

Article

Multi-Criteria Analysis of a Potential Expansion of Protected Agriculture in Imbabura, Ecuador

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Abstract

The increasing global demand for food, combined with rising climate extremes, is driving agricultural expansion—often without sufficient consideration for sustainability. Greenhouse agriculture presents a promising solution to address the dual challenges of food security and climate change mitigation. This study models potential scenarios for the expansion of greenhouse agriculture in Imbabura Province, Ecuador, while adhering to sustainability criteria. Two widely used methods were compared: the Analytical Hierarchy Process (AHP) integrated with Geographic Information Systems (GIS) and the Maximum Entropy (MaxEnt) model. The GIS-AHP method relies on expert-defined weights, whereas the MaxEnt model utilizes the probabilistic distribution of presence-only data, enabling a complementary evaluation of both subjective and data-driven approaches. Both models incorporated various factors, including topographic, climatic, hydrological, ecological, infrastructural, agricultural, and soil-related variables. The results classified the territory into five levels of suitability for greenhouse expansion. The GIS-AHP model identified 20,761.64 hectares as highly suitable, while the MaxEnt model identified only 5618.15 hectares. This discrepancy highlights the differing influences of various factors: In the GIS-AHP, land cover/use, irrigation availability, and proximity to existing greenhouses were the most influential. In contrast, in the MaxEnt model, proximity to greenhouses was the dominant factor. These findings not only provide a spatially explicit foundation for sustainable territorial planning but also contribute methodologically by integrating both data-driven and expert-driven approaches. This supports evidence-based policy-making in fragile Andean ecosystems.

Keywords: analytical hierarchy process; maximum entropy; climate change mitigation; food security; sustainable technology



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1. Introduction

Agricultural expansion and climate change mitigation are two of the most pressing and interconnected challenges of the 21st century [1,2]. As global temperatures rise and climate variability increases, concerns about food security are becoming more pronounced, especially in vulnerable regions of the Global South. Prolonged droughts, unexpected frosts,

and erratic rainfall patterns are disrupting agricultural productivity. These climatic stresses often lead to unplanned frontier expansion and deforestation, which in turn exacerbate biodiversity loss and undermine ecological resilience [3–6].

In Ecuador, the pressures on land and resources are particularly intense. Rapid population growth and increasing demand for natural resources have led to significant changes in land use, resulting in the fragmentation and conversion of both forested and agricultural areas. This situation is especially concerning in fragile Andean ecosystems, where these transformations can degrade essential ecosystem services and threaten the long-term sustainability of agriculture [7–10].

In response to these challenges, Sustainable Development Goal 2 (SDG 2) promotes food security through sustainable agricultural intensification. Key targets include doubling the productivity and incomes of small-scale producers and fostering climate-resilient agricultural systems [11]. Within this framework, protected agriculture (PA)—especially greenhouse-based cultivation—has emerged as a promising climate-smart strategy. Greenhouses provide better control over environmental conditions, stabilize yields, reduce the need for external inputs, and help mitigate the effects of climate extremes [12–14].

The advantages of greenhouse cultivation are well established. These systems enable year-round production, protect crops from adverse weather conditions, and improve the efficiency of water, nutrient, and energy use [15–18]. As a result, PA enhances crop quality and productivity while improving the economic viability of smallholder farming. Additionally, it contributes to rural development by creating jobs, stabilizing household incomes, and reducing migration pressures—especially in highland regions with limited arable land [19–22].

Regionally, the expansion of greenhouses is transforming the spatial and socio-economic landscape of agriculture. In Ecuador, particularly in provinces like Imbabura, greenhouse farming has contributed to job creation and food security by supporting both commercial production and local supply chains [23–27]. However, this growth also presents potential environmental trade-offs. The intensive use of plastics, energy, and agrochemicals in greenhouse systems can lead to localized degradation and increased greenhouse gas emissions if not managed properly [28–30].

Despite growing interest, there is still a significant lack of spatially explicit studies in the Andean region that integrate ecological, infrastructural, and social variables to inform the territorial planning of protected agriculture. Site selection is often driven by short-term economic goals rather than by comprehensive spatial planning [31–33]. Furthermore, few studies have considered how to incorporate biodiversity and ecosystem services (BES) into agricultural land-use planning, particularly in ecologically sensitive areas, such as the Andes [34,35].

In Ecuador, there is an increasing need to monitor, protect, and enhance BES in regions affected by agricultural intensification. A recent review highlighted the limited research focused on the impacts of human disturbance and climate change on BES, particularly in the central Andes, coastal regions, and the Amazon [36]. Similarly, Koo et al. (2024) [37] emphasized the urgency of conducting spatial assessments of ecosystems' capacity to provide BES under scenarios of deforestation and climate change. These findings underscore the need to integrate BES considerations into territorial planning for protected agriculture in Ecuador, where scientific evidence on this intersection remains scarce.

To meet this need, Geographic Information Systems (GIS) have been used to identify suitable areas for agricultural development. However, the integration of multi-criteria decision-making tools—such as the Analytic Hierarchy Process (AHP)—is still underutilized [33,34]. The AHP provides a structured, expert-driven approach for evaluating land suitability, while GIS support spatial analysis and visualization. In contrast, the Maximum

Entropy (MaxEnt) model uses presence-only data to statistically predict land suitability based on environmental variables [38,39]. While the AHP-GIS relies on expert-defined sustainability weights, MaxEnt is a data-driven tool that reveals spatial patterns from actual greenhouse locations. Combining both approaches offers a complementary perspective that balances subjective expert knowledge with objective, probability-based modeling.

Recent studies in Latin America provide valuable examples for agricultural spatial planning using these tools. For instance, França et al. (2023) [40] developed a GIS-AHP and optimization-based decision-support system to assess land suitability for energy infrastructure in Brazil, incorporating environmental, social, and economic criteria. Ivale and de Alencar (2022) [41] applied group the AHP for spatial vulnerability mapping, while Alshahrani et al. (2024) [42] combined GIS and machine learning to evaluate coastal risks in Vila Belmiro. In Colombia, Zuluaga et al. (2021) [43] proposed a spatially explicit multi-criteria framework to assess pastureland systems based on productivity and environmental indicators. Additionally, research by Vizuite-Moreno et al. (2024) [44] applied agroecological zoning for crops such as coffee and cacao using GIS-based models that incorporate field soil data and environmental variables.

In Ecuador, methodologies such as Geographic Information Systems (GIS) and the Analytic Hierarchy Process (AHP) have predominantly focused on physio-edaphoclimatic and socioeconomic factors. While these approaches aid informed decision-making, the integration of biodiversity and climate adaptation remains an emerging area of concern. This study builds on regional experiences by highlighting the unique challenges faced in the Ecuadorian Andes and addressing methodological gaps in high-altitude, data-scarce contexts.

The research aims to model potential expansion scenarios for protected agriculture in Imbabura Province, Ecuador, using sustainability-oriented criteria. Specifically, it compares the AHP-GIS approach with the MaxEnt method to identify areas suitable for future greenhouse development. By contrasting an expert-based method with a data-driven approach, the study offers valuable insights for spatial planning, public policy, and private sector investment. Ultimately, these findings support progress toward Sustainable Development Goal 2 (SDG 2) by promoting informed and sustainable rural development strategies in Ecuador [15,45].

This work addresses critical gaps in the planning of protected agriculture by integrating complementary methodologies. Unlike previous studies that focused on isolated variables or lacked ecological rigor, this study combines expert judgment with empirical modeling to provide robust, spatially explicit insights. By comparing Ecuador with Brazil and Colombia, the study highlights the unique opportunities and limitations faced by Ecuador, emphasizing the need for tailored, science-based strategies that consider local biophysical and socioeconomic conditions in the Andean region. As a result, this study not only advances methodologies in land suitability analysis but also aids in the design of sustainable territorial policies that align with climate adaptation and rural development goals in Latin America.

2. Materials and Methods

2.1. Study Area Description

The study was conducted in the province of Imbabura, situated in the inter-Andean region of northern Ecuador. This province is located between the coordinates of 0°21'–0°72' N latitude and 77°48'–79°12' W longitude. It covers an area of 479,489.18 hectares and has an altitudinal range that extends from 160 m to 4939 m above mean sea level (a.m.s.l.) [46]. The location map is presented in Figure 1.

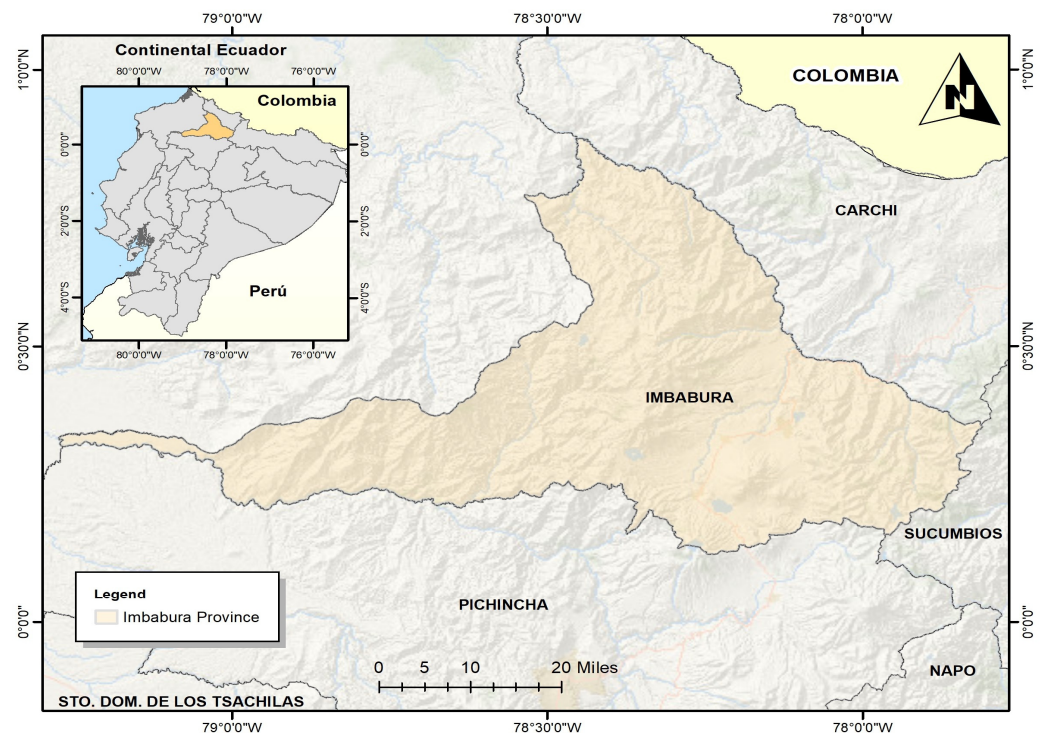


Figure 1. The location map of the province of Imbabura.

Imbabura was designated a UNESCO Global Geopark on 17 April 2019, recognizing its rich cultural, ethnic, and productive diversity alongside its unique geographical features. The province's landscape is characterized by valleys, plateaus, and high-altitude zones [47]. As of 2023, Imbabura has a strong agricultural presence, with 119,699 hectares under cultivation. Key crops include corn, beans, sugar cane, bananas, avocados, oil palm, and wheat, along with a variety of fruits, vegetables, and tubers [46].

By 2023, a total of 1958 greenhouses covering 527 hectares in the protected agriculture sector had been georeferenced. These greenhouses average 0.26 hectares in size and primarily produce kidney tomatoes, peppers, and gherkins. They are distributed across six cantons: Antonio Ante, Cotacachi, Ibarra, Otavalo, Pimampiro, and Urcuquí. Generally, the agricultural greenhouses in Imbabura feature a low level of technology. Their structures are typically constructed from wood, metal, or a combination of both and are covered with plastic. They feature natural ventilation and drip irrigation systems, with crops primarily planted in soil. Between 2016 and 2023, the number of agricultural greenhouses in the province increased by 19.77%, and this trend is expected to continue [48].

2.2. Selected Variables and Their Characteristics

Based on a literature review, expert consultations, and data availability, eleven spatial variables were selected and grouped into seven categories: (1) water resources, (2) agricultural clustering, (3) ecological criteria, (4) infrastructure, (5) climatic conditions, (6) topographic features, and (7) soil physical and chemical properties. These datasets were obtained from official Ecuadorian institutions and international open-access repositories.

Spatial distribution of irrigation systems (V1): This variable represents the spatial distribution of irrigation systems in the province. As of 2024, Imbabura has 23,672.8 hectares under irrigation. This is a key factor for greenhouse expansion, as 99.2% of producers use drip irrigation and rely on water stored in reservoirs [48].

Distance to greenhouses (V2): This variable captures the spatial concentration of greenhouses within the province of Imbabura. It reflects existing centers of agricultural intensification and market integration. Areas with a higher density of greenhouses benefit

from economies of scale, easier access to inputs, technical knowledge, and marketing channels. According to a Moran's I spatial autocorrelation analysis, a statistically significant clustering pattern was observed (z -score = 23.56, p -value < 0.00001), confirming that greenhouse installations are not randomly distributed but are instead spatially dependent and agglomerated. This underscores the importance of considering spatial concentration when identifying potential expansion zones. The locations of greenhouses were initially georeferenced in 2016 and updated in 2023 based on the spatial inventory developed by Albuja et al. (2025) [48].

Land cover and use maps (V3): This variable is derived from ecological criteria and represents the interaction between natural land characteristics and human activities across various land cover types. These categories include agricultural lands, livestock areas, mixed agriculture zones, conservation and protection areas, conservation and production lands, protection or production zones, anthropogenic (human-influenced) areas, water bodies, and unproductive lands. For the cartographic analysis, it is essential to note that protected zones, urban centers, and water bodies were excluded to focus on areas relevant for agricultural expansion and sustainability assessments.

Distance to roads (V4): This variable represents a buffer analysis around road lines based on road network data from the Ecuadorian Military Geographic Institute (IGM). Before generating this variable, an exploratory analysis was conducted to assess the spatial relationship between greenhouse locations and road categories. A 500 m buffer was applied to each road class (primary, secondary, and tertiary) to evaluate spatial preferences. The results indicated a dispersed distribution pattern, with no significant clustering near any specific type of road.

Average annual temperature (V5): This variable was derived from 30 years of meteorological data provided by the National Institute of Meteorology and Hydrology (INAMHI). Ecuador's climate is characterized mainly by two seasons differentiated by rainfall distribution: the rainy season and the dry (summer) season. Specifically, the province of Imbabura exhibits a temperate climate, with average monthly temperatures around 14.5 °C during the rainy season and approximately 15 °C in the dry season [49]. The temperature zoning was further contextualized using Holdridge's Life Zone Classification System, which serves as a reference framework for ecological and climatic classification in the region.

Slope (V6) and altitude (V7): These variables were derived from NASA's Digital Elevation Models (DEM) using ALOS Palsar data, which has a spatial resolution of 30 m. Agricultural greenhouses are distributed across various slope gradients and altitudinal ranges within the six cantons of Imbabura Province, with the highest concentrations found in Cotacachi, Otavalo, Antonio Ante, and Pimampiro [48]. About altitude (V7), this study follows Ecuador's Organic Law on Rural Lands and Ancestral Territories (Article 50), which sets limits on agricultural frontier expansion, as well as the Law for the Conservation and Sustainable Use of Biodiversity (Article 46). Consequently, the potential expansion of greenhouses is restricted to areas located below 3000 m above sea level (m.a.s.l.).

Soil texture (V8), soil depth (V9), soil drainage (V10), and soil salinity (V11): These soil variables were sourced from the General Coordination of National Agricultural Information (CGINA) of the Ministry of Agriculture of Ecuador (MAG, 2020). They are essential indicators of soil quality and suitability for agricultural use. Each variable was evaluated based on the parameters outlined by the Land Suitability Classification System of the Food and Agriculture Organization of the United Nations (FAO) [50].

These parameters provided thresholds and classifications that helped assess the suitability of soil for greenhouse agriculture. The specific suitability ranges applied to each variable in this study are detailed in Table 1.

Table 1. Characteristics of the variables identified for the GIS-AHP and MaxEnt models.

Data Category	Variable Name	Range/Units	Assigned Value	Variable Code
Water resources	Spatial distribution of irrigation systems	Yes	2	V1
		No	0	
Agricultural clustering	Distance to greenhouses	0–500 m	2	V2
		500–1000 m	1	
		>1000 m	0	
Ecological Criterion	Land cover and use maps	Agricultural	2	V3
		Livestock	1	
		Other uses	0	
Infraestructure Criterion	Distance to roads	0–500 m	2	V4
		500–1000 m	1	
		>1000 m	0	
Climatic criterion	Average anual temperature	12–24 °C	2	V5
		8–12 °C	1	
		<8 and >24	0	
Topographic criterion	Slope	0–25%	2	V6
		25–45%	1	
		>45%	0	
	Altitude	0–2700 a.m.s.l.	2	V7
		2700–3000 a.m.s.l.	1	
		>3000 a.m.s.l	0	
Soil resources	Soil texture	Sandy Loam, Loam, Clay-Loam	2	V8
		Sandy, Clay Loam, Sandy Loam, Silty Loam		
		Clay-Sandy, Clay-Silty, Silty		
	Soil depth	100% Sandy, Clayey	1	V9
		Moderately	2	
		Shallow	1	
	Soil drainage	Superficial	0	V10
		Good	2	
		Moderate	1	
	Soil salinity	Excessive	0	V11
		Non-saline	2	
		Slightly saline	1	
		Saline	0	

The figures below demonstrate the spatial distribution and characteristics of the eleven variables included in this study. These visualizations enhance our understanding

of the spatial variability and contextual factors that influence the suitability and potential expansion of protected agriculture in the province of Imbabura. A complete set of maps is provided in Figure 2.

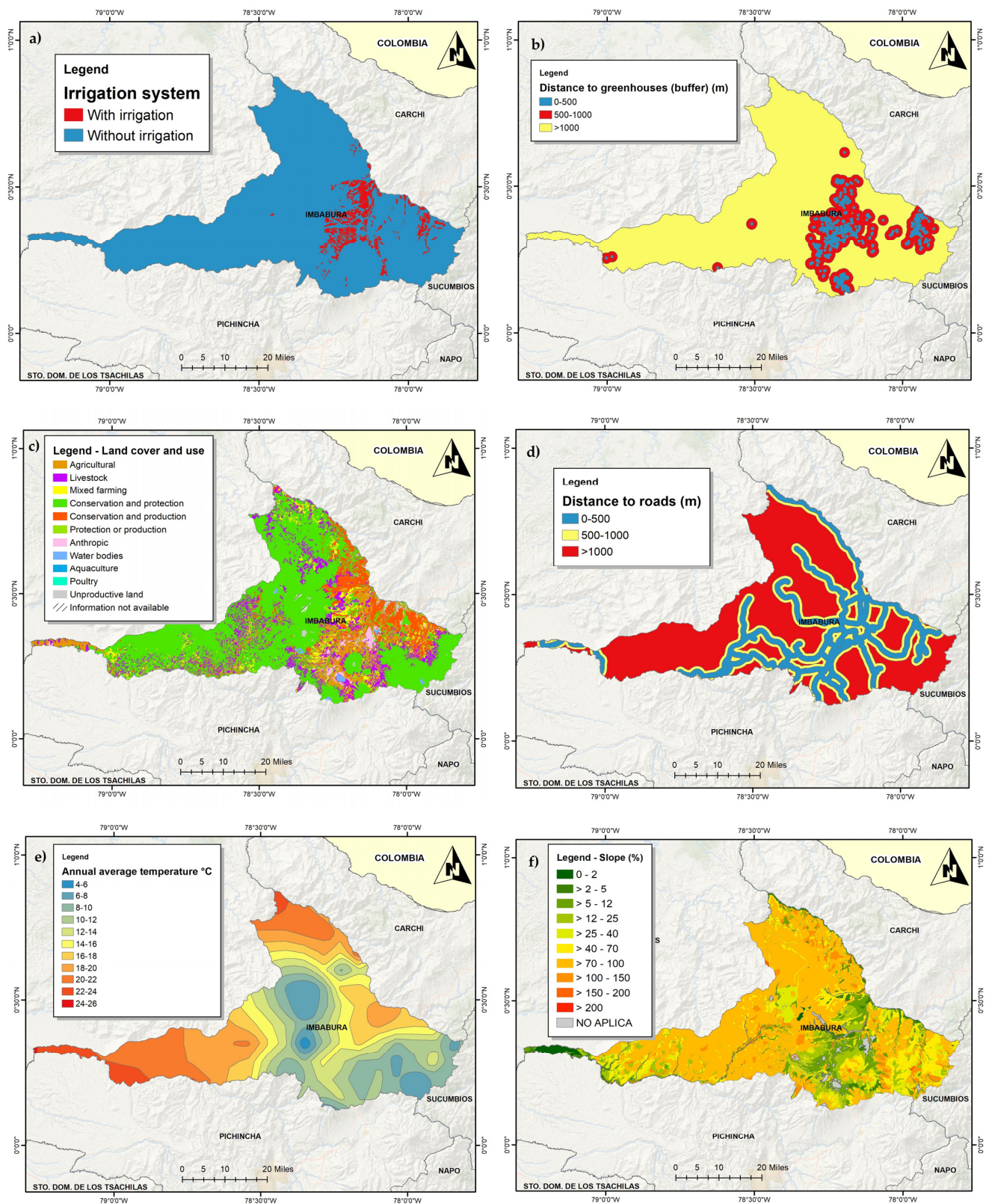


Figure 2. Cont.

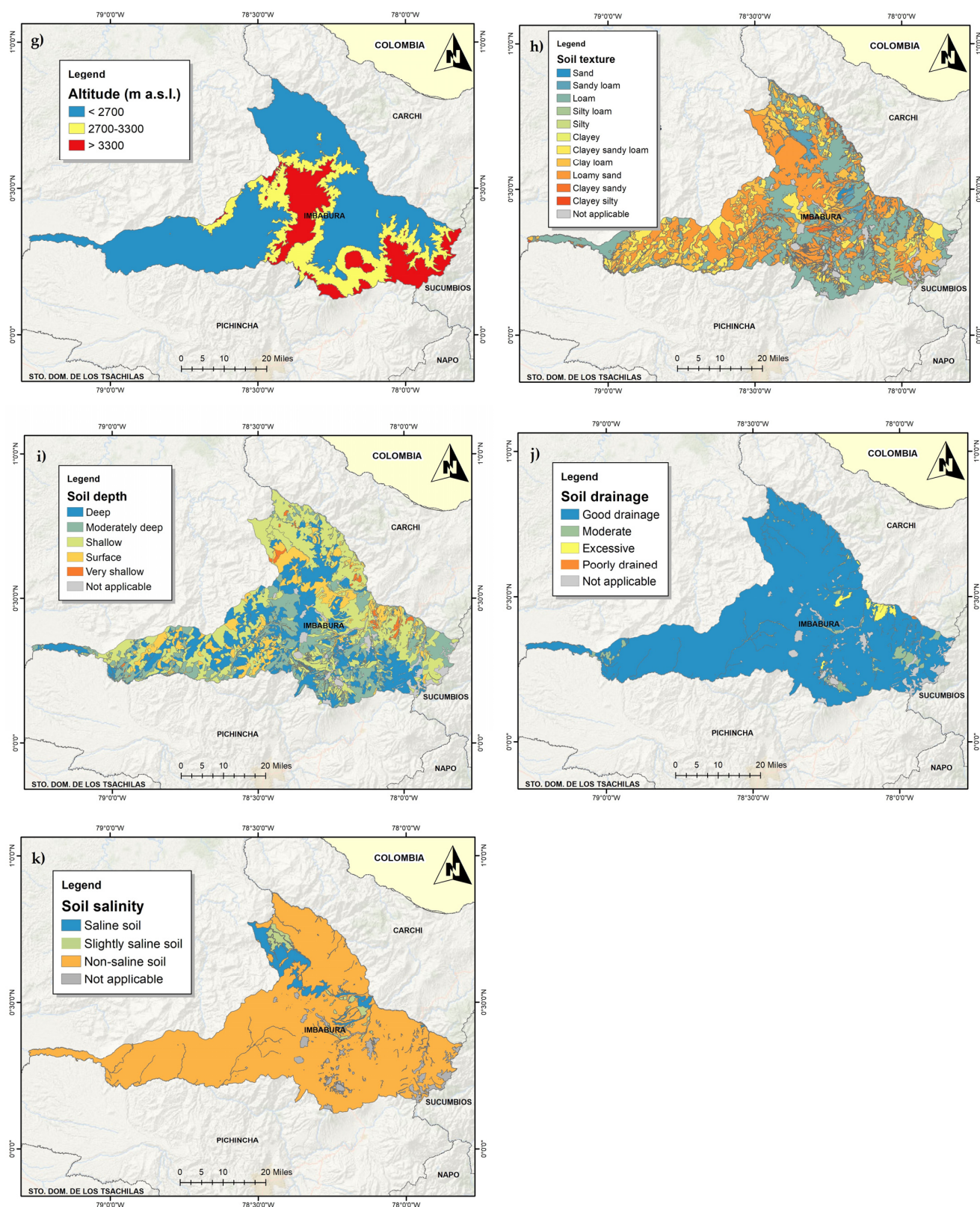


Figure 2. Spatial layers of the eleven selected criteria used to identify suitable areas for potential agricultural greenhouse expansion in Imbabura Province are as follows: (a) irrigation systems; (b) proximity to existing greenhouses; (c) land cover and use; (d) distance to roads; (e) average annual temperature; (f) slope; (g) altitude; (h) soil texture; (i) soil depth; (j) soil drainage; and (k) soil salinity.

It is essential to recognize that while the eleven selected variables were analyzed independently in the spatial analysis, many of them have conceptual and functional in-

terrelationships that could influence greenhouse suitability. For instance, land cover and land use are often closely linked to soil properties, such as texture, depth, and drainage, which in turn affect crop viability, irrigation capacity, and infrastructure planning. Similarly, altitude and slope not only influence temperature and water retention but are also indirectly connected to soil salinity and fertility, both of which are critical for the effective functioning of protected agriculture [51]. Considering these associations can enhance the interpretation of the suitability maps and strengthen future modeling approaches that integrate the interaction effects among variables.

2.3. Modeling Approaches for Greenhouse Expansion

2.3.1. GIS-AHP Integration

This study employed a modified version of the methodology developed by Khatib and Sizov [52], originally designed to assess the potential expansion of greenhouse agriculture. Additionally, we examined the parameter weighting methods proposed by Arias-Muñoz et al. [53] and Sathiyamurthi et al. [54], as they were deemed relevant to this research context.

To ensure a thorough and contextually suitable selection of criteria, we referenced standard variables used in land suitability assessments and adapted them to fit the specific conditions of the local territory and the protected agriculture system [55–58].

Given its methodological rigor and widespread use, we chose the GIS-based Analytic Hierarchy Process (GIS-AHP). This technique has been extensively employed in various fields, including agricultural land suitability studies, urban and infrastructure planning, environmental assessments, and resource management [59–63].

The methodological framework used in this study is illustrated in Figure 3.

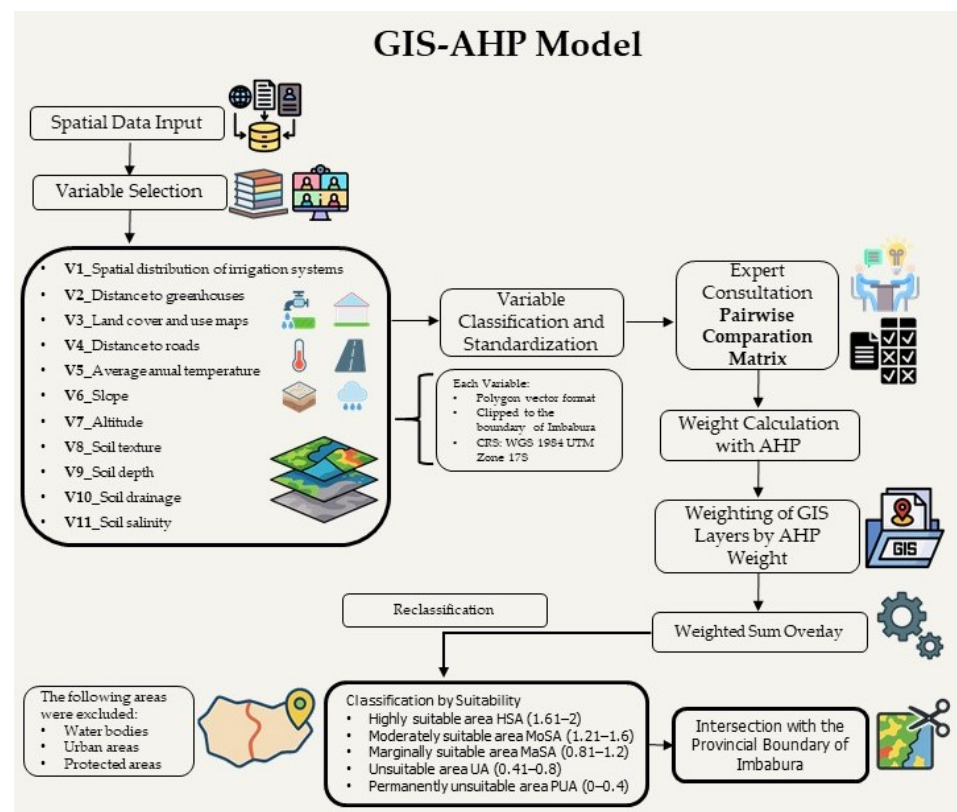


Figure 3. A schematic diagram illustrating the methodological framework that combines GIS and the Analytic Hierarchy Process (AHP) to model optimal areas for greenhouse expansion.

The GIS-AHP technique offers several significant advantages, including its ability to incorporate a wide range of criteria, its hierarchical organization, and the development of customized weighting schemes. Additionally, the AHP method allows for the inclusion of more variables than many other multi-criteria decision-making (MCDM) approaches. MCDM is particularly useful in situations where decisions need to consider multiple, often conflicting, criteria, making it especially suitable for complex spatial planning and land suitability assessments.

Variable Weighting Method

Multi-criteria analysis techniques can be broadly categorized into four methods: classification or ranking, scoring, pairwise comparison, and entropy. It is important to note that the first three methods rely on external evaluations, meaning the criteria weights are determined based on expert opinions, without necessarily considering the variability or range of the underlying data. In contrast, the pairwise comparison method evaluates the relative importance of pairs of criteria and is the most widely used approach for determining criterion weights. This method is generally regarded as superior to the alternatives in practical applications [64].

To incorporate local expert knowledge, a questionnaire was administered to a panel of seven specialists in protected agriculture to construct the pairwise comparison matrix. The pairwise comparison method uses a fundamental scale ranging from 1 to 9 to express the intensity of preference between criteria *i* and *j*, as detailed in Table 2 [65].

Table 2. The scale used for the pairwise comparison of criteria *i* and *j*.

Scale	Definition	Scale	Definition
1	<i>i</i> and <i>j</i> have equal importance		
3	<i>i</i> is slightly more preferable than <i>j</i>	1/3	<i>i</i> is slightly less preferable than <i>j</i>
5	<i>i</i> is more preferable than <i>j</i>	1/5	<i>i</i> is less preferable than <i>j</i>
7	<i>i</i> is strongly more preferable than <i>j</i>	1/7	<i>i</i> is strongly less preferable than <i>j</i>
9	<i>i</i> is extremely more preferable than <i>j</i>	1/9	<i>i</i> is extremely less preferable than <i>j</i>

To validate the calculated weights, we computed the consistency ratio (CR) (Equation (3)) using Equations (1) and (2). A CR value of 0.10 or lower is considered acceptable, as it indicates a reasonable level of consistency and ensures the reliability of the expert judgments [66].

$$CI = \lambda_{\max} - n / (n - 1) \quad (1)$$

$$Rci = (1.98 \times (n - 2)) / n \quad (2)$$

$$CR = CI / Rci \quad (3)$$

where $\lambda_{\max}$ represent the maximum eigenvalue of the matrix, *n* is the number of variables considered, and *Rci* (Random Consistency Index) is the corresponding index value associated with *n*. It is important to note that the *Rci* is dependent on the number of elements being compared.

Following this procedure and based on the responses from the questionnaire, we constructed a pairwise comparison matrix with the variables organized in rows and columns. The main diagonal was set to 1, and the relative comparison weights were assigned to each cell. Then, the vertical and horizontal averages of the pairwise comparisons were calculated, allowing us to derive the multi-criteria weight for each variable. The results are presented in Table 3.

Table 3. The pairwise comparison matrix of the evaluated criteria.

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	Ci	λ_i
V1	1	2	1/5	3	2	4	3	4	4	4	5	0.17	1.503
V2	1/2	1	1/3	2	2	2	2	3	3	3	3	0.12	1.098
V3	5	3	1	3	2	2	2	3	3	3	3	0.20	0.958
V4	1/3	1/2	1/3	1	2	2	2	3	3	3	3	0.10	1.223
V5	1/2	1/2	1/2	1/2	1	2	2	2	3	3	3	0.09	1.057
V6	1/4	1/2	1/2	1/2	1/2	1	1/3	1/3	3	1/3	3	0.05	1.204
V7	1/3	1/2	1/2	1/2	1/2	3	1	2	2	2	3	0.08	1.083
V8	1/4	1/3	1/3	1/3	1/2	3	1/2	1	2	2	3	0.06	1.212
V9	1/4	1/3	1/3	1/3	1/3	1/3	1/2	1/2	1	3	3	0.05	1.167
V10	1/4	1/3	1/3	1/3	1/3	3	1/2	1/2	1/3	1	3	0.05	1.189
V11	1/5	1/3	1/3	1/3	1/3	1/3	1/3	1/3	1/3	1/3	1	0.03	0.897
Σ	8.87	9.33	4.70	11.83	11.50	22.67	14.17	19.67	24.67	25	33	1.00	12.59

Note: Variable codes correspond to those presented in Table 1.

The calculated Consistency Index (CI) was 0.15. This figure was then divided by the Random Consistency Index (RI = 1.62) to obtain a consistency ratio (CR) of 0.09. Since the CR is below the threshold of 0.10, the consistency of the expert judgments is considered acceptable, indicating that the model is reliable.

With the validity of the weights confirmed, the map algebra technique was employed using the weighted matrix to create a preliminary suitability model for potential agricultural greenhouse expansion within a GIS environment (ArcGIS 10.8.2). A uniform spatial resolution of 30 m was utilized for all geospatial data layers, as this resolution is appropriate for the scale of analysis. All variables met or exceeded this resolution, allowing for resampling without spatial distortion [60].

The suitability index for potential greenhouse expansion was calculated as the weighted sum of the eleven selected variables:

$$\text{ITPExp} = (0.17 \times V1) + (0.12 \times V2) + (0.20 \times V3) + (0.10 \times V4) + (0.09 \times V5) + (0.05 \times V6) + (0.08 \times V7) + (0.06 \times V8) + (0.05 \times V9) + (0.05 \times V10) + (0.03 \times V11) \quad (4)$$

where ITPExp = suitability index for the potential expansion of greenhouses; V1= availability of reclassified irrigation water; V2= reclassified distance to greenhouses; V3 = reclassified land cover and use; V4 = reclassified distance to road; V5 = average annual temperature; V6 = reclassified slope; V7 = reclassified altitude; V8 = reclassified soil texture; V9= reclassified soil depth; V10 = reclassified soil drainage; and V11 = reclassified soil salinity.

Finally, the suitability map was classified into five categories based on the range of suitability values obtained from Equation 4, with minimum and maximum values of 0 and 2, respectively. Areas corresponding to water bodies, urban zones, and protected areas were assigned restrictions for greenhouse expansion and excluded from suitability classification. The ranges for each suitability class are presented in Table 4.

Table 4. Classification ranges of the suitability index for potential agricultural greenhouse expansion.

Area of Thematic Classes	Range	
	Minimum	Maximum
Highly suitable area (HSA)	1.61	2.0
Moderately suitable area (MoSA)	1.21	1.6
Marginally suitable area (MaSA)	0.81	1.2
Unsuitable area (UA)	0.41	0.8
Permanently unsuitable area (PUA)	0	0.4

2.3.2. Maximum Entropy Model (MaxEnt)

A predictive modeling approach was implemented to assess the potential expansion of agricultural greenhouses using MaxEnt software (version 3.4.4), serving as a complementary and comparative methodology. This tool has been effectively utilized in various studies, including those by Benito and Peñas [67] for modeling future greenhouse expansion scenarios, Fitzgibbon et al. [68] for analyzing the relationships between climate and maize suitability, Ahmadi et al. [69] for modeling habitat suitability of species to support conservation planning, and Su et al. [70] for predicting potentially suitable areas for rice cultivation based on short- and medium-term scenarios developed by the Intergovernmental Panel on Climate Change (IPCC).

It is important to note that the same set of eleven variables and classification categories used in the GIS-AHP model was also applied in the MaxEnt model. This approach ensures methodological consistency and enables direct comparison between the two methods.

To run MaxEnt, georeferenced data showing current greenhouse locations, along with the selected environmental variables, were input into the software. The model's performance was evaluated by comparing the area under the curve (AUC) of the receiver operating characteristic (ROC) with the actual distribution of greenhouses, thereby providing a measure of model accuracy.

Figure 4 illustrates the schematic workflow followed for the MaxEnt modeling process.

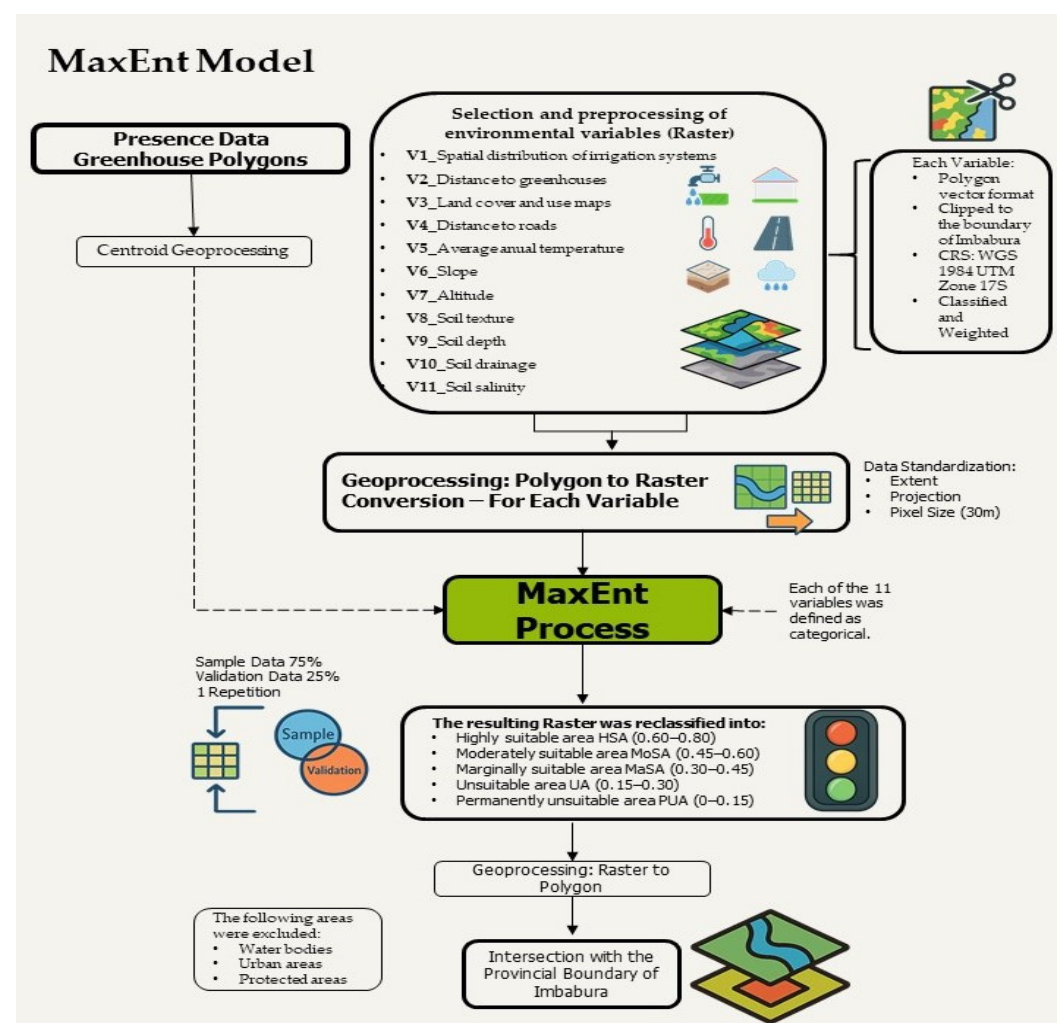


Figure 4. A schematic representation of the methodological workflow applied in the MaxEnt modeling process for identifying suitable areas for the potential expansion of agricultural greenhouses.

MaxEnt Model Application and Validation

The MaxEnt model functions by integrating species presence data within a spatial grid alongside environmental variables that reflect various ecological gradients. Using this information, the model estimates habitat suitability by determining the similarity between environmental conditions at known presence sites and those throughout the wider landscape. Suitability values range from 0 (indicating the lowest similarity) to 1 (indicating the highest similarity), which enables predictions regarding potential species distributions and their probability of occurrence [71,72].

In this study, a total of 1958 greenhouse location points were utilized as presence data for the model. Of these points, 75% were randomly selected for training the model, while the remaining 25% were used for validation. The cloglog output format was chosen because it provides an interpretable probability of presence that ranges from 0 to 1. All other parameters were maintained at their default settings.

To evaluate the performance of the model, the receiver operating characteristic (ROC) curve was employed, which is a widely accepted method for validating MaxEnt predictions. The area under the ROC curve (AUC) was calculated as a threshold-independent metric of model accuracy, with values ranging from 0 (indicating no discriminatory ability) to 1 (indicating perfect discrimination).

3. Results

3.1. GIS-AHP Modeling for the Potential Expansion of Agricultural Greenhouses in Imbabura

The results of the GIS-AHP modeling indicate that the most significant factors influencing land suitability for the potential expansion of protected agriculture are land cover and use (V3, 20%), availability of irrigation systems (V1, 17%), and proximity to existing greenhouses (V2, 12%). These three variables together account for nearly half of the total contribution to the model, highlighting the importance of current land use patterns, access to water resources, and existing infrastructure in shaping the potential for greenhouse development.

Other relevant factors include distance to roads (V4, 10%), average annual temperature (V5, 9%), altitude (V7, 8%), soil texture (V8, 6%), slope (V6, 5%), soil depth (V9, 5%), soil drainage (V10, 5%), and soil salinity (V11, 3%). While these factors also contribute to the model, they carry relatively lower weights.

These findings emphasize the multifactorial nature of land suitability, where both environmental and infrastructural variables influence strategic decisions regarding the expansion of protected agriculture in the region. These variables are essential for understanding not only the agroecological feasibility but also the logistical viability of protected agriculture systems (Table 5).

To complement the expert-based weighting results obtained from the GIS-AHP model, a bar chart was created to visually compare the relative contributions of each variable (Figure 5). This graphical representation emphasizes the significant influence of land cover and use (V3), irrigation systems (V1), and proximity to existing greenhouses (V2), which accounted for 20%, 17%, and 12% of the total weight, respectively. The chart provides a clearer and more precise interpretation of the importance distribution of the variables within the model.

The contributions shown in Figure 5 highlight the diverse factors that influence the suitability of areas for greenhouse expansion, considering both natural and infrastructural elements. These factors were weighted and integrated using the GIS-AHP model, resulting in a spatial representation of suitability across the study area. The suitability map displayed in Figure 6 translates these multi-criteria assessments into clearly defined territorial classes, allowing for the targeted identification of areas best suited for greenhouse expansion.

Table 5. The relative contributions of the eleven predictor variables to the GIS-AHP suitability model for greenhouse expansion.

Variable	Percent Contribution
V1	0.17
V2	0.12
V3	0.20
V4	0.10
V5	0.09
V6	0.05
V7	0.08
V8	0.06
V9	0.05
V10	0.05
V11	0.03

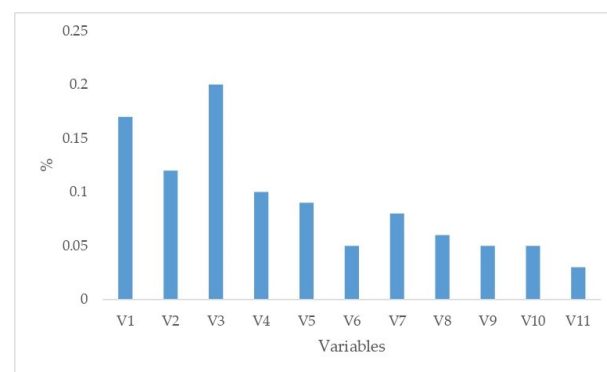


Figure 5. The relative contribution of the variables to the GIS-AHP model for determining territorial suitability for greenhouse expansion.

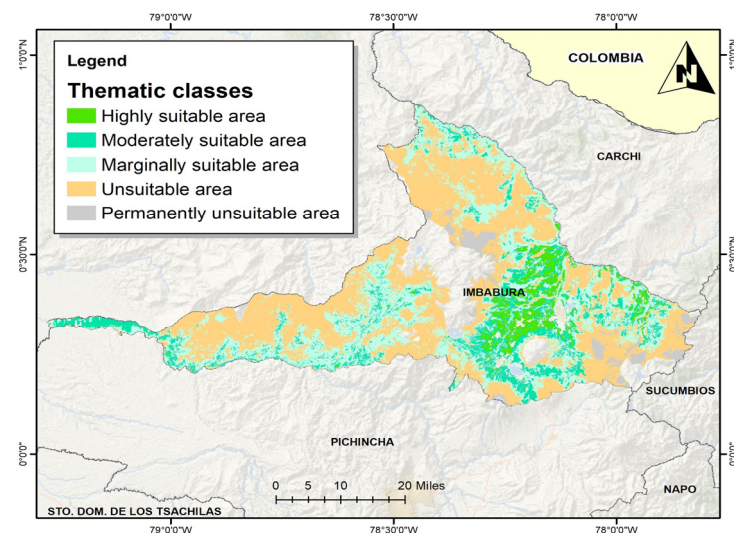


Figure 6. The suitability map for the potential expansion of protected agriculture in Imbabura, Ecuador, based on the GIS-AHP method.

Figure 6 categorizes areas of the territory into five classifications: highly suitable (HSA), moderately suitable (MoSA), marginally suitable (MaSA), unsuitable (US), and permanently unsuitable (PUA). The total analyzed area in Imbabura covers approximately 471,010.91 hectares, with only 4.4% (20,761.64 ha) classified as highly suitable for the expansion of protected agriculture.

A detailed analysis by canton (see Table 6) indicates that Ibarra and Urcuquí contain the most significant areas of highly suitable land, measuring 5497.51 hectares and 5182.61 hectares, respectively. This distribution likely results from a favorable combination of water availability, road access, and topographic conditions in these cantons. Furthermore, Cotacachi and Otavalo have significant areas of moderately suitable land that could be considered for future agricultural development, provided that appropriate technical and management conditions are met.

Table 6. Surface area available for the potential expansion of protected agriculture by cantons in Imbabura based on the GIS-AHP model.

Thematic Classes	Surface Area per Canton (ha)							%
	Antonio Ante	Cotacachi	Ibarra	Otavalo	Pimampiro	Urcuquí	Total	
HSA	3707.51	3485.74	5497.51	1188.66	1699.61	5182.61	20,761.64	4.4
MoSA	1691.94	16,444.48	12,337.95	9642.02	3308.96	5422.76	48,848.11	10.3
MaSA	1392.15	54,087.71	37,564.97	16,254.55	9259.25	15,833.06	134,391.69	28.5
US	144.33	75,708.34	48,266.54	17,255.49	16,480.37	38,206.01	196,061.08	41.6
PUA	1270.11	31,730.3	6864.49	5432.96	13,573.87	12,076.66	70,948.39	15.0
TOTAL	8206.04	181,456.57	110,531.46	49,773.68	44,322.06	76,721.1	471,010.91	100.0

The spatial distribution of suitability categories suggests that territorial planning should focus investments and production projects in areas deemed highly and moderately suitable. In contrast, marginally suitable and unsuitable regions may need targeted interventions for improvement or conservation.

3.2. Maxent Modeling for a Possible Expansion of Agricultural Greenhouses in Imbabura

The MaxEnt model evaluates the relative contributions of environmental variables through two complementary methods. The first method monitors the increase in regularized gain during each iteration of the training algorithm, attributing this increase to the corresponding variable or subtracting it if the absolute value of lambda decreases. The second method, known as permutation importance, involves randomly shuffling the values of each variable across both presence and background training data. The model is then re-evaluated to assess the resulting decrease in training AUC, which is normalized and expressed as a percentage (see Table 7).

Table 7. Estimated relative contributions of variables to the MaxEnt model.

Variable	Percent Contribution	Permutation Importance
V1	1	0.5
V2	88.7	93
V3	6.4	4.6
V4	0.2	0.1
V5	0.5	0.6
V6	1.9	0.2
V7	0	0
V8	0.2	0
V9	0.6	0.3
V10	0.5	0.2
V11	0.1	0.4

Both methods consistently identify the distance to existing greenhouses (V2) as the most influential variable, with a percent contribution of 88.7% and a permutation importance of 93%. This suggests that proximity to existing greenhouse infrastructure is the

primary factor influencing suitability in this model. In contrast, all other variables contribute less than 7% individually, with their combined contribution remaining below 15%, highlighting a significant disparity in the influence of the different predictors (see Table 7).

To enhance the understanding of these results, a comparative bar chart was created to visualize both the percentage contribution and permutation importance of each variable (Figure 7). The chart highlights the significant dominance of the variable “distance to greenhouses” (V2), reinforcing its crucial role in predicting suitable areas for protected agriculture within the MaxEnt framework. The marked difference in relative weights emphasizes the model’s sensitivity to spatial autocorrelation, as it relies on presence-only data and inherently prioritizes proximity-based patterns.

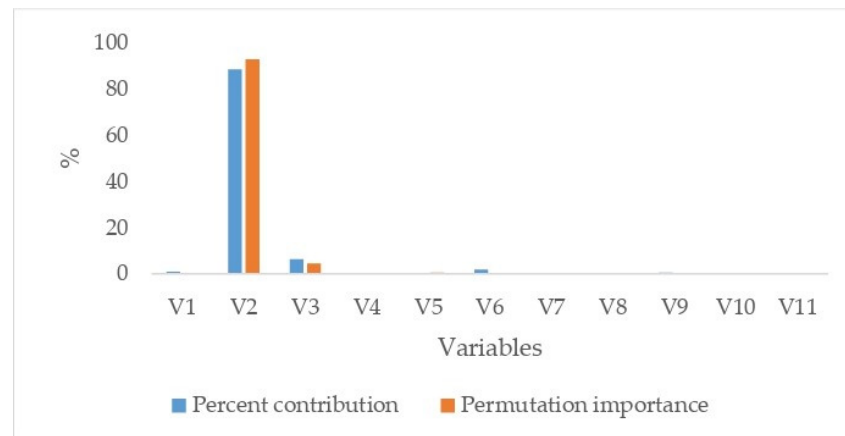


Figure 7. The relative contribution of variables to the MaxEnt model for predicting territorial suitability for greenhouse expansion.

This visual representation confirms that the MaxEnt model places disproportionate emphasis on a single variable—distance to existing greenhouses—while largely downplaying other important ecological, topographic, and infrastructural factors. Consequently, although MaxEnt is effective at capturing spatial autocorrelation and presence-based distribution patterns, it may underrepresent the multifaceted and complex nature of agricultural suitability. Therefore, its use should ideally be complemented with additional multi-criteria decision-making tools or expert knowledge frameworks to ensure a more comprehensive evaluation.

The comparative analysis of Figures 5 and 7 reveals significant differences in how each model interprets the relative importance of environmental and infrastructural variables for greenhouse expansion suitability. In the GIS-AHP model (Figure 5), a more balanced weighting is observed across multiple variables, with land cover/use (V3), irrigation availability (V1), and proximity to existing greenhouses (V2) being the most influential. This distribution reflects a broader and more integrative approach that considers biophysical, ecological, and logistical factors in assessing spatial suitability. In contrast, the MaxEnt model (Figure 7) assigns overwhelming importance to a single variable—distance to greenhouses (V2)—with a contribution exceeding 88% in both training gain and permutation importance. This disparity underscores the differing nature of the two modeling approaches: while the GIS-AHP incorporates expert-based multi-criteria reasoning, MaxEnt is inherently driven by the spatial autocorrelation of presence-only data. These distinctions are critical for interpreting the results, guiding their application, and understanding their implications for land-use planning and policy development. The following section elaborates on these implications and the broader relevance of the findings.

The territorial suitability map generated by the MaxEnt modeling approach (Figure 8) employs a classification scheme similar to that of the GIS-AHP model. Still, it identifies a

notably smaller portion of the province as highly suitable—only 1.2% (5618.15 ha) of the total area.

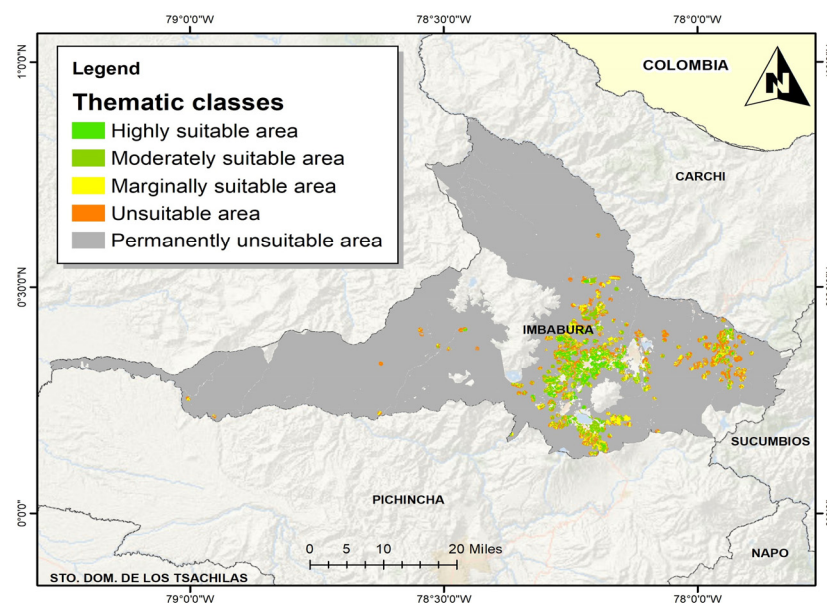


Figure 8. The suitability map for the potential expansion of protected agriculture in Imbabura, Ecuador, using the MaxEnt method.

The significant reduction observed in the analysis is due to MaxEnt’s strong dependence on proximity to existing greenhouse locations. This reliance limits the spatial extent of highly suitable areas compared to the more balanced approach of considering multiple variables in the GIS-AHP model. The map clearly shows that MaxEnt’s spatial predictions are focused around existing infrastructure, revealing distinct spatial distribution patterns when compared to those generated by the GIS-AHP.

Table 8 presents potential areas for expanding protected agriculture by canton within Imbabura based on the results from the MaxEnt model. This distribution reveals notable differences in suitability across the cantons, which reflects the model’s emphasis on proximity to existing greenhouses. These spatial variations provide valuable insights for targeted planning and resource allocation at the local level.

Table 8. The surface area available for the potential expansion of protected agriculture by cantons of Imbabura based on the MaxEnt model.

Thematic Classes	Surface Area per Canton (ha)							%
	Antonio Ante	Cotacachi	Ibarra	Otavallo	Pimampiro	Urcuquí	Total	
HSA	1898.46	1394.89	844.13	997.38	290.53	192.76	5618.15	1.2
MoSA	950.06	1782.79	1150.80	2296.57	974.91	1500.28	8655.41	1.8
MaSA	864.35	1329.74	1193.25	2287.75	1328.93	1572.34	8576.35	1.8
US	814.10	2132.76	1971.52	1916.00	2823.67	1592.79	11,250.84	2.4
PUA	11,855.77	152,958.75	109,552.49	46,691.51	40,531.87	75,319.77	436,910.16	92.8
TOTAL	16,382.74	159,598.93	114,712.19	54,189.20	45,949.90	80,177.95	471,010.91	100.00

Based on the canton-level data shown in Table 8, Antonio Ante and Cotacachi have the largest areas classified as highly suitable. However, these values are significantly lower than those predicted by the GIS-AHP analysis. Additionally, a substantial portion of the territory (92.8%) is classified as permanently unsuitable, highlighting considerable limitations throughout the province according to this modeling approach.

3.3. Suitability of Existing Greenhouse Locations

Utilizing the georeferenced database comprising 1958 greenhouses in Imbabura [48], this study evaluated the distribution of greenhouses based on the suitability classes produced by both models (Table 9).

Table 9. Suitability classes of the territory where greenhouses are located in Imbabura.

Thematic Classes	Number of Greenhouses GIS-AHP	%	Number of Greenhouses MaxEnt	%
HSA	1281	65.4	750	38.3
MoSA	552	28.2	626	32.0
MaSA	81	4.1	400	20.4
UA	8	0.4	163	8.3
PUA	0	0	19	1.0
Missing data	36	1.8		
TOTAL	1958	100	1958	100

The results indicate a consistent outcome across the different methodologies employed, as most greenhouses are found within the highly and moderately suitable categories. However, the GIS-AHP model identified eight greenhouses located in areas classified as unsuitable. Upon further investigation of the individual factors, it was determined that two of these greenhouses are situated in Pimampiro on very steep slopes exceeding 70%. The remaining six are located in Urcuquí, also on very steep slopes of over 70%, and within conservation or protection zones. These conditions account for their classification as unsuitable areas.

Additionally, data was lost for 36 greenhouses located in areas excluded from the analysis, such as urban areas and conservation or reserve zones. Consequently, they cannot be included in the suitability classifications.

These findings provide the empirical basis for the following discussion section, in which the implications, limitations, and potential applications of both models for territorial planning and policy development are further examined.

4. Discussion

The global context underlying this study is clear: to meet the anticipated food demand by 2050, global agricultural production needs to increase by approximately 70% [73]. However, conventional industrial farming systems are increasingly struggling to provide healthy and safe products while minimizing their environmental, health, and social impacts [23]. In response to these challenges—driven by factors such as climate change, decreasing arable land, water scarcity, and rapid population growth—a global shift toward protected agriculture (PA) is occurring [74], positioning it as a viable alternative for sustainable intensification.

This study's spatial analysis provides compelling evidence that Imbabura has significant potential for the expansion of PA, particularly in areas classified as highly suitable. The GIS-AHP model identified key drivers of suitability that align with findings from other global contexts. For instance, in Nigeria, agricultural expansion was primarily influenced by proximity to cities and water sources, soil depth, and pH levels [75]; in Oman, distance to roads was a statistically significant factor for greenhouse distribution [76]; while in China's Shaanxi Province, government policy and economic profitability guided expansion, favoring areas near rural roads, rivers, and high-altitude zones [32]. Consistent with these cases, the current study confirmed that accessibility to infrastructure and natural resources is crucial in determining agricultural viability in mountainous Andean regions.

The MaxEnt model further validated these findings by identifying “distance to greenhouses” as a key predictor of suitability. This aligns with observations in Spain, where regions historically concentrated on greenhouses are more likely to expand due to favorable environmental and infrastructural conditions [67]. Similarly, in Dongtai, China, greenhouse clusters have been shown to positively influence the accuracy of spatial predictions, reinforcing the notion that existing cultivation patterns can accelerate territorial diffusion [77].

Despite its potential, several challenges must be addressed to ensure the sustainable and equitable expansion of protected agriculture (PA) in Imbabura. Countries such as Spain (Almería), Italy (Sicily), Turkey (Antalya), and China (Shandong) have successfully shown the viability of sustainable greenhouse agriculture. However, the context in Latin America presents unique limitations. These include weak technology transfer mechanisms between academia and the private sector, a limited entrepreneurial ecosystem, high initial investment costs, and unreliable energy infrastructure [23]. Therefore, public policies and tailored support mechanisms are crucial for promoting scaling, particularly among smallholder farmers [24,78,79].

Imbabura presents both opportunities and challenges. Low-tech greenhouses and a high prevalence of small-scale, family-run farms characterize the province. In this context, PA can play a key role in enabling year-round production, enhancing food system resilience, and reducing dependence on imports—an especially valuable benefit in highland areas with variable agroclimatic conditions [80]. However, the high costs of infrastructure and maintenance—even for basic low-tech systems—can hinder adoption, particularly for resource-constrained producers, thus affecting the economic accessibility component of food security [81].

Environmental concerns also arise. Improper disposal of plastics and construction waste can create new sustainability issues if not managed within a circular economy framework. Mechanisms that enforce producer responsibility and recycling incentives must be implemented to mitigate these externalities [82]. Furthermore, excessive or poorly managed chemical inputs in protected cultivation systems may contribute to groundwater contamination. This emphasizes the need for multi-objective public policies and the use of agro-environmental indicators to guide safe development [83].

Additionally, spatial differences in suitability highlight the importance of targeted planning. Areas that are highly suitable for PA are typically characterized by favorable features, such as proximity to roads and greenhouses, water sources, moderate elevation, and gentle slopes—factors that collectively enable both agroecological viability and logistical accessibility [52,84]. Conversely, less suitable zones tend to be environmentally fragile or constrained by steep slopes and poor access. These findings are crucial for designing land-use strategies that balance productive development with ecosystem preservation [85,86].

Land-use competition presents another critical issue. Many areas suitable for PA also serve as strategic reserves for urban expansion, a trend observed in other rapidly urbanizing countries [87]. Water availability further limits sustainability, reinforcing the need to integrate PA expansion with broader watershed and land governance strategies [88].

Barriers to the large-scale adoption of protected agriculture include inadequate greenhouse designs that do not fit local bioclimatic conditions, limited availability of adapted seeds, insufficient technical capacity for greenhouse management, high electricity tariffs, restricted access to credit, and a lack of coordination among government programs and local enterprises [89]. In addition to these technical and economic challenges, sociocultural factors such as the age of farmers, their educational levels, household income, and access to training also influence the likelihood of adoption [90–92].

Furthermore, food localization strategies and agricultural extension services can facilitate expansion by promoting self-sufficiency and the sustainability of local food systems. While this study identifies areas that are highly suitable for protected agriculture, it is essential to emphasize that such cultivation remains input intensive and requires careful and inclusive incentivization. With the right combination of public investment, accessible financing, localized innovation, and strategic governance, protected agriculture can be a significant driver of agricultural transformation in Ecuador and the broader Andean region, greatly enhancing national food security, climate resilience, and territorial equity [93–96].

The integration of sustainability indicators into land-use planning has been emphasized as a strategy to mitigate climate change [97]. Although the referenced study focuses on forest management using life cycle assessments, it underscores the need for spatially informed strategies, which aligns with our GIS-AHP- and MaxEnt-based analysis of protected agriculture.

A similar method was employed in a previous study that combined the Analytic Hierarchy Process (AHP) with Ordered Weighted Averaging (OWA) to assess the suitability of territorial development based on various decision-making preferences in Ezhou, China [98]. Their research emphasizes that zoning based on sustainability and ecosystem service values can effectively inform land-use planning, thereby supporting the relevance of our GIS-AHP methodology. Although used in a different geographic and agricultural context, this methodology also aims to enhance decision-making by integrating environmental, farming, and infrastructural variables under sustainability criteria.

In the AHP model, the weights for the evaluation criteria were determined through expert judgment based on pairwise comparisons. However, other weighting techniques, such as the Delphi method, fuzzy AHP, or group decision-making models, could also be applied. These alternatives allow for more participatory approaches or frameworks that account for uncertainty. Future studies could benefit from incorporating fuzzy logic or ensemble modeling techniques to address uncertainties better and capture the complex, multidimensional aspects of greenhouse site suitability [99].

5. Conclusions

Protected agriculture (PA) presents a promising alternative to traditional open-field farming, with the potential to enhance food security, improve resource efficiency, and support climate change adaptation. This study, conducted in the Andean province of Imbabura, Ecuador, identified areas with high and moderate suitability for the expansion of PA through a comparative analysis of GIS-AHP and MaxEnt modeling approaches.

The GIS-AHP model effectively integrated expert-based criteria and spatial variables, allowing for a nuanced and balanced identification of suitable areas. In contrast, the MaxEnt model focused on the probabilistic influence of greenhouse proximity, offering a data-driven perspective that was somewhat narrower. The spatial outputs showed that highly suitable zones are typically characterized by access to water, roads, moderate slopes, and existing greenhouse clusters—factors that support both agroecological viability and logistical feasibility.

To translate these findings into sustainable development strategies, we recommend the following: (1) integrate suitability maps into cantonal and provincial land-use planning instruments; (2) promote targeted public investment and technical assistance in areas of high suitability; (3) strengthen local governance mechanisms to ensure that expansion aligns with environmental thresholds and social equity goals; and (4) develop financing instruments tailored for smallholder farmers, adapted to local agroclimatic conditions.

By combining expert knowledge with presence-based modeling, this study provides a replicable methodological framework that supports evidence-based decision-making

for greenhouse agriculture in mountainous regions. The findings contribute not only to territorial planning but also to the formulation of policies that balance food production, environmental sustainability, and rural development within the framework of Sustainable Development Goal 2 (SDG 2).

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Data Availability Statement: The data from this study is available in digital format, including the 11 variables used and the results of the two applied models.

Conflicts of Interest: The authors declare no conflicts of interest.

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