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Potential Coffee Distribution in a Central-Western Region of Mexico

Armando Avalos Jiménez *, Susana María Lorena Marceleño Flores, Oyolsi Nájera González and Fernando Flores Vilchez

Secretaría de Investigación y Posgrado, Universidad Autónoma de Nayarit, Ciudad de la Cultura s/n, Col. Centro, Tepic C.P. 63000, Mexico; susana.marceleno@uan.edu.mx (S.M.L.M.F.); oyolsi92@gmail.com (O.N.G.); vilchez@hotmail.com (F.F.V.)

* Correspondence: armand18_a@hotmail.com; Tel.: +52-311-122-8848

Abstract: Currently, there is a world coffee production crisis which has been attributed, among other factors, to the COVID-19 pandemic that affected the development of productive agricultural activities. In this scenario, Mexico is in a declining situation by showing a reduction in coffee production areas in recent years. Therefore, it is necessary to promote actions that contribute to the recovery of the resource, particularly in the states with agricultural potential. In the present work, the potentially suitable areas for coffee cultivation are identified through the application of tools that allow for characterizing the biophysical conditions that define the current spatial distribution and, from the analysis of these characteristics, generate a Potential Distribution Model (PDM) of the suitable zones for coffee production. The methodology was developed through the application of the Maximum Entropy (MaxEnt) algorithm, starting with the collection and preparation of coffee presence records, followed by a correlation analysis and identification of significant variables, the subsequent execution of the model in various configurations to observe the contribution of each variable through a jackknife test, and finally validation of the model with a random sample selection of 30%, to achieve an AUC of 0.98 and TSS of 0.96. The present model was able to identify and quantify the environmentally suitable zones for coffee production, highlighting the regions with ideal potential for the specie. These results are intended to serve as a basis for the generation of planning strategies aimed at managing, improving, and increasing coffee production areas, as well as being used to establish biological corridors to promote biodiversity, conservation, and alternative economic activities such as tourism and furthermore for future work on the analysis of production scenarios and impacts of climate change. It is concluded that 30% of Nayarit's territory has ideal conditions for coffee cultivation, especially the region delimited by the municipalities of Tepic and Xalisco, the eastern zone of Compostela, and the southwest of San Blas, which should be considered as a Priority Conservation Area (APC) for coffee cultivation in the state.

Keywords: MaxEnt; Species Distribution Models (SDMs); Nayarit

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1. Introduction

Coffee (*Coffea arabica* L.) is one of the main consumer products marketed worldwide due to its high energy value associated with caffeine. This last component is classified as a stimulant of the central nervous system that produces a temporary effect of sensory activation in small doses that makes it preferred by the population, to the extent that currently there is a world average consumption of 1.8 kg of coffee per capita [1]. It is the second-most traded commodity after oil, fluctuating on the main stock exchanges such as the New York Stock Exchange [2] and being of great economic, sociocultural, and environmental importance for most producing countries [3].

Just a couple of decades ago, and particularly since 2008, coffee production worldwide maintained an upward trend, on par with international consumption which was also at its maximum levels, increasing at an average annual rate of 2.80% [4]. By 2018, production reached its historical maximum in the last 20 years with a production of 10. 5 million tons of coffee, with Brazil being the main producer with more than 37% of world production, followed by Vietnam with a little more than 17% and Colombia with 8%; by this time, Mexico occupied the eighth place in world production with 2.4% according to data from the International Coffee Organization (ICO) [1].

The current situation of world production can be inferred from the most recent data of the ICO, which, for the year 2020, recorded a production of 9.9 million tons of coffee in the world, where only Brazil, Vietnam, Colombia, and Indonesia contributed 70% of total production. Since then, Brazil has stood out as the largest producer and exporter of coffee, but, in recent years (with respect to 2018), has reduced its production, reaching 33% of production. In second place is Vietnam [5], with 17% of world production, almost the same amount that is exported. In this same tenor is Mexico where, although its contribution is minimal compared to the main producers, it is of great relevance for the country, because, although it occupies the ninth place, it contributes a production of 2.3%, corresponding to almost 240 thousand tons of coffee; and it is in the eleventh place in exports, with an amount of 177 thousand tons, equivalent to more than 2% of world exports [1].

Coffee production is one of the main agricultural activities in Mexico [2], considered of great economic, sociocultural, and environmental importance [3,6,7], integrating into different production chains for the creation of employment and contribution to the economy with the generation of foreign exchange [8] that allows the subsistence of many small producers. In addition to a high economic value, coffee production has an important contribution in environmental matters as it is a species that, when developed in shaded systems, maintains an almost permanent vegetation cover on the soil with its cultivation [9], which provides important ecosystem services by reducing soil erosion problems, contributing to the conservation of biological diversity [10,11] and serving as a refuge for wildlife [12,13] by propitiating water infiltration for groundwater recovery and soil conservation [14,15], as well as favoring carbon sequestration [16,17] and oxygen production, among other effects.

In spite of the positive aspects that these data may represent, it has recently been highlighted that there is a coffee production crisis in the world that has been mainly attributed to the COVID-19 pandemic that affected the development of most of the agricultural productive activities [18–20]. In Mexico, the production is currently in a situation of decadence due to the reduction in the amount of coffee production areas observed in recent years. In view of this scenario, it is necessary to promote actions that contribute to the recovery of the resource, it being essential to identify the zones that are adequate (suitable habitats) and that provide the necessary environmental conditions and characteristics for coffee production, in order to subsequently establish planning strategies focused on managing, improving, and increasing productivity.

The combination of all these economic, social, and environmental benefits generated by coffee cultivation and the downward trend in its production makes it necessary to contribute to the recovery of the resource, and, therefore, it is essential to have spatial information that reflects the areas that are potentially suitable in the central–western region of Mexico for coffee production and whose zoning characteristics should be assessed before they are lost. In this sense, the Species Distribution Models (SDMs) have represented a good approximation to find the regions of suitable habitat for the survival of a species, contemplating the environmental conditions in which they subsist [21].

SDMs base their principles on the concept of the Ecological Niche (EN), first introduced by Evelyn Hutchinson in 1957 as the set of biotic and abiotic conditions with which the species is related, allowing its existence in a given region [22], involving all the resources present for its development. In this context, ecological niche models and SDMs have similarities: on the one hand, the former relate environmental components and presence, presence–absence, and/or abundance data [23], while SDMs relate field observations with predictive environmental variables [24], based on a statistical response [21]. These have been widely used in the scientific community due to their efficiency in predicting the geographic distribution and exploring the preferred habitat of species [25], so a large number of them have been developed; among the most-used are statistical models: generalized linear models (GLM) and generalized additive models (GAM); heuristic models such as climate envelope (BIOCLIM); or others based on artificial intelligence techniques [26] and genetic algorithms for rule prediction (GARP) [27], as well as the MaxEnt model. The latter has gained popularity for being a machine learning method that has given better results and efficiency in model execution [28], offering advantages over the others by requiring only presence data (known distribution records) and layers of information on the environmental conditions of the area of influence of the known sites, with the objective of predicting the suitability of the environment for the specie based on their ecological niche [21].

MaxEnt is an algorithm used to estimate the probability of species distribution through the principle of MaxEnt, which was developed by [29], and is based on statistical procedures from real observational data on the presence or abundance of species, which it uses to infer potentially suitability according to their environmental characteristics, thus representing the suitability of a space for the presence of a species according to the variables used. This suitability is given by the mathematical relationship between the actual known distribution and the set of independent variables used as indicators. The model can generate response curves for each of the variables and estimate the importance or contribution of each of them in the distribution, as well as evaluating the effectiveness of the model.

The use of the MaxEnt model has been widely used in the scientific literature for a variety of applications, including: for determine the potential distribution of species [30], of both flora and fauna, to identify variables that determine suitable areas for species survival and conservation in predicting spatial patterns of biodiversity [31–36], in scenario analyses in the face of climate change [37–40] and prediction of its impact on species distribution [31–46], to determining the distribution of terrestrial reptiles [47], and in ecological niche studies [48], as well as to determine the potential distribution of pest or invasive species, as in [49–51]. The algorithm was also used by [52] to predict suitable habitat for the endangered tree *Canacomyrica montícola* and in Colombia for the species *Pleurozia paradoxa* [53], among many others.

In Mexico, these models have shown their capacity to be used to evaluate the distribution risk of diseases such as dengue [54]; to establish conservation proposals under climate change scenarios [55]; to predict the potential distribution of species such as the jaguar, the Mesoamerican tortoise, and species of forest interest of the genus Pinus [56–58]; for modeling the ecological niche of pine (*Pinaceae*) [23,55]; for modeling cyanobacteria and phytoplankton distribution [59,60]; and for modeling the distribution of plants such as *Cuphea aequipetala* Cav. (*Lythraceae*) [61], Cedro (*Cedrela salvadorensis*) [62], and avocado (*Persea Mill*) [63], among others.

Therefore, the objective of this work was to model the potential distribution of coffee by using the MaxEnt algorithm to characterize the biophysical conditions of the current distribution of coffee production and determine the potentially suitable areas. The methodology was developed from the collection and preparation of coffee presence data to subsequently running the model in different configurations to observe the contribution of each of the variables through the jackknife test. Consecutively, the necessary modifications were made to obtain the best fit of the model. Finally, it was validated with random selection of 30% of the coffee records of the sample to obtain the AUC (Area Under the Curve) and TSS (True Skill Statistics) with the best fit values.

2. Materials and Methods

2.1. Study Area

The study area was focused on the state of Nayarit located in the central western region of the United Mexican States (Mexico), bordering the states of Sinaloa and Durango to the north and Jalisco to the south-southeast, and also bordering the Pacific Ocean to the west as shown in Figure 1. The entity is divided into 20 municipalities with a land area of 27,888 km^2 and a population of 1,235,456 inhabitants [64].

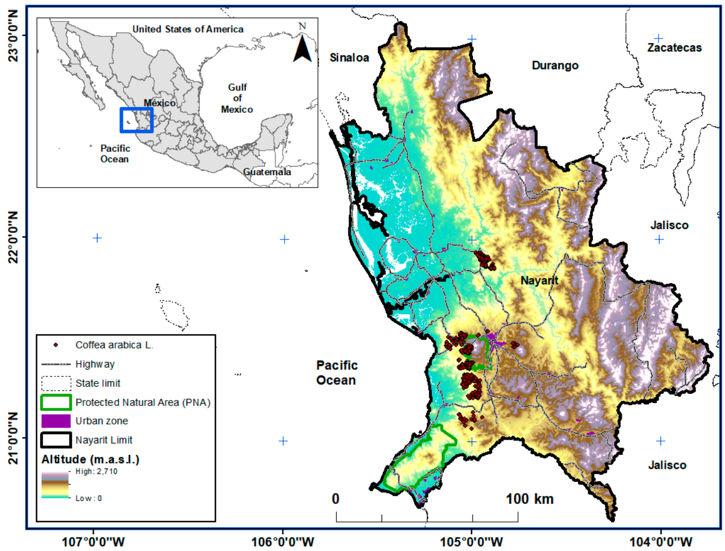

Figure 1. Location of the study area. Source: own elaboration. Has data from INEGI, (2019).

The study area focused on the central western region and particularly on the state of Nayarit from where the data were obtained, which is in the United Mexican States (Mexico) and borders the states of Sinaloa and Durango to the north and Jalisco to the south-southeast, also bordering the Pacific Ocean to the west as shown in Figure 1. The entity is divided into 20 Municipalities with a territorial extension of 27,888 km^2 and a population of 1,235,456 people [64].

The study area is characterized in biophysical terms by being located between 104° and 106° north latitude and 21° and 23° west longitude, in an altitudinal range that goes from 0 to 2710 m above sea level (m.a.s.l.). It is among the states with the highest precipitation at the national level, with an annual average of 1200 mm, and has a warm sub-humid climate with summer rains. These and other factors together create a mosaic of landscapes that are ideal for a large number of species of flora and fauna, including coffee.

According to data obtained for the year 2020, the main coffee producers in Mexico were Veracruz, Chiapas, and Jalisco with almost 45% of the total planted area in the country. In 2020, coffee production in Mexico reached a planted area of almost ninety thousand km^2 [65]. Currently, Nayarit is in a declining situation in coffee production, due to the reduction of planted area that has been occurring in recent years, according to records of the Ministry of Agriculture and Rural Development (SAGARPA). In 2012, there was a planted area of 162.46 km^2, but this situation worsened by the year 2020, with only 33 square kilometers for the entire state, representing a reduction of almost 80% in a period of 8 years. If this trend continues, by 2030 there will only be 6 km^2.

2.2. Presence Records Data

The starting point was the database of coffee presence records obtained through field visits, through interviews with producers, and with reference to the database provided by SAGARPA composed of 1658 records with three varieties of coffee of the *Coffea arabica L.* species: Typica (1604 records), Caturra (44 records), and Mundo Novo (10 records). Each record indicates the coordinate of the centroid of a polygon of land where coffee was observed.

2.3. Environmental Data

On the other hand, a set of 19 climatic variables were obtained from the WorldClim global meteorological and climatic database of high spatial resolution, which were downloaded from the web page (https://www.worldclim.org/, accessed on 20 November 2022), as well as the construction of seven other environmental variables obtained in a local representation and which are determinants for coffee production, finally resulting in a set of 26 variables described in Table 1.

Table 1. Coffee species presence and environmental variables used in the coffee distribution model.

Factor	Component	Key	Variable	Description	Unit
Species	Coffe		Coffee presence records (Dependent variable)	Centroids of the areas where there is coffee production	-
Climatic	Temperature	Bio1	Average annual temperature	Represents the average temperature throughout the year	°C
		Bio2	Mean of the diurnal range. Monthly average (max temp–min temp)	Identifies diurnal temperature fluctuations	-
		Bio3	Isothermality (Bio2/Bio7)(×100)	Describes the magnitude of temperature swings between day and night relative to the annual temperature range	-
		Bio4	Temperature seasonality (Standard deviation ×100)	Indicates peak periods between temperature ranges	-
		Bio5	Maximum temperature of the warmest month	Represents the highest temperature in the warmest month	°C
		Bio6	Minimum temperature of the coldest month	Represents the lowest temperature in the coldest month	°C
		Bio7	Annual temperature range (Bio5-Bio6)	Shows the ranges of extreme temperature conditions	°C
		Bio8	Average temperature of the most humid room	Describes the average temperature of the quarter of the year with the highest humidity	°C
		Bio9	Average temperature of the driest quarter	Indicates the average temperature of the driest quarter of the year	°C
		Bio10	Average temperature of the warmest room	Describes the average temperature of the warmest quarter of the year	°C
		Bio11	Average temperature of the coldest room	Represents the average temperature of the coldest quarter of the year	°C
	Precipitation	Bio12	Annual precipitation	It represents the frequency and amount of rainwater that falls on a specific place throughout the year.	mm
		Bio13	Rainfall of the wettest month	Represents the frequency and amount of rainfall falling on a specific location in the wettest month.	mm
		Bio14	Rainfall of the driest month	Represents the frequency and amount of rainfall falling on a specific location in the driest month.	mm
		Bio15	Precipitation seasonality (coefficient of variation)	Indicates periods of precipitation variation	-
		Bio16	Rainfall from the wettest quarter	Represents the frequency and amount of rainfall falling on a specific location in the wettest month.	mm
		Bio17	Rainfall of the driest quarter	Describes the amount of precipitation during the driest quarter of the year.	mm
		Bio18	Precipitation from the warmest quarter	Shows the amount of precipitation during the warmest quarter of the year	mm
		Bio19	Coldest room precipitation	Characterizes the amount of precipitation during the coldest quarter of the year	mm
	Solar radiation	Bio20	Solar radiation	Indicates the energy emitted by the sun through space and reaching the ground	$kJ/m^2/day$
	Wind	Bio21	Wind speed	Describes the movement of air	m/s
	Humidity	Bio22	Water vapor pressure	Provides information on the saturation pressure of the water	kPa

Table 1. *Cont.*

Factor	Component	Key	Variable	Description	Unit
Physical	Altitude	Bio23	Altitude = Digital Elevation Model	Identifies the altitudinal range of the area	-
	Slope	Bio24	Slope = Digital Elevation Model	Describe the differences in slope	
Environmental	Vegetation and land use	Bio25	Coverage and land use	Indicates the different land uses existing in each site	-
	Floors	Bio26	Type of soil: Edaphology INEGI	Describes the type and composition of the soil	-

2.4. Methodology

The methodology was developed in three stages; the first consisted of the collection of records of the presence of coffee species and the preparation of the data for the execution of the ecological niche model through the MaxEnt algorithm; the model was then run in different configurations (variation of model parameters) to analyze the contribution of each of the variables through the jackknife test and the necessary modifications were made to obtain the best fit of the model; finally, it was validated with the random selection of 30% of the species sample to obtain the AUC and TSS with the best fit values. This whole process is described in Figure 2.

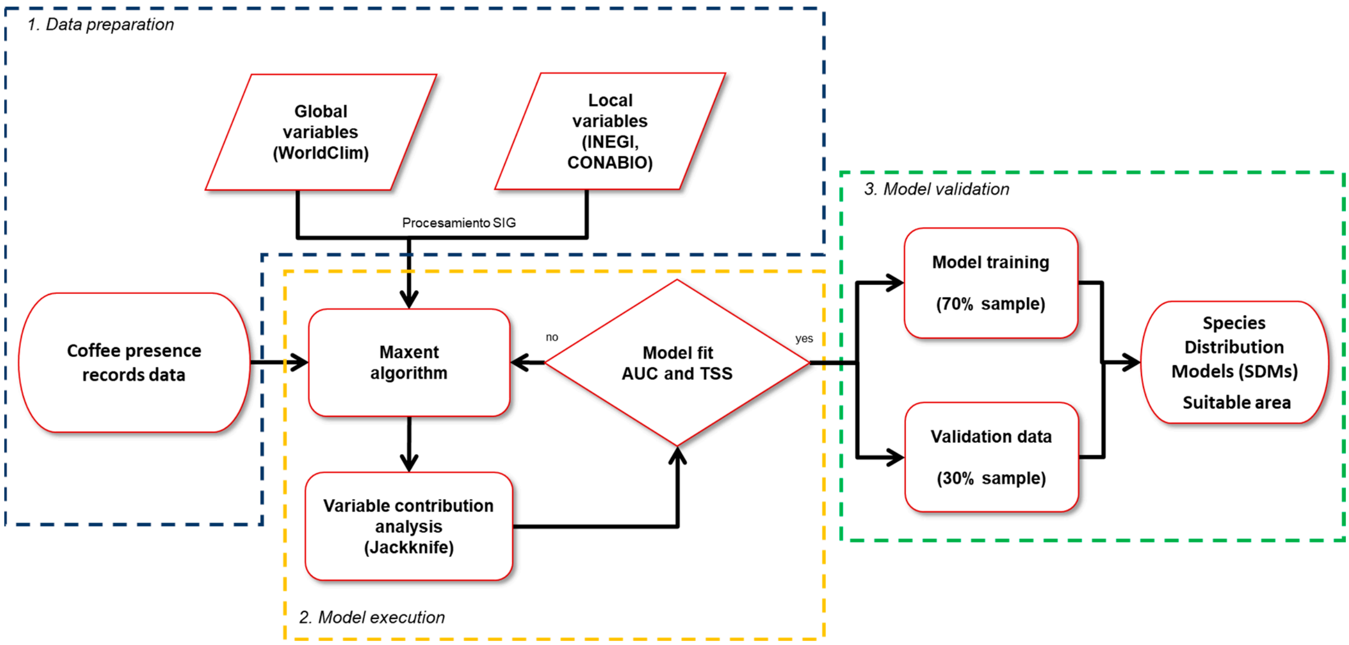

Figure 2. Methodological process for obtaining the species potential distribution model.

2.4.1. Data Preparation

The species distribution model is based on the analysis of data records of occurrence or presence of species. For this, data on the presence of coffee with georeferenced coordinates in UTM were obtained and represented through geographic information systems for a first observation of its spatial distribution. On the other hand, variables were obtained from the WorldClim database in GRID format and others were built from the elevation model for the study area, land cover, and land use.

All the variables were processed through ArcGIS 10.3; the information layers of the global variables were trimmed, projected, and resampled to the same spatial resolution for the study area and taken to ASCII format for execution in the MaxEnt model.

2.4.2. Variable Processing

Prior to the execution of the model, a first correlation analysis of the initial data was carried out using Pearson's (r) in order to discard the correlation between variables; when the coefficient of a pair of variables was r $\geq$ 0.85, only one variable of said pair was considered. Subsequently, a logistic regression analysis was performed to obtain those variables that condition the presence of coffee (significant variables) and that are statistically associated with the dependent variable (presence of coffee). The correlation and logistic regression analysis was developed through R in its version 3.4.1 [66], allowing us to determine the significant variables that influence the presence of coffee.

2.4.3. Execution of the Distribution Model

The MaxEnt Model, in its version 3.3 [21], was used to obtain the probability distribution and prediction of suitable areas for coffee cultivation in the study area. This model has been characterized as a powerful automatic learning tool that only requires presence data (known distribution records) and layers of information on the environmental conditions of the known sites for its execution [21]. From these data and by associating the variables that influence the presence of the species, it performs mathematical processing capable of estimating the probability of finding a suitable habitat [67]. The equation for determining the MaxEnt used by the model corresponds to the following [21,29].

$$H(p) = \sum\nolimits_{x \in X} p(x) lnp(x) \tag{1}$$

where "*In*" is the natural logarithm of the number of observations at x.

The execution of the model is simple and intuitive. On the one hand, the species of analysis was added, and on the other hand, the set of biophysical variables that influence its presence were added. Some configuration parameters were established both for the execution of the model and for obtaining the response curves and measurement of the variables through the jackknife test to produce the percentages of contribution and permutation of importance. The jackknife is added to Maxent's model in order to estimate the performance of the biophysical variables involved in the model and to determine their relative importance in the explanation of species occurrence and the amount of information explained by each independent variable [49,67].

Additionally, the threshold parameters (Threshold features) were considered to regularize the probability of the model as a function of the ranges of the variables and the hinge fit value (Hinge features) to regularize the falls of the prediction values, allowing for improvement of the value of the area under the curves (AUC) and the model fit. The logistic output type was also used to obtain the results in a raster-type probability image representing the probability in a range from 0 to 1 and show the species habitat suitability. All other settings were set to the default values by [21,68–70], with background values (maximum number of background points) of 10,000 because this is the value commonly used by some authors [34,37,47,50,68] and as the one that has been found to provide a better response to the TSS values; as well, number of iterations (maximum iterations) was 5000 and convergence (convergence threshold) was 0.00001.

2.4.4. Model Validation

The model validation was determined from several adjustments of the biophysical variables until the Receiver Operating Characteristic (ROC) was above 80% and the area under the curve (AUC) value was close to 1 [71]; these two parameters have been widely used in MaxEnt as measures of model accuracy and fit performance [72].

Likewise, to complement the degree of model validation, the TSS (True Skill Statistics) was obtained, whose interpretation is linked to the performance of the model through the association with the kappa statistic [73], where, like here, the TSS takes into account the errors of omission and commission to determine the degree of fit of the model [74].

The closer the values of the AUC and TSS statistics are to 1, the better the discrimination and the more accurate and informative the model. The AUC values are in the range of 0 to 1: an AUC greater than 0.5 shows that the prediction of the model is neither better nor worse than the random model (random probability); a value between 0.5 to 0.7 indicates poor performance; 0.7 to 0.9 represents moderate performance; and greater than 0.9 demonstrates excellent performance [49,75–77]. For TSS, the values range from 0 to 1, where 0 to 0.4 implies poor model performance, 0.4 to 0.5 depicts fair execution, 0.5 to 0.7 is an adequate fit, 0.7 to 0.85 is a very good fit, from 0.85 to 0.9 is an excellent model, and from 0.9 to 1 is an almost perfect model [78].

For the model validation, some configuration parameters were established through random seed analysis to generate the prediction and, at the same time, the validation of the model. A multiplier parameter (regularization multiplier) with a value of 1 was used to improve the visualization of the response curves and avoid hinges (falls of the curve), and a crossvalidate parameter was used to give preference in the prediction of the sites where the records of the coffee species are found. A total of 70% of the species presence data (1123 records) were used to train the model and the remaining 30% (481) was test data for validation; this sample was considered based on multiple authors such as [79], who indicated these ranges as adequate for model validation in this type of analysis.

2.4.5. Potential Coffee Distribution Map

The map was obtained using the logistic function of MaxEnt in order to generate the probability image with values in the range of 0 to 1, without scaling or exponentiating the values obtained. This image was exported to ArcGIS 10.3 for subsequent analysis of the classification of values and determination of the level of weighting of low, medium, and high suitability that represents the level of suitability for coffee production. Values were used indicating that a level above 0.5 represents a suitable habitat and a value of 1 characterizes a perfect habitat for the species, as according to multiple authors such as [49,67,79,80].

3. Results

The results of the correlation and logistic regression analysis obtained a set of 13 variables that are associated and statistically significant for the presence of coffee. The estimation parameters, standard error and probability value are shown in Table 2.

Table 2. Parameters estimated by the logistic regression method applied.

Clave		Coefficients Description	Estimate	Std. Error	z Value	Pr (>|z|)	
		(Intercept)	-5.30×10^{2}	8.31×10^{1}	−6.38	1.76×10^{1}	***
1	Bio1	Average annual temperature	-1.35×10^{1}	4.90×10^{0}	−2.76	5.88×10^{-3}	**
2	Bio2	Mean of the diurnal range. Monthly average (temp max–temp min)	-4.35×10^{1}	5.44×10^{0}	−8.00	1.20×10^{-15}	***
3	Bio3	Isothermality (Bio2/Bio7) (×100)	9.24×10^{0}	1.11×10^{0}	8.29	2.00×10^{-16}	***
4	Bio4	Temperature seasonality (Standard deviation ×100)	-1.91×10^{-1}	8.87×10^{-2}	−2.15	3.16×10^{-2}	*
5	Bio10	Average temperature of the warmest room	-1.14×10^{1}	3.95×10^{0}	−2.88	3.96×10^{-3}	**
6	Bio12	Annual precipitation	4.80×10^{-2}	2.70×10^{-2}	1.78	7.53×10^{-2}	*
7	Bio14	Rainfall of the driest month	-1.24×10^{0}	3.64×10^{-1}	−3.41	6.59×10^{-4}	***
8	Bio17	Rainfall of the driest quarter	-2.52×10^{-1}	1.16×10^{-1}	−2.18	2.91×10^{-2}	*
9	Bio18	Precipitation from the warmest quarter	5.32×10^{-3}	1.79×10^{-3}	2.98	2.93×10^{-3}	**
10	Bio20	Solar radiation	5.52×10^{-3}	1.90×10^{-3}	2.90	3.71×10^{-3}	**
11	Bio21	Wind speed	-1.33×10^{1}	1.30×10^{0}	−10.16	2.00×10^{-16}	***
12	Bio22	Water vapor pressure	-6.89×10^{1}	1.13×10^{1}	−6.10	1.06×10^{-9}	***
13	Bio23	Altitude = Digital Elevation Model	-4.15×10^{-2}	8.41×10^{-3}	−4.93	8.07×10^{-7}	***

***: $p < 0.001$; **: $p < 0.01$; y, *: $p < 0.05$.

From the logistic regression analysis, it can be inferred that there is a strong positive codependency of the dependent variable (presence of coffee) with the independent variables of isothermality (bio3), precipitation from the coldest room (bio18), and solar radiation (bio20), as well as a strong negative dependence on water vapor pressure (bio22), mean temperature of the daytime range (bio2), and altitude (bio23).

Figure 3 shows the sensitivity and specificity graph that quantifies the degree of fit of the model in the AUC value, indicating a model fit with a value of 99% in the training data and 98% for the test data, which was determined as an excellent model for predicting suitable habitats for the cultivation of the species [21].

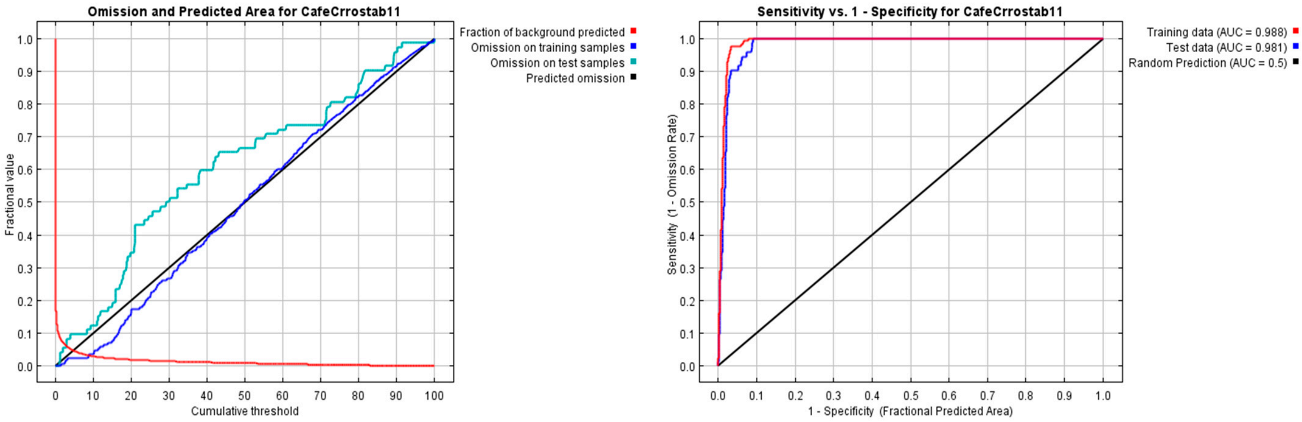

Figure 3. Omission and prediction curves of the model run in MaxEnt for the coffee specie.

The MaxEnt model was executed from the presence data with the biophysical variables, allowed generation of Table 3, which indicates the percentage contribution of each of the variables after running the jackknife test. The variable bio18, precipitation of the warmest quarter, has the highest contribution in the model with almost 33%, followed by bio3, isothermality, with 32% and bio23 with almost 13%, which together determine 77% of the contribution to the model.

Table 3. Contribution percentage and model importance permutation.

Key	Variable	Contribution (%)	Importance
Bio1	Average annual temperature	0.3	0.4
Bio2	Mean of the diurnal range. Monthly average (temp max − temp min)	0.4	0.8
Bio3	Isothermality [(Bio2/Bio7) ×100]	31.6	28.3
Bio4	Temperature seasonality (Standard deviation ×100)	0.4	0.6
Bio10	Average temperature of the warmest room	0.3	0.1
Bio12	Annual precipitation	1	0.4
Bio14	Rainfall of the driest month	1	0.1
Bio17	Rainfall of the driest quarter	8.7	4.8
Bio18	Precipitation from the warmest quarter	32.9	48.6
Bio20	Solar radiation	2	1.5
Bio21	Wind speed	2.3	3.2
Bio22	Water vapor pressure	6.6	10.6
Bio23	Altitude = Digital Elevation Model	12.4	0.6

This information is complemented with Figure 4, which shows the jackknife test indicating the contribution of each of the variables by itself and with respect to the performance of the model without/with the same variable. This was able to determine that most of the variables behave in a similar way except for bio3, which is the one that negatively affects the performance of the model (decreases the level of certainty of the model).

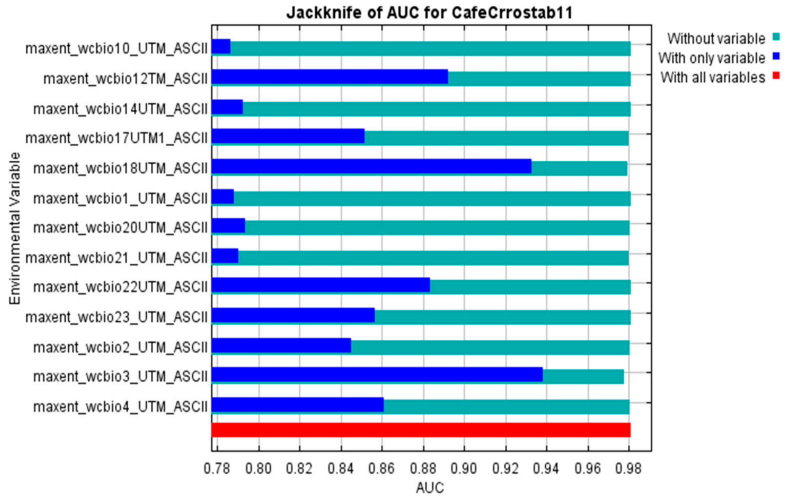

Figure 4. Jackknife test indicating contribution of variables.

The results of the jackknife evaluation yield the response curves of Figure 5, where only the variables with values greater than 10% of the model contribution are considered. It particularly indicates that the precipitation variable of the warmest quarter (bio18) determines that the probability of occurrence increases in places with high rainfall in the warmest quarter; that is, in the rainy season, for its part, bio3 implies that the probability of occurrence increases the higher the isothermal interval; that is, the species prefers sites with high thermal variation throughout the day and night.

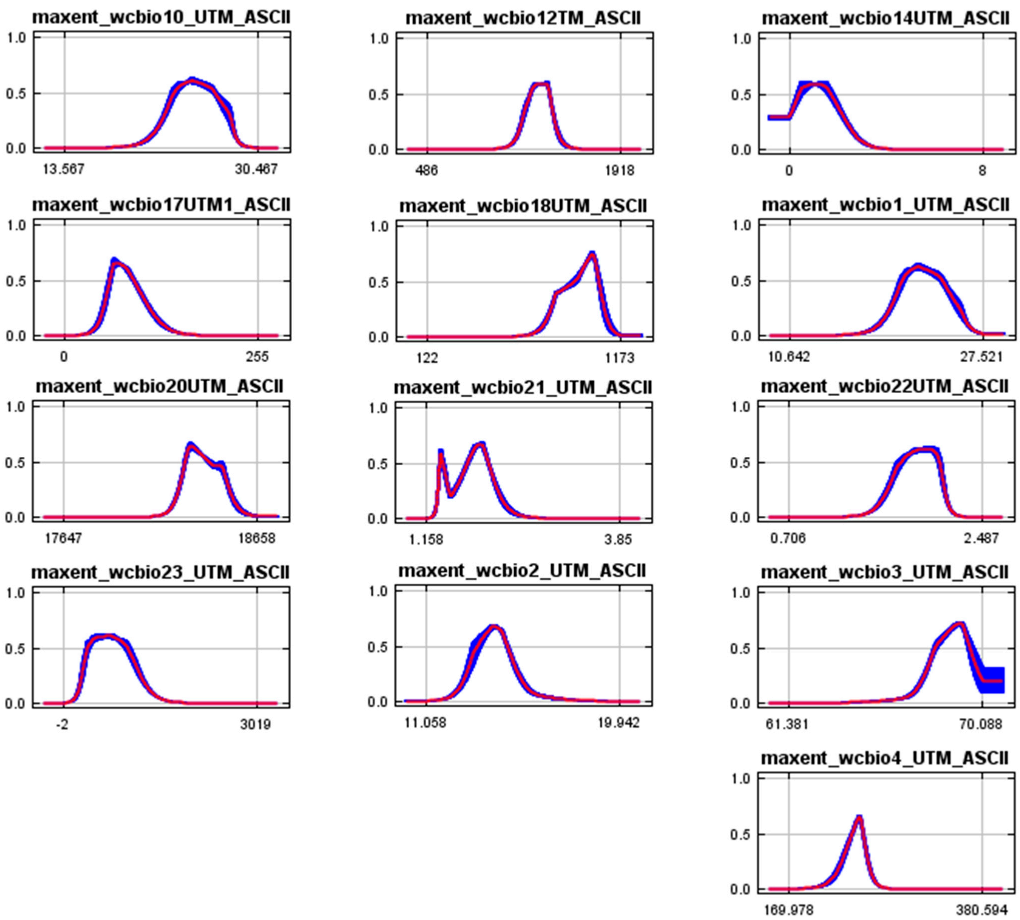

Figure 5. Response curves of the variables with values greater than 10% of the model's contribution.

From the response curves, it is possible to infer the ranges of the maximum probability values that are detailed in Table 4 and that define the behavior of the variables in determining the ideal habitat for coffee production.

Table 4. Ranges of variable values that determine the prediction of the ideal habitat for coffee.

Clave	Variable	Range
Bio1	Average annual temperature	20.8–22.2 °C
Bio2	Mean of the diurnal range	13.9–14.6 °C
Bio3	Isothermality	68.3–69.2
Bio4	Temperature seasonality	245–248
Bio10	Average temperature of the warmest room	23–26 °C
Bio12	Annual precipitation	1250–1350 mm
Bio14	Rainfall of the driest month	0.5–1.0 mm
Bio17	Rainfall of the driest quarter	60–80 mm
Bio18	Precipitation from the warmest quarter	1000–1010 mm
Bio20	Solar radiation	18,300–18,400 kj/m^2/day
Bio21	Wind speed	1.7–1.9 m/s
Bio22	Water vapor pressure	1.8–2.0 kPa
Bio23	Altitude	600–1000 m.a.s.l.

Potential Distribution Model (PDM)

The distribution model indicated in Figure 6 shows the probability of finding suitable habitat for the specie; the red color indicates a high probability of having adequate conditions for the cultivation and production of coffee; the orange and green colors show the typical conditions of those sites, in which there is a probability of cultivation of the species; and the light green tones indicate a low probability predicted to find the conditions.

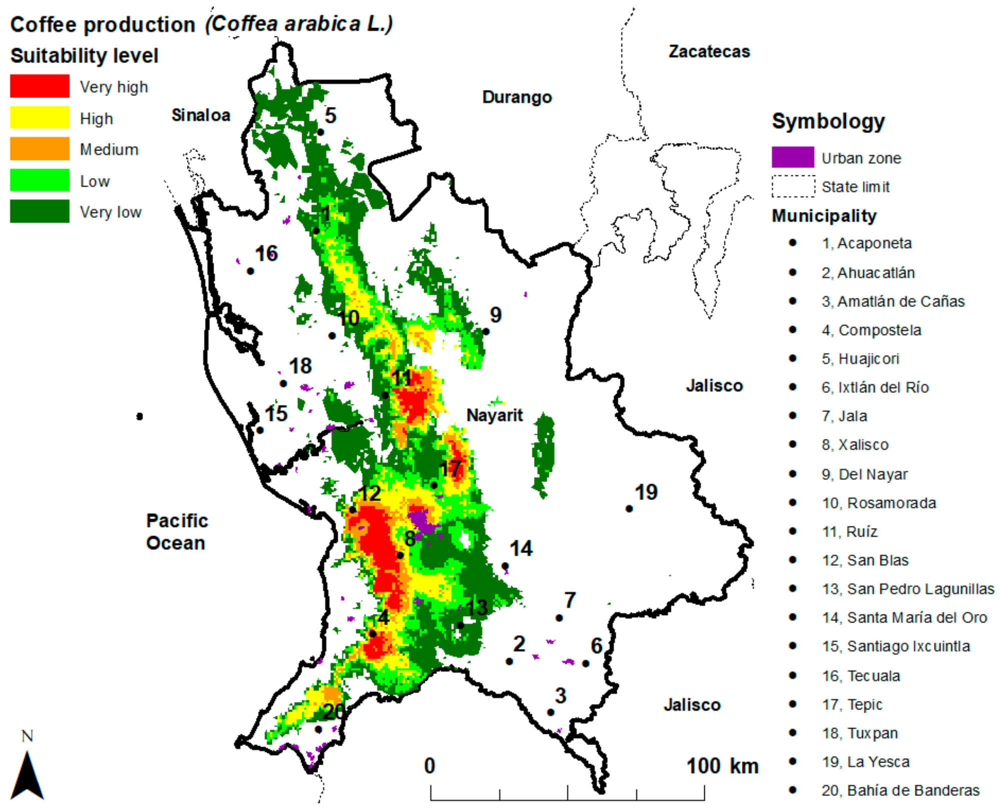

Figure 6. Map of distribution of probability of location of habitat zones with high suitability.

The generated model predicts that the suitability conditions are highly probable in the central region (vertically, crossing the state from north to south), represented by the

Municipality of Tepic, Xalisco, the eastern area of Compostela, and the southwest of San Blas, where the prevailing conditions are a precipitation of the warmest quarter in the range of 1000 to 1010 mm, an isothermality of 68.3 to 69.2, and an altitude level in the range of 600 to 1000 m above sea level, as well as the other variables analyzed, whose preference ranges are described in Table 3. In general, the areas identified by the model correspond to hills and mountains, mainly from the sub-province's physiographic sierras and northern plains, the neovolcanic sierras of Nayarit, and the sierra of the coast of Jalisco and Colima, in the physiographic provinces Sierra Madre Occidental, Eje Neovolcánico, and Sierra Madre del Sur, where different reference groups of soils predominate such as Luvisol, Cambisol, Regosol, Leptosol, Andosol, and Umbrisol.

Table 5 shows the conditions that prevail in each of the municipalities of the state of Nayarit with respect to surface suitability for coffee production, particularly highlighting the municipalities of Compostela with 27% and Xalisco (25%), the highest proportions of surfaces with very high suitability, although the municipality of Tepic can also be rescued as it reaches a surface of up to 24% with high suitability; on the other hand, the Municipalities of Amatlán de Cañas and Ixtlán del Río have no area of coffee productivity.

Table 5. Distribution of suitable areas for coffee production by municipality.

No.	Municipality	Municipality Area (km2)	Suitability Surface					Total with Respect to the Municipality
			Very High	High	Medium	Low	Very Low	
1	Acaponeta	1425	-	8% (109.56)	- (0.8)	11% (175.51)	9% (339.33)	44% (625.2)
2	Ahuacatlán	504	-	-	-	-	- (0.38)	0% (0.38)
3	Amatlán de Cañas	518	-	-	-	-	-	-
4	Bahía de Banderas	770	-	5% (75.3)	5% (31.65)	4% (64.18)	3% (99.15)	35% (270.27)
5	Compostela	1878	27% (149.52)	24% (323.4)	22% (135.87)	16% (260.78)	9% (348.27)	65% (1217.84)
6	Del Nayar	5139	3% (17.25)	6% (79.74)	6% (37.32)	13% (200.01)	12% (456.41)	15% (790.72)
7	Huajicori	2236	-	- (3.41)	-	1% (22.15)	19% (756.32)	35% (781.88)
8	Ixtlán del Río	493	-	-	-	-	-	-
9	Jala	503	-	-	-	-	- (0.01)	0% (0.01)
10	La Yesca	4314	-	-	-	- (1.36)	1% (36.85)	1% (38.2)
11	Rosamorada	1767	-	15% (200.7)	6% (35.4)	10% (153.79)	8% (299.17)	39% (689.05)
12	Ruíz	520	11% (60.37)	6% (79.46)	11% (68.23)	2% (30.18)	2% (75.87)	60% (314.11)
13	San Blas	1077	12% (66.68)	3% (38.94)	12% (76.76)	1% (21.99)	2% (92.4)	28% (296.77)
14	San Pedro Lagunillas	515	-	2% (26.53)	- (0.79)	7% (110.27)	7% (269.83)	79% (407.42)
15	Santa María del Oro	1091	-	- (1.55)	-	3% (49.82)	8% (301.06)	32% (352.43)

Table 5. *Cont.*

No.	Municipality	Municipality Area (km2)	Suitability Surface					Total with Respect to the Municipality
			Very High	High	Medium	Low	Very Low	
16	Santiago Ixcuintla	1703	7% (38.24)	2% (21.02)	7% (46.51)	1% (23.23)	8% (330.04)	27% (459.03)
17	Tecuala	987	-	-	-	-	1% (30.39)	3% (30.39)
18	Tepic	1634	15% (84.33)	24% (327.61)	22% (137.17)	24% (379.49)	10% (391.1)	81% (1319.68)
19	Tuxpan	310	-	- (0.77)	-	- (1.37)	1% (25.92)	9% (28.05)
20	Xalisco	503	25% (141.83)	6% (82.5)	9% (55.22)	6% (93.98)	3% (106.46)	95% (480)
Total, State area		27,888	2% (558.22)	5% (1370.48)	2% (625.72)	6% (1588.1)	14% (3958.95)	29% (8101.46)

4. Discussion

Coffee (*Coffea arabica* L.) is a shrubby plant of the genus Rubiaceae and its natural distribution in space is associated with its tropical origin [81], so it is commonly distributed in the regions between the Tropic of Cancer at 23°27′ N. latitude and the Tropic of Capricorn at 23°26′ S. latitude from the Equator in areas characterized by conditions of high solar radiation and altitude ranges between 1300 and 1800 m.a.s.l., with temperatures between 17 and 23 °C [82]; however, due to the genetic composition and the great variety of species, some have the capacity to respond better or worse to certain environmental conditions, adapting to different ecosystems ranging from tropical rainforest to pine-oak forests, low deciduous forests, mesophilic mountain forests [83], and tropical evergreen forest [10]. A couple of studies were identified in the scientific literature, such as those of [31,32], which tried to identify how different variables impact the determination of the habitat of some species; however, for coffee, these types of analysis were not identified.

The factors that are associated with coffee production have been classified into two groups [3,84,85]: environmental, which generate the appropriate conditions for its development; and, agro-genetic, whose characteristics determine the quality of reproduction. In the present document, only the environmental variables are addressed in order to identify how these factors determine the distribution of the conditions of suitability of the habitat for coffee production. The factors that affect the distribution of the coffee species in Mexico have been identified by some authors such as [3], who point out that coffee is distributed on steep terrain in mountainous areas with rugged topography and high slopes, coinciding with areas of greater biological diversity, where the factors associated with the sites correspond to higher altitude, available humidity, frost, and soil with higher organic matter content.

On the other hand, in Mexico, [7] point out that the productive zones are located in mountainous areas of rugged topography and coincide with the places of greatest biological diversity in the country, especially in mountain cultivation systems.

In the same way, ref. [86] indicated that coffee production is more successful when it is cultivated at altitudes ranging from 600 to 1200 m above sea level, especially on steep slopes and in the transition zone between tropical and temperate ecosystems; likewise, [87] indicated that coffee flowering is influenced by environmental factors such as solar radiation, temperature, and availability of water in the soil. Likewise, [88] estimates that for coffee to develop and produce, appropriate climatic conditions are required of between 1500 and 2500 mm of average annual precipitation, without frost or prolonged droughts, and an altitude of between 600 and 1200 m, the same altitude. Similarly, ref. [89] mentions that the climatic requirements that influence the physical quality of coffee are a precipitation of between 1000 and 2500 mm per year, a temperature of between 17 and 24 °C, and relative humidity of 55 to 65%, in addition to an exposure of more than 1000 h of light per year and an altitude of 1200 to 2000 m above sea level.

In Nayarit, [90] points out that the coffee-productive regions are characterized by an irregular topography with steep slopes, fertile soils, richness in organic matter, and shallowness with lush vegetation in jungles, mountains and sub-deciduous forests with an average annual temperature of 24 °C and rainfall of 1200 mm annually.

All the works previously reviewed and cited here consider factors such as altitude, solar radiation, precipitation, temperature, and some others with ranges that differ relatively little among them as those that condition the suitability of the regions for optimum coffee production; however, none of them make reference to the analysis of influence and much less to the valuation of the contribution that each factor has in determining the environmentally suitable conditions. This situation is addressed with the present work in such a way that it contributes to determining the degree of influence that each one of the factors has on the presence of coffee, and, from the analysis of this association, it generates a Potential Distribution Model (PDM) that shows the ideal zones for the production of coffee.

In this sense, the results obtained in the present work indicate that the main environmental factors that contribute to establish the suitability of the zones for coffee production in Nayarit are isothermality, precipitation, and altitude, which partially coincides with what was indicated by the previously mentioned authors, since it is particularly found that precipitation is one of the variables that contributes the most to the model, especially in a range of 1000 to 1010 mm, with an isothermality of 68.3 to 69.2 and an altitude in the range of 600 to 1000 m.a.s.l.

On the other hand, although the MaxEnt model has demonstrated its efficiency in the modeling of the ecological niche, some authors have indicated some recommendations that should be considered and complied with prior to the execution of MaxEnt; in the first place, it should be considered that the accuracy of the presence data will have a significant impact on the degree of model fit [91]. In this sense, the selection of the variables used in this work is not intended to be limiting or definitive for the determination of the model, since other variables that could contribute to improve the model response can be analyzed. Another important assumption is related to the fact that there must be a temporal correspondence between the presence records of the observed species and the biophysical variables [92]. Likewise, the biophysical variables must affect the distribution of the species in such a way that they have a statistically significant influence on the presence of the species [93]; the latter because the appropriate selection of variables will determine the degree of model fit at larger scales once the model is generalized to other regions outside the study area [21].

5. Conclusions

In the present work, the SDM allowed for obtaining a first and good approximation of the potentially ideal habitat for coffee production in the state of Nayarit, being defined by the region comprised by the Municipality of Tepic, Xalisco, the eastern zone of Compostela, and the southwest of San Blas. The distribution model obtained adequately predicts the ideal zones for coffee production with a level of certainty of 98% (AUC = 0.98), and therefore represents a reliable model for the zoning of areas of importance for the coffee sector.

An area of 8182 km^2 that is equivalent to approximately 30% of the surface of the territory of Nayarit has ideal conditions for coffee production, especially the landscapes of the lomerios and sierras of the Sierra Madre Occidental, Eje Neovolcánico, and Sierra Madre del Sur, in the municipalities of Tepic and Xalisco and the eastern zone of Compostela and southwest of San Blas, which should be considered as a Priority Conservation Area (PCA) for coffee production in the state.

The information resulting from the present research intends to lay the foundations for the diagnosis of coffee productivity zoning in Nayarit as knowledge that can be used by the governors to identify the zones with coffee production potential; and, secondly, to help establish planning strategies focused on managing, improving, and increasing production with a sustainable approach. The present model is also intended to be used for future work on the identification of biological corridors in order to promote tourism, as well as for further work on prediction and analysis of scenarios in the face of climate change and to see how the suitability conditions of the territory will be affected by the effect of variations of the different environmental variables.

The generation of knowledge on the identification of regions with ideal environmental conditions for coffee production in the state and the conservation strategies that are applied to them will allow generating, in the long term, the recognition of the quality of origin that the region offers.

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