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Spatiotemporal epidemiology and risk factors of scrub typhus in Hainan Province, China, 2011–2020

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ABSTRACT

Background: The re-emergence of scrub typhus in the southern provinces of China in recent decades has been validated, thereby attracting the attention of public health authorities. There has been a spatial and temporal expansion of scrub typhus in Hainan Province, but the epidemiological characteristics, environmental drivers, and potential high-risk areas for scrub typhus have not yet been investigated.
Objective: The aims of this study were to characterize the spatiotemporal epidemiology of scrub typhus, identify dominant environmental risk factors, and map potential risk areas in Hainan Province from 2011 to 2020.
Methods: The spatiotemporal dynamics of scrub typhus in Hainan Province between 2011 and 2020 were analyzed using spatial analyses and seasonal-trend decomposition using regression (STR). The maximum entropy (MaxEnt) model was applied to determine the key environmental predictors and environmentally suitable areas for scrub typhus, and the demographic diversity of the predicted suitable zones was evaluated.
Results: During 2011–2020, 3260 scrub typhus cases were recorded in Hainan Province. The number of scrub typhus cases increased continuously each year, particularly among farmers (67.61%) and individuals aged 50–59 years (23.25%) who were identified as high-risk groups. A dual epidemic peak was detected, emerging annually from April to June and from July to October. The MaxEnt-based risk map illustrated that highly suitable areas, accounting for 25.36% of the total area, were mainly distributed in the northeastern part of Hainan Province, where 75.43% of the total population lived. Jackknife tests revealed that ground surface temperature, elevation, cumulative precipitation, evaporation, land cover, population density, and ratio of dependents were the most significant environmental factors.
Conclusion: In this study, we gained insights into the spatiotemporal epidemiological dynamics, pivotal environmental drivers, and potential risk map of scrub typhus in Hainan Province. These results have important implications for researchers and public health officials in guiding future prevention and control strategies for scrub typhus.

1. Introduction

As a vector-borne disease caused by *Orientia tsutsugamushi*, scrub typhus is mainly transmitted by infectious chigger mites that bite human skin [1]. Rats are the primary source of scrub typhus infection [2]. Infected individuals may exhibit various symptoms such as eschar, ulcers, rash, lymphadenopathy, hepatosplenomegaly, or even life-threatening multiple organ failure [3,4]. Globally, it is estimated that more than one million cases of scrub typhus occurs per year, with approximately one billion people being exposed to the conventional

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endemic regions called the "tsutsugamushi triangle" (from Pakistan in the west, to far eastern Russia in the east, and to the Indo-Pacific region of northern Australia in the south) [5,6]. More alarming is the endemic re-emergence and continuous confirmation of novel natural foci in recent decades; however, detailed epidemiological analyses and risk assessments are still insufficient in high-risk regions [7].

China is situated in the center of the "tsutsugamushi triangle," and the national annual incidence of scrub typhus has increased by 4.53 times, from 0.45/100,000 to 2.04/100,000 during 2011–2020, with natural foci expanding beyond southern China [6,8]. By analyzing national surveillance data, we have observed a significant increase in the annual incidence of scrub typhus in Hainan Province. Specifically, the number of cases per 100,000 people has surged from 0.40 in 2011 to 3.82 in 2020, a nearly ten-fold increase. This finding firmly establishes Hainan Province as a recognized high-risk area for scrub typhus in China [3]. Despite the extraordinary transmission dynamics of scrub typhus in Hainan Province, few studies have described its epidemiological features and key risk factors for its expansion.

Recent research has indicated that scrub typhus dynamics can be modeled locally by multiple environmental factors, such as climate, topography, and socioeconomic factors [9–11]. Hainan Province, the second-largest island in China with a population of over 10 million, is the only province located entirely in the tropics. Its distinctive natural and social environment has driven booms in agriculture, tourism, international shipping, and aviation over the past decades and simultaneously enhances the likelihood of the epidemic and spread of scrub typhus [6]. Therefore, the presence of certain risk factors in Hainan Province could contribute to the rapid expansion of the spatiotemporal dynamics of scrub typhus.

This study systematically quantified the demographic, temporal, and spatial characteristics of scrub typhus in Hainan Province from January 2011 to December 2020. A maximum entropy model was established to identify the key environmental drivers and map potential risk areas, providing a new perspective for updating public health interventions in

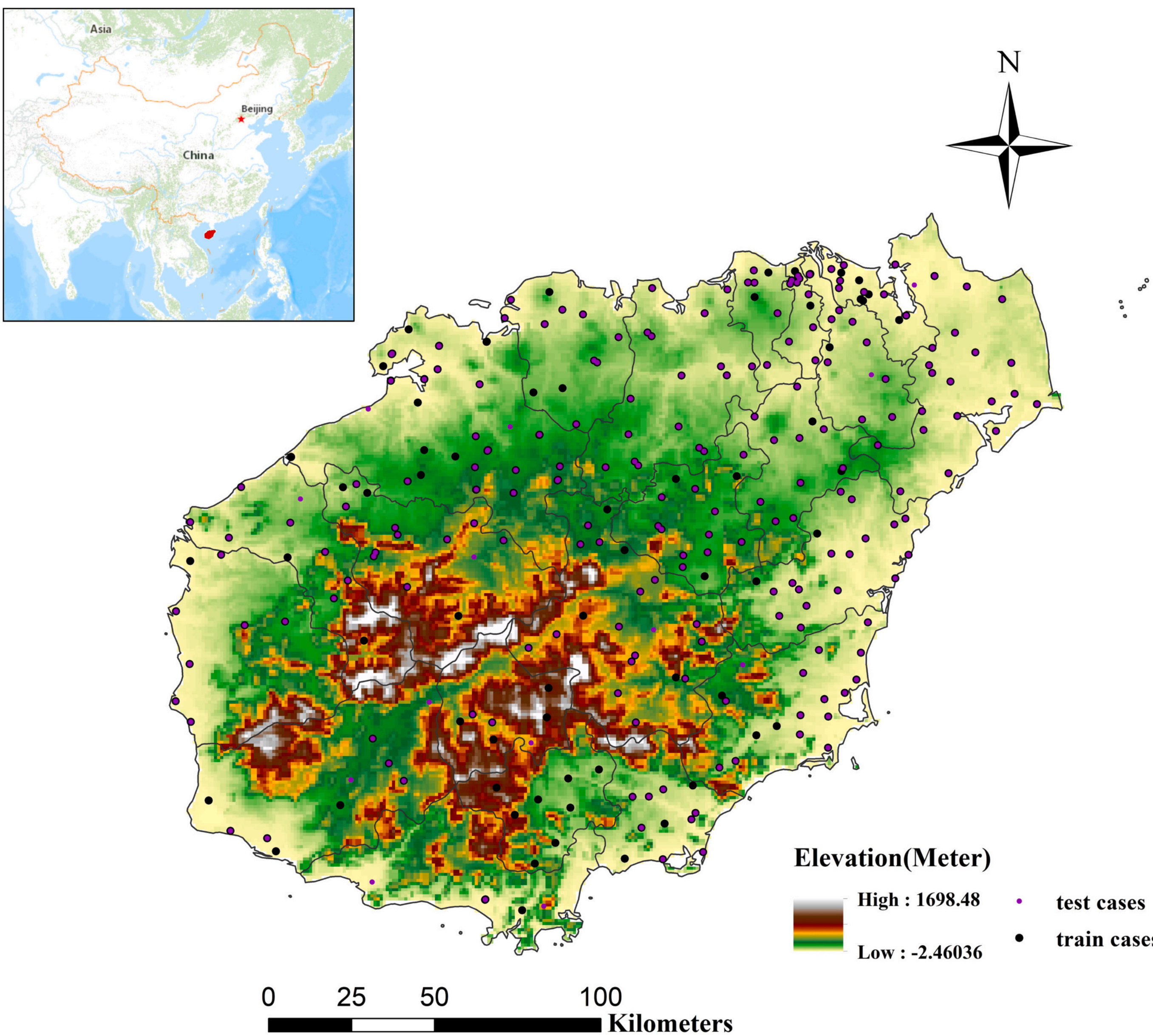

Fig. 1. Location of study area and reported cases of scrub typhus, Hainan Province, China. (Green represents low-altitude areas, and brown represents high-altitude areas. The black dots show the distribution of the cases in the testing set, and the purple dots show the distribution of the cases in the training set.) (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Hainan Province.

2. Materials and methods

2.1. Study areas

Hainan Province is situated in the northwest of the South China Sea, spanning across the latitudes 18°10′N to 20°10′N and longitudes 108°37′E to 111°03′E (Fig. 1). By the end of 2020, there were 24 county- and 218 town-level administrative districts in Hainan Province with a population of 10.08 million. The geomorphology of Hainan Province has a circular stratiform distribution with mountainous areas at the center and lowlands at the periphery. The climate feature in Hainan Province is typically a tropical monsoon climate, manifesting high temperatures throughout the year with a mean annual temperature of 22.5–25.6 °C, and rainfall divided into dry and rainy seasons with an average annual precipitation of 1640 mm. With rapid economic and societal development, Hainan Province is undergoing urbanization and demographic changes.

2.2. Data collection and management

Given the unified diagnostic criteria institutionalized by the Chinese Center for Disease Control and Prevention (China CDC), cases of scrub typhus were laboratory-confirmed, clinically diagnosed (Supplementary Table 1) [12], and directly reported to the Chinese National Notifiable Infectious Disease Reporting Information System (CNNDS). Pertinent information on individual cases was recorded by sex, date of birth, address, occupation, onset, and time of diagnosis from January 1, 2011, to December 31, 2020. To protect the privacy of individuals, cases were anonymized and preprocessed to eliminate any identifiable personal information [6,13].

The yearly demographic statistics of Hainan Province were accessed from the Provincial Bureau of Statistics in Hainan Province (http://stats.hainan.gov.cn/), and a 1:1,000,000 scale vector map of Hainan Province was downloaded from the Data Center for Geographic Sciences and Natural Resources Research (http://www.resdc.cn/). We selected and collected meteorological, socioeconomic, and land cover factor data from Hainan Province and converted them into 1 × 1 km raster images for further ArcGIS analysis and modeling (Table 1). Kriging interpolation and Zonal Statistics in ArcGIS software (version 10.6, ESRI Inc., Redlands, CA, USA) were used to calculate the average values of each meteorological variable to generate panel data.

2.3. Epidemiological features analysis

Patients, defined as clinically diagnosed or laboratory-confirmed cases in Hainan Province from January 1, 2011, to December 31, 2020, were grouped by demographic characteristics, and the geographic parameters were imported into ArcGIS and corresponded to town- and county-level administrative units to visualize the spatial distribution per year. To analyze the temporal characteristics, the monthly and cumulative cases were calculated and presented for Hainan Province over 120 months between 2011 and 2020, and seasonal-trend decomposition was deployed using regression (STR) based on R (version 4.1, Lucent Technologies Bell Laboratories, Auckland, New Zealand) to decode the trend, seasonality, and randomness.

2.4. MaxEnt procedure

To identify potential risk factors, quantify how they interact with scrub typhus occurrence, and map the risk prediction, we established an ecological niche model (ENM) based on the MaxEnt algorithm (MaxEnt, version 3.4.3, American Museum of Natural History, New York, NY, USA) [14,15]. The ENM used the known annual human infections distributed spatially and multi-environmental layer data, revealing the non-random relationship between them, which generated a probability distribution of maximum entropy and predicted a suitable habitat for the species [16]. According to previous experience [13,17], the model parameters were optimized for each run: (a) the regulation multiplier was set to 2 to reduce the influence of spatial autocorrelation; (b) for single model construction, 75% of the data were randomly selected as the training set (marked with purple dots in Fig. 1) and the remaining 25% were set for model testing (marked with black dots in Fig. 1); (c) 10 replicates based on bootstrap sampling can avoid random errors and average the results; and (d) other parameters were set as default values provided in the MaxEnt tutorial [18,19].

We chose Zhang's [20] approach to screen for the factors in this investigation. For considering the collinearity, we used a threshold value of 0.7 for the Pearson correlation coefficient ($|r| > 0.7$) to identify highly correlated factors in the ENM. If the two factors were highly correlated, the decision to delete or retain the variables was dependent on the percentage of each variable's contribution. The variables with a higher percentage contribution were retained, and none of the variables with a percentage contribution of <1% were incorporated into the final model, regardless of their correlation with other variables [21], resulting in seven variables included in final model. The jackknife test assesses the importance of each variable depending on the magnitude of the gains of the variables.

The performance of the MaxEnt model was evaluated using the external omission rate and area under the receiver operating characteristic (ROC) curve (AUC). The omission rates can highlight information about the variance and overfitting of the MaxEnt model and are reciprocally correlated with the model performance [22,23]. The AUC

Table 1
Description and data sources of climate, socioeconomic, and land cover variables used in the MaxEnt model for scrub typhus in Hainan Province.

Variable Category	Variables	Description	Source
Climate	GST	Ground surface temperature (°C)	China Meteorological Data Service Centre (www.data.cma.cn)
	PRS	Mean atmospheric pressure (hPa)	
	RHU	Mean relative humidity (%)	
	SSD	Mean sunshine duration (h)	
	TEM	Mean air temperature (°C)	
	WIN	Mean wind speed (m/s)	
	PRE	Cumulative precipitation (mm)	
	EVP	Evaporation (mm)	
Socioeconomic	Dep	The ratio of dependents (1%)	Open Spatial Demographic Data and Research (www.worldpop)
	Dep_Old	The ratio of dependents of old age (1%) (old,65+)	
	Dep_Young	The ratio of dependents of young age (1%) (young, 0 to 14)	
	Pop_den	Population density (Pop_den (10^3persons/km^2))	
	GDP	Gross domestic product (10^4RMB*/person)	
Topographical/land cover	Slope	Slope (degree)	Geospatial Data Cloud (www.gscloud.cn)
	DEM	Elevation (100 m)	
	NDVI	Annual mean normalized difference vegetation index	Resource and Environment Science and Data Center (www.resdc.cn)

* RMB Chinese renminbi.

values of the ROC curves were used to assess the model calibration and robustness. Generally, the criteria of AUC values are fail (0.5–0.6), poor (0.6–0.7), fair (0.7–0.8), good (0.8–0.9), and excellent (0.9–1) [16]. Associations between the occurrence of scrub typhus and important variables were demonstrated using response curves. To generate a risk map of scrub typhus in Hainan Province, the sites of incidence and selected variables were imported into the MaxEnt model. Environmentally suitable areas with values ranging from 0 to 1 were reclassified into four types: unsuitable (<0.25), moderately suitable (0.25–0.50), suitable (0.50–0.75), and highly suitable (>0.75). Finally, we superimposed the suitability maps with the human population raster data to show the human population exposed to different risk levels [24].

3. Result

3.1. Descriptive analysis

From 2011 to 2020, 3260 patients in Hainan Province were registered, and the number of cumulative cases increased annually (Fig. 2). The annual incidence increased tremendously from 0.40/100,000 in 2011 to 3.00/100,000 in 2013, peaked at 5.04/100,000 in 2018, and decreased to 3.82/100,000 in 2020. Of these, 51.04% were male patients and 48.96% were female, with a male-to-female ratio of 1.04:1. The age of the patients ranged from 0 to 94 years, with a median age of 51 years, and the group of 50–59 years was the most affected, accounting for 23.25% of all cases. In terms of occupation, the largest proportion of patients were farmers (67.61%), which increased from 45.71% in 2011 to 69.77% in 2020, followed by others (11.53%), retirees (7.12%), pupils (6.96%), and workers (6.78%) (Table 2).

The monthly data-based STR results displayed an overall upward trend during 2011–2020, while we also found a significant seasonal pattern, emerging as a dual peak period from April to June and July to October (Fig. 3). The spatial distribution of annualized cumulative cases at the town level demonstrated rapid geographic expansion to the north and east beginning in 2013 (Fig. 4). In general, the northeastern regions of Hainan Province were more affected than those in the southwest, such as Qionghai (642 cases) and Wenchang (471 cases), contributing 34.47% of the total cases in Hainan Province.

3.2. Key predictive variables in the model

According to the Pearson correlation analysis results (Fig. 5), the correlation coefficients were >0.7 between NDVI and slope, NDVI and forest, impervious surface and NDVI, cropland and NDVI, elevation and slope, elevation and forest, elevation and cropland, slope and forest, slope and cropland, forest and water, forest and cropland, water and cropland, and population density and impervious surface. Considering the relative contributions of predictive factors that played a role in the MaxEnt model, population density, the ratio of dependents, land cover (including grassland, water, impervious), cumulative precipitation, elevation, evaporation, and ground surface temperature were contained (cumulative contribution: 96.4%), and the percent contributions of them were ≥1% (Table 3). Jackknife tests indicated that the single variable with the highest gain was population density, and neglecting it had the greatest loss of gain, indicating that the most useful information in Pop_den would not be contained in other variables (Fig. 6).

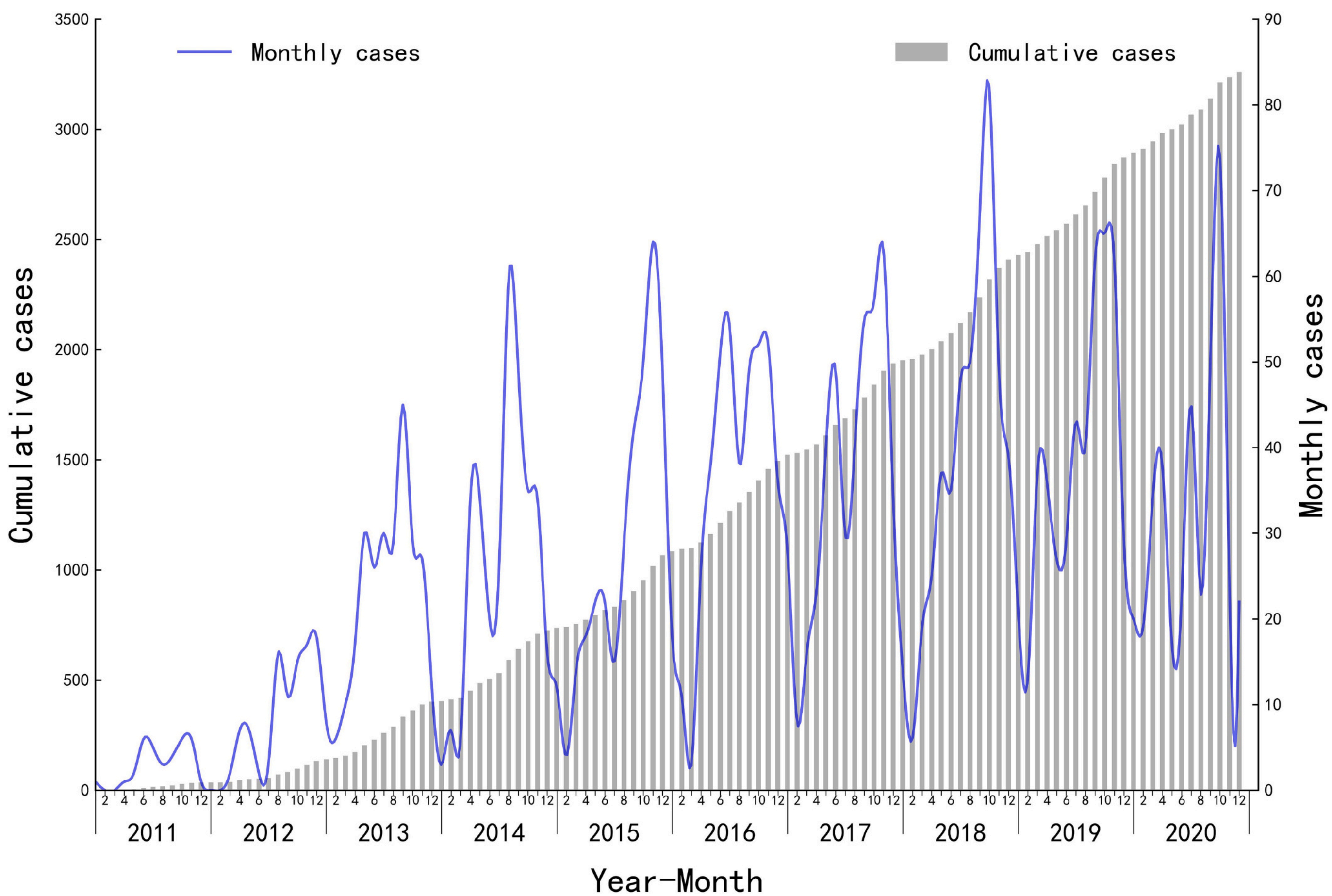

Fig. 2. Monthly and cumulative distribution of scrub typhus cases from 2011 to 2020 in Hainan Province. (The major x-axis represents years and the minor x-axis represents months. The blue line presents the monthly number of cases and the gray bars are cumulative cases.) (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2
Annual incidence, number and proportion of scrub typhus cases classified by sex, age, and occupation in Hainan Province, 2011–2020.

Characteristics	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Total (%)
Number of cases (per 100,000)	35 (0.40)	98 (1.11)	269 (3.00)	324 (3.59)	341 (3.74)	428 (4.67)	443 (4.79)	471 (5.04)	464 (4.91)	387 (3.82)	3260(100%)
Sex											
Male	19	44	126	161	198	218	216	235	240	207	1664 (51.04%)
Female	16	54	143	163	143	210	227	236	224	180	1596 (48.96%)
Age											
<10	5	10	20	16	29	18	18	14	9	12	151(4.63%)
10–19	2	7	5	14	10	14	8	10	20	12	102(3.13%)
20–29	2	5	20	27	21	32	28	32	29	30	226(6.93%)
30–39	8	9	42	49	44	56	56	53	54	51	422(12.94%)
40–49	8	28	63	77	65	83	85	91	81	80	661(20.28%)
50–59	6	21	53	59	77	107	112	110	123	90	758(23.25%)
60–69	2	11	33	48	60	61	79	110	90	67	561(17.21%)
≥70	2	7	33	34	35	57	57	51	67	45	379(11.63%)
Occupation											
Farmers	16	56	182	212	222	300	305	320	321	270	2204 (67.61%)
Workers	2	9	31	32	27	33	18	19	26	24	221(6.78%)
Pupils	7	15	25	29	36	29	24	20	22	20	227(6.96%)
Retirees	2	6	19	16	19	28	37	38	37	30	232(7.12%)
Others	8	12	12	35	37	38	59	74	58	43	376(11.53%)

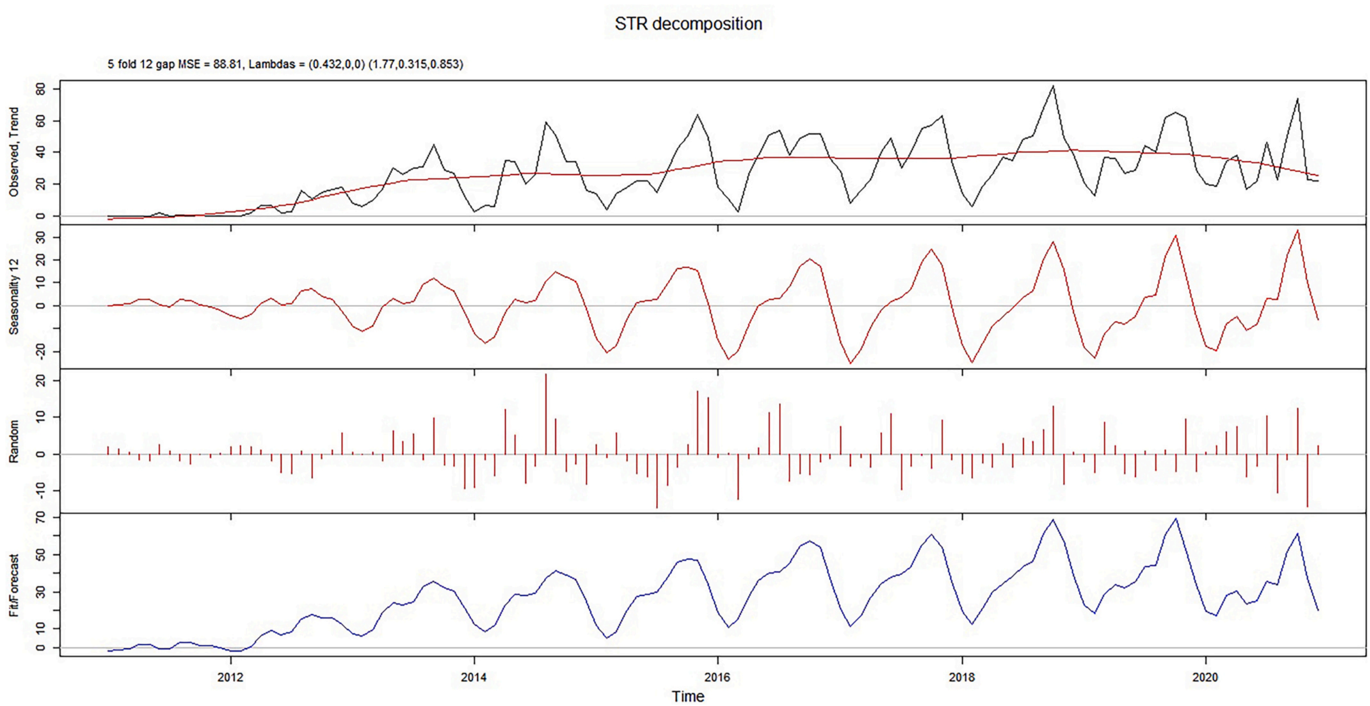

Fig. 3. Temporal decomposition of scrub typhus cases of Hainan Province, January 2011–December 2020 based on seasonal-trend decomposition using regression (STR) analysis. (STR is the decomposition of the original data into trend, seasonal, random, and fitting and forecasting results.)

Based on the response curves of the environmental variables (Fig. 7), we found that GST and Dep had a positive association with the probability of scrub typhus presence, with the highest values at approximately 29.1 °C and 50%, respectively. The change in Dem was different in that a negative correlation was drawn in the probability of scrub typhus presence, with an optimum range of 100–400 m. With an increase in population density, the probability of presence also increased sharply, topped at 4000 people/km^2, and then slowly decreased. Conversely, when the cumulative precipitation was below 1500 mm, the presence of scrub typhus decreased with increasing cumulative precipitation but increased when the cumulative precipitation exceeded 1500 mm. Evaporation in the range of 3.7–4.4 mm was related positively to the presence of scrub typhus, whereas a negative relationship was present outside this range. Impervious land, grassland, and water had the highest probability of scrub typhus among the land cover types.

3.3. Environmental suitability of scrub typhus

By importing the seven environmental variables into the MaxEnt model, we generated a risk map for scrub typhus in Hainan Province (Fig. 8). Supplementary Table 3 displays the proportion of regions and populations at different risk levels in Hainan Province on a county-level scale. These results show that the highly suitable areas (values >0.75) occupied 25.36% of the total area and were mainly concentrated in

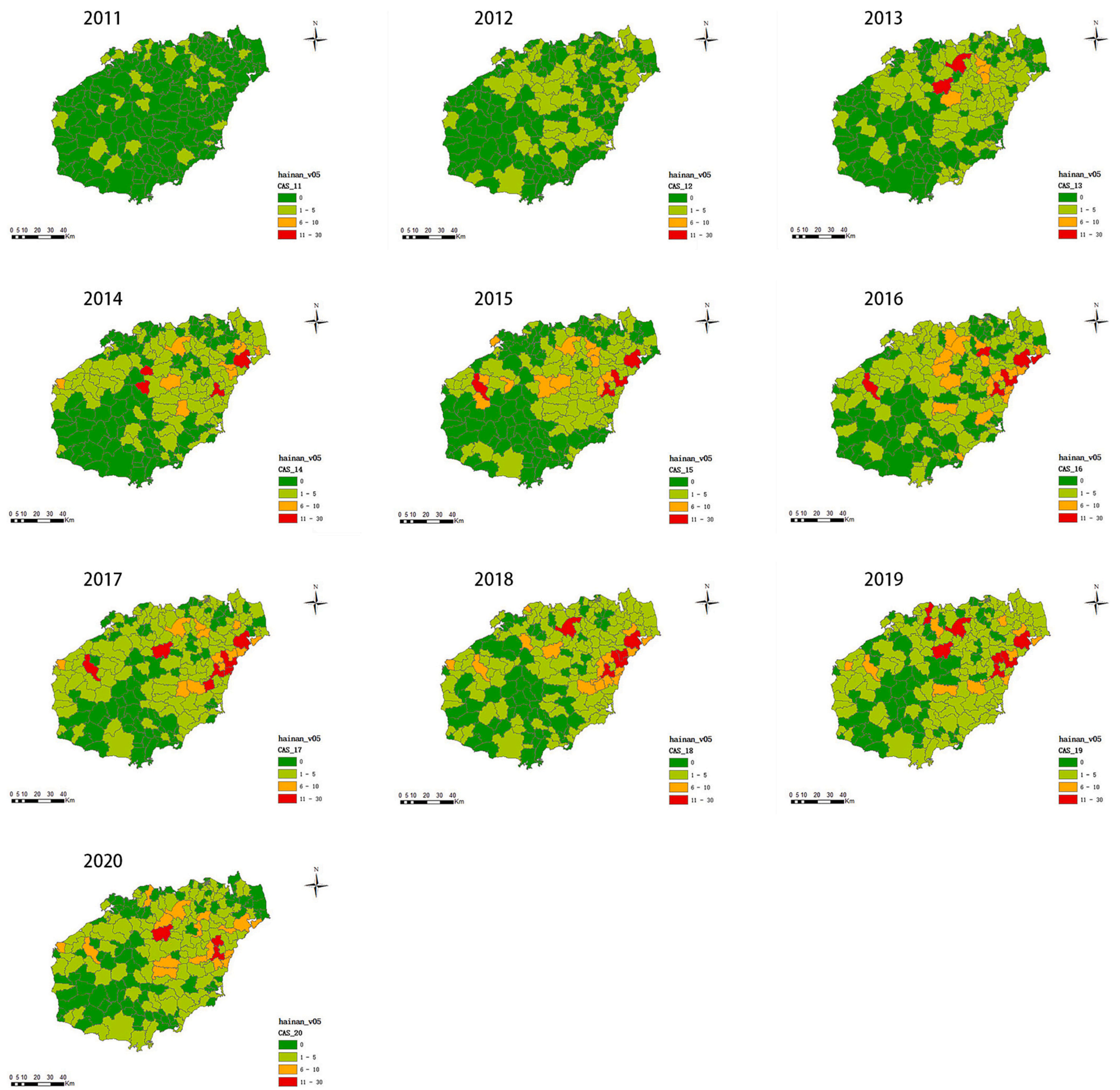

Fig. 4. Spatial distributions in the annual number of scrub typhus cases in Hainan Province, 2011–2020. (Green indicates a low number of cases and red indicates a high number of cases. The base layer of the map was from https://www.resdc.cn/Datalist1.aspx?FieldTyepID=7,1.) (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

densely populated cities located in the northeast of Hainan Province, including Wenchang, Chengmai, Longhua, Xiuying, Qiongshan, and Meilan, with the rest scattered along the western and southern coasts. The suitable areas (values 0.50–0.75; area proportion: 24.64%) were observed on the periphery of highly suitable areas generally. The moderate suitable areas (values 0.25–0.50) were mainly distributed in Wenchang (area proportion: 2.35%) and Danzhou (area proportion: 3.44%). Other areas were deemed unsuitable for scrub typhus (values <0.25; area proportion: 24.51%) and were predominantly located in southwestern coastal cities such as Sanya (area proportion: 3.93%), Dongfang (area proportion: 3.64%), and Ledong Lizu Zizhixian (area proportion: 3.31%). In addition, people living in highly suitable areas covered 75.43% of the total population in Hainan Province, suggesting an extensive risk among most residents. In areas suitable, moderately suitable, and unsuitable for scrub typhus, 7.19%, 14.11%, and 3.27% of the total population resided, respectively.

3.4. Model performance

With different cumulative thresholds, the average omission and predicted area varied for tsutsugamushi disease, and the mean omission rates were extremely close to the predicted omission in the testing set (Fig. 9). Fig. 10 shows the ROC curve with a mean AUC value of 0.88, indicating that the model's performance was good, as it fell between 0.8 and 0.9. The overall omission rates and AUC values for both the training and testing models are listed in Supplementary Table 2. With all mean AUC values ranging from 0.81 to 0.90 and omission rates of 0–1.5%, all 10 replicate runs were statistically significant at $P < 0.05$, indicating an

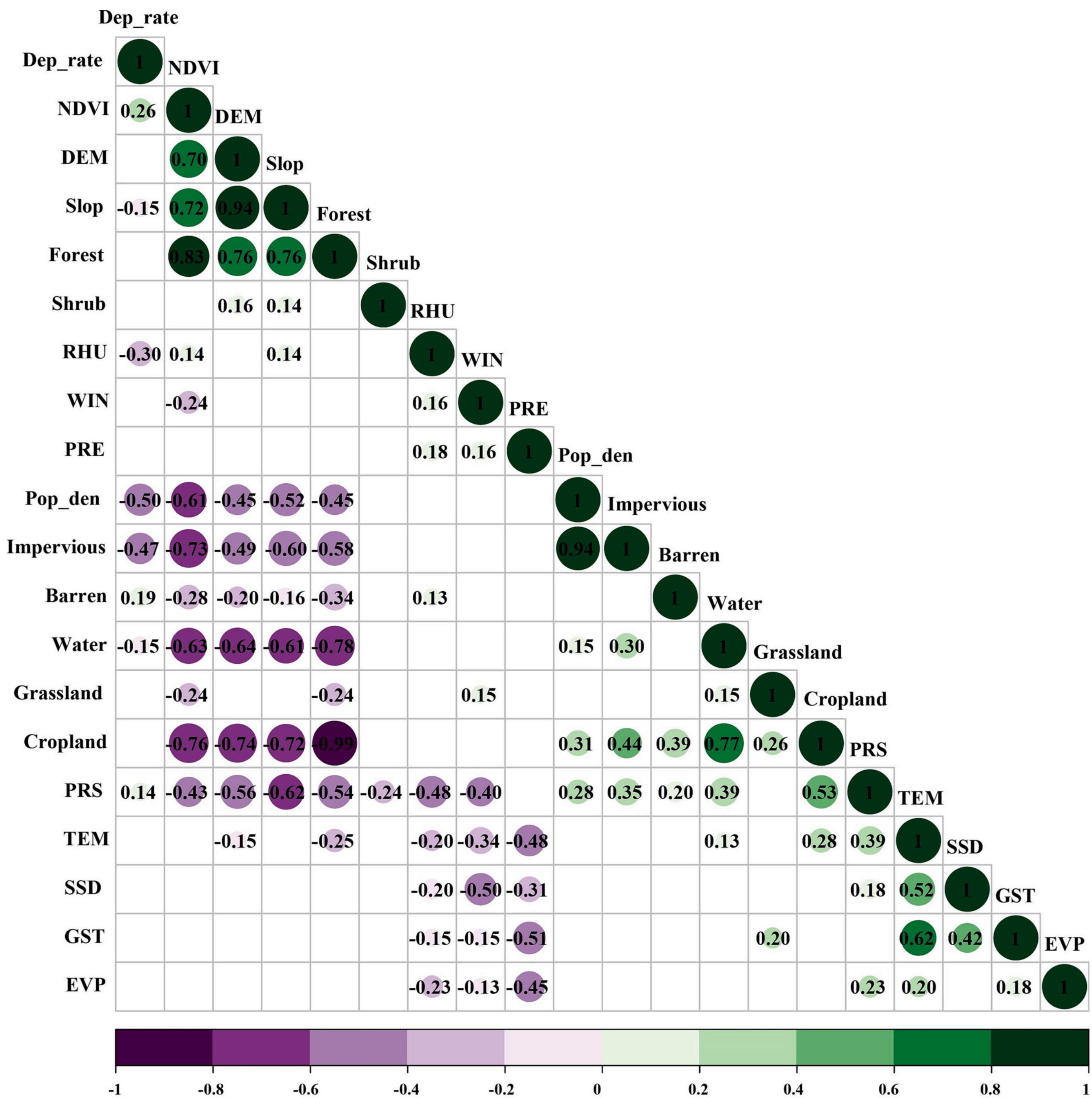

Fig. 5. Heatmap of Pearson's correlation between environmental variables in Hainan Province, 2011–2020. (Purple circles represent negative correlation, green represents positive correlation, and the darker the colors, the stronger the correlations.) (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

excellent performance in identifying and predicting high-risk areas.

4. Discussion

Although the underestimated health risks and disease burden of scrub typhus have been widely recognized, gaps remain in the dynamic monitoring and analysis of specific hotspots that can have significant public health consequences [3,25]. This study explored the spatiotemporal epidemiology of scrub typhus in Hainan Province using the MaxEnt model to identify the associations between environmental variables and scrub typhus, and to predict its distribution. Compared with the model performance in Fujian Province, the MaxEnt model showed better predictive accuracy for scrub typhus in Hainan Province [26]. With the support of well-identified epidemiological knowledge, it will be more effective to implement prospective surveillance, emergency planning, and prompt responses to high-risk periods and locations in Hainan Province.

From 2011 to 2020, the incidence of scrub typhus showed a rapid increase in Hainan Province, posing a serious threat to humans, especially middle-aged and elderly people and farmers. This finding aligned with the demographic characteristics of scrub typhus in Guangzhou, Fujian, and Taiwan [10,27,28]. This might be due to the facts that middle-aged groups in rural areas were mainly engaged in local agriculture, exposed to high contact with the chigger mites in grassland, and

Table 3
The percent contribution and cumulative importance of environmental variables to the MaxEnt model.

Environmental variables	Percent contribution	Cumulative importance
Population density	83.3	83.3
The ratio of dependents	4.9	88.2
Land cover	2.4	90.6
Cumulative precipitation	2	92.6
Elevation	1.6	94.2
Evaporation	1.2	95.4
Ground surface temperature	1	96.4
NDVI	0.7	97.1
Mean air temperature	0.7	97.8
Mean wind speed	0.7	98.5
Mean sunshine duration	0.5	99.0
Slope	0.4	99.4
Mean relative humidity	0.3	99.7
Mean atmospheric pressure	0.2	99.9

lacked personal protective awareness and knowledge of prevention. Therefore, it is crucial that we should pay more attention to the rural left-behind population with necessary education and protection, such as insect repellents or access to protective equipment. Additionally, the seasonal variation in Hainan Province differed from the autumn-type pattern reported in northern China, where human scrub typhus cases increased from September to December and peaked in October [23,29]. The epidemic peaks of scrub typhus in Hainan Province were in April–June and July–October, which coincided with the peak seasons for fruit, vegetables, and fishery products. The temperatures and products in the harvest season of Hainan Province are geared to support the rodent hosts *Leptotrombidium delicense* and *Leptotrombidium gaohuense* [30,31]. People are also prone to travel to Hainan Province during the summer months, bringing more potential opportunities for human infection.

We also estimated that northeastern Hainan Province was the most suitable area for scrub typhus, with two-thirds of the cohort residing in this area. There are two factors that could contribute to understanding the differences in the distribution of environmentally suitable zones in Hainan Province. On the one hand, the northern part of Hainan Province is more prosperous in industry and agriculture than the southern part. The urbanization of Hainan Province, with large amounts of emissions containing nutrients, such as nitrogen and phosphorus, may provide advantages for the breeding and development of vectors [32]. Highly suitable areas for scrub typhus, however, primarily exist in the plains of Hainan Province, where Anhui Province has congruent spatial distribution features [33]. Flat and comfortable topography is optimal for human habitation and survival; hence, population clustering creates conditions for the spread of scrub typhus. In the future, public health authorities need to invest more hygiene resources into these high-risk areas to reduce scrub typhus cases and epidemics.

Among the meteorological factors, ground surface temperature was a positive factor that affected the occurrence and life cycle of scrub

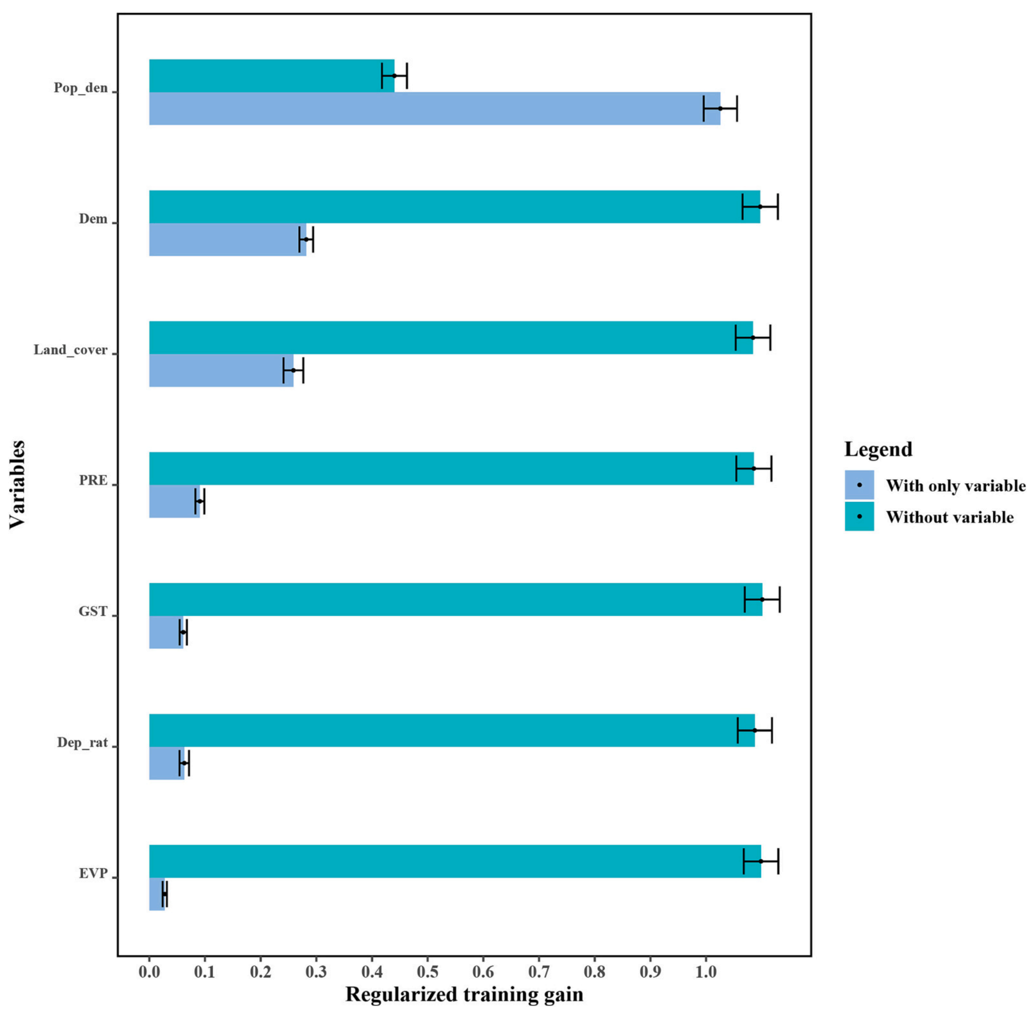

Fig. 6. Results of the jackknife test of predicted variables importance. (The blue strip includes the only variable, and the green strip excludes the variable. The length of the strip indicates the magnitude of importance.) (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

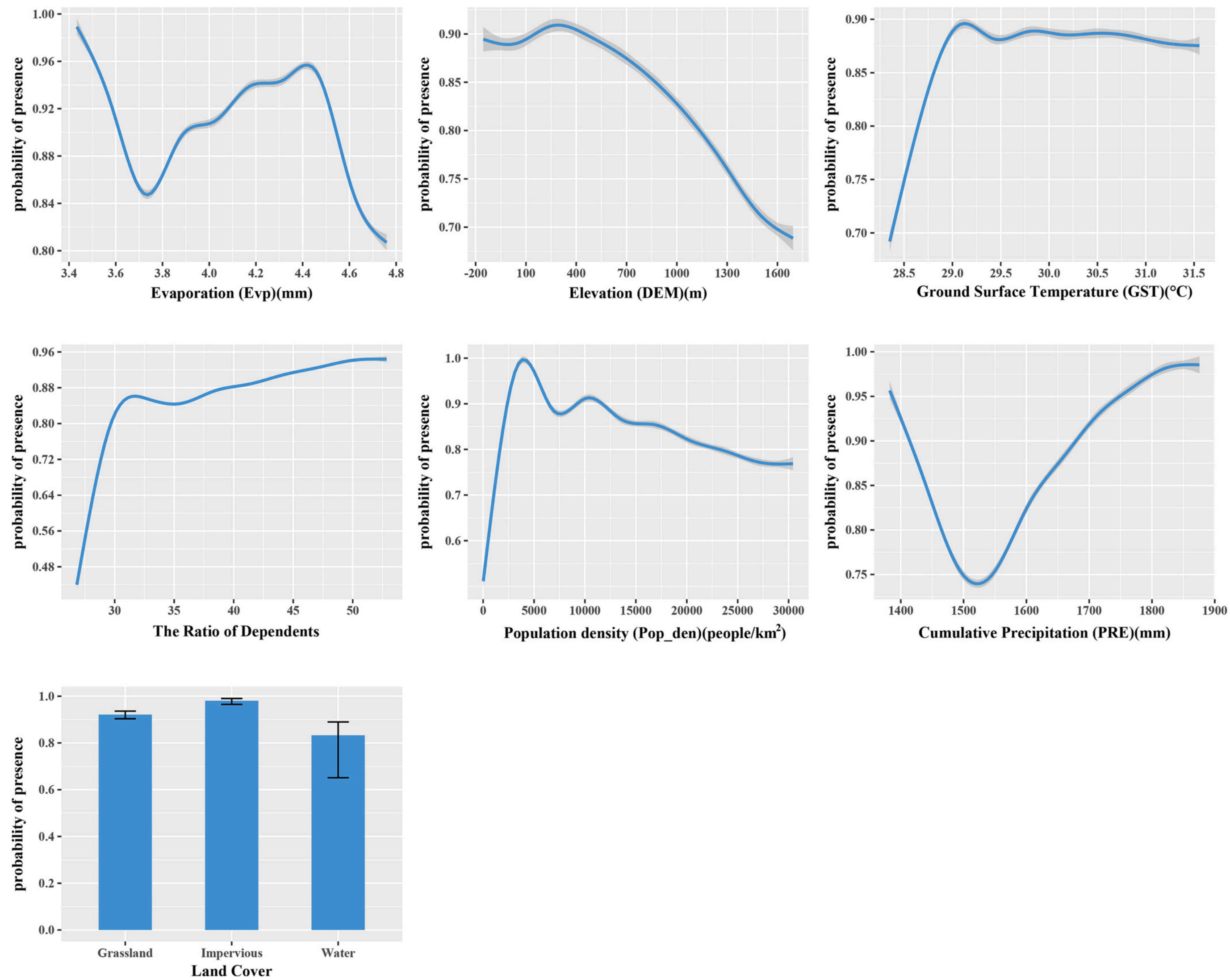

Fig. 7. Response curves for variables associated with the probability of presence of scrub typhus. (Blue lines show the mean response of the 10 replicate MaxEnt runs and gray bars are the mean ± SD. The x-axis is an important variable, and the y-axis is the probability of scrub typhus presence.) (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

typhus, which was identical to the findings in southern China regarding the relationship between temperature variations and scrub typhus [3,26,31,34]. Optimal temperatures can increase the spawning of chigger mites, shorten larval development time, and increase the density of chiggers and their host rodents [35]. High ground surface temperatures, usually accompanied by less clothing and therefore greater skin exposure, make it easier for chiggers to attach to human body surfaces and inadvertently bite humans. However, this elevation was negative for scrub typhus. At higher elevations, the temperature is lower, so the frequency of chiggers' activities and transmissions decreases or is restrained. The environment is inhospitable to chiggers' survival at higher elevations, especially in the center of Hainan Province, where elevation levels are higher than those in the surrounding regions and few people and low vegetation cover exist, creating a natural barrier to scrub typhus transmission [17]. Evaporation and cumulative precipitation are important meteorological predictors. Areas with an evaporation of 3.7–4.4 mm had a high probability of scrub typhus, and evaporation that was too low or too high was detrimental to the presence of scrub typhus. A study in Korea found that chiggers mainly depend on water evaporated into the air as their source of water for survival [9,36]; thus, when evaporation is insufficient (approximately $<$3.7 mm), the chigger mites cannot obtain enough water to complete their life cycle. In contrast, the environments were prone to drought because of excessive evaporation (approximately $>$4.4 mm), which may have caused increased mortality and reduced the dissemination of chiggers. In our study, cumulative precipitation was found to be significantly positively correlated with mean relative humidity; as cumulative precipitation increased, so did the mean relative humidity. A report from Chile showed that the survival and reproduction rates of chiggers, a vector that is fond of wet environments, were reduced at relative humidity below 50%, but that chiggers were active when the relative humidity exceeded 50%. [37,38]. This is the reason that the overall trend of cumulative precipitation presented a “V” with a turning point at 1500 mm. When the cumulative precipitation is below 1500 mm, low relative humidity is not conducive to the survival of chiggers.

Socioeconomic factors were also significant drivers of scrub typhus transmission. For example, a higher population density implies that there are more susceptible hosts, who can gather dispersed tsutsugamushi into a local area and cause outbreaks or epidemics of scrub typhus [30]. The incidence decreased or stabilized after the population density accumulated to a certain extent, probably owing to herd immunity through natural infection, resulting in a transmission constraint. The ratio of dependents determined the population composition, which was positively correlated with scrub typhus. Larger lateral values reflect a

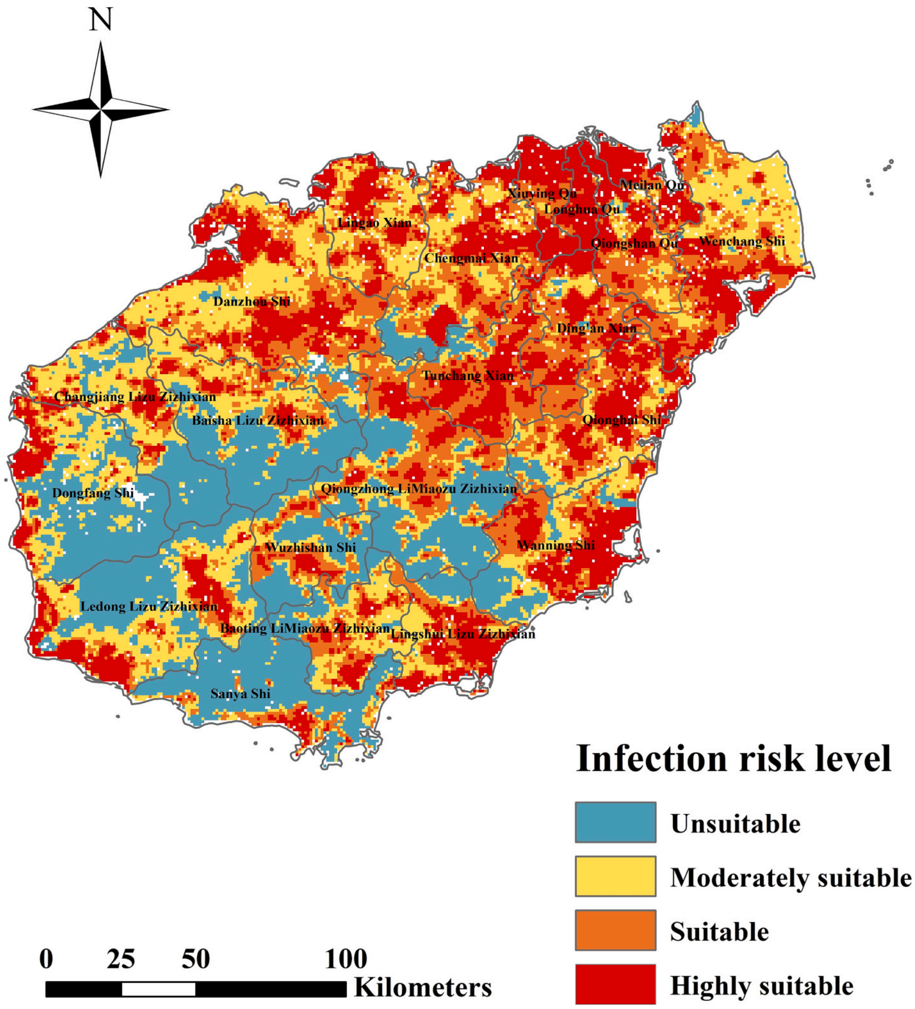

Fig. 8. Distribution of four infection risk levels of environmentally suitable areas for scrub typhus in Hainan Province. (The unsuitable, moderately suitable, suitable, and highly suitable zones are represented by the colors blue, yellow, orange, and red, respectively. The base layer of the map was from https://www.resdc.cn/Datalist1.aspx?FieldTyepID=7,1.) (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

greater proportion of elderly and underage populations, who are generally regarded as a high-risk group for the disease [39]. However, there are few studies on the interaction between scrub typhus and the ratio of dependents, and future research should consider the ratio of dependents in socioeconomic factors.

Grassland, impervious surfaces, and water were the main land cover types in the presence of scrub typhus. Chiggers commonly inhabit environments where food is conveniently obtained, such as grasslands or near water, causing farmers to be infected routinely [27]. With the ongoing urbanization of Hainan Province, building and developing impervious land will increase the chances of the urban population becoming infected with scrub typhus. This may be because green belts, parks, and other planting lands that are designed to improve the urban environment are often located near concrete buildings, which are not only places for human entertainment but also optimal places for chiggers to survive in urban areas [40,41].

Our study, for the first time, systematically analyzed the spatiotemporal characteristics and potential influences of scrub typhus in Hainan Province during 2011–2020. We used the MaxEnt model to map environmentally suitable areas by exploiting its extensive time range and comprehensive data. This study not only offers valuable references for scrub typhus epidemiology but also provides crucial information for public health workers to update preventive technical guidelines. For example, future public health education on scrub typhus should be stressed during the summer months, when chiggers are more prevalent. To this end, tourism authorities in Hainan Province should prioritize reminding tourists to adopt appropriate personal protective measures, carry insect-prevention medicines, and print information pamphlets to enhance health literacy, with a particular emphasis on outdoor enthusiasts. Furthermore, public health authorities in the Hainan Province can utilize changes in meteorological factors to forecast the future prevalence of scrub typhus. By analyzing these factors, they can generate predictive models and issue timely warning signals to the public, ensuring that proactive measures can be taken to prevent and control the spread of the disease. At the same time, considering the spatial location of the risk areas for scrub typhus in Hainan Province, it is crucial for the government to ensure that future land use planning aligns with long-term public health policies [42]. By incorporating public health considerations into land-use decisions, the government can mitigate the risk of scrub typhus and create a healthier living environment for the residents of Hainan Province. This may involve measures, such as avoiding high-risk areas for development or implementing appropriate sanitation and vector control measures in those areas.

There are still certain limitations that should be addressed in future research. First, some cases may not have been monitored or reported in the passive surveillance system, where all case data were captured [8]. Second, the potential lag effects of climatic factors on the incidence of scrub typhus were not considered [43]. Third, as ecological research was defined at the population level, we failed to obviate the potential confounding factor bias revealed in this study. Future studies should address

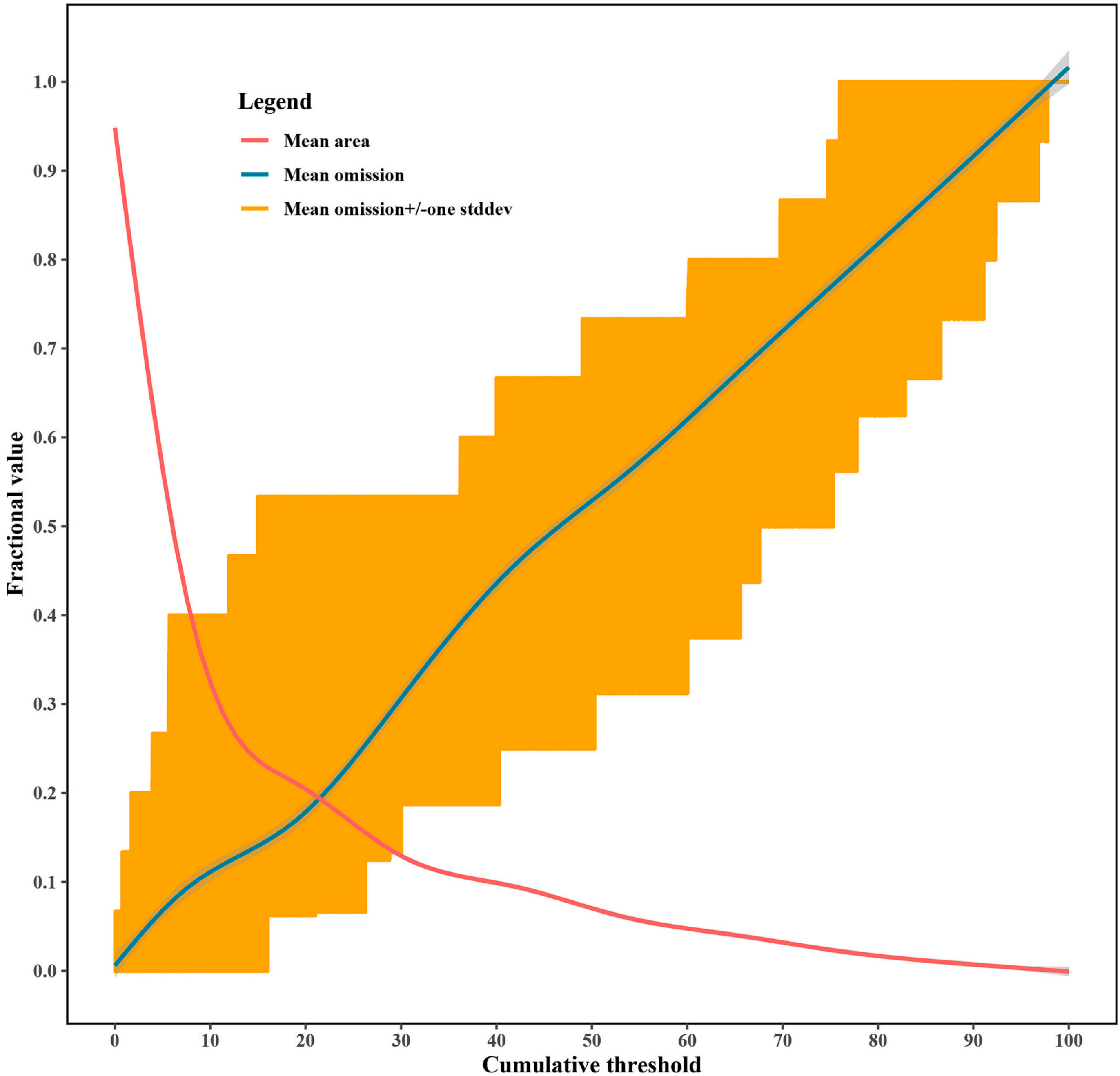

Fig. 9. Mean omission rate and predicted area for scrub typhus as a function of the cumulative threshold averaged over the replicate runs. (Orange areas indicate mean omission ± one SD.)

these limitations.

5. Conclusions

In summary, through this study in Hainan Province, we learned about key populations, seasons, and risk areas that may be in the shadow of scrub typhus, which is conducive to public health services in a rational assignment. Based on the monitoring results of meteorological changes in Hainan Province, health authorities should adjust prevention and control strategies and make targeted forecasts and early warnings of scrub typhus. During the peak of tourist seasons, it is necessary to disseminate health knowledge and awareness to tourists and provide personal protection, for example, by not sitting or lying on grass for long periods, minimizing skin exposure during outdoor activities, and promptly seeking medical attention if they find that their skin has been bitten by a chigger. Additionally, during international trade exchanges, attention should be paid to the possibility of importing cases. In conjunction with geographical information, health authorities should adopt integrated control measures tailored to local conditions to effectively prevent and control local outbreaks of scrub typhus.

Supplementary data to this article can be found online at https://doi.org/10.1016/j.onehlt.2023.100645.

Ethics statement

The ethics committee granted the conduct of this study, including the Chinese Center for Disease Control and Prevention, and the Chinese PLA Center for Disease Control and Prevention.

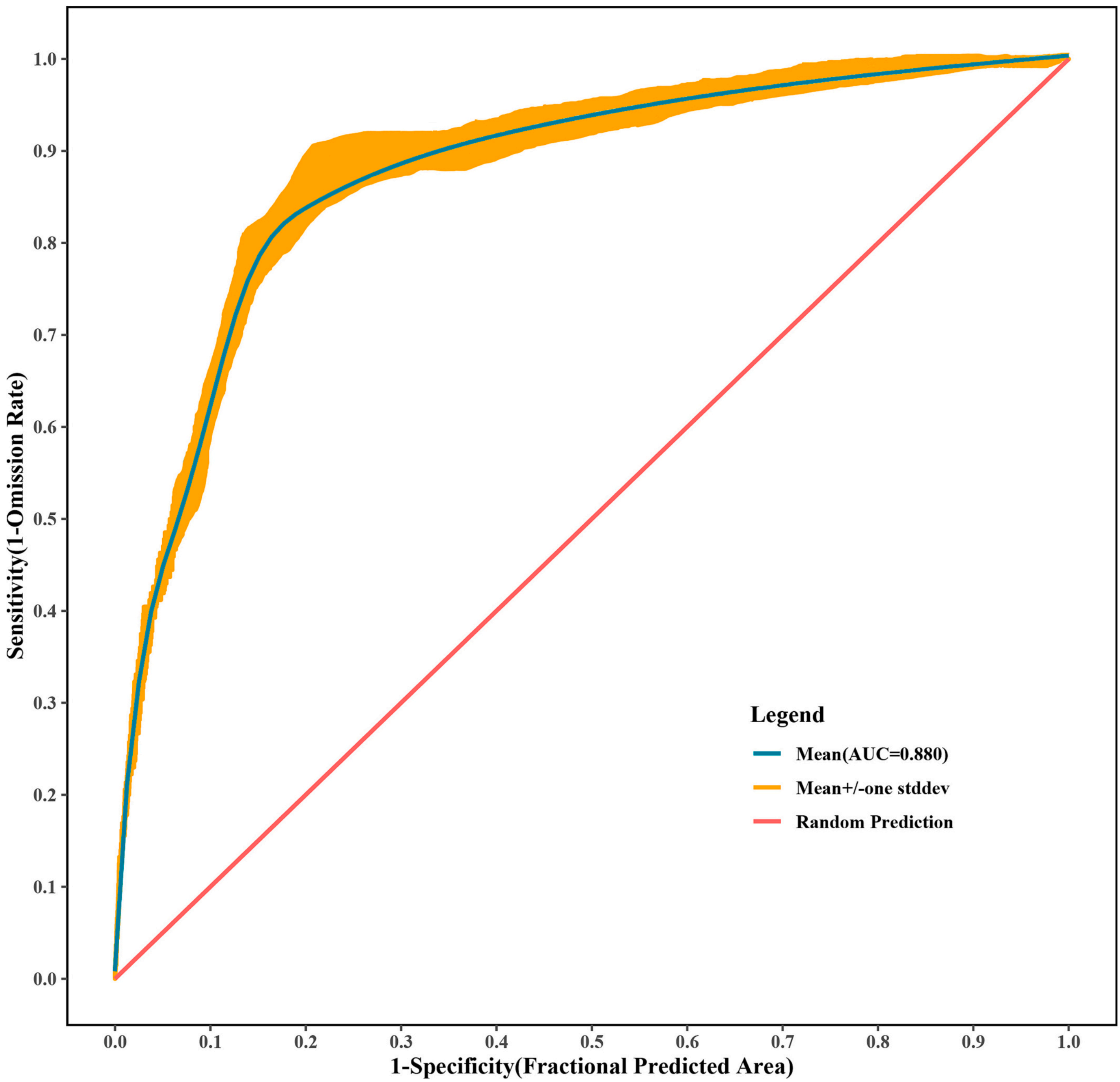

Fig. 10. Receiver operating characteristic curve (ROC) of the maximum entropy model for scrub typhus in Hainan Province, with the 2019 results as a reference. (AUC refers to the area under the ROC curve, with values ranging from 0 to 1, and a higher value indicates better model performance.)

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Author's contributions

Wenyi Zhang and Yong Wang: conceptualization, funding acquisition, supervision, and review; Lisha Liu, Yang Xiao, and Xianyu Wei: data curation, analyzed and interpreted the data, software, and drafted the manuscript; Xuan Li: data curation and analyzed data; Chunyuan Duan, Xinjing Jia: data curation and investigation; Ruizhong Jia, Jinpeng Guo, Yong Chen, and Xiushan Zhang: data curation. All authors read and approved the final manuscript.

Consent for publication

Not applicable.

Declaration of Competing Interest

The authors declare that they have no competing interests in this paper.

Data availability

In this study, the data and materials can be available with the consent of the corresponding authors.

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Not applicable.

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