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Simulation of citrus production space based on MaxEnt

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Crop production space is the most important part of land use system, and spatial simulation has always been the key task of land science. Crop production space is affected by many factors on different spatio-temporal scales, which leads to the complexity of simulation models. The existing simulation models also have the limitations of lack of human factors, large simulation area and excessive reliance on expert experience. Sichuan Province is a typical area of Citrus spatial expansion in China, so it is of great practical significance to carry out spatial regulation. From the comprehensive perspective of nature and humanity, this research uses MaxEnt, ArcGIS, Orcale, SQL to design a spatial regulation method (CSSM) for citrus, predict the citrus production space in Sichuan Province in 2025, and put forward regulation suggestions. The results showed that the citrus spatial simulation method better reflects the comprehensive effect of natural and human factors on crop space, and realizes the research on the regulation of single crop production space. The dominant environmental variables affecting citrus production in Sichuan are input of production factors, society, climate and terrain. Human activities play a leading role. The suitable environment for citrus production in Sichuan is: elevation ≤500m, annual average temperature ≥16.5 °C, aspect are northeast, southwest and northwest, supported by preferential policies, the input of Citrus fertilizer in the county is ≥ 500t, the input of Citrus labor in the county is ≥ 5,000, the input of Citrus pesticide in the county is ≥ 12.5t, and the technical progress represented by unit yield is 750–7000 t/km^2. The suitable space for citrus production in Sichuan are mainly located in Zigong, Nanchong, Ziyang, Neijiang, Meishan, Leshan, Yibin and Luzhou. The government should choose a positive low growth scenario to stabilize the citrus area in Sichuan at 3533 km^2 in 2025, and form a major citrus production area in Meishan, Ziyang, Neijiang, Chengdu, Nanchong and Yibin.

KEYWORDS

land use, crops suitability, maximum entropy model(MaxEnt), multi-scenario simulation, citrus

1 Introduction

Crop production space is the most extensive and important part of land use system (Ramankutty et al., 2008; Volk and Ewert, 2011; Tang et al., 2015). It is the spatial expression of crop type and production distribution (Tang et al., 2010). Crop spatial simulation is not only an important task of agricultural land system research, but also an industrial policy problem faced by government departments. Therefore, it has always been the research focus of land science (Liu and Chen, 2002). The purpose of crop spatial simulation is to arrange crops in the most suitable space as far as possible, form a relatively centralized regional layout, realize the optimization of agricultural land system, and obtain the best comprehensive benefits (Tang et al., 2015).

The land use change simulation model has formed SD, Markov, CA, clue, flus and their coupling models (Verburg et al., 2002; Genga et al., 2017; Mamanis et al., 2021; Zhang et al., 2021). This kind of simulation is based on driving factors, utilization needs, regional constraints and conversion order, and realizes top-down or bottom-up change simulation on different space-time scales. However, this kind of research only realizes the simulation of the primary type of agricultural land and construction land, but fails to realize the spatial simulation of the internal crop types of agricultural land, and because the simulation area is too large, it is difficult to guide the practice at the samll-scale of county (town) and even villages. Land ecological suitability evaluation (LESE) based on GIS is often used in spatial simulation. This kind of method is based on the response of crop physiological growth to the natural environment, selects representative indicators from climate, terrain and soil, identifies and divides suitable space, and realizes spatial regulation on different scales (Neamatollahi et al., 2012; Bagherzadeh and Daneshvar, 2014; Li et al., 2015; Wotlolan et al., 2021). However, this kind of method also has two limitations. The first is to ignore social and economic factors and reduce the scientificity of the results. The most suitable space is the result of agricultural land adapting to changes in natural and human factors, including natural suitability and human suitability (Lin et al., 2020). The natural environment determines the basic pattern of crop production space, and makes the natural suitable space become the initial gathering area of crops (Li et al., 2012). With the development of society, economy, science and technology, human factors have become an important inducement to cause spatial changes. The spatial heterogeneity of labor, farmers' behavior, production costs, consumption, policy and technological progress on different spatial and temporal scales has an increasingly strong impact on spatial changes (Xiang et al., 2014; Zhang and Zhang, 2016; Wang and Qi, 2018). Spatial change has changed from natural driving to common driving of nature and humanity (Lin et al., 2021). Second, it is difficult to determine the representative indicators and their thresholds. Crop growth is affected by many variables. The dominant variables affecting the spatial change of crop production in different regions are different, and the threshold of the same variable affecting the spatial change in the same region also has time differences (Zabihi et al., 2015; Mokarram and Mirsoleimani, 2018; Tercana and Dereli, 2020). Therefore, the determination of representative indicators and their thresholds is often affected by subjective experience and regional differences.

Species distribution model (SDM) provides a new idea for crop spatial simulation. According to the relationship between species distribution and eco-environmental characteristics, SDM does not need to have rich prior knowledge of species ecological characteristics. Now it has been widely used in potential distribution (Yang et al., 2013; Qin et al., 2017). A series of ecological statistical models based on ArcGIS have been widely used, such as MaxEnt (Phillips et al., 2006), BIOCLIM (Beaumont et al., 2005), ENFA (hengl et al., 2009), GARP (Stockwell and Peters, 1999). More than 1,000 studies since 2006 show that MaxEnt model has been proved to have the best prediction ability and accuracy (Wisz et al., 2008; Merow et al., 2013). MaxEnt model has achieved good results in the suitability zoning of rice, wheat, corn, potato and other crops and the assessment of the response to environmental and major climate factors (Khalil et al., 2021; Khubaib et al., 2021; Yu et al., 2022). MaxEnt model can not only consider the impact of natural variables such as climate, terrain and soil, but also consider the impact of non natural variables such as labor force and land use (Galletti et al., 2013; Yi et al., 2016; Gu et al., 2018; Cao et al., 2021; Yang et al., 2022). The change of environment and human activities has obvious uncertainty and complexity (Zhang et al., 2016; Yang et al., 2022). MaxEnt model shows applicability in coupling analysis of natural environment and human activities (Tan et al., 2019; Nyairo and Machimura, 2022), which is conducive to understanding the comprehensive impact of environment and human activities on agricultural production. Supported by Geographic Information System (GIS), MaxEnt model provides a good method for crop spatial distribution and agricultural land structure optimization.

This work uses MaxEnt, ArcGIS, Oracle, SQL to design the citrus spatial simulation method (CSSM). CSSM comprehensively considers natural and human factors, uses MaxEnt to calculate the distribution probability of citrus production, simulates the production space with the distribution probability as the standard through Oracle and SQL, and carries out empirical research on the spatial layout of citrus production in Sichuan Province of China in 2025, in order to provide a new method for the simulation of agricultural land system.

2 Study area and data source

2.1 Study area

Sichuan Province located in the southwest of China (26°03′–34°19′ N, 92°21′–108°12′ E), is the transitional area

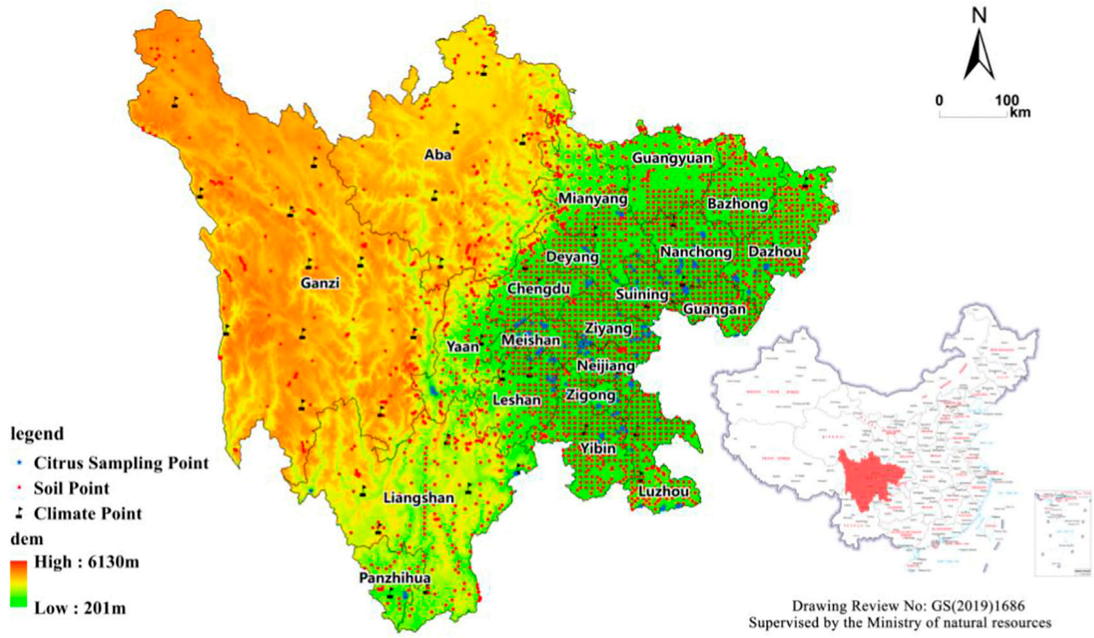


FIGURE 1
Geographical location of Sichuan Province and data distribution.

between the Qinghai-Tibet Plateau and the middle-lower Yangtze Plain (Figure 1). The western part is a plateau area, with an elevation of more than 4000m; The eastern part is the hilly plain area of the basin, with an elevation of 1,000–3,000 m. The climate types of Sichuan Province are diverse, including the mid-subtropical humid climate area in the basin, the subtropical semi humid climate area in the mountains of Southwest Sichuan, and the alpine climate area in the plateau of Northwest Sichuan. Since the reform and opening up, China's citrus production space has expanded rapidly, and has become the world's largest citrus producer. The planting area reached 2.83×10^4 km^2 in 2020 (Rural social and Economic Investigation Department of the National Bureau of statistics of China, 2021), and citrus has become an important land cover type in southern China. The citrus production in Sichuan Province has been in the forefront for a long time. In 2020, the citrus area in Sichuan reached 3,389 km^2. Since 2000, the production space has expanded by 1837 km^2(Rural social and Economic Investigation Department of the National Bureau of statistics of China, 2021), which is a typical area of Citrus spatial expansion. At present, citrus has formed Chengdu Plain production area, South Sichuan production area and Northeast Sichuan production area in Sichuan. Compared with the production space and suitable space, the production area has far exceeded the high suitable area, and there is a reality of transferring to the middle and low suitable space. It is urgent to carry out spatial regulation, reduce the supply and demand risks faced by the citrus industry, and promote the sustainable development of the citrus industry (Lin et al., 2019).

2.2 Data source and preprocessing

2.2.1 Data source

This study uses a large number of public data provided by national (provincial and municipal) data platforms, mainly including climate, topography, land and socio-economic data (Table 1).

2.2.2 Pretreatment of environmental variables

According to the existing research conclusions, 35 environmental variables of seven types affecting the distribution of citrus production were selected (Table 2) (Li and Xie, 2003; Zhang and Zhang, 2016; Su et al., 2017; Lin et al., 2019; Lin et al., 2021). Variable 1) to Variable 12) are the average annual values from 1980 to 2015 obtained from the daily meteorological data of 42 meteorological stations calculated by MATLAB (Figure 1). Variable 13) to Variable (20) are obtained by potassium dichromate volumetric method, potentiometric method, semi micro Kjeldahl method, spectrophotometry, hydrofluoric acid digestion method and hydrometer speed measurement method. Variable 24) to Variable 34) are the average value of county from 1980 to 2015 calculated by using the

TABLE 1 Datasets used in this study.

Data name	Period	Data sources
Climatic data		
Daily meteorological dataset of basic meteorological elements of China National Surface Weather Station	1951–2017	China National Meteorological Information Center (http://data.cma.cn)
Topographic data		
Elevation (SRTM 90m)	2000	Resource and environment science data center of Chinese Academy of Sciences (http://www.resdc.cn)
Land data		
Nutrient data set of soil testing and formula fertilization in Sichuan Province	2008–2010	Sichuan Provincial Department of agriculture and Rural Affairs
Land use/land cover data	2020	Resource and environment science data center of Chinese Academy of Sciences (http://www.resdc.cn)
Socio economic data		
Administrative division	2010	National Geomatics Center of China (http://www.webmap.cn)
Population、GDP	1981–2016	Sichuan statistical yearbook
Road	1981–2016	Sichuan statistical yearbook
Disposable income of residents	1981–2016	Sichuan statistical yearbook
Area and output (Citrus, Grain)	1981–2016	Sichuan Rural Statistical Yearbook
Pesticides	1981–2016	Sichuan Agricultural statistical yearbook
Fertilizer	1981–2016	Sichuan Agricultural statistical yearbook
Rural laborers	1981–2016	Sichuan Agricultural statistical yearbook
Effective irrigation area	1981–2016	Sichuan Agricultural statistical yearbook
Distribution data		
Global Biodiversity Information Facility		http://www.gbif.org

corresponding formula. The time smoothing method is used to supplement the missing data in a few counties. Variabl 35) is a dummy variable, 51 counties that implement industrial support policies are 1, and the rest are 0. The administrative divisions of Sichuan Province have been adjusted for many times. In order to ensure the consistency of data, the administrative boundaries in 2010 are taken as the benchmark and merged into 181 counties. Using ArcGIS 10.2 software to unify the boundary of all environmental variables, the coordinate system was WGS_1984_UTM_Zone_48N, the resolution was 1 km × 1 km, and data were converted to the ASCII format required by MaxEnt software.

2.2.3 Distribution data processing

There are two sources of Citrus distribution data. The longitude and latitude of the main citrus producing areas in Sichuan were obtained by handheld GPS positioning. Other distribution data are queried and supplemented by the Global Biodiversity Information Facility (http://www.gbif.org), and invalid records and duplicate records are removed. Sampling bias will lead to MaxEnt over fitting, thereby reducing the prediction ability of the model (Phillips et al., 2009). In this study, SDMtoolbox was used for spatial screening of sampling points, and one distribution point was reserved in 1 km × 1 km pixels, and 191 sampling points were finally obtained (Figure 1).

3 Research methods

3.1 Method framework

3.1.1 Probability model

CSSM simulates citrus production space with distribution probability, and MaxEnt is an important model tool of CSSM. The maximum entropy model is a mathematical method for unbiased inference of unknown distribution based on limited known information. The theory holds that, without external force, things always strive for the maximum freedom under constraint conditions. Under known conditions, things with the maximum entropy are most likely to be close to their true state (Jaynes, 1957). MaxEnt model requires two types of data. The first is the geographical location of known crop distribution, which is expressed in the form of longitude and latitude coordinates. The second is the environmental variable within the predicted spatial range (Phillips et al., 2006). The distribution of crops is affected by environmental variables. In the sample data set composed of environmental variables and crop distribution, the introduction of environmental variables will affect the distribution probability and amount of information. MaxEnt model obtains the prediction model according to the geographical coordinates of the known distribution points of species and the environmental variables of the species distribution area, and then uses the optimal model to simulate the possible distribution of the target species in the

TABLE 2 Calculation formula and raster processing of environment variables.

No	Type	Variable	Calculation formula	Raster processing
1	Climate	Annual sunshine hours	Sum of daily sunshine hours	IDW
2		Annual average temperature	(Sum of daily average temperature) ÷ (Days)	MR + Residual IDW
3		Florescence average temperature	(Sum of daily average temperature from April to may) ÷ (Days)	MR + Residual IDW
4		Average temperature in July	(Sum of daily average temperature in July) ÷ (Days)	MR + Residual IDW
5		Average temperature in January	(Sum of daily average temperature in January) ÷ (Days)	MR + Residual IDW
6		Annual temperature range	(Average temperature in July)—(average temperature in January)	IDW
7		≥0 °C accumulated temperature	the sum of daily mean temperatures above 0 °C in 1 year	MR + Residual IDW
8		≥10 °C accumulated temperature	the sum of daily mean temperatures above 10 °C in 1 year	MR + Residual IDW
9		summer ≥38 °C duration days	Cumulative days with the highest temperature ≥38 °C from July to September	IDW
10		Frost free period	Days between the last frost day and the first frost day	IDW
11		Annual precipitation	Sum of daily precipitation	Ordinary kriging
12		Annual average air humidity	(Sum of daily air humidity) ÷ (Days)	MR + Residual IDW
13	Soil	Organic matter	Potassium dichromate volumetric method	Ordinary kriging
14		pH	Potentiometric determination	Ordinary kriging
15		Total N	Semi micro Kjeldahl method	Ordinary kriging
16		Total P	Spectrophotometry	Ordinary kriging
17		Total k	Hydrofluoric acid digestion method	Ordinary kriging
18		Clay	Hydrometer speed measurement method	Ordinary kriging
19		Silt	Hydrometer speed measurement method	Ordinary kriging
20		Sand	Hydrometer speed measurement method	Ordinary kriging
21	Topography	Slope	—	Spatial Analyst Tools
22		aspect	—	Spatial Analyst Tools
23		elevation	—	Spatial Analyst Tools
24	Production	Land input	(Citrus area) ÷ (Agricultural land area)	Feature To Raster
25		Labor input	Labor input × (Citrus area) ÷ (Agricultural land area)	Feature To Raster
26		Fertilizer input	Fertilizer input× (Citrus area) ÷ (Agricultural land area)	Feature To Raster
27		Pesticide input	Pesticide input× (Citrus area) ÷ (Agricultural land area)	Feature To Raster
28		Irrigation input	Irrigation input× (Citrus area) ÷ (Agricultural land area)	Feature To Raster
29	Economics	Urbanization	(total population - rural population) ÷ Total population	Feature To Raster
30		Economic feedback	(Output value of secondary and third industry)÷(Total output value)	Feature To Raster
31		Food security	(Grain output)÷ (Total population)	Feature To Raster
32	Market	Traffic	(Highway mileage) ÷ (Total area)	Feature To Raster
33		consumption	Disposable income of urban residents	Feature To Raster
34	Sociology	technical progress	(Citrus yield) ÷ (Citrus area)	Feature To Raster
35		Policy	The county implementing the supporting policy is 1, otherwise it is 0	Feature To Raster

MR: multiple regression; IDW: inverse distance weighting.

target area, and selects the distribution with the largest entropy from the distribution that meets the conditions as the optimal distribution (Elith et al., 2006; Phillips et al., 2006; Merow et al., 2013). The maximum entropy algorithm is a constrained optimization algorithm, which is simply described as: when the output of x is known to be y, for the given training data set and characteristic function $f_i(x, y)$, where $i = 1,2,..., n$, MaxEnt solves the equation as follows (Yang et al., 2022):

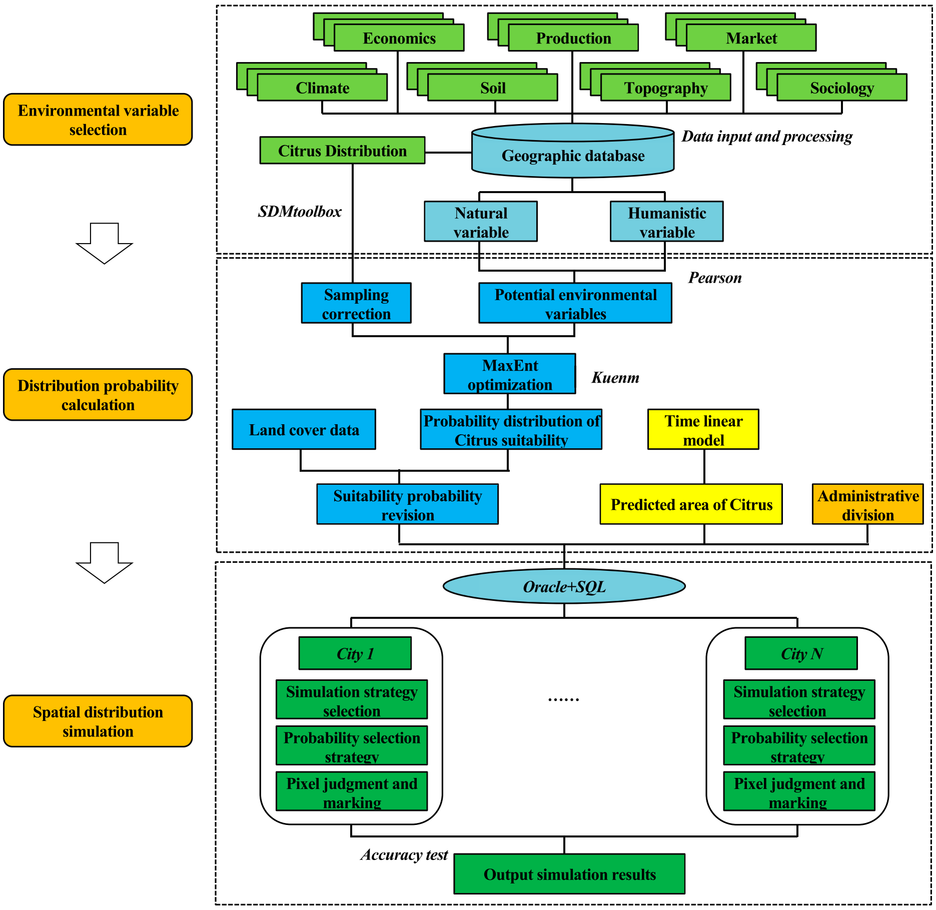


FIGURE 2
Research framework of CSSM.

$$\max_{pec} H(P) = -\sum_{x,y} \tilde{P}(x)P(y|x)logP(y|x),$$
$$\text{s.t.} E_P(f_i) = E_{\tilde{P}}(f_i),\ i = 1, 2, \cdots, n, \quad (1)$$
$$\sum_y P(y|x) = 1,$$

Where $H(P)$ is the conditional entropy, $P(y|x)$ is the conditional probability distribution assumption, $\tilde{P}(x)$ is the empirical distribution, and $E_P(f_i)$ represents the expectation of the characteristic function of the empirical distribution. Lagrangian multiplier method is used to transform the original constrained optimization problem into a dual unconstrained optimization problem.

3.1.2 Main steps

CSSM includes three steps: environmental variable selection, distribution probability calculation, and spatial distribution simulation (Figure 2). The first step is to use ArcGIS to unify the data structure, spatial resolution and geographic coordinates of various environmental variables, and establish a geographic information database. Then, Pearson correlation analysis was carried out on environmental variables to screen out the potential environmental variables that drive the spatial changes of citrus production. The second step is to calculate the distribution probability of citrus on the basis of MaxEnt parameter optimization, and revise it with land cover data. Use the prediction model to obtain the future citrus planting area. The third step is to select the simulation strategy according to the discrimination conditions to judge and mark the pixels suitable for citrus production one by one. When the threshold is reached, stop labeling, output all labeled pixels, and get the most suitable citrus production space. This step is implemented by SQL and Oracle.

3.2 Environment variable selection

In order to avoid the error caused by the over fitting of the model caused by the multicollinearity of environmental variables, and to retain the ecological significance of different

TABLE 3 Potential environmental variables affecting the spatial distribution of citrus production.

Type	Potential environment variable	Code	Factor meaning
Climate	Annual sunshine hours	Sun	Sunshine is conducive to the growth of branches, leaves and flower buds, and improves the fruit setting rate, fruit coloring and acidity. Suitable threshold: 1200–1500 h
	Annual average temperature	Ta	Citrus likes warm and humid climate, and temperature is the decisive factor of Citrus Distribution and growth. Suitable threshold: 16.5°C–23 °C
	Annual temperature range	Tad	Too high or too low is not conducive to citrus production, so Tad is used to evaluate the average temperature change range
	summer ≥38 °C duration days	Sta38d	When the temperature is higher than 38 °C, high temperature heat damage occurs, and the growth of citrus trees stops completely
	Annual precipitation	Pre	The uneven distribution of rainfall in Sichuan Province has a great impact on the growth and quality of citrus, and the appropriate threshold is 1,000–2000 mm
Soil	Organic matter	Om	Improve the physical and chemical properties of soil and affect the yield and quality of citrus
	pH	Ph	PH affects the dissolution of mineral nutrients, and the appropriate threshold is 5–6.5
	Total P	Tk	Phosphorus can reduce fruit acidity and improve solid acid ratio
	Total k	Tk	Potassium can increase single fruit weight and soluble solid content, and reduce fruit cracking
	Clay	Clay	Affect soil porosity, change soil water and gas content, and indirectly affect citrus growth
	Silt	Silt	Affect soil porosity, change soil water and gas content, and indirectly affect citrus growth
Topography	Slope	Slope	The drainage and ventilation of hillside land are good, and it is easy to form an inversion layer, which is conducive to the growth of citrus
	Aspect	Aspect	Aspect affects citrus yield and quality through light and precipitation
	Elevation	Dem	Elevation affects citrus growth through temperature
Production	Labor input	Lab	Reflect the situation of Citrus workers in the county
	Fertilizer input	Fer	Reflect the fertilization of Citrus in the county
	Pesticide input	Pes	Reflect the pesticide application of Citrus in the county
Economics	Urbanization	Ur	Reflect the land and labor environment faced by county citrus production
	Economic feedback	Neo	Reflect the supporting capacity of county economy for citrus production
	Food security	Gra	Reflect farmers' land selection behavior in the decision-making of planting grain or citrus
Market	Traffic	Traf	Reflect the market circulation of Citrus in the county
	Consumption	Cons	Reflect the willingness and ability of Citrus consumption
Sociology	Technical progress	Sci	Reflect the popularity of advanced technology and varieties of citrus
	Policy	Pol	Reflect the impact of industrial policies on citrus production

types of variables on the distribution of citrus as much as possible (Elith et al., 2011), this study conducted Pearson on the same type of environmental variables, and retained the variables with $R < 0.75$. Among the variables with $R > 0.75$, select a variable closely related to citrus distribution or convenient for model interpretation to participate in the prediction. Finally, 24 variables were identified as potential environmental variables (Table 3).

3.3 Distribution probability calculation

3.3.1 Model optimization

The parameter optimization of MaxEnt helps to improve the prediction accuracy of the model. The most important parameters are feature class (FC) and regulration multiplier (RM) (Radosavljevic and Anderson, 2014). MaxEnt provides five feature types: linear (L), quadratic (Q), hinge (H), product (P), and threshold (T), which can produce 31 feature class. RM parameter is set to 0.1–4, with an increase of 0.1 each time, a total of 40 regulration multiplier. Kuenm toolkit of R is used to optimize 1,240 parameter combinations. Among all candidate combinations, select the parameter combination with statistical significance, omission rate ≤5%, and delta. AICc = 0 for modeling (Warren and Seifert, 2011). The results show that the parameter combination when FC = h and RM = 4 is the optimal model. MaxEnt settings are as follows: ① sampling points are randomly divided into training samples (75%) and verification samples (25%). ② Select random seed. ③ The repetition type is subsample. ④ Take the average of 10 calculations as the final result.

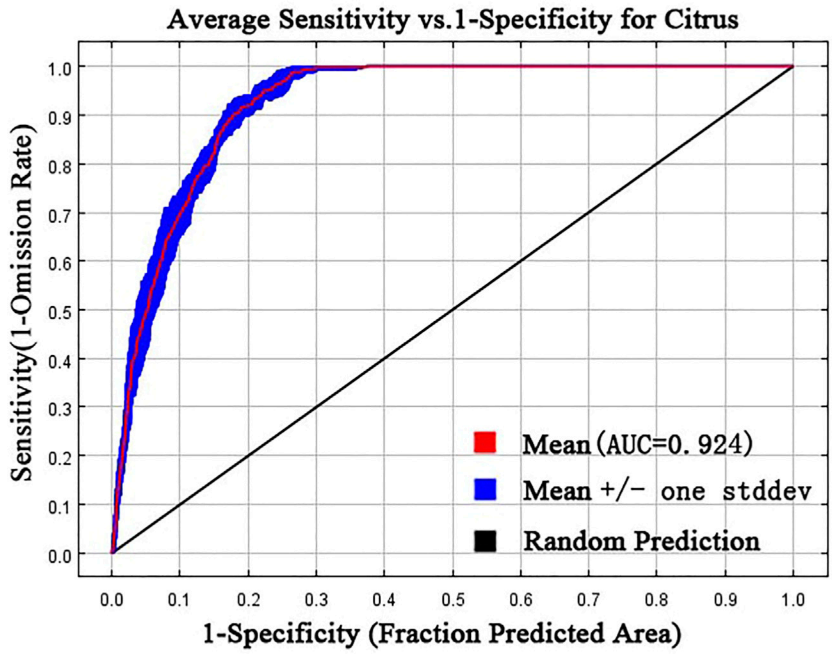


FIGURE 3
ROC curve and AUC value of MaxEnt.

3.3.2 Model accuracy

The MaxEnt model uses the receiver operating characteristic (ROC) curve to evaluate the accuracy of the analysis results for fitness area. The ROC curve takes the false positive rate as the abscissa and the true positive rate as the ordinate. The area value enclosed by the curve and abscissa is area under curve (AUC), and an AUC value between 0.5 and 0.6 is unqualified, 0.6–0.7 poor, 0.7–0.8 fair, 0.8–0.9 good, and 0.9–1.0 excellent. (Swets, 1988). The closer the AUC was to 1, the better the model performance was. In this study, the average AUC of 10 repeated runs is 0.924, and the standard deviation is 0.008 (Figure 3), indicating that the accuracy of the model is reliable.

3.3.3 Probability revision

The result of MaxEnt is the suitable distribution probability (P), and P range is 0–1. The closer the *p*-value is to 1, the more suitable the citrus production distribution is (Ma and Sun, 2018). Limited by land cover, the distribution probability results need to be revised according to the land cover type, and the probability distributed in water, construction land, grassland and unused land should be deleted.

3.4 Spatial distribution simulation

3.4.1 Area prediction

In the future, whether citrus in Sichuan Province will show spatial expansion or spatial contraction is facing great uncertainty. Different research results show different development expectations. The Sichuan provincial government has formulated the citrus industry development plan and proposed to maintain the citrus area at 3333 km^2 by 2025. According to this calculation, the average annual growth rate of Citrus area in Sichuan must reach 3.26%. The research results of China's Agricultural Outlook report (2020–2029) show that the expansion of China's fruit planting area is limited in the next 10 years, with an average annual growth rate of about 0.77% (Market early warning Expert Committee of the Ministry of agriculture and rural, 2020). Wang (Wang and Qi, 2018) used the panel data from 2005 to 2015 to quantitatively calculate the comparative advantage index of the main citrus producing areas in China. The results showed that the citrus advantage in Sichuan was in a downward trend, with a growth rate of -0.79% to -2.78%. According to the above conclusions, this study takes 2020 as the base year, and sets four scenarios of average annual growth rate, positive high growth (3.26%), positive low growth (0.77%), negative low growth (-0.79%), negative high growth (-2.78%), using a time linear model to predict the citrus planting area in Sichuan Province in 2025 (Table 4).

3.4.2 Model strategy

Taking the provincial predicted area (Q_y), provincial suitable area (Q_x), municipal predicted area ($S_{n,y}$) and municipal suitable area ($S_{n,x}$) as the discrimination conditions, four simulation strategies are set (Figure 4). The discriminant condition and

TABLE 4 Predicted area of Citrus in Sichuan Province under different scene in 2025.

City	Planting area in 2020 (km^2)	Predicted area in 2025 (km^2)			
		Positive low growth	Positive high growth	Negative low growth	Negative high growth
Chengdu	336.80	349.97	395.40	323.70	292.52
Zigong	187.80	195.14	220.47	180.50	163.11
Panzhihua	3.50	3.64	4.11	3.36	3.04
Luzhou	161.50	167.81	189.60	155.22	140.27
Deyang	50.10	52.06	58.82	48.15	43.51
Mianyang	72.50	75.33	85.11	69.68	62.97
Guangyuan	27.10	28.16	31.81	26.05	23.54
Suining	26.50	27.54	31.11	25.47	23.02
Neijiang	250.80	260.61	294.43	241.05	217.82
Leshan	125.60	130.51	147.45	120.72	109.09
Nanchong	341.50	354.85	400.91	328.22	296.60
Meishan	600.80	624.29	705.33	577.44	521.80
Yibing	303.50	315.37	356.30	291.70	263.59
Guangan	129.60	134.67	152.15	124.56	112.56
Dazhou	177.10	184.02	207.91	170.21	153.81
Yaan	45.40	47.18	53.30	43.63	39.43
Bazhong	37.80	39.28	44.38	36.33	32.83
Ziyang	471.50	489.93	553.53	453.17	409.51
Aba	0.00	0.00	0.00	0.00	0.00
Ganzi	1.20	1.25	1.41	1.15	1.04
Liangshan	38.50	40.01	45.20	37.00	33.44
Total	3,389.10	3,521.61	3,978.73	3,257.33	2,943.49

simulation strategy are implemented by Oracle and SQL. Before discrimination, the suitable probability raster is converted into points, and then spatially connected with the municipal administrative division data, so as to obtain the city name, distribution probability and predicted area fields of each point, and import them into Oracle to establish a table file. Select the corresponding strategy to store the table file according to the discrimination conditions. The simulation process of the four strategies is as follows: Strategy 1: ① take the city as the unit, sort the raster pixels one by one according to the probability from high to low. ② Take $S_{n,x}$ as the threshold, mark the raster pixels one by one according to the probability from high to low, until all raster pixels are marked, and the simulation ends. Strategy 2: ① refer to step 1 of strategy 1. ② For cities with $S_{n,y} < S_{n,x}$, take $S_{n,y}$ as the threshold, mark the suitable raster pixels one by one according to the probability from high to low, until the marked raster pixels area is greater than or equal to $S_{n,y}$, and repeat the simulation until (n-m) cities are simulated. ③ For cities with $S_{n,y} \geq S_{n,x}$, first refer to step 2 of strategy one; Secondly, calculate the difference (S_m) between the predicted area and the suitable area, and take it as the threshold, mark the suitable raster pixels that have not been marked one by one within the provincial scope according to the probability from high to low, until the marked suitable raster pixels area is greater than or equal to S_m, and end the simulation. Strategy 3: ① refer to step 1 of strategy 1. ② Take $S_{n,y}$ as the threshold, mark the suitable raster pixels one by one according to the probability from high to low, until the area of the marked suitable raster pixels is greater than or equal to $S_{n,y}$, and the simulation ends after all city simulations are completed. Strategy 4: refer to strategy 2.

Q_y is the provincial predicted area. Q_x is provincial suitable area. Q_m is the provincial simulated area. $S_{n,y}$ is the predicted area of city n. $S_{n,x}$ is the suitable area of the city n. n is the number of cities. m is the number of cities with $S_{n,y} \geq S_{n,x}$. n-m is the number of cities with $S_{n,y} < S_{n,x}$. S_m is the sum of the difference between the predicted area and the suitable area of all city with $S_{n,y} \geq S_{n,x}$

4 Results and analysis

4.1 Analysis of environmental variables

The contribution of 24 potential environmental variables to the distribution of citrus production is calculated according to the Jackknife method (Table 5). The percent contribution (PC) of pesticide input (pes, 62.1%), fertilizer input (fer, 14.26%), policy

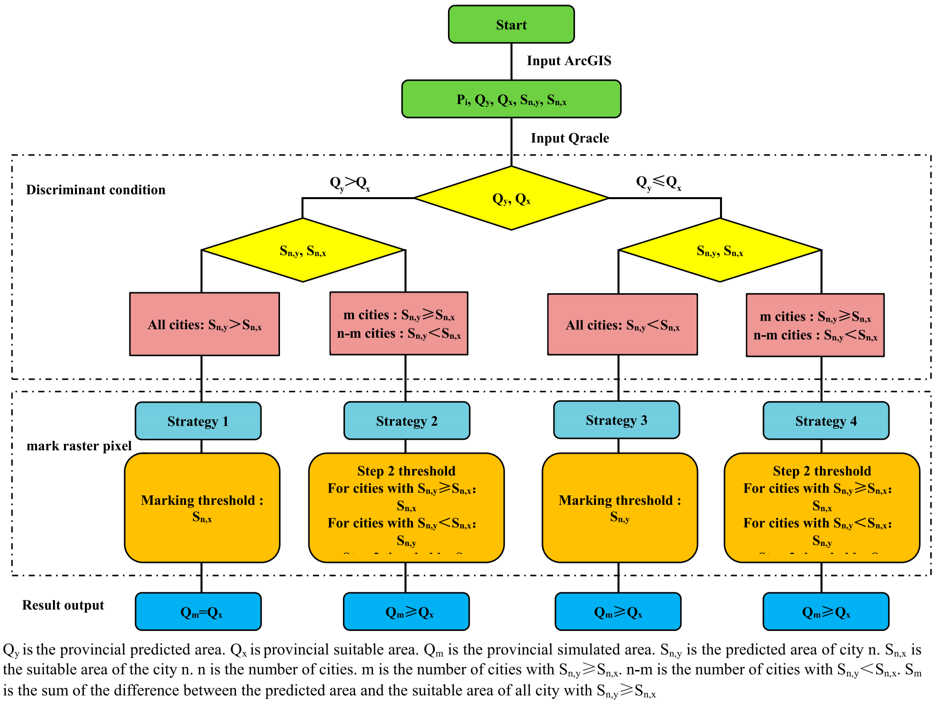


FIGURE 4
Discrimination conditions and thresholds of strategies.

(pol, 6.93%), annual average temperature (ta, 5.56%) and labor input (lab, 4.06%) ranked in the top 5, with a cumulative contribution rate of 92.91%. The permutation importance (PI) of annual average temperature (ta, 46.88%), pesticide input (pes, 29.32%), aspect (aspect, 8.44%), technical progress (sci, 4.89%) and fertilizer input (fer, 4.46%) ranked in the top 5, with a cumulative contribution rate of 93.99%. In the regularization training gain (RTGO) using this factor alone, the average annual temperature (ta) and pesticide input (pes) are 1.2, and the elevation (dem), fertilizer input (fer) and labor input (lab) are 1.19, 1.18 and 1.16 respectively, indicating that these environmental variables have more effective information than other variables. Therefore, the main environmental variables that affect the distribution of citrus production are production factors (pesticide input, fertilizer input, labor input), social factors (policy, technological progress), climate factors (annual average temperature), topography factors (aspect, elevation). The response curve of environmental factors can further clarify the relationship between Citrus Distribution Probability and environmental variables. It is generally believed that when the distribution probability is >0.5, the corresponding environmental variable value is conducive to species distribution (Wang et al., 2020). Natural environment suitable for citrus production in Sichuan Province is (Figure 5): elevation ≤500m, annual average temperature ≥16.5 ˚C, and the aspect is relatively suitable in Northeast, Southwest and Northwest. Human environment suitable for distribution is: with the support of citrus policy, the input of citrus fertilizer in the county is ≥ 500t, the input of citrus labor in the county is ≥ 5,000, the input of citrus pesticides in the county is ≥ 12.5t, and the technical progress represented by unit yield is 750–7000 t/km^2.

4.2 Citrus distribution probability in sichuan

According to the land use/land cover classification system monitored by remote sensing in China (Liu and Buhe, 2000), China's land use control policies and citrus planting habits in Sichuan Province, citrus production can only be in garden and dryland. Therefore, retain the probability of distribution on garden and dryland, and eliminate the probability of distribution on paddy field, grassland, water, unused land and urban and rural (industrial and mining, residential) construction land, and finally obtain the probability of Citrus Distribution in Sichuan Province (Figure 6). The number of pixels of citrus distribution probability is 77,906, including 34,360 pixels with $p < 0.3$, 20,520 pixels with P (0.3–0.5), 21,863 pixels with P (0.5–0.7), 1,163 pixels with $p > 0.7$, the minimum value is 0.003, and the maximum value is 0.893.

TABLE 5 Various parameters of the main environmental variables of Citrus.

Code	PC/%	PI/%	RTGO	RTGW	TGo	TGw	AUCo	AUCw
pes	62.1	29.32	1.20	1.40	1.34	1.56	0.90	0.92
fer	14.26	4.46	1.18	1.41	1.34	1.54	0.90	0.92
pol	6.93	1.26	0.70	1.41	0.96	1.54	0.82	0.92
ta	5.56	46.88	1.20	1.35	1.35	1.52	0.90	0.92
lab	4.06	1.92	1.16	1.42	1.31	1.56	0.90	0.92
slope	3.90	0.75	0.70	1.42	0.87	1.56	0.85	0.92
aspect	1.51	8.44	0.03	1.40	0.02	1.55	0.52	0.92
dem	0.70	0.00	1.19	1.42	1.33	1.56	0.90	0.92
sci	0.49	4.89	0.58	1.41	0.64	1.55	0.77	0.92
cons	0.35	0.09	0.03	1.42	0.12	1.55	0.68	0.92
pre	0.05	0.95	0.58	1.42	0.68	1.55	0.79	0.92
om	0.04	0.35	0.78	1.42	0.83	1.56	0.81	0.92
tp	0.02	0.47	0.43	1.42	0.67	1.56	0.82	0.92
clay	0.01	0.11	0.45	1.42	0.56	1.56	0.81	0.92
pH	0.01	0.02	0.17	1.42	0.21	1.56	0.72	0.92
gra	0.00	0.00	0.29	1.42	0.38	1.56	0.74	0.92
neo	0.00	0.09	0.16	1.42	0.21	1.56	0.64	0.92
silt	0.00	0.00	0.02	1.42	0.05	1.56	0.57	0.92
sta38days	0.00	0.00	0.74	1.42	0.82	1.56	0.83	0.92
sun	0.00	0.00	0.83	1.42	1.10	1.56	0.88	0.92
tad	0.00	0.01	0.21	1.42	0.28	1.56	0.71	0.92
tk	0.00	0.00	0.06	1.42	0.09	1.56	0.54	0.92
traf	0.00	0.00	0.87	1.42	0.98	1.56	0.86	0.92
ur	0.00	0.00	0.01	1.42	0.02	1.56	0.57	0.92

PC, is percent contribution; PI, is permutation importance; RTGO, is the regularization training gain using the factor alone; RTGW, is the regularization training gain using other factors; TGw, is the test gain using other factors; TGO, is the test gain using the factor alone; AUCo, is the area under the working characteristic curve of the subjects using the variable alone; AUCw, is the area under the receiver operating characteristic curve using other factors.

Most areas of Sichuan province are unsuitable areas ($p < 0.3$), low suitable areas ($0.30 \le p < 0.50$) are mainly distributed in Suining, Deyang and Mianyang, medium suitable areas ($0.50 \le p < 0.70$) are distributed in Neijiang, Meishan, Ziyang, Nanchong, Zigong, Yibin and Guang'an, and high suitable areas ($p > 0.7$) are in Neijiang, Ziyang and the south of Nanchong. In addition, in Dazhou and Zigong, high suitability areas are scattered.

4.3 Spatial regulation of citrus production in sichuan

In this study, the predicted area of Citrus in Sichuan Province in 2025 is less than the appropriate grid area of Citrus ($Qy \le Qx$), and the predicted area of all cities is less than the appropriate grid area of Citrus ($Sn,y < Sn,x$), so Strategy three simulation is selected. The spatial pattern of citrus production in the four scenarios is similar. The production space is concentrated in Central Sichuan, relatively concentrated in Meishan, Ziyang, Neijiang, Chengdu, Nanchong and Yibin, and scattered in Deyang, Mianyang, Dazhou, Luzhou, Leshan, Liangshan and Panzhihua (Figure 7). In different scenarios, the relative error between the simulated area and the predicted area of citrus production space is 0.28%–0.39%.

Using ArcGIS spatial analyst statistics, the spatial simulation data of citrus production in each city are obtained (Table 6). In the positive low growth scenario, the citrus planting area in Sichuan will reach 3533 km^2 in 2025, an increase of 143.90 km^2 compared with 2020, and the total spatial expansion will increase by about 4.25%. Meishan (24.20 km^2) is the only city with an increase of more than 20km^2, and five cities with an increase of 10–20 km^2 are Ziyang (18.5 km^2), Nanchong (13.50 km^2), Chengdu (13.20 km^2), Yibin (12.50 km^2) and Neijiang (10.20 km^2). In the positive high growth scenario, the citrus production area in Sichuan in 2025 was 3990km^2, an increase of 600.90 km^2 compared with 2020, and the total spatial expansion increased by 17.73%. There are 11 cities with an increase of more than 20km^2, of which Meishan has the largest increase (105.20 km^2). In the negative low growth scenario, the

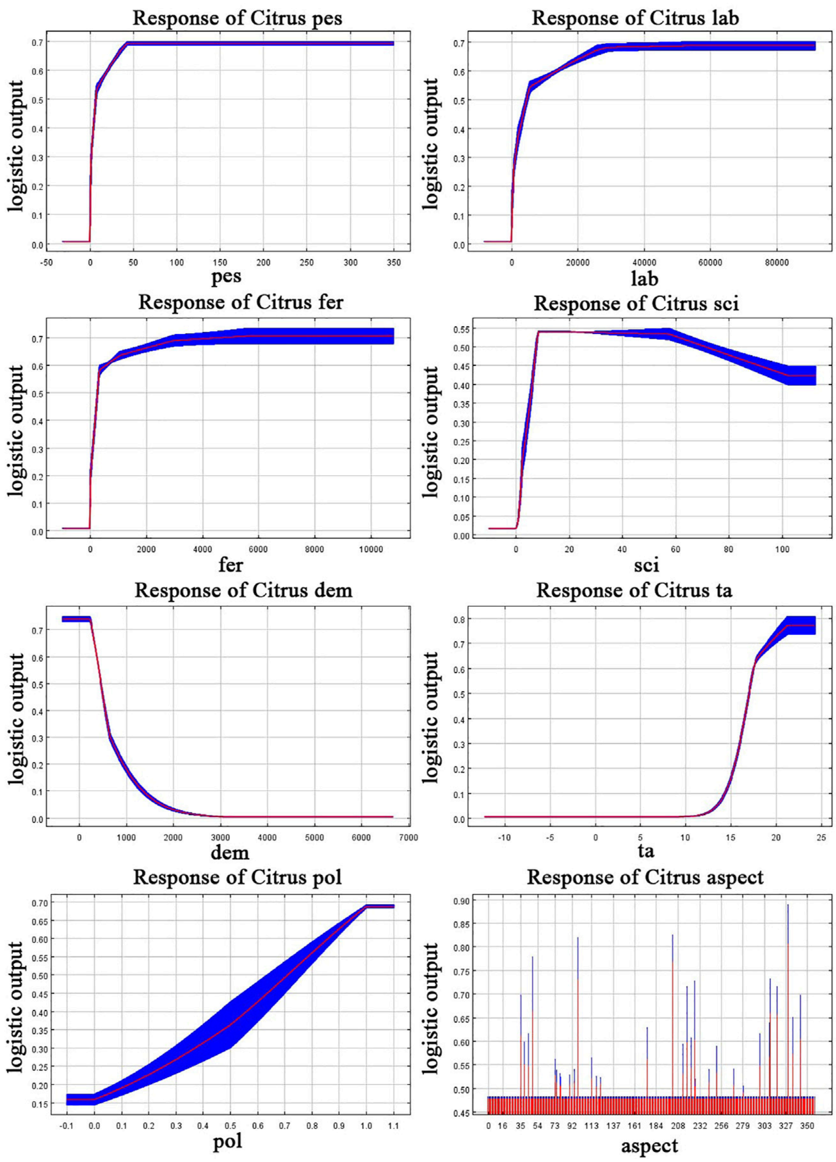


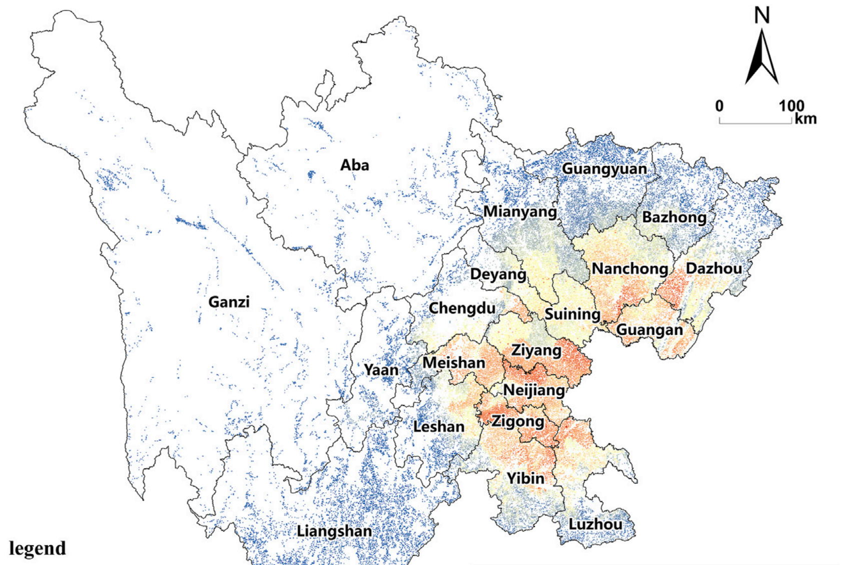
FIGURE 5
Response curves of existence probability of Citrus.

citrus production area in Sichuan will be 3270 km^2 in 2025, a decrease of 119.10 km^2 compared with 2020, and the total space needs to be reduced by 3.51%. Only Meishan (22.80 km^2) has a reduction of more than 20km^2, and there are four cities with a reduction of 10–20km^2, which are Ziyang (17.50 km^2), Chengdu (12.80 km^2), Nanchong (12.50 km^2) and Yibin (11.50 km^2). In the scenario of negative high growth, the citrus planting area in Sichuan will reach 2954 km^2 in 2025, which will be reduced by 435.10 km^2 compared with 2020. There are nine cities with a reduction of more than 20km^2, of which Meishan has the largest reduction (78.80 km^2).

5 Discussion

5.1 Applicability of MaxEnt model

MaxEnt model is a highly complex machine learning model. Like other distribution models, the basic assumption of modeling is that the study area has undergone systematic or random unbiased sampling (Phillips et al., 2009). However, samples are often taken from easily accessible areas, such as along roads and rivers, orchards and farms. Therefore, due to the influence of sampling deviation, AUC may overestimate the ability to evaluate the model (Veloz, 2009). 87% of the



Citrus Probabilty	Count	Percentage(%)	Area(km^2)
<0.3	34360	44.10	34360
0.3 ~ 0.5	20520	26.34	20520
0.5 ~0.7	21863	20.06	21863
>0.7	1163	1.49	1163
Total	77906	100	77906

FIGURE 6
Suitable distribution probability of citrus in sichuan based on natural and human factors.

previous MaxEnt model studies used data that are easy to cause sampling deviation (Yackulic et al., 2013). Spatial filtering is often used to correct sampling bias, that is, only a limited number of sites are retained within a certain distance (Syfert et al., 2013; Radosavljevic and Anderson, 2014). The difficulty of spatial screening method is the setting of spatial spacing, which should be consistent with the variation degree of environmental variables on the spatial scale (Anderson, 2012; Shcheglovitova and Anderson, 2013). There are few studies on the sampling interval of citrus sample points. In the existing research on national scale and regional scale, the space spacing of 1 km^2 shows good accuracy (Lu et al., 2012; Yan et al., 2021). Therefore, this study refers to their method and reserves one distribution point in 1 km × 1 km pixel to reduce sampling deviation.

The MaxEnt model provides a set of default parameters for modeling. The distribution model under the default parameters is sensitive to the test data and prone to over fitting. Therefore, the optimization of model parameters is crucial to improve the prediction accuracy and reliability of results (Syfert et al., 2013). In this study, Feature Class and Regulrzation Multiplier are used to constrain the complexity of the model (Cobos et al., 2019), and the combination of parameters when AICc is 0 is selected for modeling. The results show that when AICc is the smallest, AUC value is the largest, which is consistent with Anderson's research (Anderson and Gonzalez, 2011). At the same time, in recent research, Xian used MaxEnt model to simulate the spatial distribution of citrus based on nine environmental factors, with AUC values ranging from 0.888 to 0.973 (Xian et al., 2022). The average AUC of this study is 0.924 ± 0.008, which is similar to that of the study, indicating good model performance.

5.2 Dominant environmental variables

The results show that elevation, annual average temperature and aspect are important natural factors affecting citrus production in Sichuan. This finding is basically consistent with Tercan's research results. Based on ArcGIS multi criteria evaluation spatial decision support system, Tercan found that temperature is the most important variable affecting citrus production and distribution in Antalya province of Turkey, followed by elevation (Tercana and Dereli, 2020). Mokarram's research on the suitability of citrus land in Fars Province Iran, also shows that temperature, elevation and aspect are important factors affecting the distribution of citrus production (Mokarram and Mirsoleimani, 2018). In this study, soil had little influence on citrus distribution, with PC and PI tending to 0 and RTGO less than 1. However, Likhar's assessment on the suitability of citrus production in Nagpur, Maharashtra, showed that soil particle structure, pH and soil fertility also significantly affected the

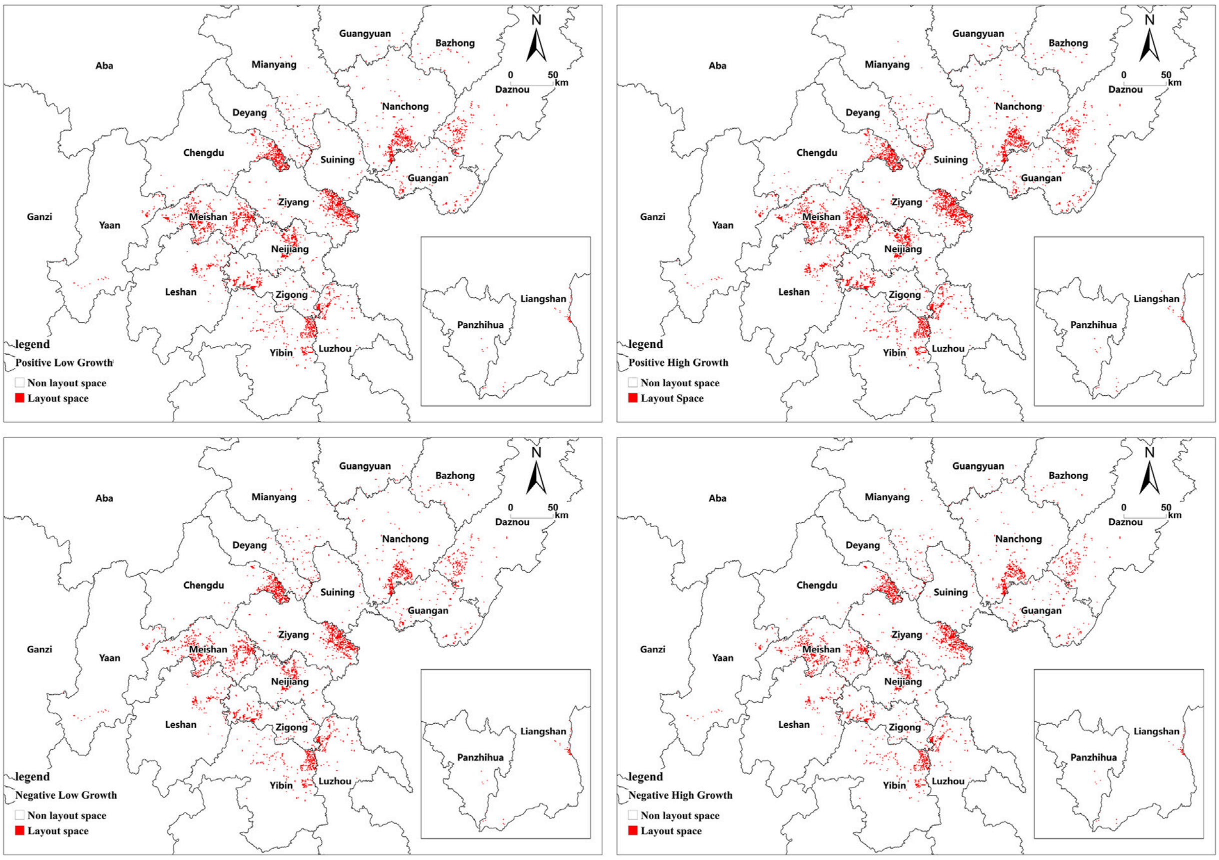


FIGURE 7
Simulation of spatial distribution of citrus production in Sichuan under different scenarios.

distribution of citrus production, which is different from this study (Likhar and Prasad, 2011). The reasons may be as follows: ① It may be caused by the spatial scale effect of variables. Most of the citrus distribution sampling points in this study are located in plain and hilly areas. The soil environmental variables in this area have obvious homogeneity, and their dispersion is small (Table 7). ② The production and management level of farmers in Sichuan Province has gradually improved, especially since 2005, with the promotion of soil testing and formulated fertilization technology, the spatial difference of soil variables has been reduced.

Crop production space has dual characteristics of nature and society, and is the result of interaction of many factors such as nature, economy, market and society. In the process of transformation from tradition to modernity, the constraint of natural environment on the formation of comparative advantage of crops has been greatly weakened, and the impact of economic and social activities has been increasing. In most existing studies, only climate factors are used to establish models (Kogo et al., 2019; Khalil et al., 2021; Khubaib et al., 2021), which reduces the scientificity and guidance of spatial regulation of crop production. In this study, both the natural environment and human activities are integrated into the model. The results show that the contribution rate of human activities (88.19%) is higher than that of the natural environment (11.81%), and pesticides (62.1%), fertilizers (14.26%), policy support (6.93%) and labor force (4.06%) are the top four leading environmental variables. The results show that with the support of production factors and financial policies, the constraints of natural environment on Sichuan citrus production space are decreasing, and human activities have become the dominant factor.

5.3 Citrus suitable space and production optimization

The research results show that the citrus suitable area in Sichuan ($p > 0.5$) covers an area of 8,549.21km^2, of which Zigong (1,698.13 km^2), Nanchong (1,571.26 km^2), Ziyang (1,211.25 km^2), Neijiang (1,035.58 km^2), Meishan (559.54 km^2), Leshan (435.92 km^2), Yibin (370.86 km^2) and Luzhou (361.10 km^2) are the main distribution areas. This is because

TABLE 6 Spatial regulation results of citrus production in Sichuan Province in different scenarios.

City	Positive low growth (km^2)		Positive high growth (km^2)		Negative low growth (km^2)		Negative high growth (km^2)	
	Simulated area	Regulation quantity	Simulated area	Regulation quantity	Simulated area	Regulation quantity	Simulated area	Regulation quantity
Chengdu	350.00	13.20	396.00	59.20	324.00	(12.80)	293.00	(43.80)
Zigong	196.00	8.20	221.00	33.20	181.00	(6.80)	164.00	(23.80)
Panzhihua	4.00	0.50	5.00	1.50	4.00	0.50	4.00	0.50
Luzhou	168.00	6.50	190.00	28.50	156.00	(5.50)	141.00	(20.50)
Deyang	53.00	2.90	59.00	8.90	49.00	(1.10)	44.00	(6.10)
Mianyang	76.00	3.50	86.00	13.50	70.00	(2.50)	63.00	(9.50)
Guangyuan	29.00	1.90	32.00	4.90	27.00	(0.10)	24.00	(3.10)
Suining	28.00	1.50	32.00	5.50	26.00	(0.50)	24.00	(2.50)
Neijiang	261.00	10.20	295.00	44.20	242.00	(8.80)	218.00	(32.80)
Leshan	131.00	5.40	148.00	22.40	121.00	(4.60)	110.00	(15.60)
Nanchong	355.00	13.50	401.00	59.50	329.00	(12.50)	297.00	(44.50)
Meishan	625.00	24.20	706.00	105.20	578.00	(22.80)	522.00	(78.80)
Yibing	316.00	12.50	357.00	53.50	292.00	(11.50)	264.00	(39.50)
Guangan	135.00	5.40	153.00	23.40	125.00	(4.60)	113.00	(16.60)
Dazhou	185.00	7.90	208.00	30.90	171.00	(6.10)	154.00	(23.10)
Yaan	48.00	2.60	54.00	8.60	44.00	(1.40)	40.00	(5.40)
Bazhong	40.00	2.20	45.00	7.20	37.00	(0.80)	33.00	(4.80)
Ziyang	490.00	18.50	554.00	82.50	454.00	(17.50)	410.00	(61.50)
Aba	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Ganzi	2.00	0.80	2.00	0.80	2.00	0.80	2.00	0.80
Liangshan	41.00	2.50	46.00	7.50	38.00	(0.50)	34.00	(4.50)
Total	3,533.00	143.90	3,990.00	600.90	3,270.00	(119.10)	2,954.00	(435.10)

Brackets represent negative values.

TABLE 7 Descriptive statistics of soil environmental variables of Citrus sampling points in plain and hilly areas.

Soil variables	Range	Minimum	Maximum	Mean	Standard deviation
Organic matter	1891	1,352	3,243	1930.78	460.109
pH	26	54	80	67.81	7.845
Total nitrogen	91	84	175	120.95	20.697
Total phosphorus	39	59	98	75.08	9.125
Total potassium	412	1723	2,135	1994.09	100.662
Clay	37	36	73	50.28	4.220
Silt	8	14	22	18.15	1.187
Sand	35	11	46	31.79	3.443

the natural and social conditions in the above areas meet the requirements of citrus production. The elevation is within 1000m, the annual average temperature is 16–18 °C, the social economy is relatively developed, the rural laborers is relatively rich, and the level of fertilizer and pesticide input is high. For example, Meishan, as a typical area, has about 13.39×10^4 workers engaged in citrus planting, and the input of chemical fertilizer and pesticide for citrus production is 1.53×10^4t and 455.79t, and the input level of production factors is in the forefront of the province.

The optimization of crop production space is to maximize the efficiency of resource allocation and realize the transfer of agricultural production to high-yield, efficient and stable regions (Wang et al., 2018; Li et al., 2020). Driven by interests, although

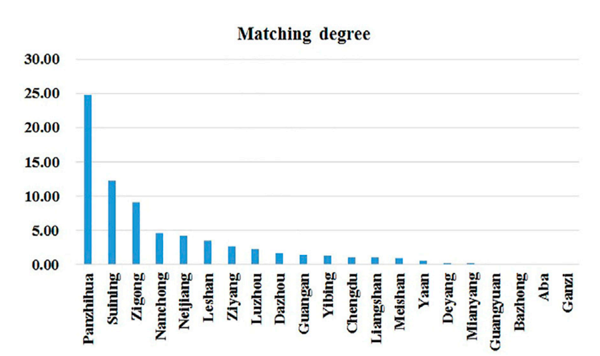


FIGURE 8
The matching degree between the suitable space and the production space of citrus in Sichuan.

technological progress has reduced the constraints of the natural environment on crop production distribution, the natural environment still determines the basic space of crop distribution (Rurinda et al., 2020). This means that arbitrarily expanding the scale of crop production will inevitably increase the cost of natural transformation, leading to increased costs of agricultural products and greater pressure on the environment. Therefore, we must respect the natural environment and minimize the impact of human activities. The citrus production space in Sichuan has experienced long-term expansion, and there is a reality that it has been distributed to low suitability areas, or even unsuitable areas. The matching result between the production space and the suitable space shows (Figure 8) that the production area in Liangshan (0.99), Meishan (0.93), Ya'an (0.53), Deyang (0.13) and Mianyang (0.07) has exceeded the suitable area. The matching degree in Panzhihua (24.79), Suining (12.28), Zigong (9.04), Nanchong (4.60), Neijiang (4.13) and Leshan (3.47) is relatively large, which still has a certain potential space. At present, the development of China's citrus industry has shifted from quantity growth to quality improvement, and the growth rate of planting area has decreased. Therefore, Sichuan should not expand the citrus space scale at a high speed. It should choose a positive low growth scenario, stabilize the citrus area at 3,533 km^2, and focus on optimizing the citrus production space. The government should speed up the elimination and transformation of low yield, low quality and low efficiency citrus orchards, encourage companies and farmers to increase production input, improve land quality, improve water conservancy facilities, production roads and trading markets, and build standardized and large-scale citrus production bases. Strengthen the training, demonstration and promotion of new varieties and technologies. Through the optimization of production space, the main citrus production areas can be formed in Meishan, Ziyang, Neijiang, Chengdu, Nanchong, Yibin.

5.4 Limitations and uncertainties

Based on MaxEnt model, this study constructed the citrus spatial simulation method (CSSM), which better reflects the comprehensive effect of natural and human factors on crop space, and realizes the regulation simulation of single crop production space. However, the study found that the method is not perfect, mainly in the following aspects: ① Crop production space is affected by many factors, including crop physiological and ecological factors, as well as many complex environmental factors and human activities, such as extreme weather events, heavy metal pollution, sales prices, import and export trade, it is difficult to include all aspects of the impact in the model. ② Citrus distribution points have an impact on MaxEnt. MaxEnt calculates the suitable distribution probability, generally taking the current position as the distribution variable. When simulating the distribution of citrus production in the future, the influence of the actual distribution points in the future may be ignored, resulting in systematic errors. The longer the citrus planting time, the more prominent the path dependence of citrus planting. Therefore, when sampling the distribution of citrus in this study, try to select citrus producing areas with planting years ≥30a to reduce the impact of the actual distribution points in the future. ③The environmental variables in CSSM are all based on the average value of many years, ignoring the time change of environmental variables, which makes the prediction results of the model have certain limitations. In the next step, the predicted value of environmental variables can be used to calculate the distribution probability to improve the accuracy of the model. Despite these limitations, the CSSM method has successfully mapped the spatial distribution of citrus in Sichuan Province under four different scenarios for the first time. The results obtained have certain reference value for guiding the spatial optimization of citrus production in Sichuan Province and the adjustment of crop structure.

6 Conclusion

This study uses MaxEnt, ArcGIS, Oracle, SQL to build citrus spatial simulation method (CSSM) to simulate the spatial distribution of citrus production in Sichuan Province under different scenarios in 2025. The following conclusions are drawn: 1) The main environmental variables affecting the distribution of citrus production in Sichuan are production factors (pesticide input, fertilizer input, labor input), social factors (policy, technological progress), climate factors (annual average temperature), Topographic factors (aspect, elevation). 2) Driven by production factors and financial policies, the constraints of natural environment on Sichuan citrus production space are gradually reducing, and human activities play a leading and decisive role. 3) Citrus suitable space in

Sichuan are mainly distributed in Zigong, Nanchong, Ziyang, Neijiang, Meishan, Leshan, Yibin and Luzhou. 4) The government should choose a positive low growth scenario to stabilize the citrus area in Sichuan at 3533 km^2 in 2025. Through the optimization of production space, the main citrus production areas are formed in Meishan, Ziyang, Neijiang, Chengdu, Nanchong and Yibin.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

ZL, CC, YL, and GL conceived and designed the CSSM. PH, GL, and WG collected the data and analyzed the data. JC and ZS helped the language correction; ZL wrote the paper.

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