Geospatial Assessment of Current and Future Land Suitability for Peruvian Amylaceous Maize (*Zea mays* L.) Using Random Forest Modeling

Sivmny V. Valqui-Reina[1,2], Cleyver Rivera[1], Carlos I. Arbizu[1,2,3*], Alex J. Vergara[4*]

[1]Facultad de Ingeniería y Ciencias Agrarias, Universidad Nacional Toribio Rodríguez de Mendoza de Amazonas, Chachapoyas 01001, Peru

[2]Programa de Genética y Mejoramiento Genético de Plantas, Universidad Nacional Toribio Rodríguez de Mendoza de Amazonas, Chachapoyas 01001, Peru

[3]Centro de Investigación en Germoplasma Vegetal y Mejoramiento Genético de Plantas (CIGEMP), Universidad Nacional Toribio Rodríguez de Mendoza de Amazonas (UNTRM), Amazonas 01001, Peru.

[4] Instituto de Investigación en Forestería y Ecosistemas Tropicales (INIFET), Escuela Profesional de Ingeniería Forestal, Universidad Nacional Toribio Rodríguez de Mendoza de Amazonas, Chachapoyas, Chachapoyas 01001, Perú.

Correspondence: carlos.arbizu@untrm.edu.pe / alex.vergara@untrm.edu.pe

Abstract

Climate change poses an increasing threat to crop suitability and food security, particularly for varieties of great cultural and economic importance, such as Peruvian starchy maize (Zea mays L.), whose optimal growing areas remain poorly characterized at the national level. This study presents the first comprehensive geospatial assessment of current and future land suitability for starchy corn in Peru, integrating bioclimatic, edaphic, and topographic variables using a machine learning approach. A dataset of georeferenced accessions, combined with pseudo-absence data, was used to train and validate a model using the Random Forest algorithm based on 29 bioclimatic, edaphic, and topographic predictors. The model demonstrated high statistical reliability (AUC-training = 0.98; AUC-validation = 0.99; precision = 0.971; recall = 0.962; F1 score = 0.966; accuracy = 0.966), with temperature-related variables (BIO09, BIO05, BIO15, and annual mean temperature) identified as the most important predictors. Projections made using the MIROC6 general circulation model under four shared socio-economic scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8. 5) for the periods 2061–2080 and 2081–2100 indicate a net expansion of highly suitable areas ranging from 20.76% to 45.46%, depending on the scenario. The most optimistic scenario (SSP1-2.6) projects the greatest gain (approximately 45% by 2070), while the most pessimistic (SSP3-7.0) shows an initial contraction followed by a marked recovery by 2100. These findings provide a robust geospatial framework for climate-smart agricultural planning, breeding

programs, and sustainable land-use policies for Peruvian starchy maize in the context of future climate change.

Keyword: Climate change, Machine learning, crops, Amilaceus maíz peruvian, food safety

I. Introduction

Agriculture is essential to the global fight against hunger and malnutrition (FAO et al., 2020), and addition to playing a crucial role in the regional economy and social stability (Hsiang et al., 2013; Wang et al., 2015). However, much of agricultural activity takes place under highly variable environmental conditions, making it one of the sectors most vulnerable to environmental stressors (Anandhi et al., 2016; Tessema & Simane, 2019) such as droughts, extreme heat waves, and changes in climate patterns, directly affecting agricultural productivity and compromising food security (Cruz et al., 2021; Gashure, 2025; Pushpakaran & Nayagam, 2025; Tessema & Simane, 2019).

Climate change and population growth have placed increasing pressure on global food security (Su et al., 2023). Several studies have noted that the changing climate has affected the productivity of key crops in many agricultural regions (Asseng et al., 2014; Challinor et al., 2014; Eck et al., 2020). However, knowledge gaps remain regarding how various climatic factors—such as temperature, water availability, and soil nutrients—interact and how their combination impacts crop productivity (Fraga et al., 2016; Webber et al., 2015). In this context, adaptive agronomic strategies (Araya et al., 2020; Luo et al., 2016) and agricultural disaster management (Hu et al., 2021; Jia et al., 2016; Sun et al., 2015) require a thorough understanding of crop distribution to plan effective interventions (Su et al., 2023).

Maize (*Zea mays L.)* is one of the world's most important crops, both for human and animal consumption, and due to its massive global production (Erenstein et al., 2022; Ramirez-Cabral et al., 2017). Globally, the area planted with maize reached approximately 208.2 million hectares in 2023, establishing it as a key crop for food security, especially in Latin America and sub-Saharan Africa (FAO, 2024; Ramirez-Cabral et al., 2017). In Peru, starchy maize is essential for the diet and livelihood of rural communities, particularly in high Andean areas, where traditional varieties are cultivated (Salvador-Reyes & Clerici, 2020; Zambrano et al., 2021). In 2024, national corn production exceeded 853,700 tons, of which 80% was dry grain, 19% to sweet corn, and 1% to purple corn, underscoring its agronomic and socioeconomic importance, with production concentrated mainly in the coastal and highland regions (Ministry of Agricultural Development and Irrigation [Midagri], 2025).

The Peruvian Amylaceous Maize exhibits remarkable ecological adaptability, as it can be grown at a wide range of altitudes, from 1,700 to over 3,800 meters above sea level, and in regions with annual precipitation ranging from 200 to 2,000 mm (Chen et al., 2025; Zambrano et al., 2021; Ramirez-Cabral et al., 2017). However, its productivity is limited by abiotic factors, such as climate and soil properties, as well as by biotic factors such as pests and diseases. In addition, socioeconomic conditions associated with agricultural management can further restrict production (Meng et al., 2024; Ocwa et al., 2023; Su et al., 2023). Nevertheless, environmental factors primarily determine areas suitable for cultivation, while socioeconomic factors significantly influence the spatial configuration of agricultural systems (Nkurunziza et al., 2020; Vilakazi et al., 2025; Su et al., 2023).

To assess potential changes in the distribution of Peruvian amyloceous maize in response to climate change, it is necessary to apply appropriate modeling techniques. Species distribution models (SDMs) have been widely adopted in ecology (Zhang et al., 2021) to assess the distribution of microorganisms, wild plants, and animals, as well as to identify suitable areas for crop cultivation (de Barros et al., 2024; Wang et al., 2024). Some widely used distribution models include EcoCrop, a mechanistic model that integrates the FAO-EcoCrop database and uses climate variables and growing season length (Egbebiyi et al., 2019); CLIMEX, a hybrid statistical-mechanistic model that combines biological parameters and climate data to estimate geographic distribution (Early et al., 2022); and machine learning approaches, such as MaxEnt, based on presence records (Fitzgibbon et al., 2022), and Random Forest, which allow for capturing complex relationships between environmental variables and crop presence (Mushagalusa et al., 2024; Serra et al., 2025).

Machine learning methods enable the analysis of the relationship between land suitability and environmental variables such as climate, soil, and topography, facilitating the identification of potentially suitable areas under complex environmental scenarios by handling large volumes of data and capturing the nonlinear relationships that influence crop growth (Fontanelli et al., 2025). Among these models, Random Forest (RF) stands out for its ability to handle large volumes of data and nonlinear relationships between environmental variables and the presence of the species or crop (Gábor et al., 2024; L. Zhang et al., 2019), using multiple decision trees built from random subsets of the data and combining their results to generate robust predictions and reduce overfitting (Mushagalusa et al., 2024; Wu et al., 2025). Due to these characteristics, Random Forest is a particularly suitable tool for modeling the potential distribution of crops under current and future conditions, considering climate change scenarios and socioeconomic variables, and integrating multiple environmental factors (Porfirio et al., 2016).

In the world the spatial distribution of maize has been studied using modeling approaches that integrate environmental variables and, in some cases, socioeconomic factors, in order to understand its suitability under current and future climate change conditions. For example, Su et al. (2023) combined species distribution models with climatic and socioeconomic factors to simulate the potential distribution of areas suitable for maize cultivation worldwide, demonstrating that incorporating these factors improves projections of future crop distribution. Complementarily, Fitzgibbon et al. (2022) evaluated the use of the MaxEnt model to analyze the relationship between climate and land suitability for maize production in the United States, finding that this approach can identify areas with a high probability of crop suitability and correlate modeled suitability with observed yield statistics. Large-scale research indicates that patterns of land suitability for maize may change significantly under climate change scenarios, with decreases in highly suitable areas at low latitudes and spatial shifts toward higher latitudes in the future, which is crucial for planning adaptation strategies in global agriculture (Gao et al., 2021).

In Peru, studies on the spatial distribution of crops remain very limited. However, some research has applied distribution models to assess the response of different crops to climate change and anthropogenic pressures, identifying areas potentially suitable for their cultivation under various environmental conditions. For example, Rojas-Briceño et al. (2022) analyzed soil suitability for cacao (*Theobroma cacao*) using combined multi-criteria AHP and MaxEnt approaches, finding that between 1.5% (AHP) and 23% (AHP–MaxEnt) of Peruvian territory is highly suitable, concentrated mainly in San Martín, Amazonas, and Loreto, followed by Ucayali, Madre de Dios, Cusco, Junín, and Puno. Similarly, Ccoyllar -Quintanilla et al. (2021) assessed the vulnerability of quinoa (*Chenopodium quinoa*) to environmental stress events in the high Andean regions of Peru by constructing current distribution models and projections for 2050 and 2070 under RCP 2.6, 4.5, and 8.5 climate scenarios. The results showed that quinoa exhibits high tolerance to abiotic stresses, such as drought and high temperatures, and that the optimal zones for its growth are concentrated in Puno, Apurímac, Ayacucho, and Cusco. Yarlequé et al. (2024) used the EcoCrop-FAO model with GIS to assess the suitability of *Coffea arabica* and *Musa paradisiaca* under future climate scenarios. Their results showed that the optimal suitability of coffee in regions such as Amazonas, San Martín, and Junín would remain above 83% until 2040, while in Piura, climatic suitability would fall below 17%. For bananas, areas such as Loreto could see increases of up to 60% in suitability, while others, such as Ucayali and Cusco, could experience reductions of up to 72%.

Although Peruvian Amylaceous maize is a staple food for the Peruvian population and a pillar of the national agricultural economy (MIDAGRI, 2025), no comprehensive study has yet been conducted on its spatial distribution under climate change scenarios, taking socio-environmental variables into account. The limited information available on optimal growing areas restricts the ability to plan adaptive agricultural management strategies and ensure food security in the face of environmental and anthropogenic pressures. Therefore, this study aims to map the current and future spatial distribution of maize in Peru, under shared climate scenarios and socioeconomic pathways (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5) for the years 2050 and 2070, thereby identifying areas potentially suitable for its cultivation and contributing to the planning of more efficient, sustainable, and resilient agricultural management in the face of environmental changes.

II. Materials and methods

2.1. Study area

This study was conducted for the territory of the Republic of Peru, which is located in the western region of South America, between approximately 0°02′ and 18°21′34″ south latitude, and 68°39′07″ and 81°20′13″ west longitude. Peru covers an area of 1,285,215.9 km^2 and exhibits high agro-environmental diversity, which is associated with an altitudinal gradient ranging from low-lying coastal areas below sea level to Andean regions exceeding 6,700 m above sea level (Figure 1). Peru is divided into three natural regions: (a) the coastal region, characterized by arid and semi-arid conditions where production depends mainly on irrigation; (b) the highland region, characterized by mountains and inter-Andean valleys where altitude determines temperature; and finally (c) the Amazon region, characterized by a humid tropical climate and high water availability. On the other hand, the country's climate is highly variable and is one of the main factors determining the spatial distribution of agricultural activities; rainfall is concentrated mainly in the Amazon region and on the eastern slope of the Andes, while in the Andean region it exhibits marked spatial and seasonal variability (MINAM, 2020).

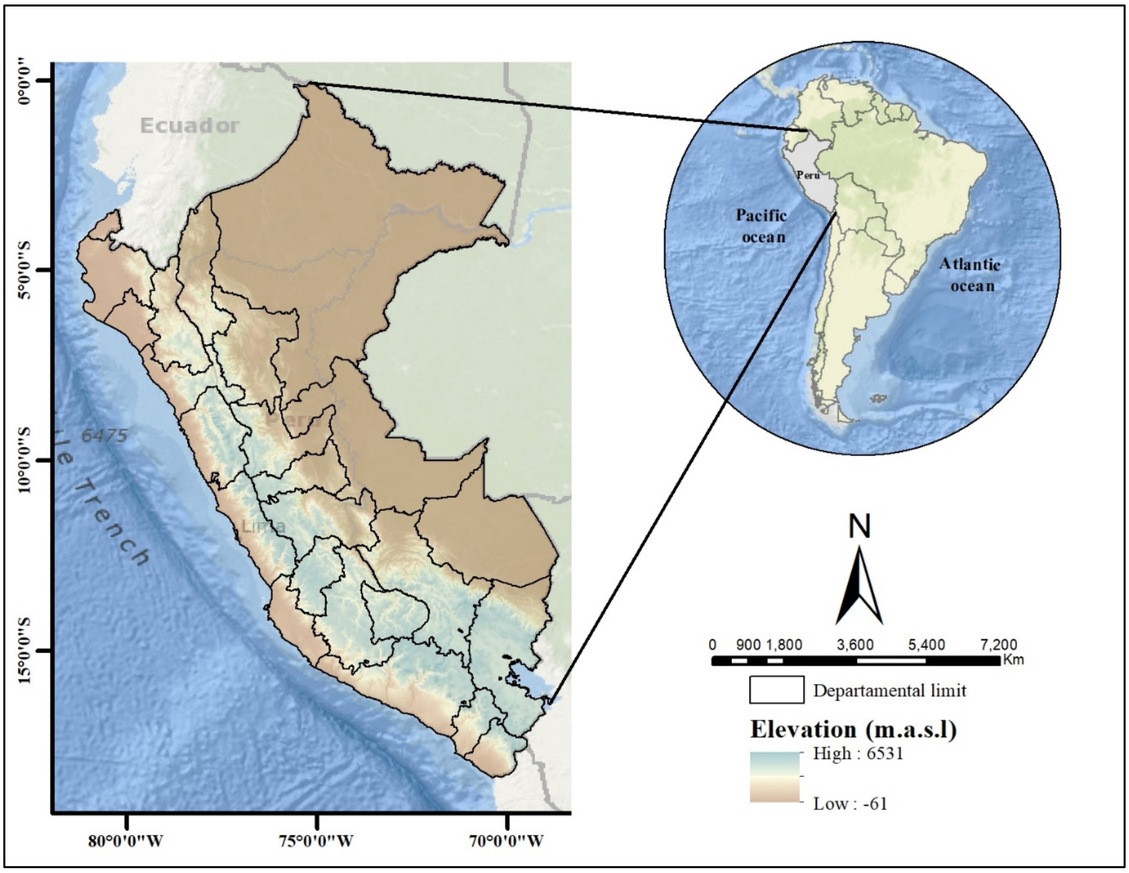


Figure 1. Localization of study area.

2.2. Database compilation

A total of 347 records of the presence of different starchy maize accessions throughout Peru were compiled, obtained from the passport data of the germplasm bank at the National Agrarian University of La Molina (UNALM). The obtained records underwent a cleaning process that included the identification and removal of empty and duplicate data to ensure the geographic accuracy of the datasets and reduce potential biases and multicollinearity among them (Koldasbayeva et al., 2024). Additionally, 347 pseudo-absence points were randomly generated and distributed representatively throughout the study area, with the aim of balancing the ratio between presence data and reducing the risk of spatial correlation and bias in the predictive models (Wang et al., 2023). Subsequently, both datasets were integrated into a single binary dataset coded with values of 0 (absence) and 1 (presence), which was used for spatial modeling (Bzonek et al., 2024). This binary dataset was randomly divided into two subsets: 75% for model training and 25% for model validation, with the aim of evaluating predictive capacity and reducing the risk of overfitting in the results (Barreñada et al., 2024).

2.3. Selection and Processing of Variables

A total of 29 variables in raster format were used (Table 1), grouped into three main categories based on their nature. Nineteen (19) bioclimatic variables were obtained from the WorldClim 2.1

platform (https://www.worldclim.org/) (Taonda et al., 2024), one (01) topographic variable was obtained from the Alaska Satellite Facility (ASF) repository (https://search. asf.alaska.edu/) (MacDonald et al., 2025), and nine (09) edaphological variables obtained from the SoilGrids 2.0 database platform (https://soilgrids.org/) (Poma-chamana et al., 2025). All layers were downloaded at a spatial resolution of 2.5 arcminutes (~21 km^2 per pixel), providing sufficient detail for national-scale analysis and ensuring spatial consistency among the variables used (Qin et al., 2024). All variables were standardized to a spatial resolution of 90 x 90 m using bilinear interpolation to ensure compatibility and comparability between layers (Vergara et al., 2025). Subsequently, a Pearson correlation analysis was performed to identify and exclude variables with high multicollinearity, thereby removing those variables with a correlation coefficient ≥ 0.90 (Bonneu et al., 2024). All processing was carried out in the R programming environment, using version 4.5 of RStudio.

Table 1. Inputs variables for the models

Factor	Variables	Description	Source
Topographic	Elevation*	Elevation (masl)	ASF
Edaphic	Silt content*	Silt content (kg)	SoilGrids
	Sand content*	Sand content (kg)	
	Clay content	Clay content (kg)	
	Nitrogen*	Nitrogen in the soil (cg/kg)	
	pH	pH soil	
	SOC*	Soil organic carbon (t/ha)	
	Coarse fragments	Coarse fragments content (cm^3)	
	CEC*	Cation exchange capacity (mmol/kg)	
	Apparent density	Apparent density (cg/cm^3)	
Bioclimatic	bio01	Annual Mean Temperature	WorldClim
	bio02	Mean Diurnal Range (Mean of monthly (max temp–min temp))	
	bio03	Isothermality (BIO2/BIO7) (×100)	
	bio04	Temperature Seasonality (standard deviation ×100)	
	bio05	Max Temperature of Warmest Month	
	bio06	Min Temperature of Coldest Month	
	bio07	Temperature Annual Range (BIO5-BIO6)	
	bio08	Mean Temperature of Wettest Quarter	
	bio09	Mean Temperature of Driest Quarter	
	bio10	Mean Temperature of Warmest Quarter	

bio11	Mean Temperature of Coldest Quarter
bio12	Annual Precipitation
bio13	Precipitation of Wettest Month
bio14	Precipitation of Driest Month
bio15	Precipitation Seasonality (Coefficient of Variación)
bio16	Precipitation of Wettest Quarter
bio17	Precipitation of Driest Quarter
bio18	Precipitation of Warmest Quarter
bio19	Precipitation of Coldest Quarter

Note: (*) variables excluded ($r < 0.9$)

2.4. Selection of future climate models

The future projection of the potential distribution of Peruvian Amilaceus Maize was conducted using the MIROC6 general circulation climate model, part of the sixth phase of the Coupled Model Intercomparison Project (CMIP6) (Islam et al., 2025). This model has demonstrated consistent performance in simulating key climate variables, such as temperature and precipitation, particularly in regions characterized by dry and humid tropical climates, supporting its applicability in agroclimatic studies (Torres Parra et al., 2024). Likewise, climate projections were conducted using two Shared Socioeconomic Pathways (SSPs), as they represent different levels of greenhouse gas emissions, land-use changes, and socioeconomic conditions through the year 2100 (Wang et al., 2025). The pathways include SSP2-4.5 and SSP5-8.5, and for each pathway, two time periods were evaluated: 2061–2080 (2070) and 2081–2100 (2100), so that medium- and long-term changes can be analyzed.

2.5. Spatial modeling of Peruavian Amilaceus maize using Random Forest

Spatial modeling to determine the potential distribution of Peruvian Amilaceus Maize was performed using the Random Forest algorithm, a machine learning method based on ensembles of decision trees that allows for the capture of nonlinear and complex relationships between crop occurrence records and the bioclimatic, topographic, and edaphic variables used as predictors (Li et al., 2024; Serra et al., 2026). This algorithm is characterized by its high predictive power, its robustness against overfitting, and its efficiency in handling multivariate and collinear data—conditions frequently encountered in agroclimatic studies (Faisal et al., 2025; Mpakairi et al., 2025). In this context, it was determined that the hyperparameter configuration with the best predictive performance for a Random Forest model applied to agricultural crops consists of 400 decision trees (ntree = 400) and four predictor variables selected at random in each split (mtry = 4), with this configuration maximizing the model's accuracy during the training and validation process (Heidari & Milan, 2025; Tamang et al., 2025).

2.6. Statistical validation

The area under the ROC curve (AUC-ROC) was used as a quantitative measure of the discriminatory power of predictive models applied to agricultural systems (Mpakairi et al., 2025), by evaluating their performance against binary data on crop presence and absence, independent of the classification threshold (Gelete et al., 2025). The AUC is derived from the integration of the ROC curve, which is constructed based on the functional relationship between the true positive rate (sensitivity) and the false positive rate (1 − specificity) across all possible cutoff values of the model (Hou et al., 2025). Its values range from 0 to 1 and are interpreted as follows: AUC values close to 0.5 indicate a lack of discriminatory power, values above 0.7 indicate acceptable predictive ability, and values above 0.9 indicate a high level of accuracy and robustness of the model (Guo et al., 2025).

$$AUC = \sum_{i=1}^{n-1} \frac{(X_i + 1 - X_i) * (Y_i + 1 - Y_i)}{2}$$

Were: $X_i + 1 - X_i$ corresponds to the false positive rate between two consecutive points; Y_(i+1) − Y_i represents the corresponding true positive rate.

In addition, accuracy was evaluated; this metric was used to estimate the proportion of correctly classified positive predictions out of the total number of predictions generated, providing a direct indicator of the model’s consistency in identifying the presence of the crop (Cabot & Ross, 2023).

$$Presición = \frac{VP}{VP + FP}$$

Were: VP stands for true positives and FP for false positives.

The recall metric was also used to measure the model’s ability to correctly identify true positives during the binary classification process of the crop under evaluation (Fu et al., 2020).

$$Recall = \frac{VP}{VP + FN}$$

Where: TP stands for true positives and FN for false negatives.

The F1-score is calculated based on precision and sensitivity, combining both metrics into a single indicator ranging from 0 to 1, where higher values reflect better model performance in balancing the correct identification of crop presence with the reduction of classification errors (Wang et al., 2021).

$$F1\ score = 2 * \frac{presición * recall}{presición + recall}$$

III. Results

3.1. Statistical metrics of the land suitable areas for Peruvian Amilaceus Maize

The model for determining soil suitability for Peruvian Amilaceus Maize demonstrated high accuracy, achieving an area under the curve (AUC) of 0.98 during training and 0.99 during validation (Figure 2A), indicating that the developed model has high statistical reliability. Furthermore, the predictor variables had a balanced contribution ranging from 2.5% to 8.6%, demonstrating that no single variable makes a disproportionate contribution (Figure 2B).

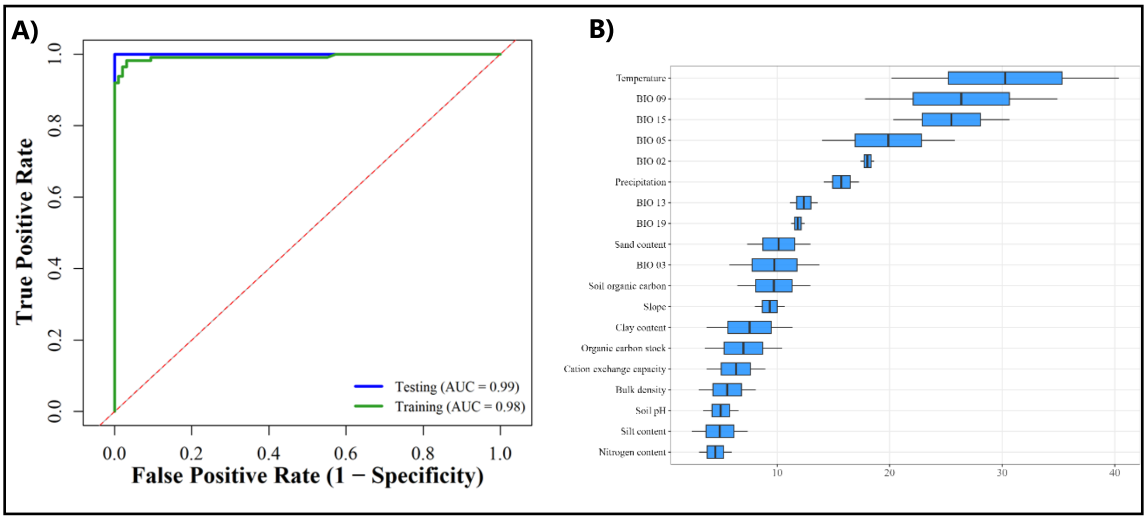


Figure 2. Statistcal metrics for land suitable areas. (A) AUC-ROC. (B) Importance of the variables included in the model

In addition, the statistical metrics reported for the model were: precision of 0.971, recall of 0.962, F1 score of 0.966, and accuracy of 0.966, indicating a high degree of reliability in the results generated in this study for determining soil suitability for the cultivation of starchy corn in Peru (Table 2).

Table 2. Statistical metrics of soil suitability for starchy corn in Peru.

Model	**Precision**	**Recall**	**F1-Score**	**Accuracy**
Random Forest	0.971	0.962	0.966	0.966

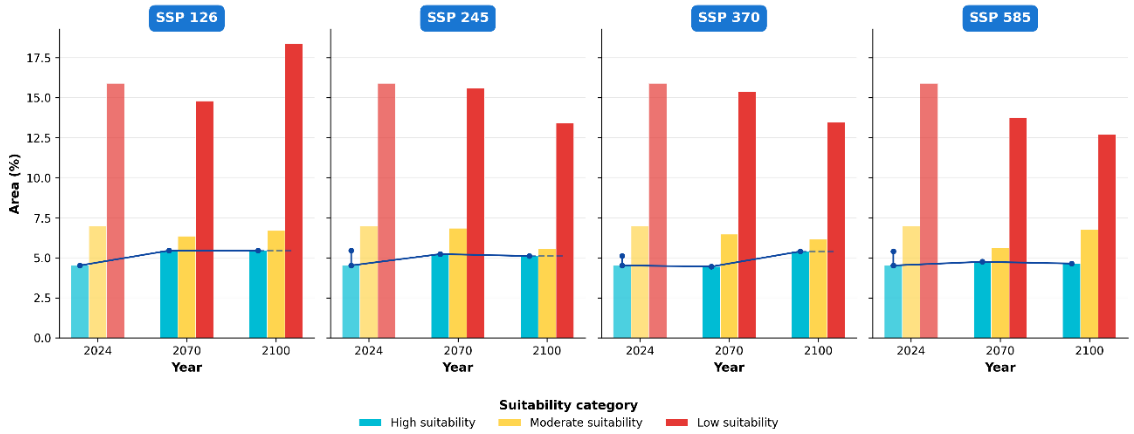
3.2. Current and future suitability land for Peruvian Amilaceus Maize in Peru

The results obtained regarding the suitability of land for growing Peruvian Amilaceus Maize are positive, showing a slight increase in the area suitable for this beneficial crop, which is essential for Peru’s socioeconomic development. Thus, it can be observed that according to the current model (year 2024), 4.52% of Peru’s territory is highly suitable for this crop, with a slight increase in areas in this suitability class (Table 6). On the other hand, a minimal but significant increase is observed in SSPs 126 and 245, and there is a slight decrease in this suitability class in SSP 370 for the year 2070; in SSP 585, there is a minimal increase in the area of high suitability for Peruvian territory (Figure 4).

Table 3. *Current and future areas for suitability land for Amylaceous Peruvian maize.*

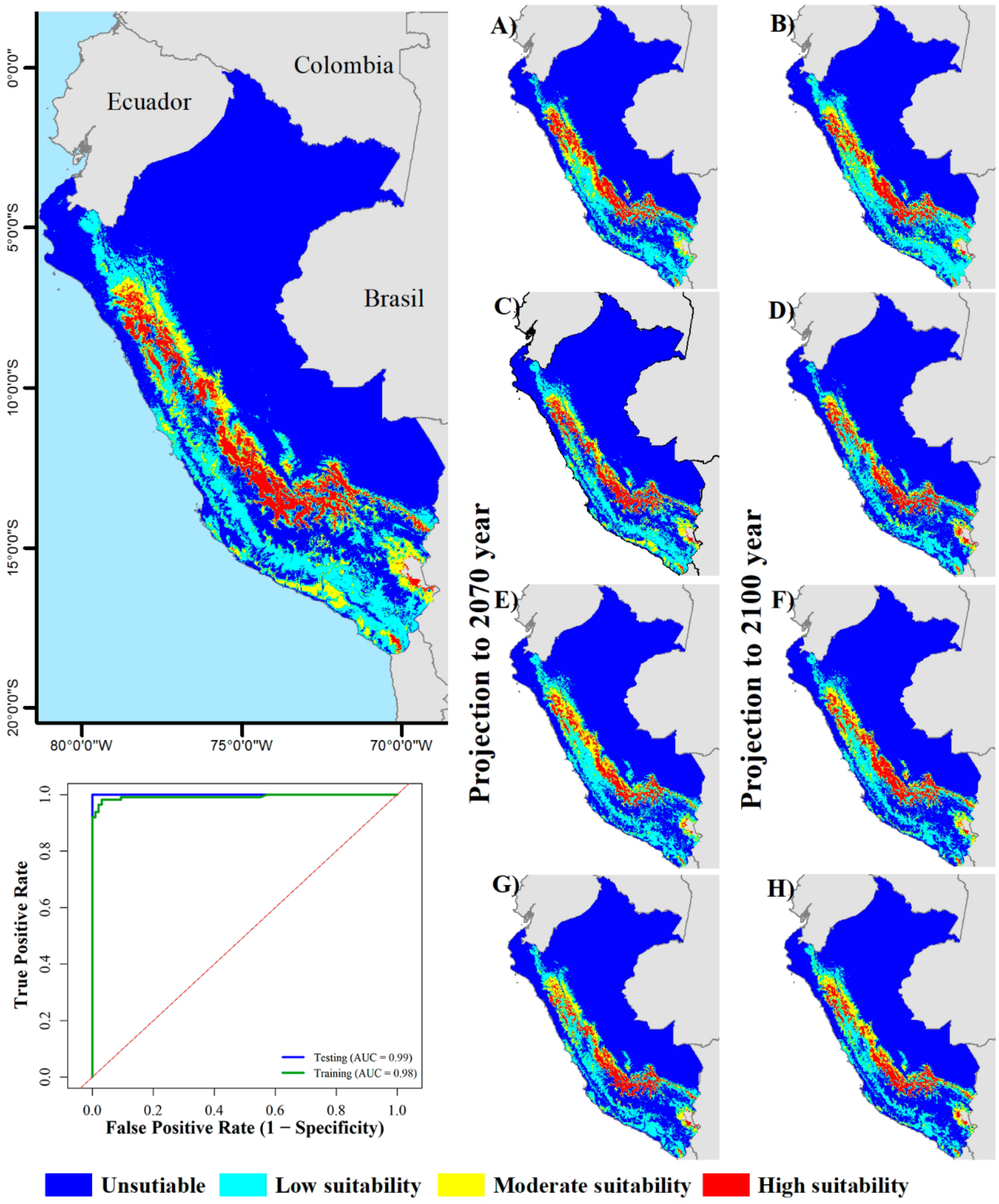
Climatic model	SSP	Year	Low suitability		Moderate suitability		High suitability	
			Km	%	Km	%	Km	%
Actuality		2024	204,450.40	15.89	89,961.85	6.99	58,188.95	4.52
MIROC6	**126**	2070	190,431.38	14.80	81,846.45	6.36	70,064.29	5.45
		2100	236,365.99	18.37	86,183.25	6.70	70,098.90	5.45
	245	2070	199,391.19	15.58	87,449.23	6.84	66,976.48	5.23
		2100	171,776.73	13.43	71,006.92	5.55	65,403.16	5.11
	370	2070	197,945.48	15.39	83,374.58	6.48	57,194.44	4.45
		2100	173,150.38	13.46	79,131.89	6.15	69,484.40	5.40
	585	2070	176,115.85	13.77	72,107.17	5.64	60,770.96	4.75
		2100	162,572.04	12.71	86,527.06	6.76	59,307.12	4.64

Figure 4. Percentage area of suitability category under SSP's for Amylaceous Peruvian maize



Among other findings, based on the edaphic, topographic, and bioclimatic variables incorporated into the land suitability model developed in this study, it can be seen that land highly suitable for growing Z. maize is mainly in the south-central region of Peru (Figure 5), where the Andean zone is located, thus demonstrating that this is the area with the best edaphic, climatic, and topographic conditions for the optimal development of this crop. It can also be seen that this zonal preference is projected to persist into the future, extending to the years 2070 and 2100.

Figure 5. Current and future projection of suitability of areas for *Amylaceous Peruvian maize*



3.3. Analysis of future trends in the suitability land for *Peruvian Amilaceus Maize* under climate scenarios

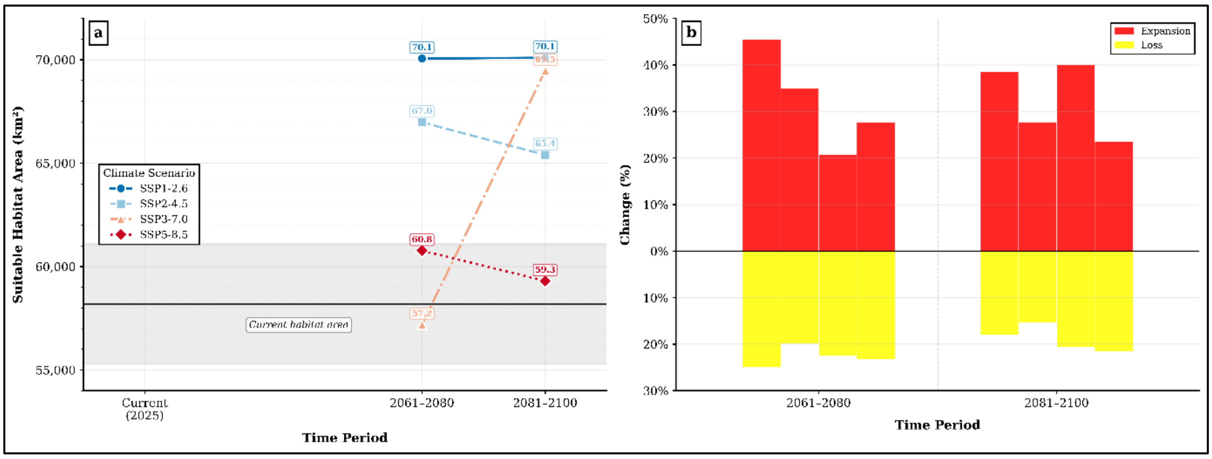
Based on an analysis of future trends in land suitability for the distribution of Peruvian Amilaceus Maize according to climate change scenarios, it was determined that the percentage of land gained and lost for this crop is determined by future development pathways (SSPs) (Table 4). Thus, regarding the evolution of the area (Figure 6A), it can be seen how the area of suitable habitat will change from the present (2025) to the end of the century, with the most notable findings being that in SSP1-2.6 the greatest expansion is projected, reaching ~70,100 km^2 and remaining stable in both periods, while in SSP2-4. 5 shows moderate expansion (~67,000 km^2 → ~65,400 km^2) with a slight decrease toward the end of the century, and in SSP3-7.0, the pattern is the most volatile—initially contracting to ~57,200 km^2 (below the current area), but then recovering dramatically to ~69,500 km^2.

Table 4. Trends in the suitability land area for *Amylaceous Peruvian maize* under climate scenarios

Period	Climate scenario	Area	Loss	Maintain	Gain	Porcentage loss (%)	Porcentage gain (%)
Current	-	58,188.95	-	-	-	-	-
2061 - 2080	SSP 126	70,064.29	14,578.60	43,610.34	26,453.94	25.05	45.46
	SSP 245	66,976.48	11,557.55	46,614.44	20,343.01	19.86	34.96
	SSP 370	57,194.44	13,073.97	45,114.97	12,079.47	22.47	20.76
	SSP 585	60,770.96	13,533.50	44,638.49	16,113.43	23.26	27.69
2081 - 2100	SSP 126	70,098.90	10,506.61	47,682.33	22,416.57	18.06	38.52
	SSP 245	65,403.16	8,929.84	49,242.15	16,138.66	15.35	27.73
	SSP 370	69,484.40	11,989.84	46,199.11	23,285.30	20.61	40.02
	SSP 585	59,307.12	12,581.60	45,590.39	13,701.47	21.62	23.55

Furthermore, by analyzing land expansion (red bars) and loss (yellow bars) (Figure 6B) for each scenario and period, a positive balance is observed, as all scenarios show a predominance of area gain over loss, with SSP1-2.6 being: The most favorable scenario, with ~45% expansion vs. ~25% loss in 2061–2080, while SSP3-7.0 shows the lowest relative expansion (~21% in 2061–2080) but recovers in the second period (~40%).

Figure 6. Current and future projection of suitability of areas for *Amylaceous Peruvian maize*



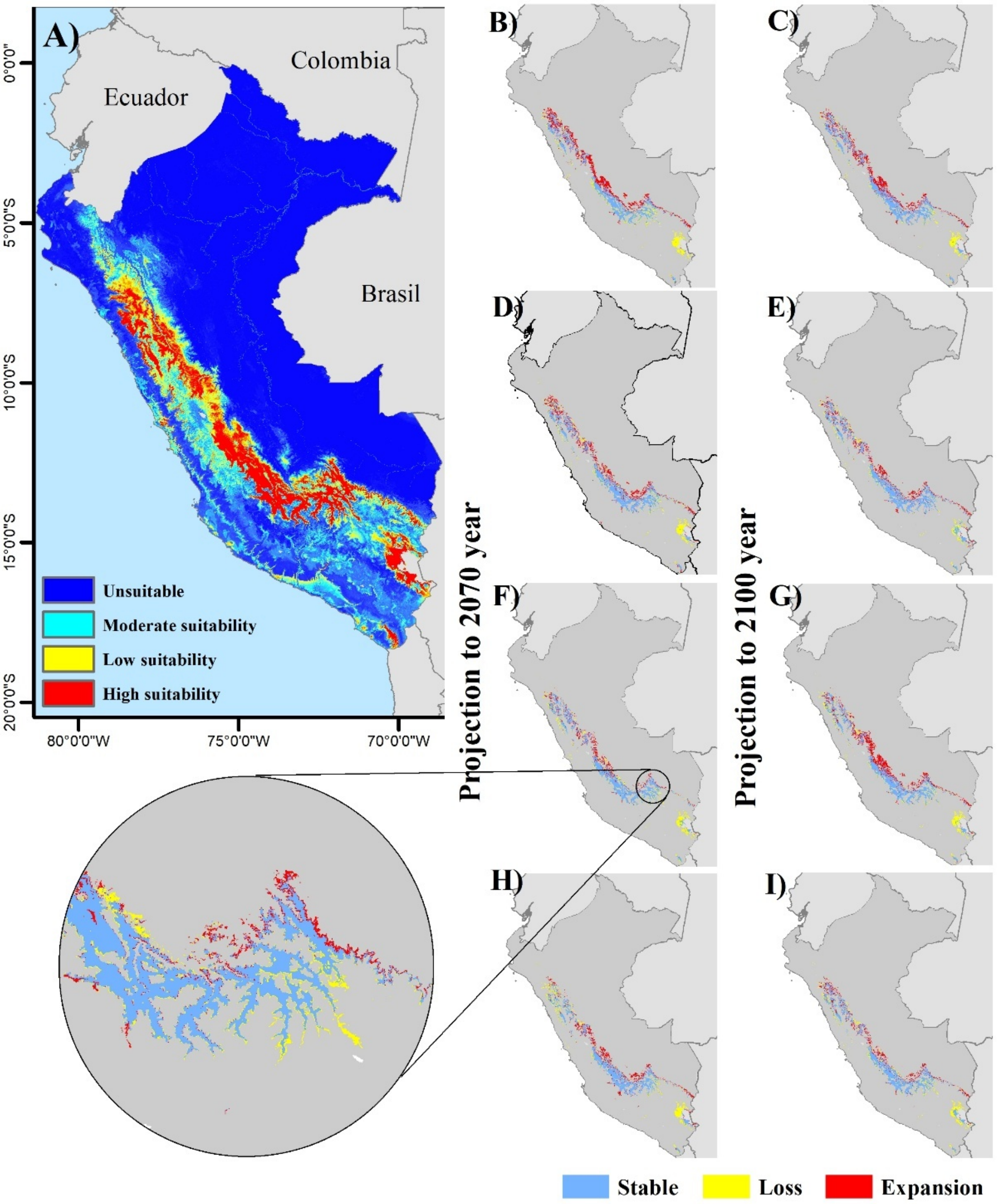


Figure 7. Dynamic change in the distribution of *Amylaceous Peruvian maize* under climate scenarios

IV. Discussions

Maize is one of the most valuable crops worldwide in terms of area and production volume, which translates into nutritional benefits for humans (Chemura et al., 2022) and provides economic support for many families; making it one of the crops with the highest socioeconomic value and in high demand by the global population (Ramirez-Cabral et al., 2017). Although this crop is one of the most sought-after due to its high nutritional and sociocultural value, it also faces challenges such as the reduction of land suitable for its cultivation due to factors like urban expansion, soil overexploitation, and climate change (Bandaru et al., 2022), therefore, it is necessary to understand land suitability based on bioclimatic, topographic, and edaphic factors to safeguard its production against these problems.

In this study, we present a comprehensive analysis based on geospatial modeling to determine the suitability of land for Peruvian Amilaceus Maize, taking into account variables derived from bioclimatic, topographic, and edaphic factors that directly influence land suitability for crops (Kogo et al., 2019; Nykytiuk & Kravchenko, 2025) and the use of the Random Forest algorithm. Such analyses are important for identifying which regions and areas are suitable for certain crops and for formulating appropriate policies and preventive measures (Dos Santos et al., 2025).

Statistically, the model exhibits high reliability, with AUC values close to 1 (0.99 in the test set and 0.98 in the training set) (Fitzgibbon et al., 2022), the model's reliability was further supported by other statistical metrics such as precision (0.971), recall (0.962), F1-score (0.966), and accuracy (0.966), confirming the model's high precision and low error rate (values close to 1), these statistical results are characteristic of the Random Forest algorithm, which has high precision values (Xu et al., 2022) and enables the model generated in this study to be replicated in future research on maize in similar áreas.

In this study, the results indicate that, in the current context, 4.52% of Peru has land highly suitable for the cultivation of this crop; these lands are located primarily in the high Andean region of Peru. The spatial results (maps) of this modeling reinforce the statistical findings, as various authors note that this crop is a high priority in high-altitude areas such as the high Andean regions of Peru, Ecuador, and Bolivia (John & Associates, 2016; Zambrano et al., 2021), demonstrating that the model developed in this study yields statistically consistent and realistic results regarding land suitability and confirming that areas with high suitability are scarce (4.52% of all of Peru), it is necessary to apply sustainable management practices to reduce the risk of soil degradation and loss of fertility due to overexploitation (Choudhary et al., 2023; Han et al., 2021).

While it is true that our research included a set of 19 variables, upon conducting a direct analysis of the variables that directly influence the identification of suitable areas for corn, our study found that in Peru, the bioclimatic variables (BIO09, BIO05, BIO15, and average temperature) these results are supported by the findings of (Yang et al., 2022), who note that temperature has a greater influence on crop development; these results are similar to those found in China by (He & Zhou, 2012), who state that temperature-related variables are more important factors for maize suitability than precipitation, This contrasts with studies such as the one conducted in Africa by (Chemura et al., 2020), who note that in Ghana, precipitation-based factors are the most important for land suitability for maize. From a meteorological perspective, (Sharma et al., 2022) note that most agricultural crops are susceptible to variations in meteorological parameters, which impact agricultural production; therefore, of these two variables (temperature and precipitation), temperature is of greater concern since it is a megavariable that cannot be controlled on-site, unlike precipitation, for which farmers can implement cropping calendars in relation to the rainy seasons (Zimmermann et al., 2017).

In this study, we also investigated how the suitability of land for corn will change in the future under simulated climate change conditions, since corn, like other agricultural crops, is directly influenced by climate change trends (Dhaliwal & Williams, 2022); for this reason, we studied the future trend of land suitability under climate change, using the MIROC6 global climate model from the CMIP6 ensemble and four socio-economic scenarios (SSPs). The results of this analysis indicate that all scenarios project a slight increase in these areas by both 2070 and 2100; These results contrast with the findings of (Gao et al., 2021), who state that by 2070 and 2100, global suitability for maize would decrease compared to the 2000s, especially under higher-emission scenarios and at lower latitudes (K. Li et al., 2022); our results refute the aforementioned findings and demonstrate that, at a smaller scale, future projections based on climate change using the CMIP6 ensemble indicate that areas highly suitable for maize will increase.

In the future, the spatial dynamics of climatic suitability for maize in Peru, under SSP scenarios, will see net expansions of 20.76–45.46% by 2070 and 23.55–40.02% by 2100. However, these net gains mask significant losses of currently suitable areas (15.35–25.05%), offset by the opening up of new zones—a common occurrence in the development of crops that cause soil degradation and depletion, leading to shifting agriculture.

The SSP 126 scenario, which is the most optimistic, shows the most favorable outcome—a 45.46% net gain by 2070—similar to other results that hypothetically project that the impacts of climate change will be beneficial for high-Andean agriculture (Ortiz-Bobea et al., 2021; Zhang & Cai, 2011), as it is believed that higher-altitude areas will not experience heat and water stress compared to lower-altitude areas (Challinor et al., 2018). In contrast, the SSP 370 scenario, which is the most pessimistic, yields negative results with the lowest gain by 2070 (20.76%) but a dramatic increase to 40.02% by 2100. These values can be explained by the delayed suitability of high-elevation areas, which only become suitable under pronounced warming (Chisanga et al., 2022); however, although it is believed that in this scenario the suitable areas expand more, these results should be interpreted with caution, as extreme temperature increases can affect maize physiology, reducing potential yields not captured by suitability analyses based solely on climate averages (Tigchelaar et al., 2018).

Future spatial trends in maize cultivation indicate that, in a hypothetical scenario involving temperature increases exceeding 30°C, 11,557–14,578 ha of currently suitable areas would be lost, posing a significant challenge for smallholder farmers who have few adaptation strategies (Thornton & Lipper, 2014). These areas are likely to experience temperature increases exceeding 30°C during the vegetative growth stage and water deficits during flowering, which are critical phases for maize yield (Sánchez et al., 2014).

In our study, we present a concise analysis of land suitability for corn cultivation; We believe this is the first of its kind, as no other study has been reported that spatially models land suitability for maize in Peru. With our results, we lay the groundwork for agricultural management agencies to establish agronomic management and genetic improvement strategies for maize that are stress-tolerant and climate-smart (Aryal et al., 2019). Furthermore, our model is balanced and can be interpreted as identifying lands suitable for maize cultivation that ensure agronomic viability, as we integrated edaphic, topographic, and bioclimatic factors that were explicitly modeled (Paudel et al., 2020).

V. Conclusiones

The land suitability model for Peruvian Amilaceus Maize developed in this study demonstrated highly robust statistical performance, with AUC values of 0.98 in the training set and 0.99 in the validation set, as well as high complementary metrics (precision = 0.971; recall = 0.962; F1-score = 0.966; accuracy = 0.966), confirming its high predictive capacity and methodological reliability.

Based on this, in the current scenario, only 4.52% of Peruvian territory is highly suitable for corn cultivation, concentrated mainly in the south-central high Andean region. This confirms that optimal areas are spatially limited and depend on a specific combination of bioclimatic, edaphic, and topographic variables, with temperature playing a decisive role. Consequently, national agricultural planning must prioritize sustainable management and soil conservation strategies in these strategic zones to prevent degradation and loss of fertility.

Projections under climate change scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8. 5) indicate a general trend toward the net expansion of areas highly suitable for Peruvian Amilaceus Maize cultivation by 2070 and 2100, with increases ranging from 20.76% to 45.46% depending on the scenario and the period evaluated. However, these net gains mask significant losses of currently suitable areas (15.35–25.05%), suggesting a spatial redistribution rather than a simple homogeneous expansion. This altitudinal shift toward high-Andean zones confirms that moderate warming could favor new productive areas, although more extreme scenarios could generate thermal stress not fully captured by models based on climate averages. In this context, the results provide a solid scientific basis for the design of agricultural adaptation policies, genetic improvement programs, and climate-smart land-use planning in Peru.

Acknowledgments

The authors thank the Laboratorio de Analisis Geoespacial y Manejo Forestal (GEOFOREST) of the UNTRM for allowing the development of this research in its facilities and equipment, and the Instituto de Investigación, Innovación y Desarrollo para el Sector Agrario y Agroindustrial (IIDAA) of the Universidad Toribio Rodriguez de Mendoza de Amazonas (UNTRM). In addition, we thank Project aMAIZEing (Contract: PE501096197): Integrando la Selección Genómica y GWAS para una Agricultura Resiliente: Desarrollo y Validación de Herramientas Genéticas Modernas para Optimizar el Mejoramiento del Maíz Peruano.

Author contributions

Conceptualization: S.V.V-R., C.A.R., C.I.A., and A.J.V.; Data curation: S.V.V-R., and A.J.V.; Formal analysis: S.V.-R., C.A.R and S.V.V-R.; Funding acquisition: A.J.V and C.I.A.; Investigation: S.V.V-R, C.A.R., and A.J.V.; Methodology: S.V.V-R, C.A.R., and A.J.V.; Project administration: A.J.V. and C.I.A.; Resources: A.J.V. and C.I.A.; Software: S.V.V-R., and A.J.V; Supervision: A.J.V. and C.I.A.; Validation: S.V.V-R., and A.J.V.; Visualization: S.V.V-R, C.A.R., and A.J.V.; Writing – original draft: S S.V.V-R, C.A.R., and A.J.V.; Writing – review and editing: S.V.V-R, C.IA., and A.J.V

Data availability

The datasets used and/or analyzed during the present study are available upon reasonable request to the corresponding author

Declarations Competing interests

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.

Funding

This research was funded by the project “Mejoramiento del servicio de formación de pre grado en educación superior universitaria de la Escuela Profesional de Ingeniería Forestal de la UNTRM Distrito De Chachapoyas—Provincia De Chachapoyas—Departamento De Amazonas”, of the Peruvian Government, with the grant number CUI 2513702. Additionally, the APC was funded by the Vicerrectorado de Investigación, Universidad Nacional Toribio Rodríguez de Mendoza de Amazonas.

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