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Influence of Temperature and Precipitation on the Climate Suitability of Severe Acute Respiratory Syndrome Coronavirus 2

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Abstract: The severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) pandemic has caused enormous losses worldwide since its emergence in 2019. We aimed to further understand how temperature and precipitation affect distribution of the virus, to facilitate taking preventive actions against the disease in a timely manner under varying climatic conditions. In this study, we used the MaxEnt model and R software to investigate temperature and precipitation factors that affect the fitness of SARS-CoV-2. Our results showed that low temperatures (approximately 0–17.5°C) and low precipitation (approximately 30 mm) greatly influence survival of the virus. However, the output value of the response curve was close to 1 with temperatures between 31°C and 37°C and monthly average precipitation 200 mm, which indicates that a high risk of SARS-CoV-2 transmission may also exist under these environmental conditions. SARS-CoV-2 can easily survive under conditions of low temperature and low precipitation; however, the virus also presents a high risk at 31–37°C and monthly precipitation of 200 mm. The results of this study provide a theoretical basis for predicting the spread of SARS-CoV-2.

Keywords: Severe acute respiratory syndrome coronavirus 2; Temperature; Precipitation; MaxEnt model; Akaike information criterion; True skill statistic.

1. Introduction

Health and surveillance systems worldwide have faced unprecedented challenges since the emergence of the coronavirus disease 2019 (COVID-19) pandemic at the end of 2019 [1] which continues to cause tremendous damage and loss to the international community [2]. At present, the source of the causative agent, severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), is not completely clear. It is generally believed that the virus spread from bats [3], pangolins [4] or other wild animals to humans and has subsequently spread among humans. According to recent clinical case reports, pet cats [5], tigers [6] and African lions [7] have been diagnosed with SARS-CoV-2 infection, making this pandemic is a huge challenge for the survival of humans and other animals.

SARS-CoV-2 can be spread through droplets when an infected patient coughs or sneezes, among other possible routes [8]. Common clinical manifestations of SARS-CoV-2 infection include fever, dry cough, breathing difficulties (dyspnea), headache, severe respiratory illness, and pneumonia [3]. Serious illness can lead to progressive respiratory failure and death owing to alveolar damage [9](Hui et al., 2020). Transmission electron cryomicroscopy has revealed that the SARS-CoV-2 S protein binds angiotensin-converting enzyme 2 (ACE2) with higher affinity than does its predecessor, SARS-CoV [10].

Therefore, SARS-CoV-2 is more harmful to humans than SARS-CoV. Changes in global climate may have an important role in outbreaks of infectious diseases [11,12,13]. Previous research of malaria, dengue, chikungunya, Murray Valley encephalitis, Ross River, Rift Valley fever viruses, influenza, Varicella, hantavirus, and hand, foot and mouth disease (HFMD) have shown that extreme climate conditions are likely to affect the occurrence and spread of these diseases [12,14-23]. Research shows that temperature and precipitation climate variables have a significant influence on the occurrence of infectious disease epidemics [24] . Therefore, in the study of SARS-CoV-2, some researchers have analyzed the relationship of temperature and precipitation with the virus by calculating the R value of Effective Reproductive Numbers [25] and Pearson's correlation analysis [26] .

The MaxEnt model adopts ecological niche modeling based on the maximum entropy theory first proposed by Phillips in 2004 [27]. This model can be used to analyze the niche needs of species and predict their potential geographic distribution using present or absent information of the target species and environmental data. In recent years, this model has been widely applied in the prediction of both human and animal infectious diseases and analysis of environmental factors in infectious diseases [28-32].

SARS-CoV-2 research is mainly focused on etiology and virus infectivity, clinical drug screening, and detection and traceability, among other aspects [9, 33-36]. Research is relatively lacking regarding important environmental variables and fitness analysis related to SARS-CoV-2. The arrival of the summer and autumn seasons may lead to resurgence in COVID-19 outbreaks. In this article, we aimed to analyze and discuss extreme values of temperature and precipitation that could affect SARS-CoV-2 transmission, using the MaxEnt model and R software package, based on the niche theory of pathogens. Our findings can provide a theoretical basis for future measures to prevent the spread of SARS-CoV-2 in regions around the world.

2. Materials and Methods

2.1. Data sources and processing

The geographic location of our study area was the site of the original outbreak of SARS-CoV-2 in Wuhan, China (113°41′–115°05′E, 29°58′–31°22′N). We minimized the spatial auto-correlation between geographic locations [28], then extracted geographic locations within a 10-km range. At last, we got 289 geographic sites. We selected 19 biometeorological factors (bio-1 to bio-19) representing extreme values of temperature and precipitation, as environmental variables [32, 37], to further analyze the relationship of climate factors and risk of virus survival.

2.2. Model construction and evaluation

The model with the smallest corrected Akaike information criterion (AICc) value was calculated using the R package "ENMeval" (Cobos et al., 2019a, Muscarella et al., 2014). The AIC value (or ΔAICc) was calculated using the "lambdas" file in the MaxEnt model. Finally, the AIC value (or ΔAICc) was used to measure the complexity of the model with different combinations of MaxEnt (Cobos et al., 2019b). The MaxEnt model specifies the feature classes allowed (L = linear, Q = quadratic, H = hinge, P = product and T = threshold). The feature combinations (FCs) were set as L, H, LQ, LQH, LQPH, and LQPHT; the regularization multiplier (RM) was set at 0.5–4 with an interval of 0.5. The test and training sets were categorized as 25% and 75% of all data. We performed logistic regression with 10 replicates.

In this study, we used the area under the receiver operating characteristic (ROC) curve (AUC) value and average standard deviation to measure the accuracy of the model; we also used the R package "PresenceAbsence" to calculate the sensitivity and specificity of the model. PresenceAbsence was used to calculate the true skill statistic (TSS) of the predicted values of sample points and background points, to measure the sensitivity and specificity of the model.

3. Results

3.1. Model selection results

The best model was selected, based on the AIC using ENMeval (Figure. 1 and Table S2). The FC was LQ and RM was 0.5.

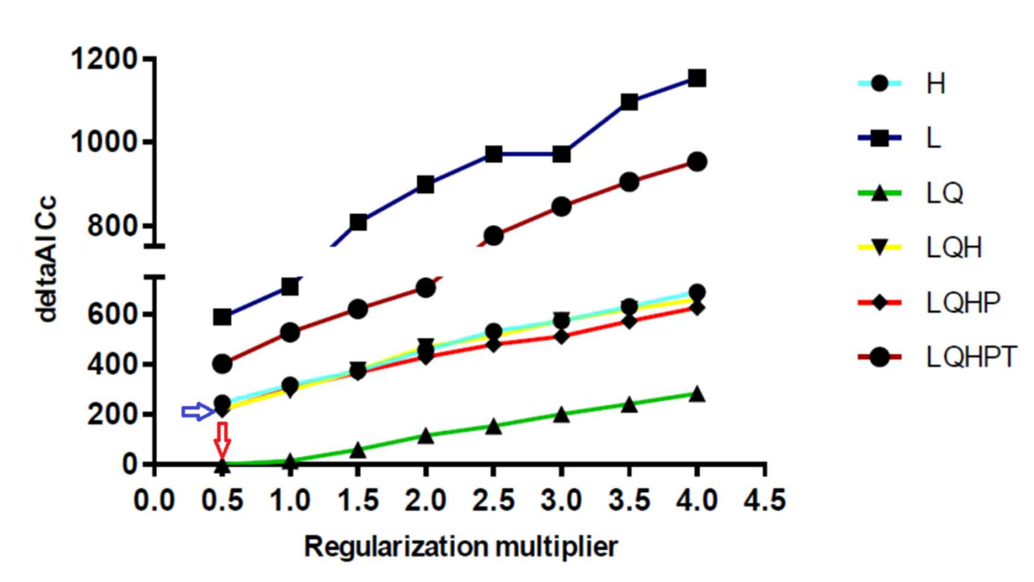

Figure 1. Default settings (LQHP) and settings (LQ) that yielded the minimum corrected Aikake information criterion (AICc) are indicated with arrows. Legends denote feature classes allowed (L = linear, Q = quadratic, H = hinge, P = product and T = threshold). Note that for severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), AICc-selected settings (based on all localities) resulted in substantially lower omission rates than were achieved using the default settings.

3.2. Response curve

3.2.1. Temperature variable

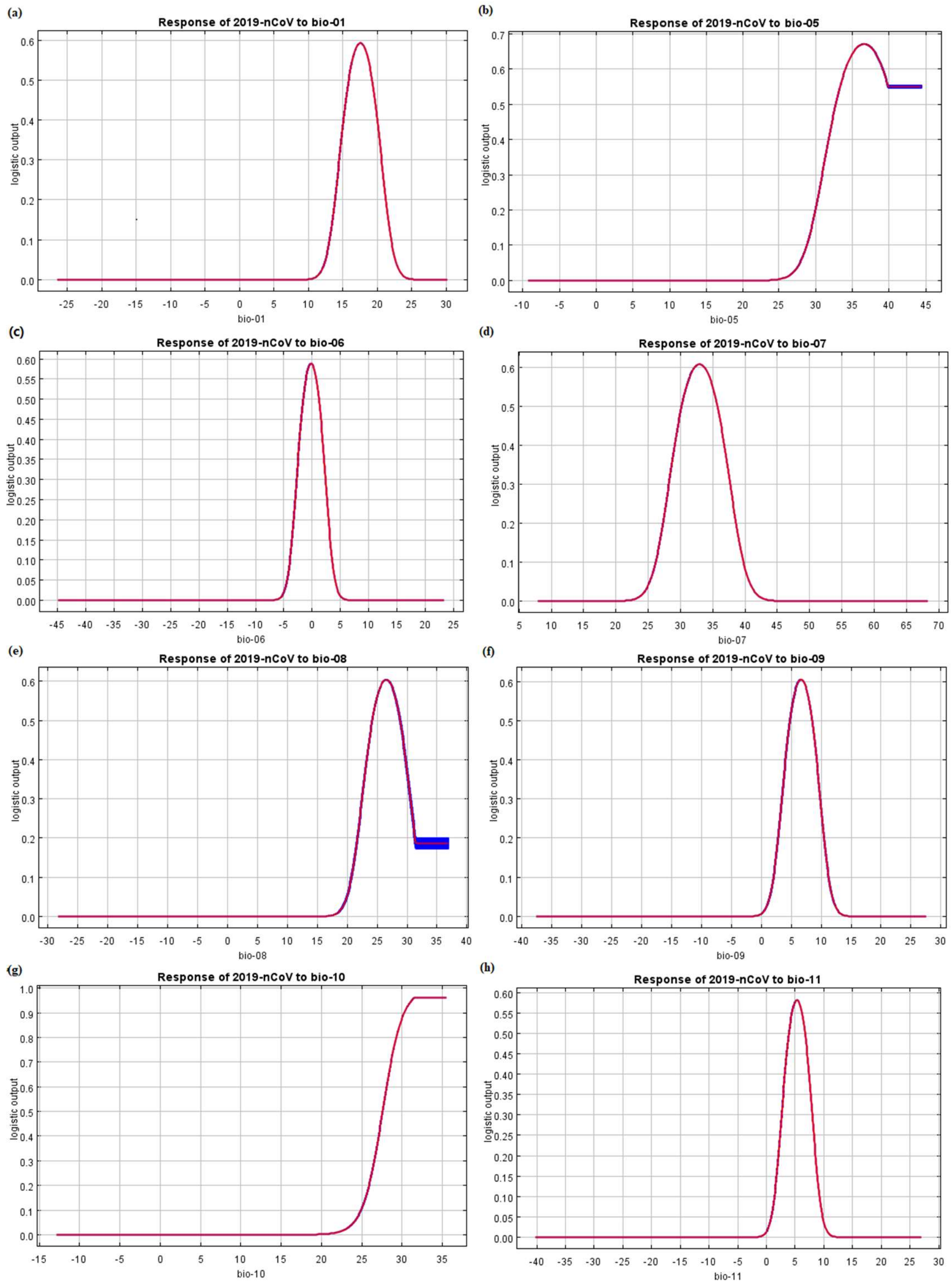

Figure 2. Response curves of biometeorological factors representing temperature.

In Figure. 2, peak response curves appear under the following conditions: when the annual mean temperature (bio-01) is approximately 17.5℃, when the maximum temperature of the warmest month (bio-05) is approximately 37℃, when the minimum temperature of the coldest month (bio-06) is approximately 0℃, when the annual temperature range (bio-07) is approximately 32.5℃, when the mean temperature of the wettest quarter (bio-08) is approximately 30℃, when the mean temperature of the driest quarter (bio-09) is approximately 7℃, when the mean temperature of the warmest quarter (bio-10) is approximately 31.5℃, or when the mean temperature of the coldest quarter (bio-11) is approximately 5℃. In other words, the risk of a SARS-CoV-2 outbreak is highest under these temperature conditions. In addition, the peak logistic output values of bio-05 and bio-10 were higher than those of the other temperature variables (approximately equal to 0.6).

3.2.2. Precipitation variable

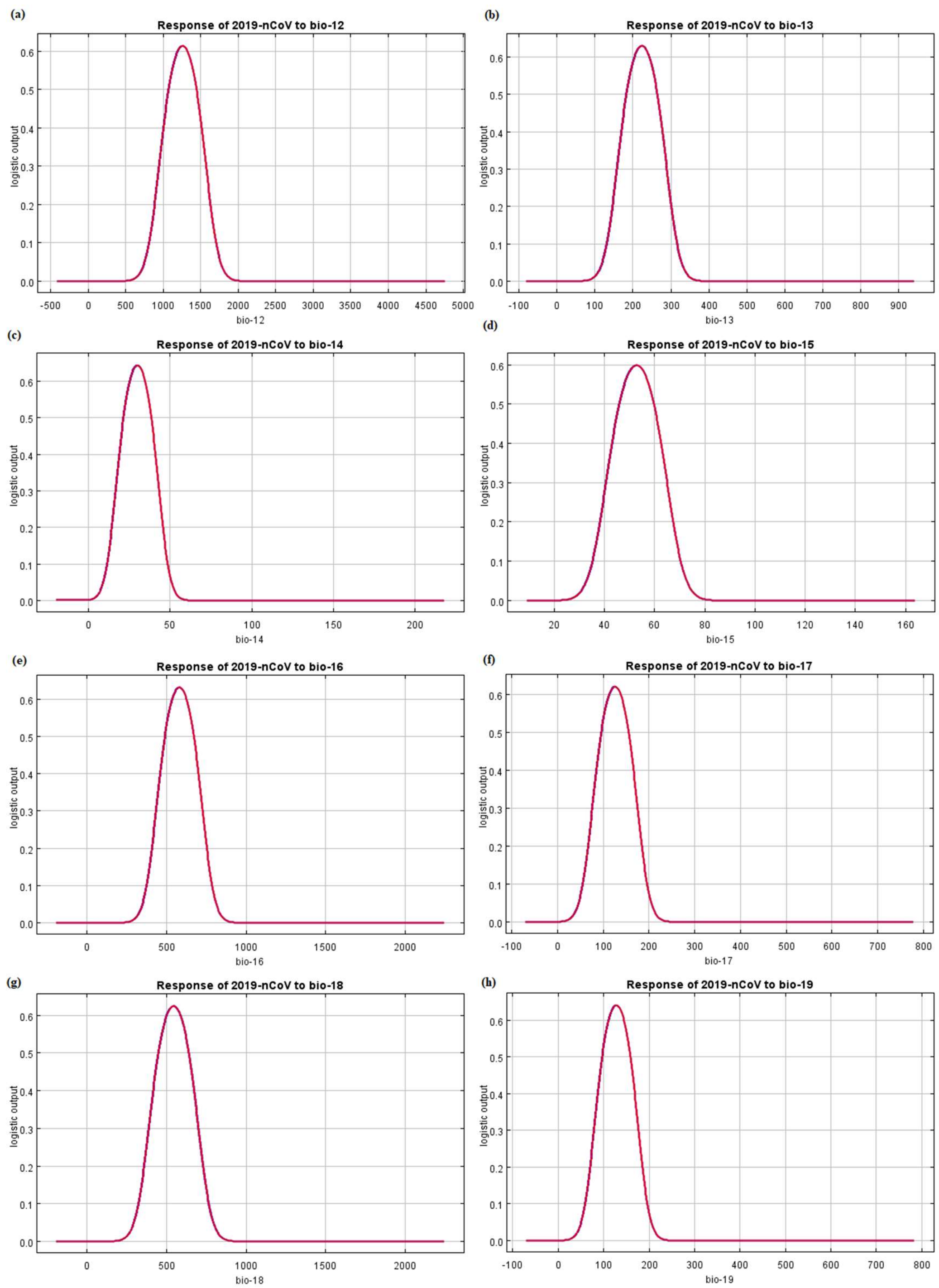

Figure 3. Response curve of biometeorological factors representing precipitation.

In Figure. 3, peak response curves appear with annual precipitation (bio-12) approximately 1250 mm, precipitation in the wettest month (bio-13) approximately 210 mm, precipitation in the driest month (bio-14) approximately 30 mm, precipitation in the wettest quarter (bio-16) approximately 600 mm, precipitation in the driest quarter (bio-17) approximately 120 mm, precipitation in the warmest quarter (bio-18) approximately 600 mm, and precipitation in the coldest quarter (bio-19) approximately 120 mm. The risk of a SARS-CoV-2 outbreak is highest under these precipitation conditions.

3.3. Jackknife test of variable importance

Figure 4 shows that the environmental variable with the highest gain when used in isolation was bio-19, which appears to have the most useful information by itself. The environmental variable with the largest decrease in gain when omitted is bio-06, which appears to have the most information that is not present in the other variables.

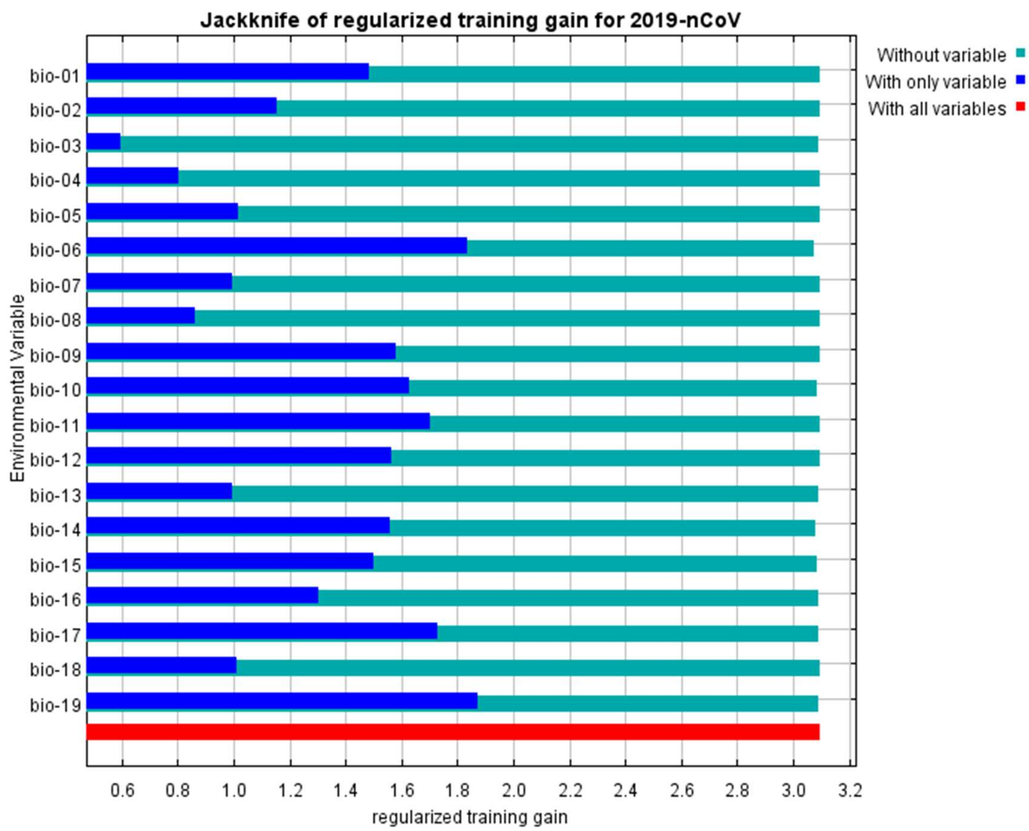

Figure 4. Jackknife test of variable importance.

3.4. Model validation

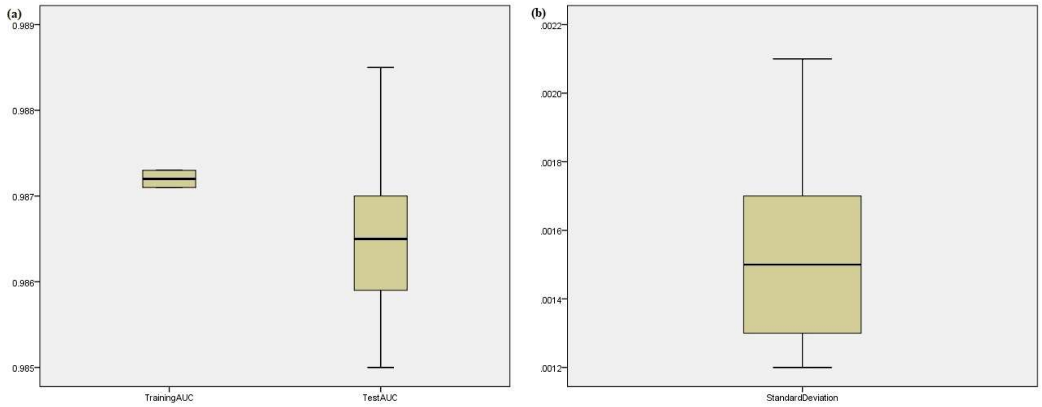

Figure 5. (a) Variations in the area under the receiver operating characteristic curve (AUC) for training localities (AUC training) and AUC for test localities (AUC test); (b) Standard deviation with 95% confidence intervals.

In Figure. 5, all AUC values were greater than 0.9; the mean AUC_{Test} was 0.9866, and the mean AUC_{Train} was 0.9872. With 95% confidence intervals, the average standard deviation was 0.0015. In addition, the logistic output results of background data of the MaxEnt model were calculated using the PresenceAbsence package. We subsequently obtained a maximum sensitivity (Max-Sensitivity) of 0.989619, maximum specificity (Max-Specificity) 0.9719, TSS value 0.961519, and AUC value 0.99758; the AUC standard deviation (AUC.sd) was 0.000455. This prediction model shows very high stability, and the results are scientific and credible.

4. Discussion

SARS-CoV-2 is a novel coronavirus strain that has never been found in humans until now. Individuals with SARS-CoV-2 infection have symptoms such as fever as well as respiratory symptoms including cough, shortness of breath, and difficulty breathing. In more severe cases, patients can develop pneumonia, SARS, kidney failure, and the infection can even lead to death. At present, there is no specific treatment for COVID-19, which has become the most challenging infectious disease worldwide because of its rapid spread and high variability. Temperature and precipitation are two important environmental factors affecting epidemics [24]. SARS-CoV-2 emerged during the winter, so it has been unclear how seasonal changes in temperature and precipitation would affect spread of the virus.

In this study, we explored this problem using a MaxEnt model based on the niche theory. We considered the effect of model complexity in the calculation results. The ΔAIC value under different combination models was calculated with the ENMeval software package to select the most suitable MaxEnt model for SARS-CoV-2 research [38,39. The mean AUC obtained after calculating the selected model was higher than 0.95 (Fig. 5), and the Max-sensitivity, Max-specificity, and TSS value of the model obtained using "PresenceAbsence" were close to 1. Previous researchers have mainly used the missing rate curve to compare and evaluate the MaxEnt model X, or a partial ROC scheme to test the local prediction ability and transfer ability of the model [40]. We used the R package "PresenceAbsence" to calculate model sensitivity and specificity. The range is −1 to 1, with 1 indicating that the experimental result is the best and 0 or less that the performance of the model is very poor [41,42,43].

From the previous relevant literature, the TSS value can be used to avoid evaluation bias caused by the positive rate of the sample, and it is a good value for measuring the accuracy of the model [41,42,43]. Therefore, the results of this experiment have a high degree of reliability.

The jackknife result graph is mainly used to measure the effect of variable factors on the fitness of the target species. The longer the blue band, the greater the impact on the fitness of the target species. When the green band is shorter than the red band, the variable contains more biological information than other variables [44]. In Fig. 4, the lowest temperature in the coldest month (bio-06) showed significant importance. The significant reduction in the gain value of bio-06 shows that the factor has special biological information that other variables do not. In addition, bio-06 also showed a very high contribution rate from the perspective of the contribution of each factor to the model (Table S3). Figure 4 shows that precipitation had a stronger influence than temperature, from the length of the blue band for SARS-CoV-2. The coldest season precipitation (bio-19) is particularly prominent. Several other variable factors (bio-14, bio-17) representing low precipitation showed much greater importance than high precipitation factors (bio-13, bio-16). Therefore, combining these points, we speculate that the virus is more suited to conditions of low temperature (approximately 0–17.5°C, bio-01, bio-06) and low precipitation.

From the experimental results, we postulate that SARS-CoV-2 outbreaks are more likely under conditions of low temperature and low precipitation. Wang et al. proposed that high temperatures and high precipitation can reduce the spread of SARS-CoV-2, so our research results are basically consistent with that study. However, from the response curve results of the investigated factors (Fig. 2b, 2g), the output value is higher than that of other variables when the temperature is 37°C (bio-05) and 31.5°C (bio-10) (logistic output >0.65). The logistic output is close to 1, especially when the temperature is 31.5°C (bio-10), so we think that the risk of infection is very high under this temperature condition. At the same time, from results of the response curves (Fig. 3b, 3e, 3g), the output values of the bio-13, bio-16, and bio-18 peaks occurred when the average monthly precipitation was approximately 200 mm. Therefore, even if the virus is more suited to survive under low temperatures and sparse precipitation, special vigilance is needed to detect the peak period of disease during the summer and autumn, especially around 31–37°C and when the average monthly precipitation is approximately 200 mm. This is consistent with previous research results [26].

5. Conclusions

In this experiment, we sought to identify an optimal model to predict SARS-CoV-2 survival under varying climate conditions, and we evaluated the sensitivity and specificity of the selected model; our results showed extremely high reliability. From the experimental results, SARS-CoV-2 is most likely to survive under environmental conditions of low temperature and low precipitation. At the same time, the possibility of increased virus survival risk with high temperatures (above 30°C) and high precipitation (approximately 200 mm) should not be underestimated. In general, this study provides a basis for ongoing research into suitable climate conditions for the spread of SARS-CoV-2.

This section is not mandatory, but may be added if there are patents resulting from the work reported in this manuscript.

Author Contributions: "Conceptualization, B.W. and Z.X.; methodology, B.W.; software, B.W.; validation, R.H.K.., B.W. and Z.X.; formal analysis, B.W.; investigation, B.W.; resources, Z.X.; data curation, R.H.K; writing—original draft preparation, B.W.; writing—review and editing, R.H.K; visualization, R.H.K; supervision, Z.X.; project administration, Z.X.; funding acquisition, Z.X. All authors have read and agreed to the published version of the manuscript

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Conflicts of Interest: Authors declares no conflict of interest

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