | >1.5 | 0.8-1.5 | <0.8 | – | (Djaenudin et al., 2003; Ritung et al., 2007; Rojas-Briceño et al., 2022; Sys, 1985) |
| Total nitrogen | **>0.21** | **0.1–0.21** | **<0.1** | **–** | (Hidayat et al., 2020) |
| | >0.18 | 0.15-0.18 | 0.1–0.15 | <0.1 | (Ayorinde et al., 2015) |
| Coarse fragment content$^1$ | <15 | 15–35 | 35–60 | >60 | (Grüter et al., 2022; Ritung et al., 2007) |
| **Topographic** | | | | | |
| Elevation (m) | **800–1500** | **1500–1800** | **300–800<br>1800–2000** | **<300;<br>>2000** | (Zhang et al., 2021b) |
| | 400–800 | 1000–1500<br>0–400;<br>800–1200 | 1200–1600 | >1600 | (Arvelo et al., 2017; García et al., 2004; Rojas-Briceño et al., 2022) |
| Slope | **<15** | **15–20** | **20–35** | **>35** | (Zhang et al., 2021b) |
| | <8 | 8–16 | 16–30 | >30 | (Djaenudin et al., 2003; Merchán-Benavides et al., 2018; Ritung et al., 2007; Rojas-Briceño et al., 2022; Sys, 1985) |
| Aspect$^1$ | N, NE, NW, Flat | W, E | SE, SW | S | (Lara et al., 2016; Rojas-Briceño et al., 2022; Salas-López et al., 2020; Zhang et al., 2021b) |
| **Socioeconomic** | | | | | |
| LULC$^1$ | 40 | 20 | 30 | 0; 50–90;<br>>100 | (Iliquín Trigoso et al., 2020; Rojas-Briceño et al., 2022; Salas-López et al., 2020) |
| Distance to rivers$^1$ | 0–0.5 | 0.5–2 | 2–5 | >5 | (Pramanik, 2016; Rojas-Briceño et al., 2022; Salas-López et al., 2020; Yalew et al., 2016) |
| Distance to UC$^1$ | 0–3 | 3–6 | 6–10 | >10 | |
| Distance to roads$^1$ | 0–4 | 4–8 | 8–10 | >10 | |
| Distance to PNA$^1$ | Out | – | Buffer zone | Within | (Ministerio de Justicia, 2011) |

**Note:** The superscript **1** indicates that the same suitability levels were considered for both crops.

consider a data transformation if normality was assumed needed. The distribution of the data is shown in Fig. 4 (cyan line: normal distribution; black line: data distribution). For more details of the normality tests, refer to Table S2 in the Supplementary Material.

Therefore, on the basis of the statistical tests performed, the EBK transformation parameter was set to “Empirical,” and EBK was applied in a multiplicative bias transformation with an empirical base function to reduce bias and improve interpolation quality. The K-Bessel semivariogram model was selected owing to its flexibility and accuracy, with 100 semivariogram simulations and a maximum of 100 points in each local model. A neighbor search was performed in circular standard mode with a minimum of 10 and a maximum of 15 neighbors, considering computational resources.

*2.3.2.2. Mapping edaphological subcriteria.* All the raster layers for the edaphological subcriteria were obtained from the Global Soil Mapping System - Soil Grids (Hengl et al., 2017). Using the GEE (Gorelick et al., 2017), layers were clipped to the study area, and averages for both crops were obtained at 5 depths (0–5, 5–15, 15–30, 30–60, and 60–100 cm).

The texture layer was generated using the raster calculator and the sand, clay, and silt layers from Soil Grids on the basis of the conditions and percentages established by the United States Department of Agriculture (USDA). With respect to the CEC, the pH in $H_2O$, organic carbon, total nitrogen, and coarse fragment content layers were converted to the conventional units shown in Table 1, without additional processing.

*2.3.2.3. Mapping topographic subcriteria.* Topographic subcriteria were obtained from the 30-m spatial resolution product of NASA’s Shuttle Radar Topography Mission (SRTM) (Farr et al., 2007). The elevation layer was generated using the SRTM digital elevation model (DEM), from which the slope and aspect layers were derived using the ***Slope*** and ***Aspect*** tools from the spatial analysis toolbox in ArcGIS Pro v.3.4.

*2.3.2.4. Mapping socioeconomic subcriteria.* The LULC layer was generated by merging the Copernicus Global Land Service (CGLS) layer with the national agricultural surface generated by the Ministry of the Environment – Peru.

The river layer was extracted from national maps provided by the National Geographic Institute, while the urban center layer was obtained by merging artificial/urban polygons from the LULC layer with point data from the Ministry of Education.

With respect to the protected natural areas (PNA) layer, all the individual layers of the protected area types were merged with their respective buffer zones, which are updated by the National Service of Protected Natural Areas (SERNANP).

Finally, the road network layer was downloaded from the Ministry of Transport and Communications, spanning the neighborhood, departmental, and national levels. The Euclidean distance tool from the spatial analysis toolbox in ArcGIS Pro v.3.4 was used to calculate distances to each object of interest.

## 2.4. Obtaining importance weights

The importance weights for the criteria and subcriteria were calculated on the basis of pairwise comparison matrices completed by experts in coffee and cocoa cultivation. To ensure the robustness of these assessments, experts, including agronomists, researchers, and professionals with diverse career paths, were selected on the basis of their extensive field experience and expertise. Initially, the relative importance of each subcriterion and criterion was quantified through the AHP. The weights obtained through the AHP were subsequently adjusted using an entropy-based weighting technique (EWT).

**Table 4**

Transformation parameters for the subcriteria.

| Sub criteria | Function | Key values: Coffee | Key values: Cocoa |
|---|---|---|---|
| Annual mean temperature | Gaussian | MP: 20<br>LT: 16<br>UT: 23 | MP: 23<br>LT: 20<br>UT: 28 |
| Annual mean rainfall | Gaussian | MP: 1200<br>LT: 1000<br>UT: 2500 | MP: 1400<br>LT: 800<br>UT: 2500 |
| Dry months | Near | MP: 4<br>LT: 0<br>UT: 12 | MP: 3<br>LT: 0<br>UT: 12 |
| Relative humidity | Gaussian | MP: 70<br>LT: 60<br>UT: 75 | MP: 60<br>LT: 40<br>UT: 65 |
| Texture | Unique categories | * | * |
| CEC | Large | MP: 20<br>LT: 10<br>UT: 45 | MP: 24<br>LT: 10<br>UT: 45 |
| pH in $H_2O$ | Gaussian | MP: 5.5<br>LT: 5<br>UT: 7.5 | MP: 6<br>LT: 5<br>UT: 7 |
| Organic carbon | Large | MP: 2<br>LT: 0<br>UT: 15 | MP: 1.5<br>LT: 0<br>UT: 15 |
| Total nitrogen | Gaussian | MP: 2.5<br>LT: 1<br>UT: 4 | MP: 2<br>LT: 1<br>UT: 4 |
| Coarse fragment content | Small | MP: 15<br>LT: 0<br>UT: 35 | |
| Elevation | Gaussian | MP: 1500<br>LT: 1000<br>UT: 2100 | MP: 400<br>LT: 800<br>UT: 1200 |
| Slope | Gaussian | MP: 20<br>LT: 5<br>UT: 40 | MP: 15<br>LT: 5<br>UT: 30 |
| Aspect | Gaussian inversion | MP: 65<br>LT: 1<br>UT: 80 | |
| LULC | Unique categories | * | |
| Distance to rivers | MSSmall | MM: 1<br>LT: 0<br>UT: 5 | |
| Distance to UC | MSSmall | MM: 1<br>LT: 0<br>UT: 52 | |
| Distance to roads | MSSmall | MM: 1<br>LT: 0<br>UT: 45 | |
| Distance to PNA | Unique categories | * | |

[*] Values were initially grouped according to their original suitability in Table 3.

### 2.4.1. Analytical hierarchy process (AHP)

The experts included in the panel individually generated pairwise comparison matrices for coffee and cocoa using the importance scale shown in Table 2, as proposed by Saaty (1980).

Next, a normalized matrix was constructed to obtain the importance weights (w). The consistency of the matrices was then reviewed, and if the consistency ratio (CR) was less than 10 %, the obtained weights were used in the subsequent step. The CR calculation was based on the consistency index (CI), random index (RI), and matrix size (n), as shown in Eqs. (2) and (3).

$$H = A*W$$

$$= \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix} * \begin{bmatrix} w_1 \\ \vdots \\ w_n \end{bmatrix} = \begin{bmatrix} h_1 \\ \vdots \\ h_n \end{bmatrix}$$

$$= \begin{bmatrix} \lambda_1 \\ \vdots \\ \lambda_n \end{bmatrix} = \begin{bmatrix} h_1/w_1 \\ \vdots \\ h_n/w_n \end{bmatrix} \tag{2}$$

$$\lambda_{avg} = \left| \frac{\sum \lambda_i}{n} \right|$$

$$CI = \left| \frac{\lambda_{avg} - n}{n - 1} \right|$$

$$CR = \frac{CI}{RI} \tag{3}$$

### 2.4.2. Entropy weighting technique—Shannon entropy

In this study, the information theory methodology proposed by Shannon was applied (Shannon, 1948). Through the AHP, 15 and 12 pairwise comparison matrices for coffee and cocoa, respectively, were obtained, all with a CR below 10 %. Given that expert opinions can vary, the normalized value ($V_{ij}$) for each of the previously determined importance weights $x_{ij}$ was calculated. The entropy of each ($Z_j$) was subsequently determined on the basis of the summation of the normalized values ($V_{ij}$) and the number of alternatives (m). Finally, the objective weights for each criterion and subcriterion were obtained, considering their respective entropy and the matrix size (n) or the number of criteria and subcriteria, as shown in Eqs. (4), (5), and (6).

$$V_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{4}$$

$$Z_j = -k \sum_{i=1}^{m} v_{ij} \ln(v_{ij}) = -\frac{1}{\ln(m)} \sum_{i=1}^{m} v_{ij} \ln(v_{ij}) \tag{5}$$

$$W_j^{obj} = \frac{1 - Z_j}{\sum_{J=1}^{n} (1 - Z_j)} \tag{6}$$

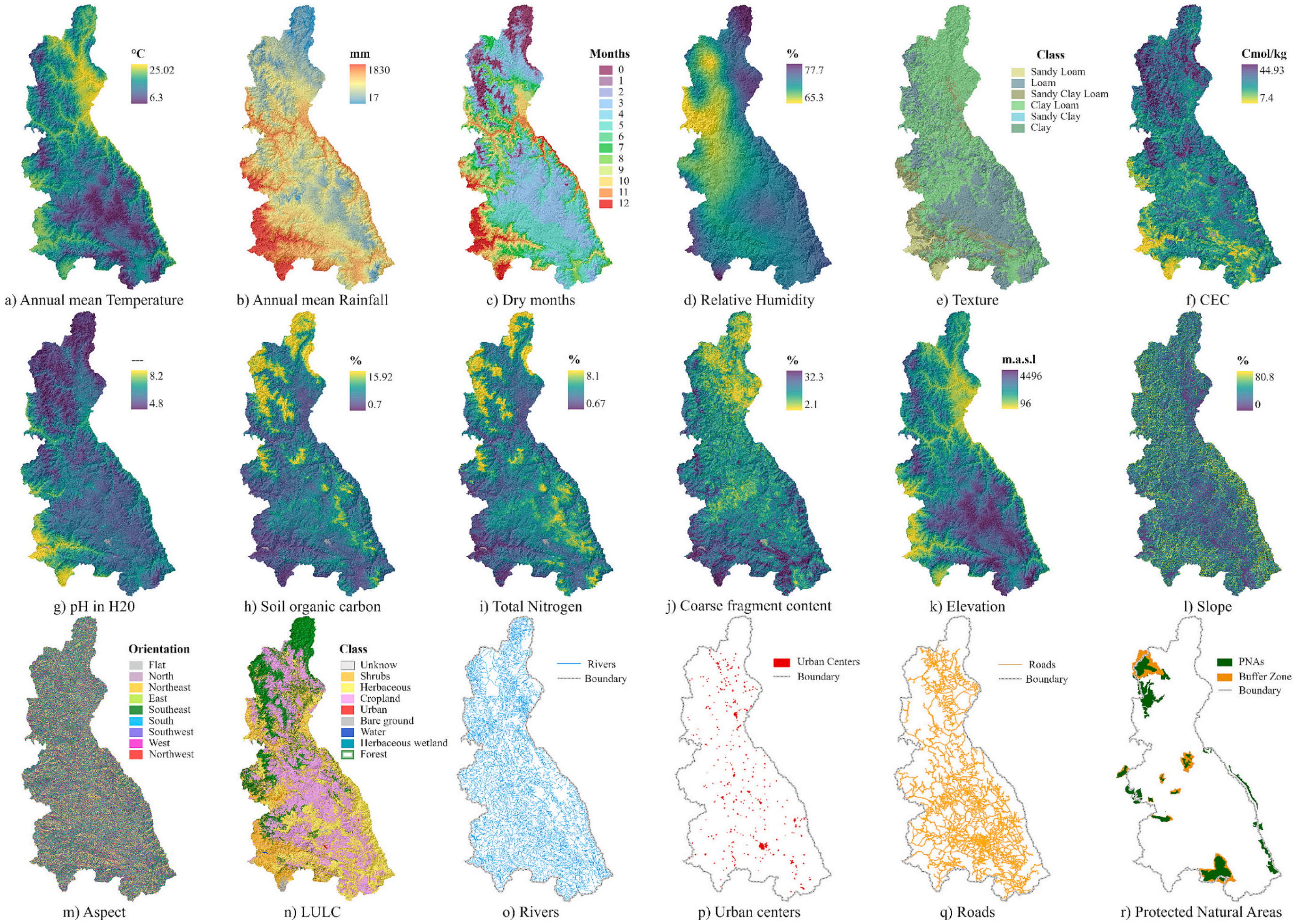
## 2.5. Obtaining suitability models

In this research, two approaches for generating suitability models for coffee and cocoa crops were compared. The first approach was based on reclassification using fixed thresholds, whereas the second used transformation functions and subcriteria adjustment.

### 2.5.1. Threshold-based suitability modeling

On the basis of the land evaluation approach and the classification used in other studies, four levels of suitability were considered for both crops being evaluated (Table 3): highly suitable (4), moderately suitable (3), marginally suitable (2), and not suitable (1) for the development of coffee and cocoa in the Cajamarca region, Peru.

The 18 subcriteria were reclassified into four suitability levels on the basis of the value ranges established in Table 3. This step was performed



a) Annual mean Temperature b) Annual mean Rainfall c) Dry months d) Relative Humidity e) Texture f) CEC

g) pH in H20 h) Soil organic carbon i) Total Nitrogen j) Coarse fragment content k) Elevation l) Slope

m) Aspect n) LULC o) Rivers p) Urban centers q) Roads r) Protected Natural Areas

**Fig. 5.** Mapped subcriteria used to determine the suitability of the Cajamarca region for coffee and cocoa cultivation.

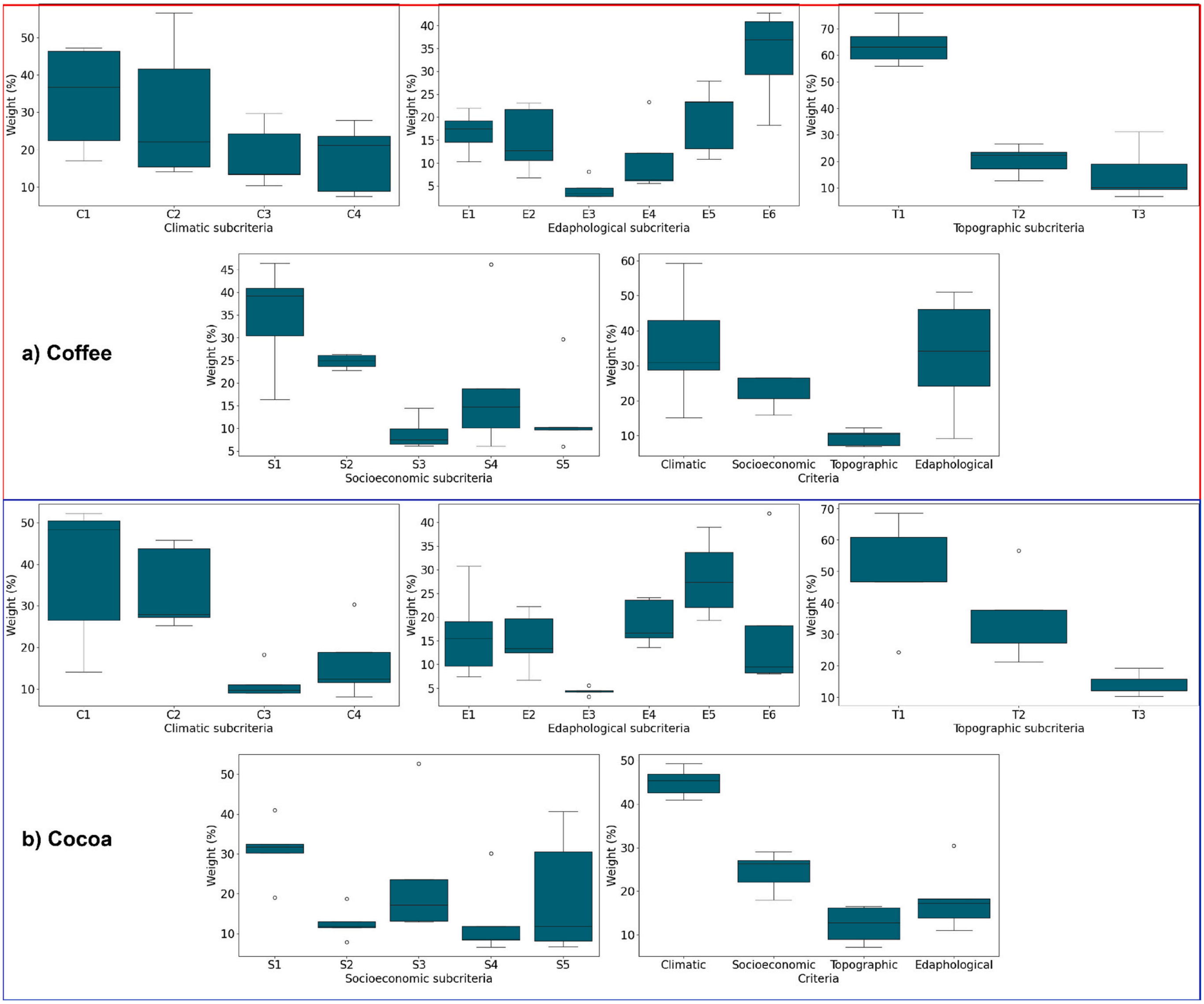


**Fig. 6.** Variation in the weights calculated for the subcriteria of coffee (red box) and cocoa (blue box) cultivation. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

using the *Reclassify* tool in ArcGIS Pro v.3.4. The climatic, edaphological, topographic, and socioeconomic submodels were subsequently generated through a weighted overlay technique using the *Weighted Overlay* tool. In this stage, the reclassified layers were combined with the relative importance weights assigned to each subcriterion within the corresponding category. Finally, the overall suitability model for each crop was obtained by integrating the submodels and applying the weights assigned to each main criterion.

### 2.5.2. Function-based suitability modeling

The proposed approach is implemented with the *Suitability Modeler* module in ArcGIS Pro v.3.4 to transform the subcriteria using continuous suitability functions. Unlike the threshold-based approach, which requires explicit classification into predefined levels, this method allows for a more flexible representation of suitability, minimizing the subjectivity associated with fixed-value segmentation. Key transformation values such as the midpoint (MP), lower threshold (LT), and upper threshold (UT) were adapted on the basis of the suitability ranges in Table 3.

Subcriteria were transformed using specific functions tailored to the expected behavior of each variable. The Gaussian function assigns the highest suitability to the midpoint and progressively penalizes values further from the optimum. The *Large* function favors higher values, whereas the *Small* function does the opposite, prioritizing lower values. The *MSSmall* function prioritizes minimum values on the basis of the mean and standard deviation of the selected variable. For categorical variables such as soil texture or land use, the *Unique Categories* function was used to assign specific suitability levels to each class.

Table 4 summarizes the functions applied and the key transformation values defined for each subcriterion in both the coffee and cocoa suitability models.

The transformed subcriteria were then organized under four main criteria classes: climatic, edaphological, topographic, and socioeconomic. Submodels were generated using the *Suitability Modeler* module in ArcGIS Pro v.3.4. The overall suitability model for each crop was subsequently obtained by integrating the four submodels and applying the corresponding importance weights defined for each group.

### 2.6. Validation and performance of the suitability models

In the validation, 3886 georeferenced points for coffee and 671 for cocoa were used. For each point, we extracted the suitability with both

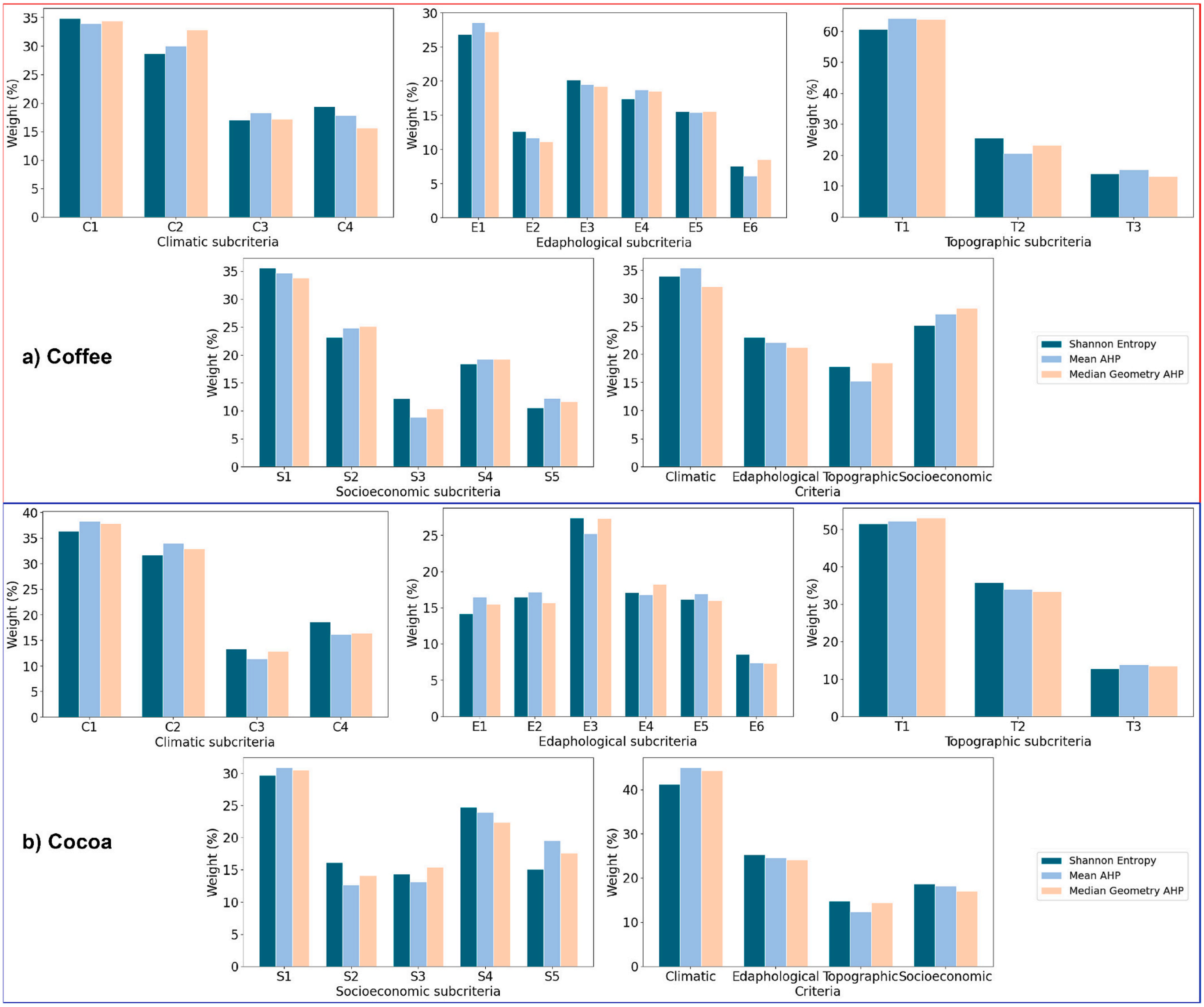


**Fig. 7.** Comparison of weighting methods: Shannon entropy (cyan), arithmetic mean AHP (light blue), and geometric mean AHP (beige) for coffee (a) and cocoa (b) cultivation. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

approaches: the threshold-based model for discrete classes (1–4) and the function-based model for continuous scores derived from transformation functions. The same points were used for both approaches to ensure strict comparability.

We characterized the continuous scores with descriptive statistics and histograms/KDEs, including KDEs stratified on the basis of the discrete classes. We then tested the normality of the continuous scores within each class using the Shapiro–Wilk test; because most groups were nonnormal, we compared classes with the Kruskal–Wallis test ($\alpha = 0.05$, two-sided). Spearman's rank correlation was used to assess structural consistency between discrete classes and continuous scores. As additional robustness checks, we computed quadratic weighted Cohen's $\kappa$ between the threshold classes (1–4) and the quartiled continuous scores to quantify ordinal agreement, and we reported the Kruskal–Wallis effect size ($\varepsilon^2$) to gauge the magnitude of between-class differences.

### *2.7. Geospatial data hosting and visualization*

To ensure open access to spatial information and support informed decision-making in territorial planning, we developed an interactive web-based application using the GEE platform. This application integrates the outputs of the suitability models along with the 18 subcriteria, which are organized under climatic, edaphological, topographic, and socioeconomic criteria classes. The tool allows users to visualize, explore, and interpret suitability maps in real time through a modular and intuitive interface, facilitating stakeholder engagement and spatial transparency.

The platform incorporates a multicomponent layout that includes (i) a selector interface to filter subcriteria; (ii) raster visualizations of suitability models for coffee and cocoa; (iii) a dynamic overlay of district boundaries to support spatial referencing; and (iv) a pixel-level inspector tool that provides suitability scores, district names, and information on spatial restrictions. The application is deployed entirely within the GEE Code Editor and constructed using native client-side UI elements (ui. Panel, ui. Select, ui. Map, etc.).

## 3. Results

### *3.1. Mapped subcriteria for coffee and cocoa cultivation*

The 18 mapped subcriteria for coffee and cocoa cultivation are presented in Fig. 5 and are grouped into climatic (a–d), edaphological

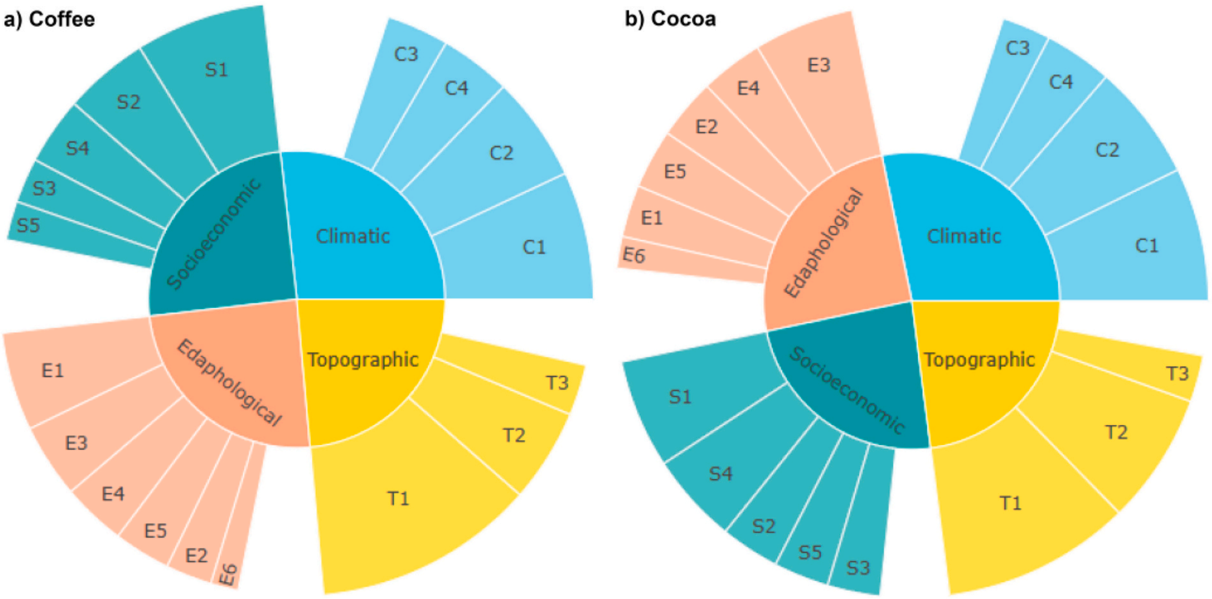


**Fig. 8.** Hierarchical distribution of importance weights for criteria and subcriteria of coffee (a) and cocoa (b) crops.

**Table 5**
Weighting of criteria and subcriteria for coffee and cocoa cultivation.

| Criteria | Weight (%) | | Subcriteria | Weights (%) | | Standardized Weight (%) | |
|---|---|---|---|---|---|---|---|
| | Coffee | Cocoa | | Coffee | Cocoa | Coffee | Cocoa |
| Climatic | 33.9 | 41.2 | Annual mean temperature | **34.9** | **36.4** | **11.8** | **15.0** |
| | | | Annual mean rainfall | 28.7 | 31.7 | 9.7 | 13.1 |
| | | | Dry months | 17 | 13.3 | 5.8 | 5.5 |
| | | | Relative humidity | 19.4 | 18.5 | 6.6 | 7.6 |
| Edaphological | 23.1 | 25.3 | Texture | **26.8** | 14.2 | 6.2 | 3.6 |
| | | | CEC | 12.6 | 16.5 | 2.9 | 4.2 |
| | | | pH in $H_2O$ | 20.2 | **27.4** | 4.7 | 6.9 |
| | | | Organic carbon | 17.4 | 17.1 | 4.0 | 4.3 |
| | | | Total nitrogen | 15.5 | 16.2 | 3.6 | 4.1 |
| | | | Coarse fragment content | 7.5 | 8.6 | 1.7 | 2.2 |
| Topographic | 17.8 | 14.8 | Elevation | **60.6** | **51.5** | 10.8 | 7.6 |
| | | | Slope | 25.5 | 35.8 | 4.5 | 5.3 |
| | | | Aspect | 13.9 | 12.7 | 2.5 | 1.9 |
| Socioeconomic | 25.2 | 18.7 | LULC | **35.6** | **29.7** | 9.0 | 5.6 |
| | | | Distance to rivers | 23.2 | 16.1 | 5.8 | 3.0 |
| | | | Distance to UC | 12.2 | 14.4 | 3.1 | 2.7 |
| | | | Distance to roads | 18.4 | 24.7 | 4.6 | 4.6 |
| | | | Distance to PNA | 10.6 | 15.1 | 2.7 | 2.8 |

(e–j), topographic (k–m), and socioeconomic (n–r) subcriteria.

### 3.2. Importance of criteria and subcriteria

The distribution of weights assigned by experts to the criteria and subcriteria considered for coffee (a) and cocoa (b) cultivation is shown in Fig. 6. The boxplots reflect the variability and dispersion of the judgments obtained through the AHP method, retaining only matrices with a consistency ratio below 10 %. This dispersion is particularly evident for certain climatic, edaphological, and socioeconomic subcriteria.

Given the variability in importance weights, Fig. 7 compares three consolidation metrics: the arithmetic mean of the AHP weights, the geometric mean, and the Shannon entropy. The latter was selected for the final calculation, as it captures the degree of dispersion and uncertainty in expert assessments, assigning greater weights to criteria with higher levels of agreement. Unlike the arithmetic mean, which can be influenced by outliers, or the geometric mean, which does not account for interexpert variability, the Shannon entropy provides a more robust and unbiased representation of relative importance.

The final suitability models for coffee and cocoa were constructed using the consolidated weights obtained through the Shannon entropy method. The hierarchical distributions of the considered criteria and subcriteria are shown in Fig. 8. The radial layout reflects their relative importance, which is ordered counterclockwise from the highest weight to the lowest weight.

Fig. 8 emphasizes structural interpretation, and individual percentage values are not displayed directly; these are provided in Table 5, which complements the graphical representation and includes the weights assigned to each criterion and subcriterion, as well as the standardized weights used for model normalization.

### 3.3. Subcriteria suitability based on thresholds

The spatial distributions of the most influential subcriteria for coffee and cocoa cultivation, which were selected on the basis of their relative importance adjusted considering the Shannon entropy, are shown in Fig. 9. The maps represent the suitability levels obtained through

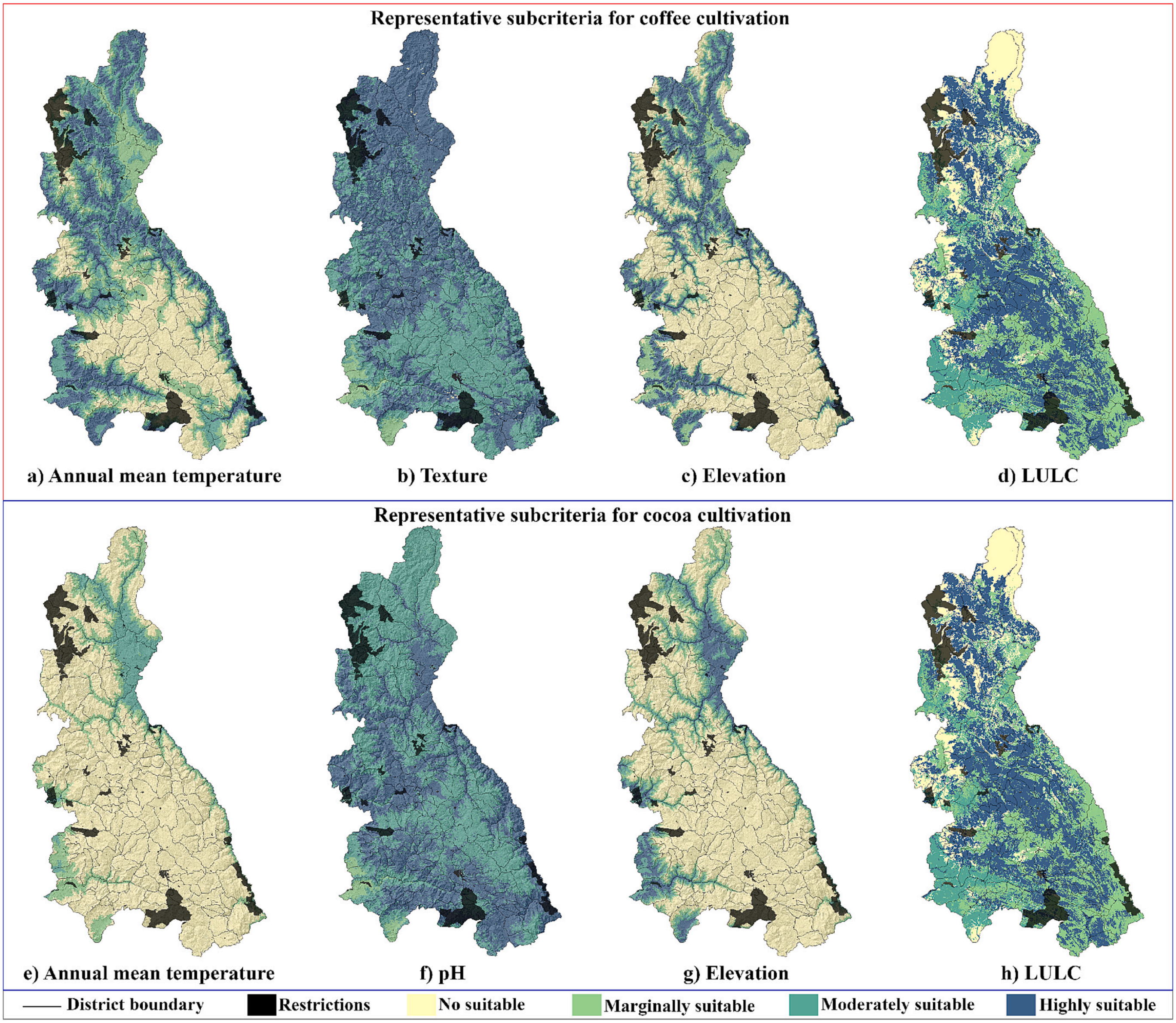


**Fig. 9.** Spatial distribution based on the thresholds of the most influential subcriteria for coffee (a–d) and cocoa (e–h).

threshold-based reclassification, resulting in discrete classes from 1 (very low suitability) to 4 (high suitability). The full set of maps is available in Supplementary Figs. S2 and S3. These outputs highlight categorical patterns that facilitate the identification of priority areas under each criterion.

### *3.4. Subcriteria suitability based on suitability functions*

The transformation functions applied to the 18 subcriteria for coffee cultivation, along with their value distribution histograms, are shown in Fig. 10. These transformations convert original values to a continuous suitability scale from 1 to 10, thus supporting a more detailed representation of how each variable aligns with optimal growing conditions. The corresponding graphs for cocoa are provided in Supplementary Fig. S4.

On the other hand, Fig. 11 presents the spatial distributions of the transformed subcriteria with the highest weights. These maps reveal the variation in suitability across the territory and enhance the interpretation of spatial gradients not captured by discrete classification.

### *3.5. Integrated suitability models*

The climatic, edaphological, topographic, and socioeconomic suitability submodels for coffee and cocoa cultivation, obtained with both threshold-based and suitability function-based approaches, are shown in Fig. 12.

In general, the suitability function-based submodels exhibit smoother spatial transitions, allowing the identification of intermediate suitability zones that are less evident in the threshold-based approach. This is particularly noticeable for the edaphological submodels, for which similar input values led to high suitability across large areas in the threshold-based method, whereas the function-based approach better differentiated truly optimal zones.

In the case of the socioeconomic submodels, both approaches yield comparable patterns, likely because of the use of categorical and distance-based variables.

These results highlight how the choice of modeling approach influences the spatial resolution and interpretation of land suitability, particularly for criteria with high internal variability.

The final suitability models for coffee and cocoa generated by

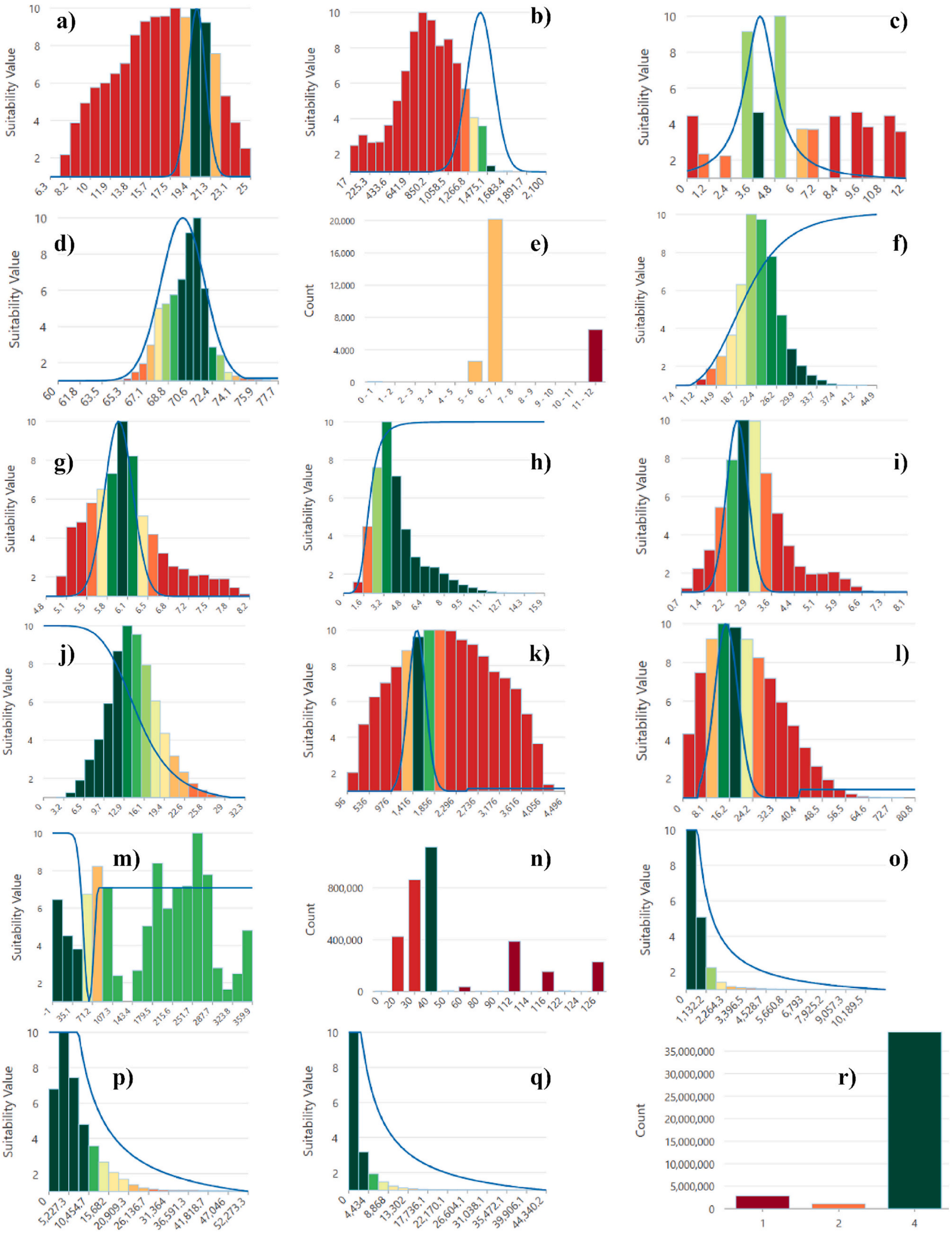


**Fig. 10.** Transformation of subcriteria using continuous suitability functions for coffee cultivation. The letters (a–r) correspond to the subcriteria identified in the "Code" column of Table 1.

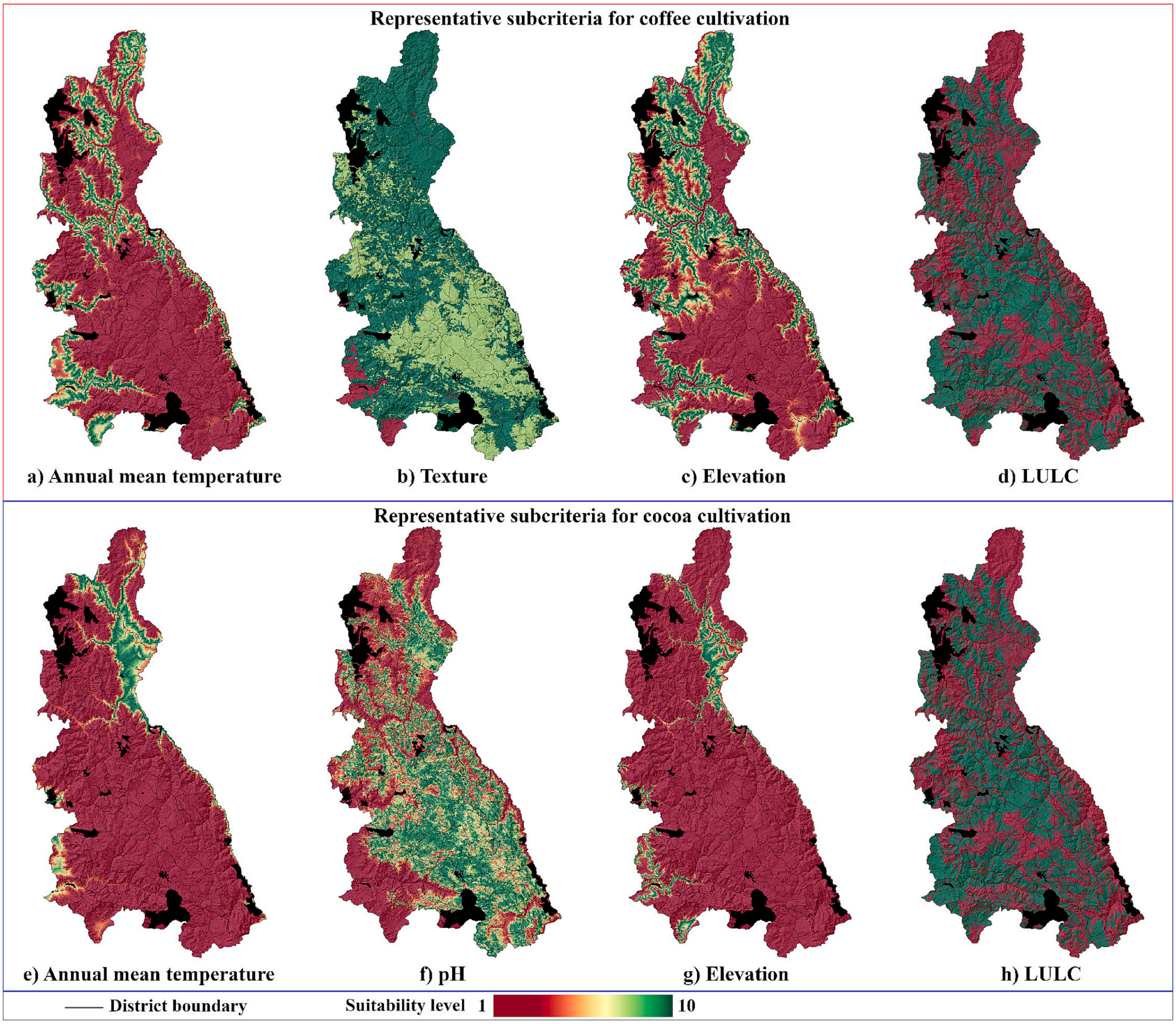


**Fig. 11.** Spatial distribution of the most influential subcriteria after transformation based on suitability functions for coffee and cocoa cultivation.

aggregating the four submodels per approach using the standardized weights derived from Shannon entropy are shown in Fig. 13. While threshold-based models classify land into four discrete levels, function-based models offer a continuous scale that captures subtle spatial variations.

### 3.6. Performance evaluation and model validation

The evaluation was based on suitability values extracted at 3886 points for coffee and 671 for cocoa. In the case of coffee, the threshold-based approach concentrated most values in the highest class (mode = 4), and the results displayed low variability (standard deviation = 0.52). In contrast, the suitability function-based approach produced a broader range of values (3.56 to 8.65), a mean score of 6.47, and greater dispersion (standard deviation = 1.00).

For cocoa, a similar trend was observed. The threshold-based approach assigned most values to class 3 (mode = 3), and the results displayed low variability (standard deviation = 0.30), suggesting a reduced capacity to reflect spatial variations. The function-based approach covered a wider range (3.45 to 8.22), with a mean value of 5.60 and a standard deviation of 1.03, indicating better spatial sensitivity and more detailed suitability representation.

The histograms of the suitability levels are presented in Fig. 14. The threshold-based approach displays categorical clustering, whereas the function-based outputs reveal more continuous and symmetric distributions. These results highlight the greater discriminatory power of the continuous approach for conditions of exclusive presence.

The density distributions of the suitability values from the function-based approach, grouped according to the suitability classes defined by the threshold-based approach, are presented in Fig. 15. In the case of coffee, the distributions clearly differ: class 4 is associated with the highest suitability values, followed by class 3 and then class 2, with minimal overlap. This reflects consistency between approaches and confirms that the function-based values preserve the relative ordering of suitability while capturing internal variation within each class. For cocoa, the distribution follows a similar pattern, although greater overlap between classes 3 and 4 suggests greater variability in predicted suitability. Overall, the function-based approach aligns with the discrete classification while providing a more detailed representation of suitability conditions.

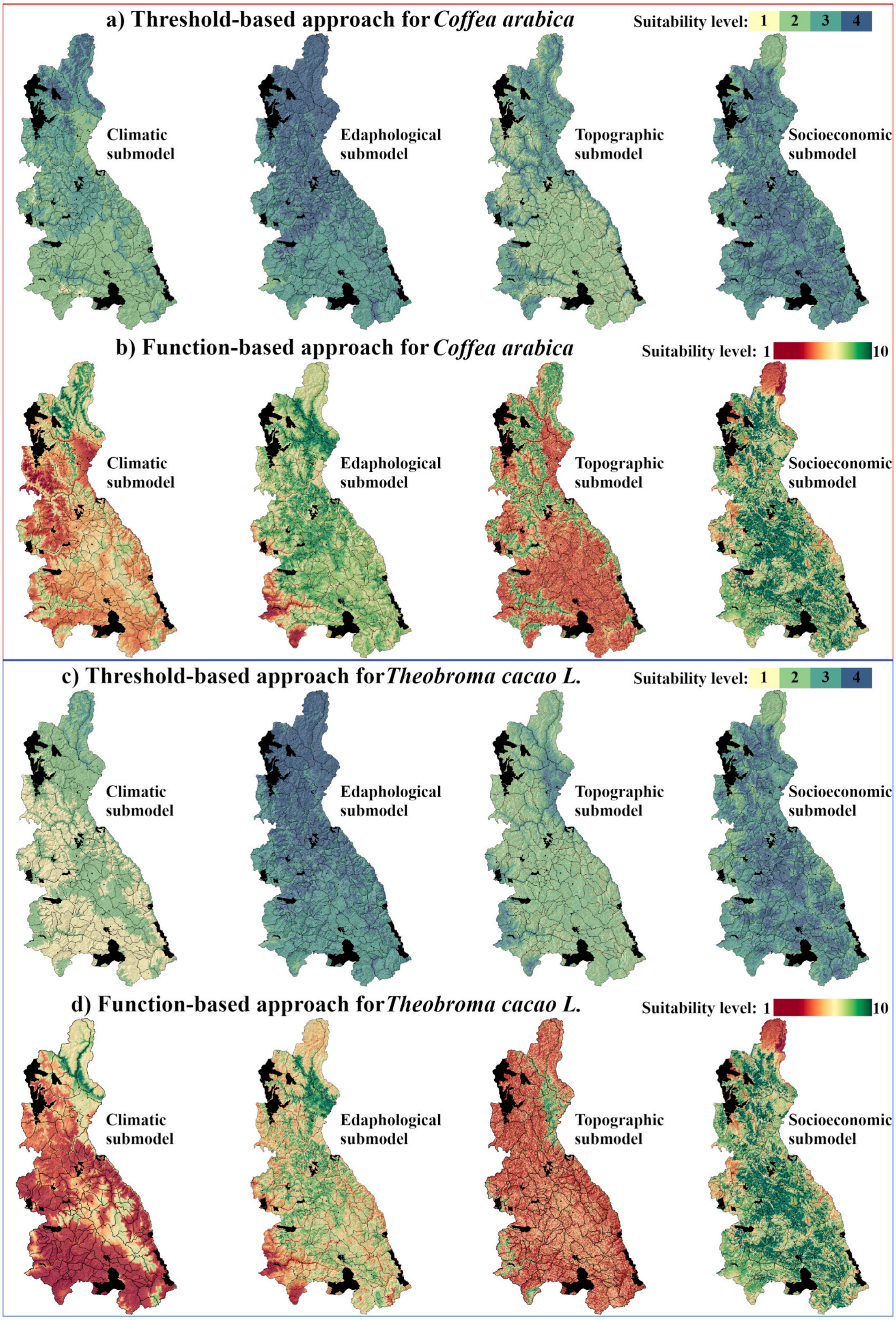


**Fig. 12.** Suitability submodels: climatic, edaphological, topographic, and socioeconomic for coffee (a–b) and cocoa cultivation (c–d).

The statistical validation confirms a strong correspondence between the threshold-based (discrete) and function-based (continuous) suitability modeling approaches. Both approaches demonstrate structural alignment, as evidenced by the progressive increase in function-based suitability values across the discrete classes defined on the basis of threshold-based classification. Moreover, the function-based approach clearly accounts for internal variability and spatial detail, as further supported by the large Kruskal–Wallis effect size ($\varepsilon^2$) for both crops.

For coffee, the continuous suitability values follow a well-ordered progression across classes, supported by distinct KDE distributions

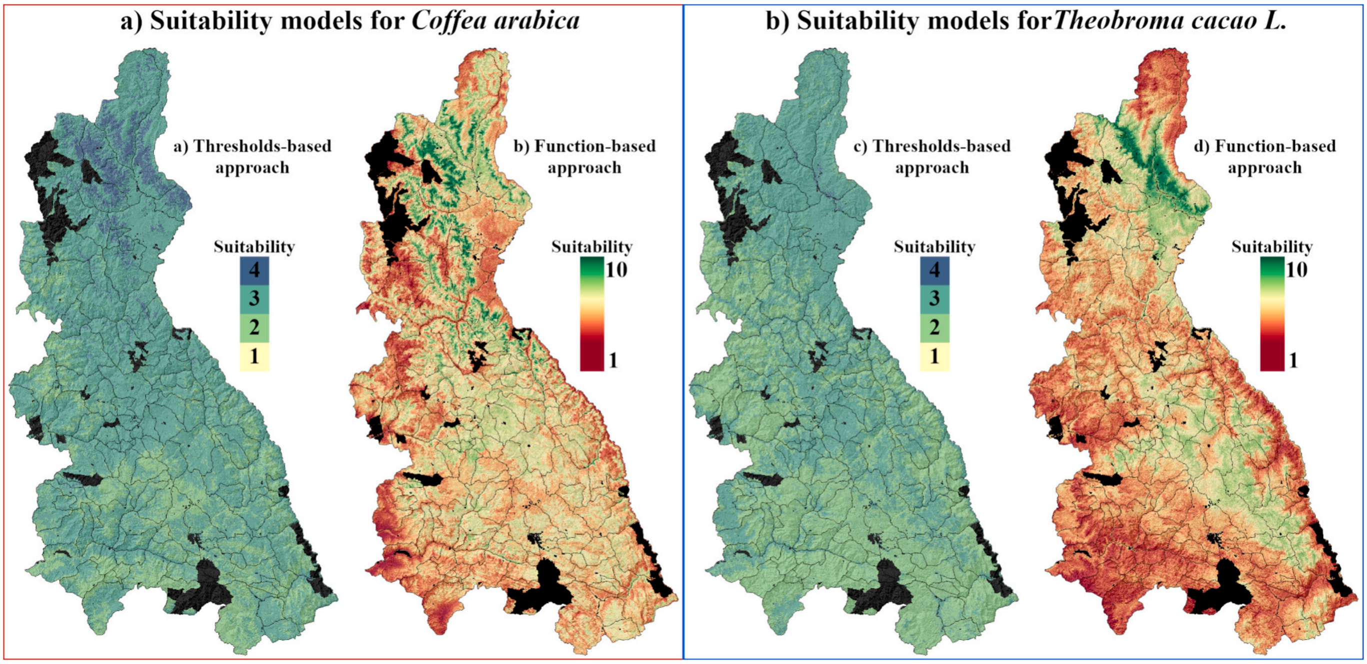


**Fig. 13.** Suitability models based on threshold classification and suitability function transformation approaches for the Cajamarca region, Peru.

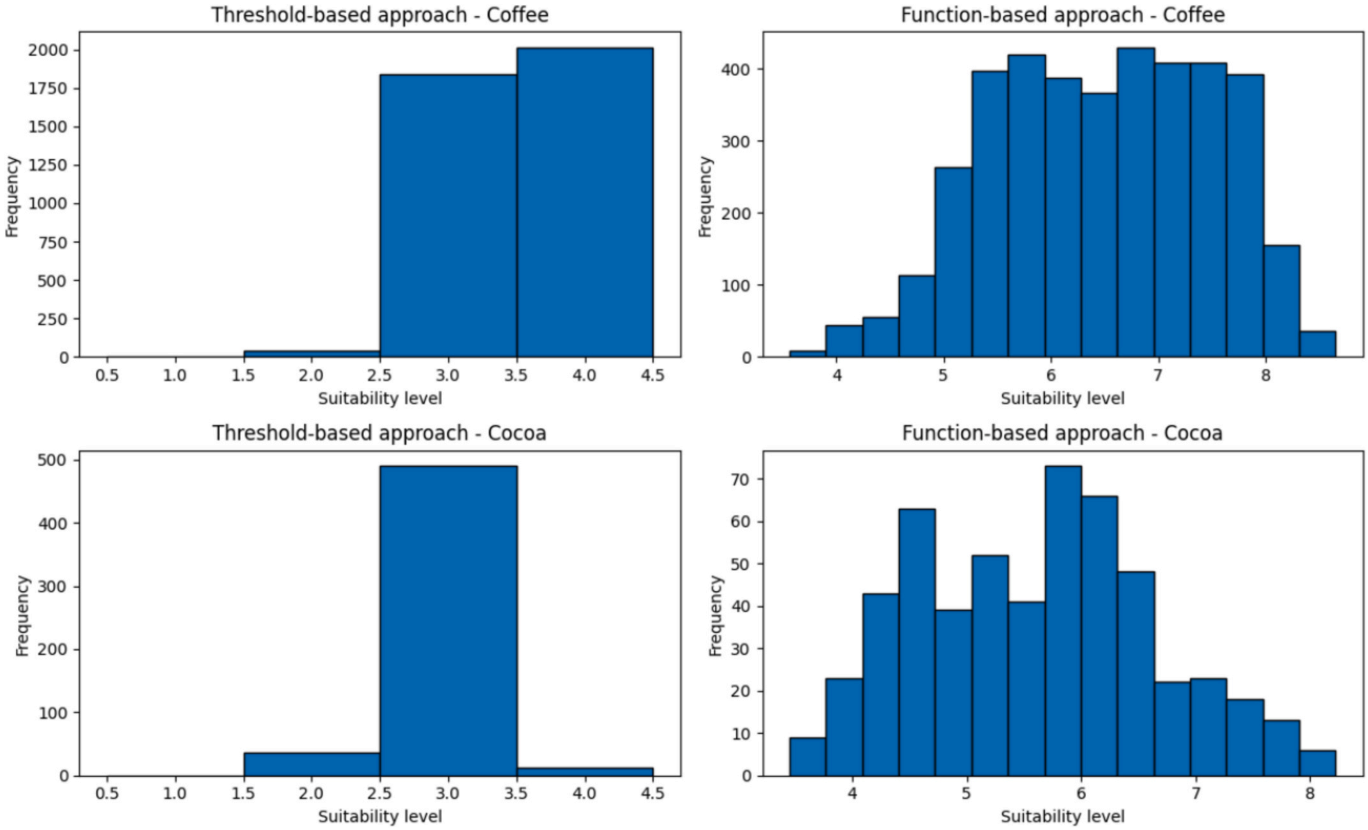


**Fig. 14.** Suitability score distributions obtained with both modeling approaches for coffee and cocoa.

(Fig. 15), significant differences detected in the Kruskal–Wallis test ($H = 1224.77$, $p < 0.001$), and a moderately strong positive correlation (Spearman $\rho = 0.56$, $p \approx 0$). For cocoa, the alignment is less marked but remains statistically significant, with observable differences across classes ($H = 80.74$, $p < 0.001$) and a moderate positive correlation ($\rho = 0.39$, $p \approx 0$).

These findings support the function-based approach as a more informative alternative capable of enhancing the representation of agroecological variations while preserving the interpretability offered by categorical classification schemes.

Table 6 summarizes the main validation metrics and statistical tests used to compare the threshold-based (Approach 1) and function-based

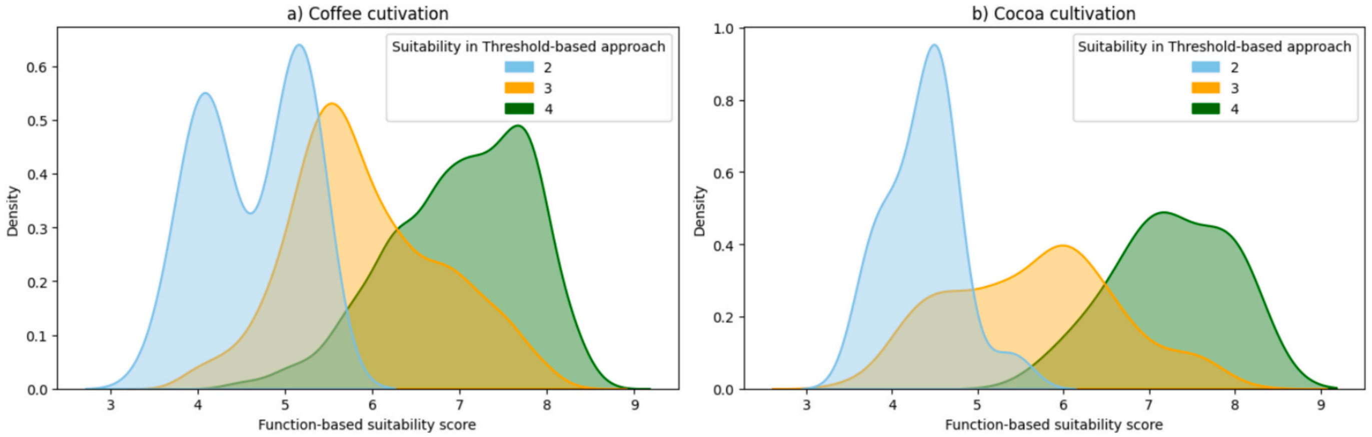


**Fig. 15.** Kernel density estimates of suitability values from the function-based approach, grouped based on threshold-based suitability classes for coffee (a) and cocoa (b) cultivation.

**Table 6**

Summary of the validation metrics and test results for the two suitability modeling approaches.

| Analysis type | Metric/Test | Coffee | Cocoa | Interpretation |
|---|---|---|---|---|
| Descriptive statistics | Mean (Approach 2) | 6.47 | 5.60 | Higher values of function-based scores support better suitability expression |
| | Std. deviation (Approach 2) | 1.00 | 1.03 | Greater variation reflects enhanced internal differentiation in the continuous approach |
| | Mode (Approach 1) | 4 | 3 | Discrete approach concentrates values in single classes, limiting detail |
| | Range (Approach 2) | 3.56–8.65 | 3.45–8.22 | Broader ranges in function-based models support a fine suitability resolution |
| Normality test | Shapiro–Wilk (p value) | All classes $p < 0.05$ (nonnormal) | Class 2: $p = 0.19$; others $<0.05$ | Nonnormality justifies the use of nonparametric tests (e.g., Kruskal–Wallis test) |
| Group comparison | Kruskal–Wallis H (p value) | 1224.77 ($p \approx 1.1 \times 10^{-266}$) | 80.74 ($p \approx 2.9 \times 10^{-18}$) | Statistically significant differences confirm that continuous scores vary meaningfully across discrete classes |
| Correlation | Spearman ρ (p value) | 0.56 ($p \approx 0$) | 0.39 ($p \approx 0$) | Moderate to strong positive correlations indicate internal consistency between approaches |
| Ordinal agreement | Quadratic weighted κ | 0.25 (fair) | 0.16 (fair) | Ordinal consistency between formulations; conservative due to nonmatching cutoffs and class imbalance |
| Effect size | Kruskal–Wallis $\varepsilon^2$ | 0.315 (large) | 0.147 (large) | Large between-class differences for continuous scores |

(Approach 2) modeling approaches.

Therefore, the spatial distribution of crop presence overlaid on the suitability maps generated using the function-based approach is presented. In both crops, a clear concentration of points is observed in areas with high suitability values, reinforcing the ability of this approach to represent favorable agroecological conditions with high precision (See Fig. 16).

### 3.7. Analysis of level suitability by crop

To provide detailed information that supports decision-making, Fig. 17 was established; it presents the main districts (a–k) with the greatest areas of land classified as highly suitable for coffee and cocoa cultivation. This figure specifically highlights the areas within each district where the highest suitability values are concentrated, allowing for the precise identification of priority zones for agricultural development.

The districts are labeled with letters corresponding to the coding used in Table 7, which summarizes the total district area, the highly suitable area, and its proportion relative to the district territory.

Finally, Table 7 lists the key districts from Fig. 17 with the largest areas classified as highly suitable for coffee and cocoa cultivation. For a detailed view of all the districts, refer to Table S3 in the Supplementary Material.

### 3.8. Visualization of the geospatial data with the GEE

The application (app), named Suitability Watch Cajamarca (SWC), was developed in the GEE and provides detailed access to the products used in this research. The app is structured with two-layer selectors and a value inspection tool. The main interface of the application and its components are shown in Fig. 18.

The application interface is shown in Fig. 19, with the suitability model for coffee cultivation selected. The app can be accessed at https://ee-dagofer1017.projects.earthengine.app/view/suitability-watch-cajamarca.

## 4. Discussion

In this research, the suitability of the Cajamarca region for coffee and cocoa cultivation was assessed using 18 subcriteria, a number similar to that used in other studies (Esponda-Bernal et al., 2024; Mighty, 2015; Singh et al., 2021; Zhang et al., 2021a). However, in this study, the subcriteria were grouped into 4 main criteria—4 climatic, 6 edaphological, 3 topographic, and 5 socioeconomic—to avoid overwhelming or confusing the specialists during pairwise comparisons. This approach led to better consistency in the comparisons of the 3 topographic subcriteria than in the comparisons of the 6 edaphological and 5 socioeconomic subcriteria. Therefore, grouping subcriteria in future studies is recommended to enhance prioritization.

A proper suitability analysis involves integrating multicriteria evaluation (MCE) techniques with data obtained in situ and through remote sensing (Rojas-Briceño et al., 2022; Salas-López et al., 2020). Nationally and internationally, various researchers have employed the AHP (Dedeoğlu and Dengiz, 2019; Gómez-Fernández et al., 2025; Iliquín Trigoso et al., 2020; Jayasinghe et al., 2019; Mighty, 2015; Salas-López

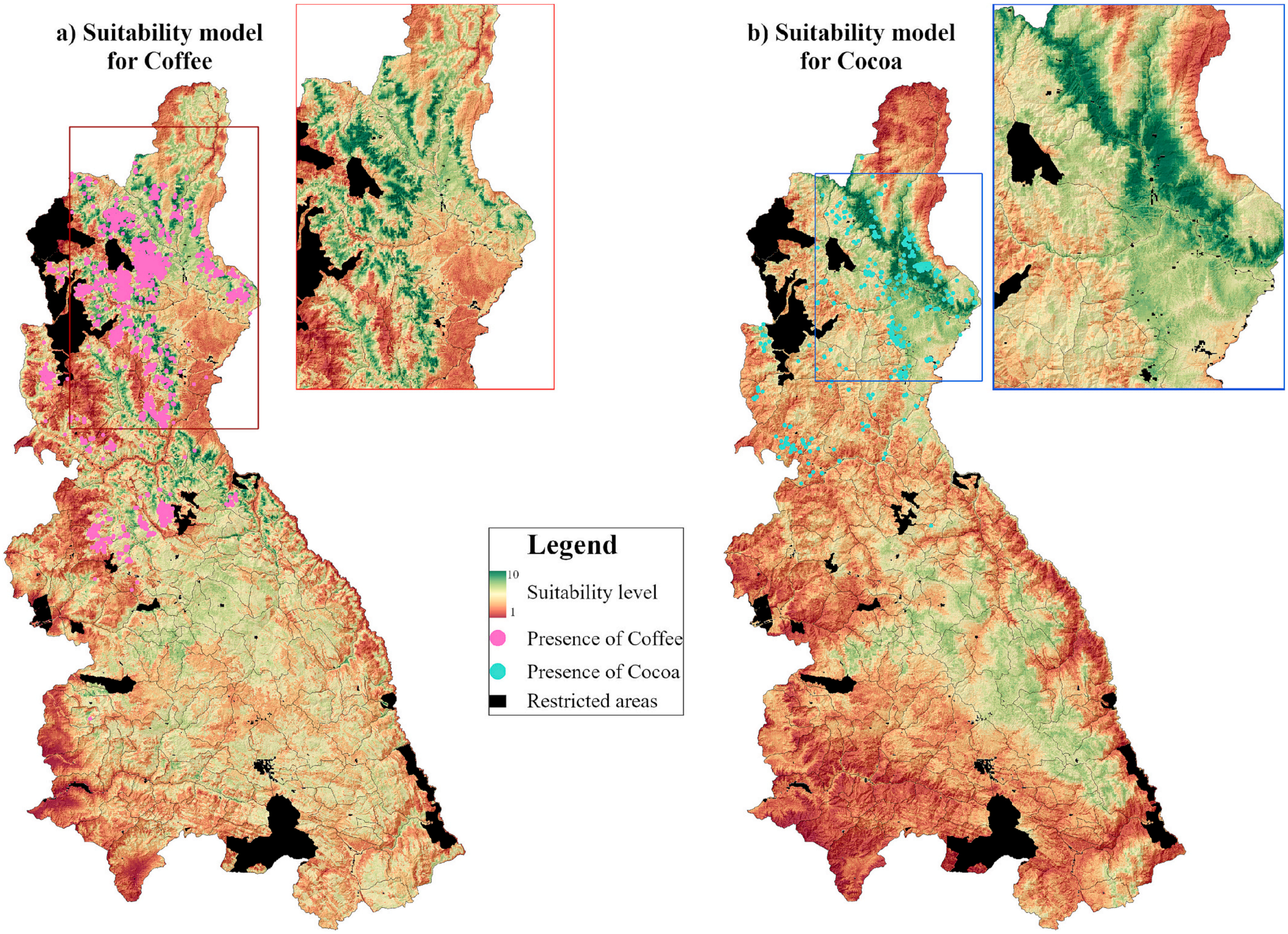


**Fig. 16.** Spatial validation of continuous suitability models based on the presence of coffee (a) and cocoa (b).

et al., 2020; Singh et al., 2021), fuzzy (Feng et al., 2017; Holzkämper et al., 2013; Reshmidevi et al., 2009), and MaxEnt (Rojas-Briceño et al., 2022; Zhang et al., 2021a) among others (Akpoti et al., 2019; Huang et al., 2025; Kamga et al., 2025; Ljubičić et al., 2023), either individually or in combination. In this study, in addition to the AHP and geospatial data, the Shannon entropy technique was applied to objectively calculate and consolidate the importance weights derived from the AHP.

It is well known that the weights provided by various specialists inevitably vary (see Fig. 6). To address this issue, instead of consolidating the weights from each specialist through averaging or calculating the geometric mean, we employed the Shannon entropy technique (see Fig. 7). This method ensures that the final importance weight reflects the variability in the ratings, resulting in more accurate outcomes than those obtained with other methods. A similar approach was applied by Esmaili and Karipour (2024), as the weights generated on the basis of Shannon entropy produced more precise flood risk indices in their work.

In the development of threshold-based suitability models for coffee and cocoa cultivation, adjusted importance weights and mapped geospatial data were used in the *Weighted Overlay* tool in ArcGIS Pro v.3.4. This zoning approach was used in previous research (Gómez-Fernández et al., 2025; Iliquín Trigoso et al., 2020; Rojas-Briceño et al., 2022; Salas-López et al., 2020), although it has limitations associated with representing areas of intermediate suitability. The continuous transformation approach using suitability functions aligns with of the preferred methods of other authors (Dedeoğlu and Dengiz, 2019; Jayasinghe et al., 2019; Mighty, 2015; Singh et al., 2021) who prefer to generate a single suitability model by overlaying all the subcriteria simultaneously. However, to control potential errors arising from numerous comparisons, standardized weights were applied on the basis of the relative weight of each main criterion (Saaty, 1990).

The suitability models for coffee and cocoa cultivation were influenced by climatic, edaphological, topographic, and socioeconomic criteria, with climatic and edaphological criteria dominating, depending on the crop (Table 5). For both crops, climatic criteria had the greatest influence (33.9 % for coffee and 41.2 % for cocoa), followed by socioeconomic criteria for coffee (25.2 %) and edaphological criteria for cocoa (25.3 %). Similarly, Rojas-Briceño et al. (2022), reported, a climatic influence of 35.7 % and an edaphological influence of 29.1 % for cocoa cultivation. In contrast, Salas-López et al. (2020), reported a climatic influence of 28.31 % and an edaphological influence of 25.03 % for coffee. These results highlight the importance of climatic and edaphological conditions when determining the territorial suitability of both crops.

With respect to the most influential subcriteria for the coffee suitability models, the annual mean temperature, soil texture, elevation, and LULC had weights of 34.9 %, 26.8 %, 60.6 %, and 35.6 %, respectively, in the context of the corresponding criteria. For cocoa cultivation, the most influential subcriteria were annual mean temperature, soil pH, elevation, and LULC, with weights of 36.4 %, 27.4 %, 51.5 %, and 29.7 %, respectively, given the corresponding criteria. These findings are consistent with those of other researchers (Gómez-Fernández et al., 2025; Mighty, 2015; Rojas-Briceño et al., 2022; Salas-López et al., 2020; Singh et al., 2021) who also identified temperature, elevation, and LULC as the most influential subcriteria in suitability models. This findings is

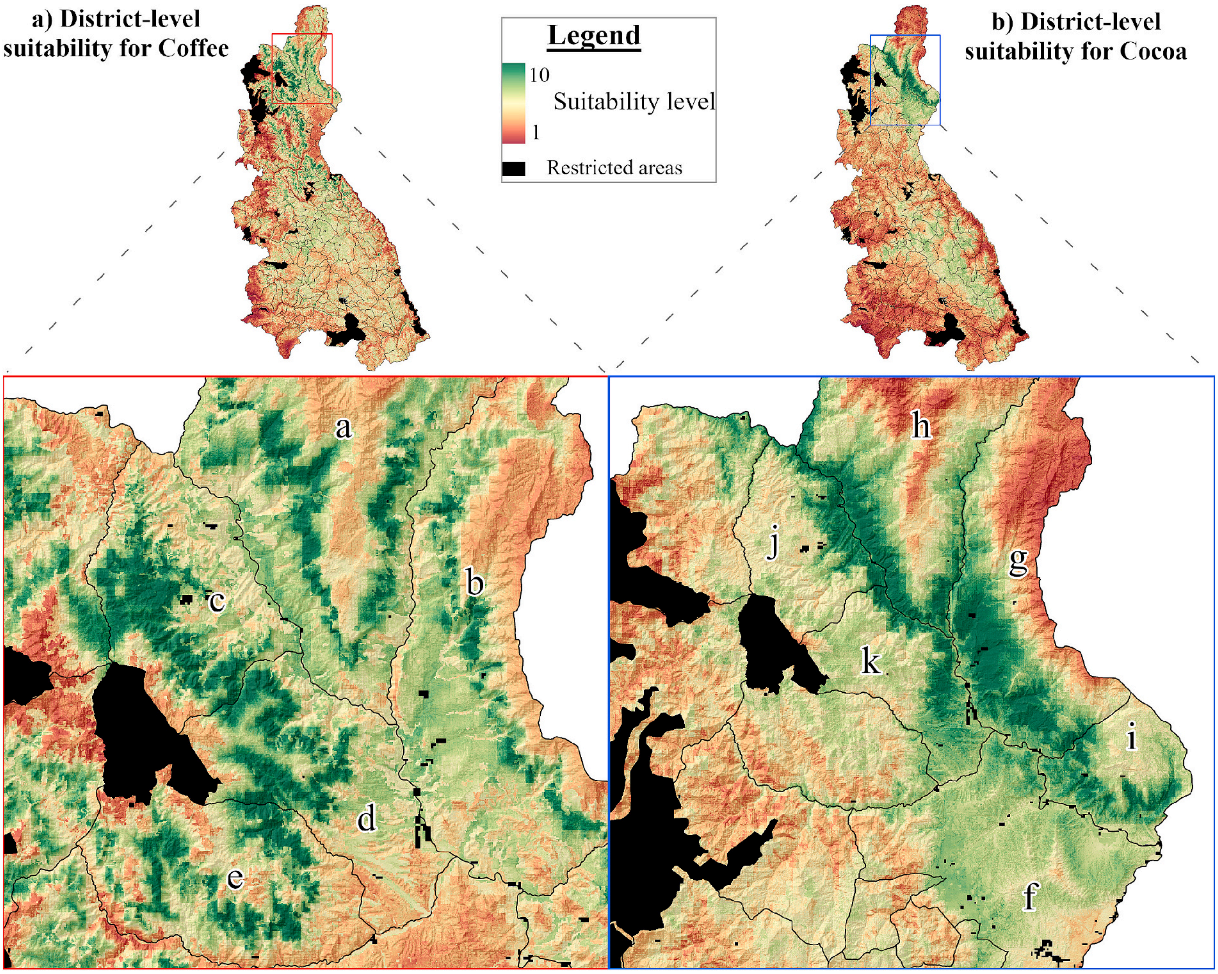


**Fig. 17.** District-level suitability for coffee and cocoa cultivation in Cajamarca, Peru.

**Table 7**
District-level areas classified as highly suitable for coffee and cocoa cultivation.

| Crop | ID* | District | Legal area (ha) | Suitable area (ha) | Territory suitable (%) |
|---|---|---|---|---|---|
| Coffee | a | San José de Lourdes | 136,047.86 | 30,971.79 | 22.7 |
| | b | Huarango | 90,393.59 | 19,850.47 | 21.9 |
| | c | San Ignacio | 35,625.81 | 16,936.09 | 47.5 |
| | d | Chirinos | 35,707.53 | 14,615.99 | 40.9 |
| | e | La Coipa | 40,360.42 | 13,979.91 | 34.6 |
| Cocoa | f | Bellavista | 86,664.59 | 36,423.75 | 42.1 |
| | g | Huarango | 90,393.59 | 31,452.21 | 34.7 |
| | h | San José de Lourdes | 136,047.86 | 28,160.81 | 20.1 |
| | i | Santa Rosa | 26,823.72 | 16,043.82 | 59.8 |
| | j | San Ignacio | 35,625.81 | 13,271.04 | 37.2 |
| | k | Chirinos | 35,707.53 | 12,877.13 | 36.1 |

Note: *The ID corresponds to indicators a–k in Fig. 17.

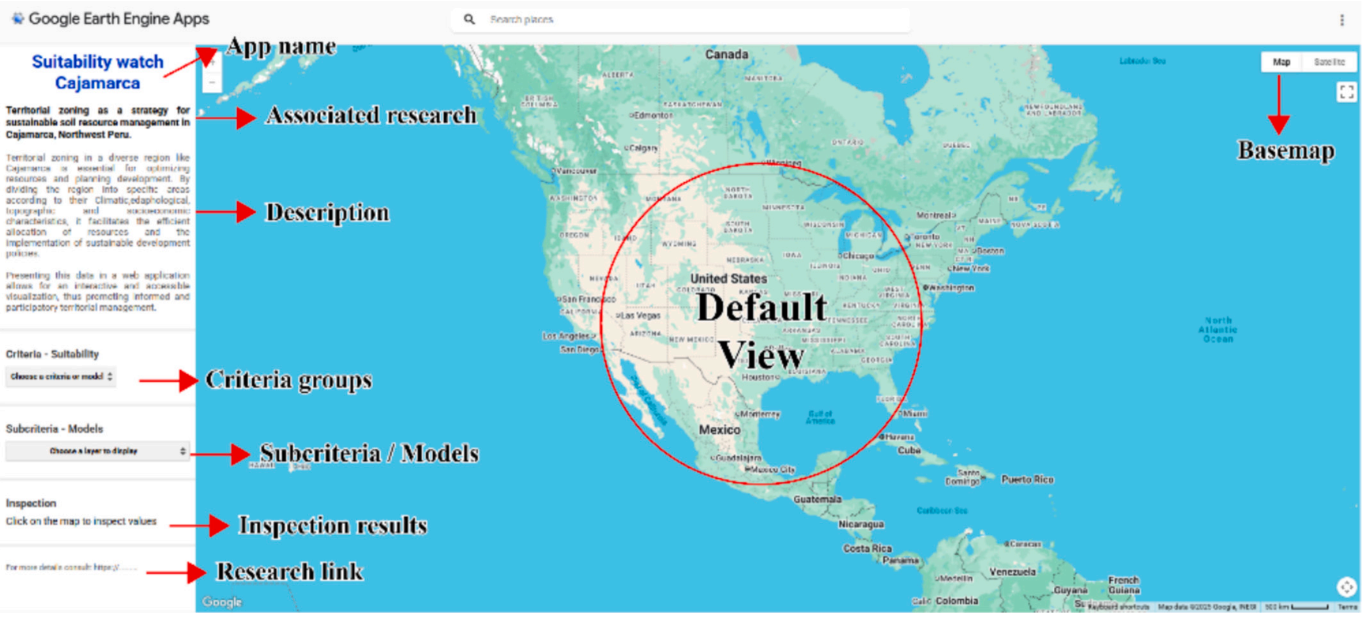
largely explained by the strong influence of elevation on temperature, which in turn affects precipitation patterns in a given territory (Dimri et al., 2022; Imfeld et al., 2020). Furthermore, LULC is a highly influential subcriterion in suitability models, as inadequate land cover or use can render even optimal climatic or edaphological conditions insufficient for the sustainable cultivation of coffee, cocoa, or any other crop of interest.

Additionally, to avoid overload and confusion during pairwise comparisons, it is recommended to group subcriteria or determine the relationships between them (Saaty, 1990). One alternative is DEMATEL technique, which identifies the relationships or influences between system components (Fontela and Gabus, 1976). In this study, subcriteria were grouped, and the importance weights were adjusted using Shannon entropy.

The grouping of subcriteria and the use of relationship-influence measurement techniques allow for the integration of more evaluation subcriteria, such as economic aspects, producers' education levels, water quality, and proximity to mining or protected areas, among others, than do traditional methods. In this study, a conservative approach was taken by restricting all protected natural areas recognized by Peruvian government agencies within the study area, making these areas transparent in the visualization of the suitability modeling results in the SWC app.

Beyond excluding protected areas from cultivation zones, the results provide actionable inputs for regional governments to guide crop expansion, avoid soil degradation, and improve land use planning (Singh et al., 2022). Policies could include formal zoning of priority crops, restriction of planting permits in low-suitability areas, and spatially targeted incentives or technical assistance for sustainable coffee and cocoa production.

In several contexts, targeted interventions have been implemented to control forestland loss and manage land sustainably; understanding how such government-led strategies influence land use can help align habitat suitability assessments with real-world decision-making (Agarwal and Lambin, 2024). From an ecological management perspective, suitability maps can support reforestation in marginal land areas, protect erosion-prone zones, and aid in the design of agroforestry corridors (Serrano-Ramírez et al., 2021).



**Suitability watch Cajamarca**

**Territorial zoning as a strategy for sustainable soil resource management in Cajamarca, Northwest Peru.**

Territorial zoning in a diverse region like Cajamarca is essential for optimizing resources and planning development. By dividing the region into specific areas according to their Climatic,edaphological, topographic and socioeconomic characteristics, it facilitates the efficient allocation of resources and the implementation of sustainable development policies.

Presenting this data in a web application allows for an interactive and accessible visualization, thus promoting informed and participatory territorial management.

Criteria - Suitability: Choose a criteria or model

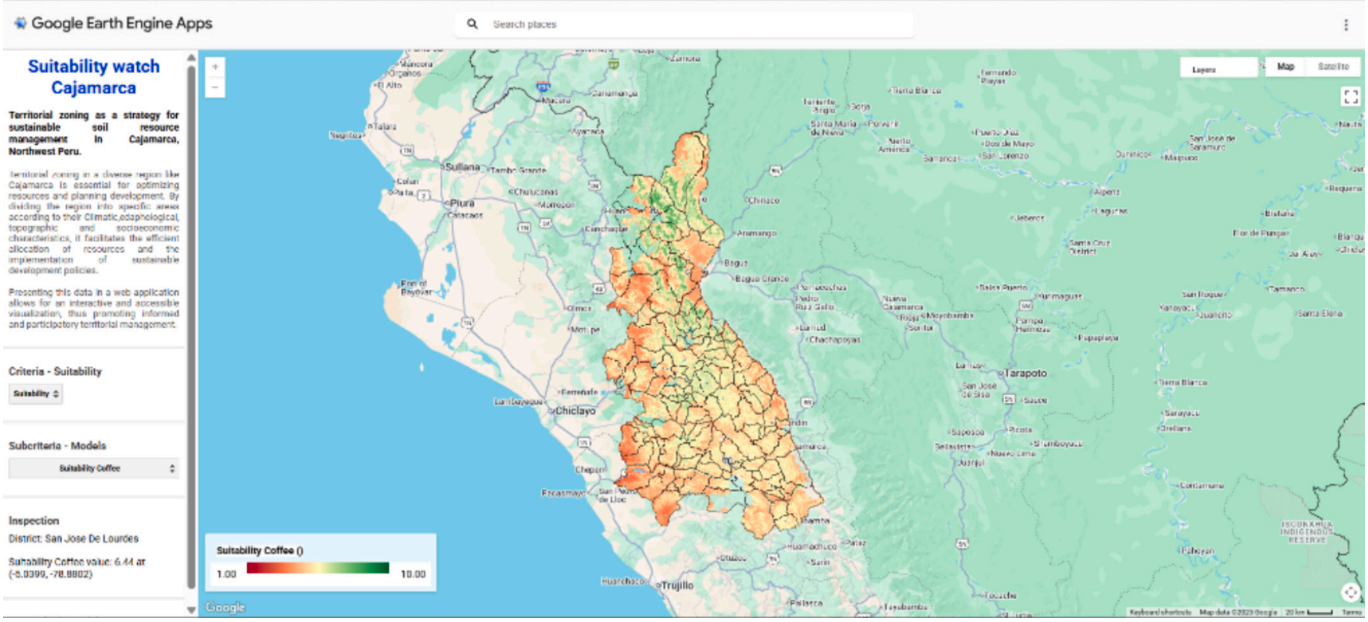
Subcriteria - Models: Choose a layer to display

Inspection

Click on the map to inspect values

For more details consult: https://……

**Fig. 18.** Interface of the Suitability Watch Cajamarca application.



**Suitability watch Cajamarca**

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Criteria - Suitability: Suitability

Subcriteria - Models: Suitability Coffee

Inspection

District: San Jose De Lourdes

Suitability Coffee value: 6.44 at (-5.0399, -78.8802)

**Fig. 19.** View of the app in use, with a suitability model for coffee cultivation in Cajamarca, Peru, selected. In the suitability models, restricted areas (urban areas, water bodies, and protected natural areas) have been masked to simplify visualization; these areas appear transparent on the map.

Accordingly, the Suitability Watch Cajamarca (SWC) application serves as a spatial tool for enhancing coffee and cacao production systems. Developed on the GEE platform, SWC integrates land suitability models based on the AHP and continuous suitability functions, following validated methodological frameworks (Esponda-Bernal et al., 2024; Zhang et al., 2021a). The models were calibrated and validated using more than 4500 presence points, with high technical robustness. SWC enables the identification of areas with high suitability to guide renovation and expansion efforts, optimize input allocation, and improve the targeting of extension services. Furthermore, the platform facilitates visual exploration of spatial conditions that are relevant for agronomic decision-making.

Beyond displaying model outputs, the application organizes both the spatial datasets and the underlying suitability models within an interactive and user-friendly environment. Unlike broader platforms such as GAEZ (Food and Agriculture Organization, 2014) or global forest monitoring datasets (Hansen et al., 2013; Pekel et al., 2016), SWC provides region-specific and crop-oriented information tailored to local planning needs. Its design aims to close the gap between technical modeling and operational decision-making, supporting evidence-based territorial strategies that help prevent soil degradation and promote more resilient and sustainable agricultural systems.

## 5. Conclusions

The suitability of the Cajamarca region for coffee and cocoa cultivation was evaluated using 18 subcriteria grouped into climatic, edaphological, topographic, and socioeconomic criteria. This structure improved consistency in pairwise comparisons and reduced potential bias during weighting. The application of multicriteria evaluation techniques, including the AHP and Shannon entropy method, allowed for objective assignment of importance weights.

The most influential subcriteria for coffee cultivation were annual mean temperature (34.9 %), soil texture (26.8 %), elevation (60.6 %), and LULC (35.6 %). For cocoa, the key subcriteria were annual mean temperature (36.4 %), soil pH (27.4 %), elevation (51.5 %), and LULC (29.7 %). Among the two modeling approaches, the continuous suitability function method displayed a greater ability to discriminate among spatial conditions. It produced broader value ranges, greater variability, and significant differences across suitability classes. Its consistency with the threshold-based classification result confirms structural alignment, while its ability to reflect internal variability makes it more suitable for spatial planning with presence-only data.

The results were integrated into the SWC application, developed in the GEE. This tool provides regional information to support agricultural decision-making and policy design focused on preventing soil overexploitation. Its application could be expanded to the national scale, and additional crops could be assessed on the basis of the relevant spatial data.

## CRediT authorship contribution statement

**Darwin Gómez-Fernández:** Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Nilton Atalaya-Marin:** Writing – review & editing, Software, Methodology, Investigation. **Marielita Arce-Inga:** Validation, Formal analysis, Data curation. **Daniel Tineo:** Writing – review & editing, Validation, Formal analysis, Data curation. **Jorge A. Fernandez-Jibaja:** Writing – review & editing, Validation, Formal analysis, Data curation. **Victor H. Taboada-Mitma:** Visualization, Validation, Supervision, Project administration, Funding acquisition. **Héctor Cabrera-Hoyos:** Visualization, Validation, Supervision, Data curation. **Juancarlos Cruz-Luis:** Validation, Supervision, Resources, Project administration. **Malluri Goñas:** Writing – review & editing, Supervision, Resources, Project administration, Data curation.

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

During the preparation of this work, the author used Chat GPT 4o to improve readability and language of the manuscript. 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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## Declaration of competing interest

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

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecoinf.2025.103440.

## Data availability

All supplementary material and the main results (web application) of this research can be found in the following repository:

https://next.data.4tu.nl/private_datasets/21ABatsHYuim2HyHuDRmPiY2G_JelFY2PExoDXsNAO4

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