Effect of Climate Change on the Distribution of Zoonotic Cutaneous Leishmaniasis in Iraq

Mohammed J. Al-Obaidi1* Hayder B. Ali2
1Top. Biol. Res. Unit, Coll. Sci. University of Baghdad, Baghdad, Iraq
2 Biology Dep. Coll. Sci. University of Baghdad, Baghdad, Iraq

The corresponding author: *lafta@sc.uobaghdad.edu.iq.

Abstract. Phlebotomus papatasi sand fly is the main vector of Zoonotic Cutaneous Leishmaniasis (ZCL) in Iraq. The aim of this study was to assess and predict the effects of climate change on the distribution of the cutaneous leishmaniasis (CL) cases and the main vector presently and in the future. Data of the CL cases were collected for the period (2000-2018) in addition to sand fly (SF) abundance. Geographic information system, R studio and MaxEnt (Maximum entropy niche model) software were used for analysis and predict effect of (elevation, population, Bio1-19, and Bio28-35) on CL cases distribution and SF occurrence. HadGEM2-ES model with two climate change scenarios, RCP 4.5 and RCP 8.5 were used for future projections 2050. The results showed that the CL case trend was increased over the period (2000-2018) with highest peak observed in 2017. Incidence rate for same period was varied and increased. Near perfect crimination (SF as vector) led to high predictive performance of the model in 2050. The study concluded that the climate conditions are the major determinants of ZCL distribution and SF occurrence. Habitats suitability for the ZCL and SF will be stay in the future comparing with the current conditions. Evaluation of the effect of environmental conditions and bioclimatic factors on ZCL distribution and SF occurrence may provide a guide for CL prevention and control programmers.

1. Introduction
Leishmaniasis is a main public health problem in both tropical and subtropical areas mostly in all times [25]. Iraq is one of areas which endemic with both visceral and cutaneous leishmaniasis [2, 18]. This disease is caused by parasite belonging to the genus Leishmania transferred to human through biting of Phlebotomine insects [52].

Three forms of leishmaniasis clinical features are known: visceral (VL), cutaneous (CL) and mucocutaneous (MCL). In general, CL form is the most common and widespread [36].

Cutaneous form of the disease normally produces skin ulcers on the exposed parts of the body, such as the face, arms and legs. There may be a large number of lesions may be include 200 lesions. When the ulcers heal, it often let permanent scars, which are cause serious social problem [31].

CL is endemic in 88 countries including Africa, Asia, southern Europe, and America. About 350 million persons are thought to be at risk with CL, 12 million are worldwide prevalence and 1.5 million cases annual incidence. The causes of high CL cases are exclusive to global warming and changes in anthropological ecology [15].
The global incidence of CL is 0.7 to 1.2 million annually [3]. In Iran, the reported prevalence ranged from 0.7 to 4.7% [32]. A study conducted in India was recorded the incidence rate of cutaneous leishmaniasis as 2.5 per 1000 person per year [8].

In Iraq, leishmaniasis is widespread. The incidence rate of CL is 5/100,000 person-years; in 1992, the number of CL peaked at 45.5 cases per 100,000 and, in 2008; an outbreak of CL was reported in Diwaniyah province where 300 cases and 400 cases of CL were registered, respectively [25]. In 2020, more than 200 cases were recorded by the author in Al- Madhatiya, Babylon Governorate through survey visitors to the schools, health centers and rural areas.

In general, there are 14 known species of Leishmania that commonly cause human Leishmaniasis; these types of leishmaniasis may have similar and different clinical syndromes [9].

The causative agents of CL are confirmed in many countries. A study conducted in Morocco reported that the cutaneous leishmaniasis (CL) is caused by three species, L. major, L. tropica and L. infantum [42]. In Iran, L. tropica is the causative agent of anthroponotic cutaneous leishmaniasis (ACL); L. major is the causative agent of zoonotic cutaneous leishmaniasis (ZCL) [19]. In KSA, both types of parasites L. major and L. tropica were reported as etiological causes of cutaneous leishmaniasis [27, 47]. In Kuwait, L. major is the causative agent of cutaneous leishmaniasis [18]. In Turkey, it’s well-known that anthroponotic cutaneous leishmaniasis is caused by L. tropica and zoonotic CL is caused by L. infantum and L. major [39]. And in Jordan, CL is caused by L. major and L. tropica [37].

The MaxEnt software package is widespread tool dealing with species distribution and environmental niche modeling. MaxEnt benefits are, typically used for predictive accuracy, relaxed to handle, ability to select the data input and select suitable settings at building the model [35], estimate distribution of species [40], estimate environmental predictions [22], estimate genetic algorithms and regression trees distributions [17, 40], developing the models for biological diversity, suitable for analysis of diseases endemics [34, 40], getting spatially continuous and better detail with graphic outputs [38], identification and explanation of non-linear responses [21].

MaxEnt software was used in many studies, to estimate the probability of Phlebotomus papatasi presence with factors affecting this distribution [49], to find the areas with a higher risk of leishmaniasis infection considering the distribution of P. papatasi vector, Rhombomys opium reservoir hosts and human infection [48], for characterizing the distribution and ecology of leishmaniasis vectors [12, 14].

AUC (Receiver Operating Characteristic) curve and Jackknife analysis can be used to assess the generated models. The AUC curve was common used in the publications dealing with species distribution and evaluate the capability of a model to differentiate between places where a species is present against absent [49]. It ranges from 0 to 1, if the value is 1 that point to perfect discrimination, a value is 0.5 suggests predictive discrimination that is no better than a random estimate, and values lower than 0.5 point to act poorer than random [46].

Jackknife analysis evaluates the influence of each environmental variable to the model as long as response curves viewing the impact of a variable on the probability of presence. The evaluation is performed in three ways; exclusion of each variable in the run, with each variable in isolation, and by using all variables. The result is a series of plots of the predicted changes as each environmental variable changes [28].

The aim of this study was to predict the effects of climate change on the distribution of the CL cases and sandfly vector in Iraq with sight of view in the future.
2. Materials and methods

2.1. Cutaneous leishmaniasis distribution and Sandfly occurrence data.

The data of the CL spatial occurrence in Iraq were collected from many sources; Ministry of Health and Environment, previous studies [24], in addition to the cases that recorded in this work (n = 71, of which 25 were used for MaxEnt training and [44] for additional accuracy test).

For SF occurrence, the occurrence data were collected from many sources too; the Iraqi centre for disease control (CDC), previous studies in addition to the cases that recorded in this work (n = 39, of which 25 were used for MaxEnt training and 14 for additional accuracy test), were considered in the SF model.

CL and SF databases were developed in ArcGIS 10.2 and quantitative maps were created to show the mean cases. In addition, further occurrence data for CL and SF were extracted from previously published works (until 2020).

2.2. Environmental variables

Seventy two variables were used as environmental variables in the Ecological Niche Model (ENM) (Table1). Data for the present climate were obtained from the WorldClim database (http://www.worldclim.org/bioclim ) version 2.1, for the period from 1970 to 2000 which released in January 2020. The environmental data were constructed to include long-term-normal monthly climate data at 1km spatial resolution from WorldClim on mean annual temperature, minimal annual temperature, maximal annual temperature, precipitation, derived bioclimatic data, and altitude [20]. Bio28-35 variables which specialized to the soil were downloaded from the Climond (France word) (global climatology for bioclimatic modelling) [30].

2.3. Ecological niche model (ENM)

ENM used in this work was created using the MaxEnt software package (Version 3.4.1) [50]. MaxEnt was running with default settings applied to the MaxEnt model [41].

To evaluate the accuracy of every model, calculation of AUC for every model depending on the percentage of the study area in which the species is forecast to be found. AUC is routinely created by MaxEnt which hypotheses ROC curves using haphazardly choose pseudo absences. Satisfactory of model is requiring AUC threshold value between 0.7 and 0.8 for both training and test data. AUC values up to 0.5 indicate random occurrence of leishmaniasis in the study area, whereas values close to 1.0 indicate a statistically perfect discrimination of occurrence. Prediction power of variables was evaluated by Jackknife analysis. Maps of the spatial distribution of VL and CL and prediction model surfaces were created using ArcMap version 10.1 (ESRI company) [47]. Furthermore, binomial exams of the model presentation (MaxEnt output) has been conducted. These exams must be significant at p<0.01 [24].

2.4. Bioclimatic variables

Nineteen Bioclimatic variables (30 seconds of spatial resolutions, ~1 km2) were downloaded from WorldClim (generated in January 2020) https://www.worldclim.org/data/worldclim21.html .These factors are extracted from the monthly temperature and rainfall values. Bioclimatic variables are used in species distribution modelling and related ecological modelling techniques. The bioclimatic variables represent annual trends (e.g., mean annual temperature, annual precipitation) seasonality (e.g., annual range in temperature and precipitation) and controlling environmental elements (e.g., temperature of the coldest and warmest month, and precipitation of the wet and dry quarters). A quarter is a period of three months (1/4 of the year). The codes of these variables are coded as described in table1.
2.5. Analysis of omission/commission
The omission rate is calculated both on the training presence records, and (if test data are used) on the test records. While the omission rate close to the predicted omission, according to the definition of the cumulative threshold.

2.6. Analysis of variable contributions
Jackknife is an option in the MaxEnt modelling software that allows measurement of the effects of environmental variables. This option allows determination of the priority degrees of all independent variables in the form of the model.

2.7. Future modelling
To predict the future environmental variables (2050), two models (RCP 4.5) and (RCP 8.5) were used including stabilization and high increase respectively. These models demonstrative concentration pathways (RCPs) of the HadGEM2-ES model were performed to predict the future effect of environmental variables on the distribution of CL and SF in Iraq. RCPs data were downscaled and calibrated from the fifth assessment report of the International Panel on Climate Change (IPCC, 2014); https://www.worldclim.org/data/cmip6/cmip6_clim2.5m.html. These were selected to represent contrasting scenarios in projections of climate change. RCP 4.5 represents a relatively optimistic scenario and assumes that the radioactive forcing of greenhouse gas stabilizes shortly after 2100, and RCP 8.5, more pessimistic, radioactive forcing keeps rising after 2100 [53].

To make these files suitable to work with MaxEnt environment, extract by masking in spatial analyst at Arc Toolbox of Arc map, and convert raster to ASCII by at Toolbox of Arc map were followed [42].

2.8. Statistical Analysis
Statistical analyses as significant differences, percentages, and descriptive statistics were analysed using the Statistical Package for Social Sciences (SPSS) version 25. Map of study area was created by GIS v10.2.

3. Results and discussion

3.1. Modelling of distribution
3.1.1. Modelling for CL cases and SF occurrence currently.
In map1, colour’s keys were used to indicate the current distribution of CL and SF. conditions are suitable with red indicating high probability of suitable for CL and SF, green indicating conditions typical of those where the CL or SF is found and lighter shades of blue indicating low predicted probability of suitable conditions. The logical output results generated using MaxEnt software are expressed in terms of probability and ranged between zero and one. The modelled results were divided into four levels, where (0–0.15) was considered not suitable, (0.23–0.31) considered low suitable, (0.38–0.77) considered moderately suitable and (0.85–1) considered highly suitable. The results of this study showed that the occurring distribution of CL cases and SF occurrence in Iraq indicated that it focused in central of the country and extended toward the north and in less percent to the south. The following map show the point-wise (occurring at each point of CL data) calculated as the mean and standard deviation of the 10 output grid (Map1).

By using the reclassify tool in ArcMap 10.2, suitable areas for CL and SF were found to be mainly distributed in Baghdad, Babylon, Diyala, Karbala, Najaf, Missan, Salah-Edin, Kirkuk, and Erbil provinces. About the predicted situation of CL distribution, the results of this study predicted that the middle area of Iraq will be high suitable for CL distribution extended towered the north and east, high suitable areas are surrounding with mid suitable areas, and low suitable areas were in the west of
country extended toward the border with Syria and toward the border with KSA. In the following map the test omission rate and predicted area for CL calculated as a function of the cumulative threshold of occurrence (Map1). This finding was supported with previous study which recorded that the CL cases were distributed several provinces of Iraq such as AL-Diwaniyah, Wassit, Najaf, Thi-Qar, Basrah, Baghdad, Diyala, and Salah-Edin [4]. Also, this result was in agreed with a study which reported that the CL is distributed in eastern provinces of Diyala, Wassit, Missan, and Basrah. However, it is documented that CL is endemic in all parts of the country except the North-eastern provinces of Sulaymaniyah, Erbil and Dohuk [23, 45].

![Map1](image)

**Map1.** The test omission rate and predicted areas for A-CL and B-SF calculated as a function of the cumulative threshold of occurrence at current environmental variables.

The following Figures (1A and B) show the test omission rate and predicted area as a function of the cumulative threshold, averaged over the replicate runs. The omission rate should be close to the predicted omission, because of the definition of the cumulative threshold. In the model of the study, the AUC was (0.909± 0.02) for CL and (0.943 ±0.05) for SF (Figure 1C and D). These results indicate high predictive performance of the model and it is the best model because of each species and nearest of perfect discrimination. AUC for P. papatasi distribution in Iran was calculated as 0.917 [50], and indicate that the occurrence of SF is affected by environmental variables. In addition, results of AUC for CL were supported with another study in Turkey which found that the AUC of CL distribution was above 0.5 [6].

In this model, the red line shows the fit of the model to the training data which means a near perfect discrimination, therefore a high predictive performance of the model and it is the best model because for each species had AUCs > 0.75.

### 3.1.2. Contribution of environmental variables for CL and SF

Variable response in table 1 shows how each environmental variable effect the MaxEnt prediction, indicating how the logistic prediction changes with alteration of each environmental variable. The results of this study, according the response curves, referred to positive relationship between habitat suitability for both CL and SF with Bio1- 19 are found except Bio4, Bio14, Bio17 and Bio18 (Table1). These results were in agree with other study conducted in Turkey and reported 8 environmental factors in the response of *P. tobbi* for current and future depending on the base that bioclimatic data are likely
to be compatible with each other in the ecological models of the vector sand fly and the disease it infects [7].

Figure 1. A and B, average omission and predicted areas for CL and SF; C and D, ROC curves current for CL and SF

Table 1. Environmental variables (average for the years 1970-2000) used to model the potential distribution of Phlebotomus papatasi and cutaneous leishmaniasis resampled from original resolution at 30 second (~1 km²) to Iraq with CL and SF responses to the environmental variables [20].

| Environmental variables                                      | Acronym | CL | SF |
|-------------------------------------------------------------|---------|----|----|
| Annual Mean Temperature                                     | BIO1    | +  | +  |
| Mean Diurnal Range (Mean of monthly (max temp - min temp))  | BIO2    | +  | +  |
| Isothermality (BIO2/BIO7) (× 100)                           | BIO3    | +  | +  |
| Temperature Seasonality (standard deviation ×100)           | BIO4    | -  | -  |
| Max Temperature of Warmest Month                           | BIO5    | +  | +  |
| Min Temperature of Coldest Month                           | BIO6    | +  | +  |
| Temperature Annual Range (BIO5-BIO6)                        | BIO7    | +  | +  |
| Mean Temperature of Wettest Quarter                        | BIO8    | +  | +  |
| Mean Temperature of Driest Quarter                         | BIO9    | +  | +  |
| Mean Temperature of Warmest Quarter                        | BIO10   | +  | +  |
| Mean Temperature of Coldest Quarter                        | BIO11   | +  | +  |
| Annual Precipitation                                       | BIO12   | +  | +  |
| Precipitation of Wettest Month                             | BIO13   | +  | +  |
| Precipitation of Driest Month                              | BIO14   | -  | -  |
| Precipitation Seasonality (Coefficient of Variation)       | BIO15   | -  | -  |
| Precipitation of Wettest Quarter                           | BIO16   | +  | +  |
| Precipitation of Driest Quarter                            | BIO17   | +  | +  |
| Precipitation of Warmest Quarter                           | BIO18   | -  | -  |
| Precipitation of Coldest Quarter                           | BIO19   | -  | -  |
| Annual mean moisture index                                 | BIO28   | +  | +  |
| Highest weekly moisture index                               | BIO29   | +  | +  |
| Lowest weekly moisture index                                | BIO30   | +  | +  |
| Moisture index seasonality (C of V)                         | BIO31   | +  | +  |
| Mean moisture index of wettest quarter                      | BIO32   | +  | +  |
| Mean moisture index of driest quarter                       | BIO33   | +  | +  |
| Mean moisture index of warmest quarter                      | BIO34   | +  | +  |
| Mean moisture index of coldest quarter                      | BIO35   | +  | +  |
3.1.3. Variable contributions for CL and SF

According to the results in table 2, all environmental variables have an effect on the distribution of both CL and SF except Bio4, Bio17, and Bio18. One variable of temperature, precipitation, and soil moisture were chosen for comparison purposes. The variable with the highest percent contribution were Precipitation of Warmest Quarter (Bio18) [24.8% for CL and 0.8% for SF], Max Temperature of Warmest Month (Bio5) [23.2% for CL and 1.8% for SF], Mean Diurnal Range (Bio2) [50.4% for SF and 0% for CL], Precipitation Seasonality (Bio15) [12.7% for SF and 11.2% for CL]. In contrast, the variables with no contributions were the mean temperature of coldest quarter (Bio11), precipitation of Driest Quarter (Bio17), and precipitation of driest month (Bio14) 0% for both CL and SF (Table2). Our results were similar to the results of [11], which found that the Bio5 and Bio15 were significantly associated with the presence of CL cases. They reported that ambient temperature is one of the most important factors affecting developmental times and survival of sand flies. Also, they concluded that higher densities of leishmaniasis vectors are associated with lower annual mean precipitation. Now, it is be known that the temperature is one of the most important factors affecting developmental times and survival of sand flies [16]. In addition, our results were in agree with another study which found that the Bio2 was more important factor in prediction models for sand flies in Bahia state, China [14]. Furthermore, Bio18 was found to be had a role in distribution of CL in Morocco [13].

| Environmental variables | CL  | SF  |
|-------------------------|-----|-----|
| Bio1                    | 0.7 | 0   |
| Bio2                    | 0   | 50.4|
| Bio3                    | 2   | 0.6 |
| Bio4                    | 0   | 0   |
| Bio5                    | 23.2| 1.8 |
| Bio6                    | 0.8 | 2.1 |
| Bio7                    | 13.3| 0   |
| Bio8                    | 3.6 | 3.5 |
| Bio9                    | 0.9 | 1.5 |
| Bio10                   | 0.7 | 0   |
| Bio11                   | 0   | 0   |
| Bio12                   | 0   | 0   |
| Bio13                   | 0.3 | 10.5|
| Bio14                   | 0   | 0   |
| Bio15                   | 11.2| 12.7|
| Bio16                   | 0   | 1.2 |
| Bio17                   | 0   | 0   |
| Bio18                   | 24.8| 0.8 |
| Bio19                   | 0.4 | 0.6 |
| Bio28                   | 0   | 0   |
| Bio29                   | 3.4 | 0   |
| Bio30                   | 0   | 3.4 |
| Bio31                   | 11.4| 6.6 |
| Bio32                   | 3.1 | 0   |
| Bio33                   | 0.1 | 1.3 |
| Bio34                   | 0   | 2.8 |
| Bio35                   | 0   | 0.1 |

In map2, the results was recorded that 70% of the mean of CL cases had occurred, at the temperature range (10-25°C), the precipitation rang (255-456mm), the annual mean moisture index
0.38 (Map 2A, 2B, 2C) respectively. The results of this study were agreed with a study which found that Bio1 was important variable to the Distribution of *P. tobbi* in Turkey [33]. Also, these results were supported by a study which found that the regions receiving little precipitation (<50 mm) had a reduced probability of *P. papatasi* in Libya [1]. The effect of soil moisture was studied by another study and found an indirect correlation between soil moisture and distributing of CL. This relation represented by the effect on the vector of the disease, so reduced soil moisture within the burrow would also adversely affect sandfly larval development. In addition, it was obviously higher in the fallow field adjacent to a cultivated field irrigated for much of the year [54].

![Map2](image)

**Map2.** Mean of CL cases overlaid on A. Bio1, B. Bio12, C. Bio28 maps of Iraq.

### 3.1.4. Jackknife analysis for CL and SF

The Jackknife gain analyses for CL and SF are given in (Figure2). For CL, when the training data were used, the environmental variables with the highest gain were Bio5 followed by Bio15, Bio7, and Bio31. While the variable reduced the gains were Bio8 followed by Bio18. Response curves of the highest gain variables Bio5 and Bio31 are shown in (Figure2 left B).

For SF, the environmental variable with the highest gain was Bio2 followed by Bio9, Bio10, and Bio31. While the variable reduced the gains were Bio2 and Bio15. Response curves of the highest gain
variables, Bio2 and Bio31 are showing in (Figure 2, right B). In this work, the Max Temperature of Warmest Month (Bio5) which was suitable for CL distribution was ranged from 37-44°C. This result was in agree with the result which found that the Max Temperature of Warmest Month range of 3.6–26.5°C was found to be favourable for 60% of *P. papatasi* abundance [26]. Moisture index seasonality (Bio31) found to be effective variable to CL distribution. No available references in the literature including study the effect of soil characteristics (Bio28-Bio35) on CL and SF distribution.

![Figure 2](image.png)

**Figure 2.** Left for CL: A. Jackknife analysis, B. response curves of Bio5 and Bio31, Right for SF: A. Jackknife analysis, B. response curves of Bio2 and Bio31 the highest gain variables in Iraq.

3.2. Modelling for CL cases and SF occurrence projection (2050)

3.2.1. HadGEM2-ES scenario RCP 4.5 and RCP 8.5 models

The results of the occurring distribution of CL cases and SF occurrence in Iraq at 2050 depending on Representative Concentration Pathway (RCP4.5 and RCP8.5) scenarios HadGEM2-ES model were shown in Map 3. The results indicated that the occurrences will be concentrated in central of the country extended toward the north and in less percent to the south. According to RCP 4.5 scenario HadGEM2-ES model (2050), the suitable areas for CL and SF were found to be mainly distributed in Baghdad, Babylon, Diayla, Karbala, Najaf, Missan, Salah din, Kirkuk, and Erbil provinces. About the predicted situation of CL distribution, the results of this study predicted that the middle area of Iraq will be high suitable for CL distribution extended towered the north and east, high suitable areas are surrounding with mid suitable areas, and low suitable areas were in the west of country extended toward the border with Syria and toward the border with KSA. In the following map the test omission rate and predicted area for CL and SF calculated as a function of the cumulative threshold of occurrence.
SF have ability to adapt with different of environmental conditions, this ability was approved by a study which found that SF species *P. papatasi*, *P. sergenti*, and *P. similis* will be colonized in 2060 and be potentially distributed in different areas such as Mediterranean Basin. In addition, 8 species of Phlebotominae found to be distributed in different areas in 2060, depending on various species [51].

**Map3.** The test omission rate and predicted areas for A-CL and B-SF calculated as a function of the cumulative threshold of occurrence at future environmental variables RCP 4.5 scenario HadGEM2-ES model (2050).

3.2.2. *Analysis of omission/commission*

In Figure 3, the values of the AUCs of CL distribution models were (0.897± 0.02) and (0.891±0.03) for RCP4.5 and RCP8.5 scenarios respectively. AUCs values of SF distribution model were (0.940 ±0.03) and (0.944±0.03) at the RCP4.5 and RCP8.5 scenarios respectively. These results indicate that near perfect discrimination led to high predictive performance of the model in 2050. These results indicate that near perfect discrimination led to high predictive performance of the model in 2050. Both AUC values (for CL and SF) of this study were found to give well indicate for model predictive because both values were more than 0.5 [40].
3.2.3. Analysis of variable contributions

The Jackknife gain analysis for CL and SF for both models RCP4.5 and RCP8.5 at 2050 are given in (Figure 4). When the training data were used in isolation for CL (RCP4.5), the environmental variable with the highest gain was Bio7 followed by Bio5 and Bio19. While the variable that reduced the gain the most when it was omitted was Bio7 followed by Bio12 (Figure 4A). When the training data were used in isolation for CL (RCP8.5), the environmental variable with the highest gain was Bio7 followed by Bio5 and Bio13. While the variable that reduced the gain the most when it was omitted was Bio13 followed by Bio7 (Figure 4B).

When the training data were used in isolation for SF (RCP4.5), the environmental variable with the highest gain was Bio5 followed by Bio9 and Bio10. While the variable that reduced the gain the most when it was omitted was Bio5 followed by Bio2 (Figure 4C). When the training data were used in isolation for SF (RCP8.5), the environmental variable with the highest gain was Bio2 followed by Bio9 and Bio10. While the variable that reduced the gain the most when it was omitted was Bio2 followed by Bio5 (Figure 4D).
4. Conclusion
The study concluded that the CL has been found to continue to be spread in Iraq by 2050. Iraq's environmental variables are sufficient for the distribution of CL, there was a positive relation between CL and sandfly distribution, and a good way to consider the possible distribution of CL cases and a good way to predict the potential future distribution is the maximum entropy niche model. The study recommended that there is a need for survey research and CL program monitoring in all provinces of Iraq, more environmental and social factors that may affect the distribution of CL must be checked, molecular recognition of the vector and reservoir leishmania parasite must be achieved, the distribution of CL reservoirs must be investigated and the coordination must be limited, and further studies on disease distribution are needed for the MaxEnt application.

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References

[1] Abdel-Dayem M S, Annajar B B, Hanafi H A, and Obenauer P J 2012 *J. of Med. Entomol.* **49** 3 739–45.
[2] Al-Obaidi M J, Al-hussein M Y A, and Ihsan M 2016 *Iraqi J. of Sci.* **57** 3 2181–87.
[3] Alvar J, Vélez I D, Bern C, Herrera M, Desjeux P, Cano J, Jannin J, and de Boer M 2012 *PLoSONE* **75**.
[4] Ali M A, Khamesipour A, Rahi A A, Mohebali M, Akhavan A, Firooz A, and Keshavarz H V 2018 *J. of Men’s Infec. Dis.* **14** 1 18–24.
[5] Al-Samarai A M, and Al-Obaidi H S 2009 *J. of Infect. in Develop. Countries* **3** 2 123–29.
[6] Artun O 2019 *J. of Vector Borne Dis.* **56** 2 127–33.
[7] Artun O, and Kavur H 2018 *Turkiye Parazitoloji Dergisi* **42** 3 191–95.
[8] Barnett P G, Singh S P, Bern C, Hightower A W, and Sundar S 2005 *American J. of Trop Med. and Hygiene* **73** 4 720–25.
[9] Bailey M S, and Lockwood D N J 2007 *Clin. in derma* 25 2 203–11.
[10] Carvalho B M, Rangel E F, Ready P D, and Vale M M 2015 *PLoS ONE* **10** 11 1–21.
[11] Chalghaf B, Chlif S, Mayala B, Ghawar W, Bettaieb J, Harrabi M, Benie G B, Michael E, and Salah A Ben 2016 *American J. of Trop. Med. and Hygiene* **94** 4 844–51.
[12] Da Costa S M, Cordeiro J L P, and Rangel E F 2018 *Parasites and Vectors* **11** 1 1–10.
[13] Daoudi M M, Bousaa S, and Boumezzough A 2020 *J. of Arthropod-Borne Dis.* 14 17–28.
[14] De Santana Martins Rodgers M, Bavia M E, Fonseca E O L, Cova B O, Silva M M N, Carneiro D D M T, Cardim L L, and Malone J B 2019 *Environ. Monitor. and Assess.* **191**.
[15] Desjeux P 2001 *Trans. of the Royal Society of Trop. Med. and Hygiene* **95** 3 239–43.
[16] El-Shazly M M, Soliman M M, and Zayed A 2012 *Environ. Entomol* **41** 1 11–19.
[17] Elith J et al 2006 *Ecography* **292** 129–51.
[18] EMRO 2020 *WHO EMRO* February 2020.
[19] Farahmand, M., Nahrevanian, H., Shirazi, H. A., Naemi, S., and Farzanehnejad, Z. 2011 *The Brazilian J. of Infec. Dis.* **15** 1 17–21.
[20] Fick S E, and Hijmans R J 2017 *Inter. J. of Clim.* **37** 12 4302–43.
[21] Fletcher R, and Fortin M J 2018 *Springer Nature*
[22] Fourcade Y, Engler J O, Rödder D, and Secondi J 2014 *PLoS ONE* **9** 5 1–13.
[23] Ghatee M A, Taylor W R, and Karamian, M 2020 *Front Public Health* **8** 111-13.
[24] González C, Wang O, Strutz S E, González-Salazar C, Sánchez-Cordero V, and Sarkar S 2010 *PLoS Negl. Trop. Dis.* **4** 1.
[25] Hailu A, Dagne DA, Boelaert M 2016 *Springer, Cham* 87-112.
[26] Hanafi-Bojd A A, Yaghoobi-Ershadi M R, Haghdoost A A, Akhavan A A, Rassi Y, Karimi A, & Charrahy Z 2015 *J. of Med. Ento.* **52** 4 557–65.
[27] Haouas N, Amer O, Alshammari F F, Al-Shammari S, Remadi L, and Ashankyty I 2017 *Parasites and Vectors* **11** 1 28–111.
[28] Held L, Hens N, O’Neill P W and Wallinga J 2019 *Handbook of infectious disease data analysis*. Chapman and Hall/CRC.
[29] Hlavacova J, Votyoka J, and Volf P 2013 *J. of Med. Ento.* **50** 4 1–4.
[30] Kriticos D J, Jarosik V, and Ota N 2015 *Methods in Ecology and Evolution* 956–60.
[31] Khanjani N et al 2020 *J. of Vacc. and Vacc. Studies* **11** 1 19–28.
[32] Khosravi A, Sharifi I, Dortaj E, Aghaei Afshar A, and Mostafavi M 2013 *Iranian J. of Public Health* **42** 2 182–87.
[33] Kavur H, 2019 *J. of med. Ento.* **563** 690-96.
[34] Li J, Fan G, and He Y 2020 *Science of the Total Enviro.* **698** 134-41.
[35] Merow C, Smith MJ, and Silander J A 2013 *Ecography* **36** 10 1058–69.
[36] Mcgwire B S, and Satoskar A R 2014 *Qjm* **107** 1 7–14.
[37] Mosleh I M, Schönnian G, Kanani K, and Shadfan B 2018 *Pathogens and Global Health* **112** 1
22–28.

[38] Murphy K P 2012 *Learning - A Probabilistic Perspective* The MIT Press.

[39] Özbilgin A 2019 *In Acta Tropica* (Vol. 190).

[40] Phillips S J 2017 *A Brief Tutorial on MaxEnt*.

[41] Pigott D M 2014 *ELife* 3 1–21.

[42] Rhajaoui M, Sebti F, Fellah H, Alam M Z, Nasereddin A, Abbas I, and Schönian G 2012 *Parasite* 19 1 81–84.

[43] Ready P D 2013 *Annual Review of Entomology* 58 1 227–50.

[44] Salam N, Al-Shaqha W M, and Azzi A 2014 *PLoS Neglected Tropical Diseases* 810 1–8.

[45] Salem A et al 2019 *Parasites & Vectors* 1–9.

[46] Santos J, and Meneses B M 2017 *Acta Tropica* 168 80–90.

[47] Shabani F, Kumar L, and Ahmadi M 2018 *Global J. of Human Sci*. Sci. 18 1 6–18.

[48] Shiravand B, Ali A, Tafti D, Ali A, and Almodaresi S A 2018 *Acta Tropica* 185 327–35.

[49] Sofizadeh A, Rassi Y, Vatandoost H, Ali Hanafi-Bojd A, Mollalo A, Rafizadeh S, Akhavan A A, and Lysyk T 2018 *J. of Medical Entomology* 54 2 312–20.

[50] Steven J Phillips, Miroslav Dudík R E S 2020 *MaxEnt software for modeling species niches and distributions* (Version 3.4.1).

[51] Trájer A J, Bede-Fazekas A, Hufnagel L, Horváth L, Bobvos J, and Páldy A 2013 *Applied Eco. and Environ. Res.* 11 2 189–08.

[52] WHO 2014 *Manual for case management of cutaneous leishmaniasis in the WHO Eastern Mediterranean Region*.

[53] Wayne G 2013 *The Beginner’s Guide to Representative Concentration Pathways* In: Skeptical Science (Vol 1) Written by Graham Wayne.

[54] Zeimes C B, Olsson G E, Ahlm C, and Vanwambeke S O 2012 *Int. J. of Health Geographics* 11 1–12.