

1 **Potential geographic distribution of *Rhipicephalus sanguineus* sensu**  
2 **lato in Tunisia: review and modelling**

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25

26 **Abstract**

27 *Rhipicephalus sanguineus* sensu lato (*R. sanguineus* s.l.) is an important group of ticks that infest a  
28 large panel of animals' species and are vectors of multiple pathogens of medical and veterinary  
29 importance. As the biology of ticks is driven by abiotic factors, mainly temperature and humidity,  
30 climate changes are incriminated in increasing ticks and tick-borne pathogens incidence. The aim of  
31 this study was to map the current potential geographic distribution of *R. sanguineus* s.l. in Tunisia to  
32 help anticipating control measures to prevent tick-borne pathogens transmitted by these ticks.  
33 Extracted *R. sanguineus* s.l. occurrence records from the literature and a field survey across Tunisia  
34 were combined with environmental predictors using the maximum-entropy (MaxEnt) approach. The  
35 higher habitat suitability is expected for *R. sanguineus* s.l. along the coasts of Tunisia than in the

36 internal regions, in particular in the north-east and the north-west of the country. Nevertheless,  
37 suitability reaches the lowest level in the plateau of Kasserine district, center west. The probability of  
38 *R. sanguineus* s.l. occurrence is positively correlated to the mean temperature of the coldest quarter  
39 and the mean specific humidity of the least humid quarter. The Mediterranean climate which is  
40 prevalent in north and coastal Tunisian regions is favorable to *R. sanguineus* s.l. occurrence, while  
41 the harsh conditions of the southern and the central-west region is unfavorable for the presence of  
42 this tick. Getting a detailed view of *R. sanguineus* s.l. potential distribution is of paramount  
43 importance for public health and veterinary decision makers to implement adequate control measures  
44 in the present.

45

## 46 1 INTRODUCTION

47 Ixodid ticks are considered as the second most important disease vector to both humans and animals  
48 after mosquitos (1). Globally, their geographic distribution continues to expand inducing an increase  
49 in the tick-borne pathogens in both tropical and temperate regions nowadays (2). The main cause of  
50 this expansion is climate changes, which is affecting more severely the Northern rather than the  
51 Southern hemisphere (3). Mediterranean regions are considered as hotspots of climatic extremes with  
52 increased precipitation and drought in winter and summer, respectively (4). As a consequence of such  
53 climatic changes, it was shown that the geographic distribution of some tick species will increase in  
54 the Mediterranean countries in 2050 (5).

55 Depending on the geographic region, multiple tick species are threatening animal and human health,  
56 among them, *R. sanguineus* sensu lato (s.l.) is an important group of tick species including *R.*  
57 *sanguineus* sensu stricto (s.s.) which is considered as the most important tick species worldwide (6).

58 The *R. sanguineus* s.l. infest large panel of both domestic animals, including dogs, livestock (cattle,  
59 sheep and goats), and wild species, such as reptiles, insectivores and rodents (7). *Rhipicephalus*  
60 *sanguineus* s.l. are vectors of multiple pathogens such as *Ehrlichia canis*, *Anaplasma platys*,  
61 *Bartonella henselae*, *Mycoplasma canis*, *Mycoplasma ovis*, *Rickettsia rickettsii*, *R. conorii* and  
62 several *Babesia* species (1). Based on their geographic distribution, two main genetic lineages are  
63 described within this tick group: the tropical lineage, which comprises ticks from tropical countries  
64 such as Thailand and Brazil; and the temperate lineage, encompassing ticks from Spain, France and  
65 Italy (8,9).

66 Although *R. sanguineus* s.s. natural habitat is more commonly associated with the Mediterranean  
67 region, where it is active from spring to autumn (10), it was shown that the suitable area for its  
68 reproduction has dramatically expanded in Europe by 66% between 1960 and 2000 (11), with a  
69 marked expansion to the northern regions. Indeed, its geographic range extended to UK (12) and  
70 Slovakia (13), where it was reported for the first time in 2014 and 2017, respectively.

71 As the biology of ticks is driven by both biotic and abiotic factors (mainly temperature and  
72 humidity), mathematical models combining field, spatial and climatic data were shown to be good  
73 predictors of tick and tick-borne pathogens geographic distribution (14). Predicting the risk of tick  
74 infestation may improve the implementation of tick control by both animal and human health  
75 decision makers, and also by farmers (15).

76 Several methodologies were developed to estimate distributional areas on the basis of correlations on  
77 known occurrences with environmental variables (16). Ecological niche modelling (ENM) and

78 species distribution modelling (SDM), have been extensively used in the last 20 years to  
79 understand geographic distribution and mapping of disease vectors (17). While SDM focuses on the  
80 actual distribution of the species, the ENM involves more the estimation of invasive potential niche  
81 or assessment of environmental effects changes on species distribution potential (18).

82 Among the tools deployed for ENM, the maximum-entropy (MaxEnt) approach has a predictive  
83 performance considered as consistently competitive with the highest performing methods (19).  
84 Available since 2004, MaxEnt has been widely used in recent years for predicting the potential  
85 geographic distribution of several tick species under current and future conditions using different  
86 climate changes scenarios in several regions around the world (20–23).

87 Climate change is incriminated in increasing ticks and tick-borne pathogens incidence (24). As  
88 Tunisia is situated in a hotspot region for climate change (25), it's expected that ticks will shift their  
89 geographic distribution in the near future inducing an important modification of the epidemiological  
90 patterns of tick-borne diseases.

91 In Tunisia, *R. sanguineus* s.l. infest a wide range of animal species and transmit several pathogens of  
92 public health and veterinary (26–28) importance (29). As the geographic distribution of these ticks  
93 was not well documented in Tunisia, the aim of this study was to map their potential geographic  
94 distribution under current conditions. This work will provide a guide on the suitable geographic areas  
95 for *R. sanguineus* s.l., and help anticipating control measures to prevent pathogens transmitted by  
96 these tick species.

97

## 98 2 MATERIALS AND METHODS

### 99 2.1 Study Area

100 Tunisia, is located in North Africa, and is situated at the south of the Mediterranean basin with 1,445  
101 km long coast that extends from the extreme north-west to the south-east.

102 The climate in Tunisia consists of three Köppen-Grieg patterns (30) (Figure 1). The northern,  
103 mountainous (maximum altitude 1203 meter above the sea level) and forestall region is characterized  
104 by a Mediterranean climate with mild, rainy winters and hot, dry summers, where the average annual  
105 precipitation reaches 1,500 mm. During winter, the temperature can decrease to 10°C in the  
106 Kroumirie Mountains (Districts of Jendouba, Béja and Bizerte).

107 The south is occupied by the desert, with an average summer temperature in July and August  
108 reaching 40°C and precipitations in winter below 100 mm (31). The eastern coastal border has an  
109 arid steppe climate where temperature ranges from 10°C in winter (December to February) to 27°C  
110 in summer (June-August) in northern part. In central western regions, temperature ranges from 11°C  
111 in winter to 32°C in summer, drought can be frequent (32).

112

113 **FIGURE 1. Köppen-Geiger climate classification map for Tunisia (1980-2016) at 1 km**  
114 **resolution (30)**

115

116

## 117 2.2 Tick Collection and Identification

118 Between April 2018 and January 2020 repeated cross-sectional trimestral visits were performed to 15  
 119 small and extensively managed sheep flocks randomly selected from six Tunisian localities. A total  
 120 of 459 ear-tagged yearling and ewes were monitored. Sheep are reared in mixed flocks with goats,  
 121 cows, mules and dogs, and graze all the year-round on natural range-lands and cereal stubbles in  
 122 summer. This survey was part of a large study on ticks and tick-borne pathogens in sheep in Tunisia.

123 During each visit, animals were clinically examined and all attached ticks were collected and stored  
 124 in identified tubes (one tube per animal) containing 70% ethanol. Ticks were identified under a  
 125 stereomicroscope according to the key of Walker et al. (33).

126 As mentioned by Nava et al. (34), studies on several specimens from the *R. sanguineus* complex,  
 127 showed that they are morphologically and genetically very close, suggesting that 12 *Rhipicephalus*  
 128 species could be considered as conspecific. For this reason, we pooled the three *Rhipicephalus* ticks  
 129 found in Tunisia (*R. turanicus*, *R. camicasi*, and *R. sanguineus* sensu stricto), as *R. sanguineus* s.l.

130

## 131 2.3 *Rhipicephalus sanguineus* s.l. Data Sources and Data Preparation

### 132 2.3.1.1 Data sources

133 A total number of 16 peer-reviewed articles from PubMed database and 8 Tunisian doctor in  
 134 veterinary medicine dissertations were reviewed from the Database of ticks in livestock species in  
 135 Tunisia website (35) (Supplementary Material D). This database is managed by the International  
 136 Center for Agricultural Research in the Dry Areas (ICARDA) and the National School of Veterinary  
 137 Medicine of Sidi Thabet, Tunisia, it contains an exhaustive literature about ticks and tick-borne  
 138 pathogens in Tunisia published since 1935. Additional records were included from the database  
 139 published as supplementary material by Estrada-Peña and de la Fuente (36) to get totally 103 records  
 140 (Table 1).

141

### 142 TABLE 1. *Rhipicephalus sanguineus* s.l. occurrence number and sources

143

## 144 2.3.2 Literature Selection

### 145 2.3.2.1 Inclusion criteria

146 All studies reporting *R. sanguineus* s.s., *R. camicasi*, *R. turanicus* the only species from the *R.*  
 147 *sanguineus* s.l. present in Tunisia and collected from different host species (cattle, sheep, goats, and  
 148 dogs) were selected. The included studies must indicate the geographic coordinates (latitude and  
 149 longitude) of the sampled farms or at least the correct name of the smallest Tunisian administrative  
 150 subdivision (it corresponds to village called in Tunisian Arabic “imada”).

### 151 2.3.2.2 Exclusion criteria

152 All the studies where not indicating one of the following information were excluded: GPS  
153 coordinates, a clear indication about the location name of the sampled farms or animals.

154

### 155 2.3.3 Occurrence Data Preparation

156 Each tick occurrence record was defined by its geographic coordinates (longitude and latitude in  
157 decimal degrees). From the selected documents, coordinates corresponding to *R. sanguineus* s.l.  
158 occurrence were extracted and checked in Google Earth ([www.google.com](http://www.google.com)) according to the  
159 recommendations of Hijman (37). For occurrences without georeferencing, the centroid coordinates  
160 of the smallest administrative subdivision of the mentioned locality was considered. As different  
161 published studies mentioned the same localities, all duplicated coordinates were considered once.  
162 The extracted records from the data of Estrada-Peña and de la Fuente (36), were combined with the  
163 retrieved data from the Database of ticks in livestock species in Tunisia website and those of the  
164 present field records by resulting in a total of 87 eligible records (Figure 2) (Supplementary Material  
165 E).

166

167 **FIGURE 2. Map of Tunisia showing the location of *Rhipicephalus sanguineus* s.l. collection**  
168 **sites.**

169 **Circles: localities of the field work**

170 **Triangles: metadata derivative localities**

171 **Red polygon: calibration (M) area**

172

173 To avoid model bias and overfitting resulting from spatial autocorrelation (38), we thinned the 87  
174 records using a spatial distance filter of 15 km (spThin package) (39). Several iterations on R using  
175 increasing thinning distance were tested. The 15 km filter distance was selected as the best in terms  
176 of having a good number of occurrence points to run the models.

177 Finally, a total of 45 occurrence points was used to model *R. sanguineus* s.l. potential distribution  
178 over Tunisia. The data was divided randomly into two sets: 50% for model calibration and 50% for  
179 model evaluation. Then, the full set of data was used for creating the final models (40).

180

### 181 2.3.4 Climatic Variables Selection and Preparation, and Calibration Area Definition

182 The effect of climate on tick distribution was well described in the literature, where temperature and  
183 humidity were identified to play a major role (10). Indeed, engorged larvae and nymphs enter in  
184 diapause phase at low temperatures whereas the molting period is shorter at higher temperatures (41).  
185 Thus, heat, humidity, and moisture are very important factors of tick survival and dispersion (42).

186 To prevent final models from bias, the accessible area (termed **M**) of the studied species is to be  
 187 considered during tick modelling (43). This area describes the dispersal capacities of the tick species  
 188 from established populations, by either their own movements or by the host-mediated movements  
 189 (44). Assuming the latter play a key role in dispersing *R. sanguineus* s.l., the **M** area (study area, or  
 190 calibration area) was delimited based on a 50 km buffer zone around the available occurrence points  
 191 and used in model calibration (Figure 2). As far as it could be ascertained, there is no publication  
 192 indicating the distance to be used for the calibration area, thus we performed several iterations on  
 193 QGIS using increasing calibration area radius. The best calibration area was 50 km since it covers the  
 194 whole country and we considered that this radius covers the distance reached by different mammal  
 195 hosts.

196 Among the 19 bioclimatic variables, fourteen were removed for the following considerations:

- 197 (i) Variables with known spatial artefacts were removed (Bio8, Bio9, Bio18, and Bio19)  
 198 (Bede-Fazekas and Somodi. 2020).
- 199 (ii) Variables expressing annual mean values (Bio1 and Bio12) were removed because the  
 200 range of temperature between summer and winter in Tunisia is big.
- 201 (iii) Variables of extreme values (Bio5, Bio6, Bio13, and Bio14) were removed because  
 202 activity of ticks is not conditioned by these extreme values which represent peaks and are  
 203 not persistent in time.
- 204 (iv) Due to high correlation, variable expressed as a synthetic indicator of other bioclimatic  
 205 variables (Bio3) was removed.
- 206 (v) Variables expressing seasonality (Bio4, and Bio15) were removed since they provide  
 207 information about the whole season.

208 Five variables were considered in modelling; three related to temperature (BIO2, BIO10 and BIO11)  
 209 and two related to humidity (BIO16 and BIO17) (Table 2). This set of five bioclimatic variables were  
 210 retrieved from MERRAclim dataset (45), which contains three different version of the same 19  
 211 bioclimatic variables corresponding to the last three decades (1980s, 1990s and 2000s), presented as  
 212 minimum, maximum and mean values, and available at three resolutions (2.5, 5 and 10 arc-minutes)  
 213 (45). Contrarily to the commonly used Worldclim dataset ([www.worldclim.org](http://www.worldclim.org)), whose variables  
 214 derive from spatially interpolated climate surfaces as obtained from ground weather stations,  
 215 MERRAclim uses satellite-based observations (46).

216 To match our sampling dates (extending from 1999 to 2016) with climatic information, the dataset  
 217 for the 2000 decade was considered at 2.5 arc-minutes resolution corresponding to approximately 4  
 218 km. The predictors were masked to the **M** area, then combined to generate five candidate sets to  
 219 improve model calibration, with one predictor removed in each dataset except the set 1 (Table 2).  
 220 Indeed, using various candidate sets of predictors improves the model calibration (40).

221

222 **TABLE 2. Predictors used in the maximum entropy for *Rhipicephalus sanguineus* sensu lato**  
 223 **modelling (46)**

224

225 **2.4 *Rhipicephalus Sanguineus* sensu lato Distribution Modelling**

226 **2.4.1 Ecological Niche Modelling**

227 We used maximum entropy (MaxEnt) that is implemented in MaxEnt (49). All implementation was  
 228 performed with R software, using the “kuenm” package (50). By combining R and MaxEnt  
 229 softwares, the “kuenm” package allows model calibration, final model selection, evaluation and  
 230 extrapolation risk analysis through a simple processing (40).

231 Here, the ODMAP protocol was used to document all the key steps for producing the final model  
 232 ((51); Supplementary material A).

233

234 **2.4.2 Model Calibration**

235 For model calibration, we tested 15 combinations among linear (l), quadratic (q), product (p), and  
 236 hinge (h) features and 17 regularization multiplier values (Supplementary materials B). In turn, each  
 237 feature-regularization multiplier combination was tested separately for each environmental dataset.  
 238 Candidate models were tested and evaluated based on the statistical significance of the partial  
 239 receiver operating characteristic (ROC) at  $\alpha < 0.05$  (52) and omission rate ( $E < 5\%$ ) thresholds (38).  
 240 Finally, among significant, low-omission models, we estimated the Akaike Information Criterion  
 241 corrected for small sampling sizes (AICc) (53) and delta AICc ( $\Delta AICc$ ). We retained 7 models as the  
 242 best candidates ( $\Delta AICc < 2$ ) to be included for modelling the potential geographic distribution of *R.*  
 243 *sanguineus* s.l. in Tunisia (Figure 3).

244

245 **FIGURE 3. Calibration result and best selected models used for modelling the potential**  
 246 **geographic distribution of *Rhipicephalus sanguineus* s.l. in Tunisia**

247

248 **2.4.3 Final Models**

249 Seven models were finally retained having  $\Delta AICc < 2$  to model the potential geographic distribution  
 250 of *R. sanguineus* s.l. in Tunisia (Figure 3). For each final model, we used a 50% bootstrap with 10  
 251 replicates to quantify the uncertainty associated with the available occurrence data, and transferred  
 252 the model prediction throughout the whole study area. In particular, the geographic representation of  
 253 the final models was obtained by using the median value of the relative occurrence rate (ROR)  
 254 among the bootstrapped replicates from each spatial unit (40).

255 An extrapolation process was necessary to predict the potential geographic distribution of *R.*  
 256 *sanguineus* s.l. outside the calibration area. To this aim, we used ‘free extrapolation’ by assuming the  
 257 species-environment relationship as observed within the calibration area to remain constant outside  
 258 the calibration area itself (54).

259

260 **3 RESULTS**

261 **3.1 Calibration models**

262 From total of 2,635 candidate models, 1,948 were statistically significant ( $P \leq 0.05$ ). Seven were  
 263 identified as the best models based on their AICc ( $\Delta AICc < 2$ ), but none of them met the omission rate  
 264 criteria ( $OR \leq 0.05$ ; Table 3). All best models were characterized by the “product” feature class  
 265 accounting for interaction among the predictors. One of the seven models was selected based on  
 266 variables in Set 1, while the remaining models were chosen based on variables in Set 5 (Table 2).

267

268 **TABLE 3. Best models after model calibration**

269 In the seven retained models, three variables (Bio2, Bio11, and Bio17) were positively correlated  
 270 with tick occurrence probability in the study area (Figure 4).

271

272 **FIGURE 4: Mean responses of *Rhipicephalus sanguineus* s.l. to the Bio2, Bio10, Bio11, Bio16,  
 273 and Bio17 predictors in the 7 models after 10 replicates**

274

275 **3.2 Current potential distribution**

276 Current predictions for *R. sanguineus* s.l. showed higher suitability along the coasts of Tunisia than  
 277 in the internal regions. In particular, higher suitability was observed in the north-east and north-west  
 278 of the country specially in two districts (Jendouba and Nabeul) and two islands (Kerkennah and  
 279 Djerba), respectively. Low suitability areas were observed as the distance increased from the coastal  
 280 areas inside to Central and West Tunisia, in which reaching the lowest level in Kasserine district  
 281 (Figure 5).

282

283 **FIGURE 5. Potential distribution of *Rhipicephalus sanguineus* s.l. in Tunisia based on MaxEnt  
 284 modelling (Black dots corresponds to districts)**

285

286 **4 DISCUSSION**

287 The present study aimed, for the first time, to model the current potential geographic distribution of  
 288 *R. sanguineus* s.l. ticks, using MERRAclim variables. When compared to other algorithms applied to  
 289 species distribution modelling (e.g. generalized linear models and generalized additive models),  
 290 MaxEnt was the best for tick distribution modelling (20). Indeed, since its development in 2004,  
 291 MaxEnt was improved markedly by adding several options (55,56). We performed the most up-to-  
 292 date MaxEnt methodology in ecological niche modelling using the kuenm R package (40), which  
 293 allows model calibration and selection, final model creation, and evaluation in a unified way from  
 294 within the open source R environment. The candidate model performances are evaluated based on the  
 295 significance of partial ROC, which is better than the full area under the ROC curve (52,57,58).

296 Models' performance was also evaluated by estimating the omission rate, which denotes how well a  
 297 model based on the training data is able to predict the occurrences in the testing dataset. The fact that  
 298 all final models showed 8.7% omission rate (a value slightly higher than the selected 5% threshold)

299 could be due to the low number of occurrences in the training data (n=22), but does not compromise  
 300 the good performance of the models. Indeed, we believe that our model is performant, also because  
 301 we used remotely sensed predictors (eg. MerraClim) that allows better model performance than  
 302 interpolated ground derived measurements (eg. Worldclim) as argued by Estrada-Peña et al. (14,59).  
 303 However, considering that MaxEnt algorithm is performant to manage collinearity (48) we did not  
 304 remove predictors with multicollinearity and having ecological significance to *R. sanguineus*, which  
 305 potentially could hamper the analysis.

306 Although animal hosts play an important role in geographic distribution of ticks, we did not consider  
 307 this factor because *R. sanguineus* s.l. species could be collected from a wide range of animal hosts,  
 308 moreover, data regarding the geographic distribution of different domestic mammals are not available  
 309 in Tunisia. This omission represents a limitation in the present work. Moreover, there is possibly a  
 310 sampling bias due to using occurrence data with different sampling strategies and efforts, which  
 311 could hamper the performances of modelling (60).

312 Assuming that *R. sanguineus* s.l. species behave equally to climatic variables, could possibly  
 313 introduce another limitation to the present study. It was not possible to consider this aspect in the  
 314 discussion because of the scarcity of data gathered through natural or experimental observations  
 315 regarding the effect of temperature and humidity on *R. sanguineus* species other than *R. sanguineus*  
 316 s.s. The difficulty of considering separately the behavior of *R. sanguineus* s.l. species may impact  
 317 also the accessible area (M) determination which already suffers from the lack of objective criteria  
 318 and detailed protocol for its estimation. Moreover, personal observation of one of the co-authors  
 319 showed that in Southern Tunisia, there are probably a wild population of *R. sanguineus* linked to  
 320 desertic wild animals (foxes, rodents...). This *R. sanguineus* wild population displays a different  
 321 biological natural cycle than does the domestic population. This observation needs further  
 322 investigations at the field. In addition, there are two reported lineages for *R. sanguineus* s.l. in the  
 323 world depending on the geographic regions. Indeed, *R. sanguineus* s.l. temperate lineage is present in  
 324 areas where the land surface temperature ranges between 10 and 20°C (9,61). Whereas, the tropical  
 325 lineage of these ticks is more adapted to a higher land surface temperature, ranging between 20 and  
 326 30°C (9). Although there is no information about the type of lineage present in Tunisia, it seems that  
 327 it's more likely to be a temperate lineage as in Spain, France and Italy (62).

328 In the present study, we estimated *R. sanguineus* s.l. potential geographic distribution in Tunisia, the  
 329 coastal regions, showed the highest suitability. These areas have a temperate climate, according to the  
 330 classification of Köppen-Geiger (30). Furthermore, high habitat suitability is also predicted in both  
 331 Kerkennah archipelago and Djerba island despite their Köppen-Geiger classification as arid and  
 332 desertic, respectively, possibly due to the tempered effect of sea in these islands (30). These islands  
 333 are small in area (the maximum radius does not exceed 18 km for Djerba island), so they benefit of  
 334 the moderation effect of the sea on both temperature and humidity. The geographic distribution we  
 335 mapped overlays to the results obtained by Estarda-Peña and Venzal (63), and Alkische et al. (23) for  
 336 *R. turanicus* and *R. sanguineus* s.l., respectively, showing a high suitability of both of these ticks to  
 337 northern and central-east coastal regions of Tunisia.

338 The high suitability of *R. sanguineus* s.l. in coastal region is concordant with the finding of Beugnet  
 339 et al. (2009) for *R. sanguineus* s.s., where a weather research and forecasting (WRF) meteorological  
 340 model was used and showed that the best combination of temperature and humidity was 20-30°C and  
 341 50-100%, respectively for *R. sanguineus* s.s. in terms of ability to attach to hosts, take blood meals  
 342 and reproduce (activity index). The same model also evidenced how the combination of higher

343 temperatures (30-35°C) and humidity (above 60%) leads to a lower activity index that varies between  
 344 60 and 80% (15).

345 The very low to low suitability in the central-western regions of Tunisia (Kasserine and Gafsa  
 346 districts) could be explained by the big distance to the sea leading to unsuitable climatic conditions in  
 347 addition to the limiting effect exercised by the variable Bio11 (mean temperature in the coldest  
 348 quarter of the year), which appears to be among the main ecological variables driving habitat  
 349 suitability for *R. sanguineus* s.l. in Tunisia. In this region the dry period is very long, it extends from  
 350 April to September with high summer temperatures during long periods (reaching 43°C in August)  
 351 and long cold periods in winter (reaching -4°C in January) (64,65). Based on our field survey from  
 352 April 2018 to January 2020, no tick was found in Sebeitla (Kasserine district) during two winter  
 353 seasons (January 2019 and January 2020) (Supplementary Material C), where the mean temperatures  
 354 recorded in both periods, ranged between 8 and 10°C, respectively (66). These temperatures are  
 355 below the theoretical minimal threshold necessary to the tick to initiate molting, which is estimated to  
 356 10.8 and 13.9°C for *R. sanguineus* s.s. larvae and nymphs, respectively (67). Such a limiting factor  
 357 for ticks' development could have been grasped by Bio11, whose mean response curve indicates  
 358 increased habitat suitability when mean temperature exceeds 14°C. This behavior is consistent with  
 359 the ecology of the species where the long-term low temperature is the major limiting factor for the  
 360 establishment of *R. sanguineus* population in cold regions (68).

361 In Southern Italy, where the climate is similar to northern Tunisia, *R. sanguineus* s.s., is influenced  
 362 by the Mediterranean climate in natural conditions but behaves differently in spring, summer and  
 363 autumn (10). It was observed that the number of eggs laid by female ticks is positively correlated  
 364 with humidity and negatively correlated to temperature during spring, which indicates the vital role  
 365 of relative humidity when associated to high temperature. This situation is similar to what we see in  
 366 Northern and coastal Tunisian regions, where *R. sanguineus* activity starts in spring and continues  
 367 during the summer (69). Indeed, the north-west is characterized by a maximal temperature below  
 368 35°C in August, tempered by the proximity to the sea and the rain during the winter. However, in  
 369 Southern Tunisia, during the same period, the maximum temperature reaches 45.8°C (Tataouine  
 370 district), combined with a low relative humidity, decreases the suitability for *R. sanguineus*. The  
 371 harsh climate in Southern Tunisia, is concordant with the scarcity of *R. sanguineus* s.l. in this region,  
 372 confirmed by the absence of ticks in July 2018, during our field survey. Nevertheless, in July 2019,  
 373 we collected in the same region 40 specimens of *R. sanguineus* s.l. from 19 sheep probably due to the  
 374 particular climate of 2019, that was cold and relatively rainy in winter and spring, associated to a hot  
 375 summer classified as the third hottest one since 1950 (66). Despite the low suitability in Tataouine  
 376 district, the presence of *R. sanguineus* s.l. could be also explained by the behavior of these tick  
 377 species. *R. sanguineus* withstands the low relative humidity rates (67,70) and on the other hand, *R.*  
 378 *sanguineus* free stages have both endophilic and exophilic behaviour, they hide in refuges, under  
 379 stones and wall crevasses when temperatures increases (71).

380 Other factors than temperature and humidity, can determine *R. sanguineus* s.l. distribution such as  
 381 host availability and abundance. In the review by Estrada-Peña et al. (7), multiple animal species are  
 382 reported to serve as host for *R. sanguineus* s.l. Indeed, among the 478 *R. sanguineus* s.l. collected in  
 383 the western Palearctic and recovered between 1975 and 2010, 37% were represented by carnivores,  
 384 35% by insectivores, 24% by rodents, 13% by sheep, and 12% by equids. In our case, no accurate  
 385 data on the distribution of the major host species in Tunisia was available and no information related  
 386 to hosts could be included into the model we built. Furthermore, the extent of urban area was  
 387 identified as a key factor for *R. sanguineus* s.l. distribution in China, which could be possibly  
 388 associated with the presence of dogs (72).

## 389 5 CONCLUSIONS

390 Getting a detailed pattern of *R. sanguineus* s.l. geographical distribution is of paramount importance  
 391 for public and animal health point of view in order to implement adequate control measures in the  
 392 present and to identify new areas of expansion under different climate change scenarios. Indeed, due  
 393 to global warming, the geographic distribution of *R. sanguineus* is extending to new regions. This  
 394 extension was reported in northern Europe and southern America (13,73,74).

395 The high adaptative capacity of *R. sanguineus* to different biotopes and its vector role increase the  
 396 importance of studying its geographic distribution. The dual endophilic and exophilic behaviour of *R.*  
 397 *sanguineus* makes their survival possible in large range of environmental conditions, excepting in  
 398 very cold regions.

399 Species distribution modelling showed its efficacy to predict *Rhipicephalus* spp. potential  
 400 distributions both under current and future abiotic conditions in several regions of the world  
 401 including Africa (75). However, spatial predictions from such models must be validated by field  
 402 observations, which is often hampered by the paucity of the collected data mainly in developing  
 403 countries. As many limitations (tick collection efforts, sampling bias, accuracy of occurrence  
 404 records...) could affect modelling performance, interpretation should be made carefully to avoid  
 405 misunderstanding of such models. To circumvent this limit, we strongly encourage the creation of a  
 406 regional network for tick and tick-borne pathogens monitoring in North Africa with an online free  
 407 database. In this system, new tick records should be always georeferenced and climatic data collected  
 408 with optimal resolution (76). Citizen science should be encouraged through different channels (direct  
 409 reporting, GSM transmission...) to improve the knowledge about different tick species phenology  
 410 mainly in remote African regions (Sahara, Savannah...).

411

## 412 6 CONFLICT OF INTEREST

413 *The authors declare that the research was conducted in the absence of any commercial or financial*  
 414 *relationships that could be construed as a potential conflict of interest.*

415

## 416 7 AUTHOR CONTRIBUTIONS

417 MKK participated to field investigation, to data curation and to modelling, wrote the manuscript and  
 418 finalized it. EV contributed to data analysis, manuscript writing—review and editing. AA performed  
 419 the modelling, contributed in manuscript review and editing. EH performed the literature data  
 420 extraction. RR and LS carried out the field investigation. MR was in charge of the conceptualization,  
 421 the funding acquisition, the project administration at ICARDA, and contributed in manuscript review  
 422 and editing. MG was responsible of the conceptualization, the project administration at the national  
 423 school of veterinary medicine, the supervision, the validation of results, and contributed in  
 424 manuscript review and editing. All authors read and approved the final version.

425

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433

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437

## 438 **10 SUPPLEMENTARY MATERIAL**

439 A. The ODMAP protocol

440 B. Parameters of the candidate models

441 C. *Rhipicephalus sanguineus* s.l. collected during two-years field visits in 6 localities in Tunisia

442 D. Occurrences records sources

443 E. Final occurrences records coordinates used for modelling

444

## 445 **11 DATA AVAILABILITY STATEMENT**

446 The datasets presented in this study can be found in online repositories. The names of the  
447 repository/repositories and accession number(s) can be found in the article/supplementary material.

448

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680 TABLE 1. *Rhipicephalus sanguineus* s.l. occurrence number and sources

Source	Occurrence records
Our field survey	22
DVM dissertation and peer-reviewed articles	48
Estrada Peña and de la Fuente (2016)	33
<b>Total</b>	<b>103</b>

681

682 TABLE 2. Predictors used in the maximum entropy for *Rhipicephalus sanguineus* sensu lato  
683 modelling (46)

Description	Bioclimatic variable	Set 1	Set 2	Set 3	Set 4	Set 5
Mean diurnal range (mean of monthly (max temp - min temp))	BIO2	x	x	x	x	x
Mean temperature of warmest quarter	BIO10	x	x	x	x	
Mean temperature of coldest quarter	BIO11	x	x	x		x
Specific humidity (mean of most humid quarter)	BIO16	x	x		x	x
Specific humidity (mean of least humid quarter)	BIO17	x		x	x	x

684

685 TABLE 3. Best models as resulting from model calibration

N°	Regularization multiplier	Variable set	Mean AUC ratio	Partial ROC	Omission rate at 5%	AICc	$\Delta$ AICc	Parameters
1	0.3	Set 5	1.042	0.00	0.087	772.683	0.000	2
2	0.4	Set 5	1.049	0.00	0.087	772.707	0.023	2
3	0.5	Set 5	1.042	0.00	0.087	772.736	0.053	2
4	0.6	Set 5	1.040	0.00	0.087	772.772	0.089	2
5	0.7	Set 5	1.047	0.00	0.087	772.815	0.132	2
6	0.8	Set 5	1.035	0.00	0.087	772.864	0.181	2
7	1	Set 1	1.031	0.00	0.087	772.989	0.305	2

686 *AUC = area under the curve.*

687 *ROC* = receiver operating characteristic.

688 *AICc* = Akaike information criterion corrected for small sample size.

689

690 **FIGURE 3. Köppen-Geiger climate classification map for Tunisia (1980-2016) at 1 km**  
691 **resolution (30)**

692 **FIGURE 4. Map of Tunisia showing the location of *Rhipicephalus sanguineus* s.l. collection**  
693 **sites.**

694 **Circles: localities of the field work**

695 **Triangles: metadata derivative localities**

696 **Red polygon: calibration (M) area**

697

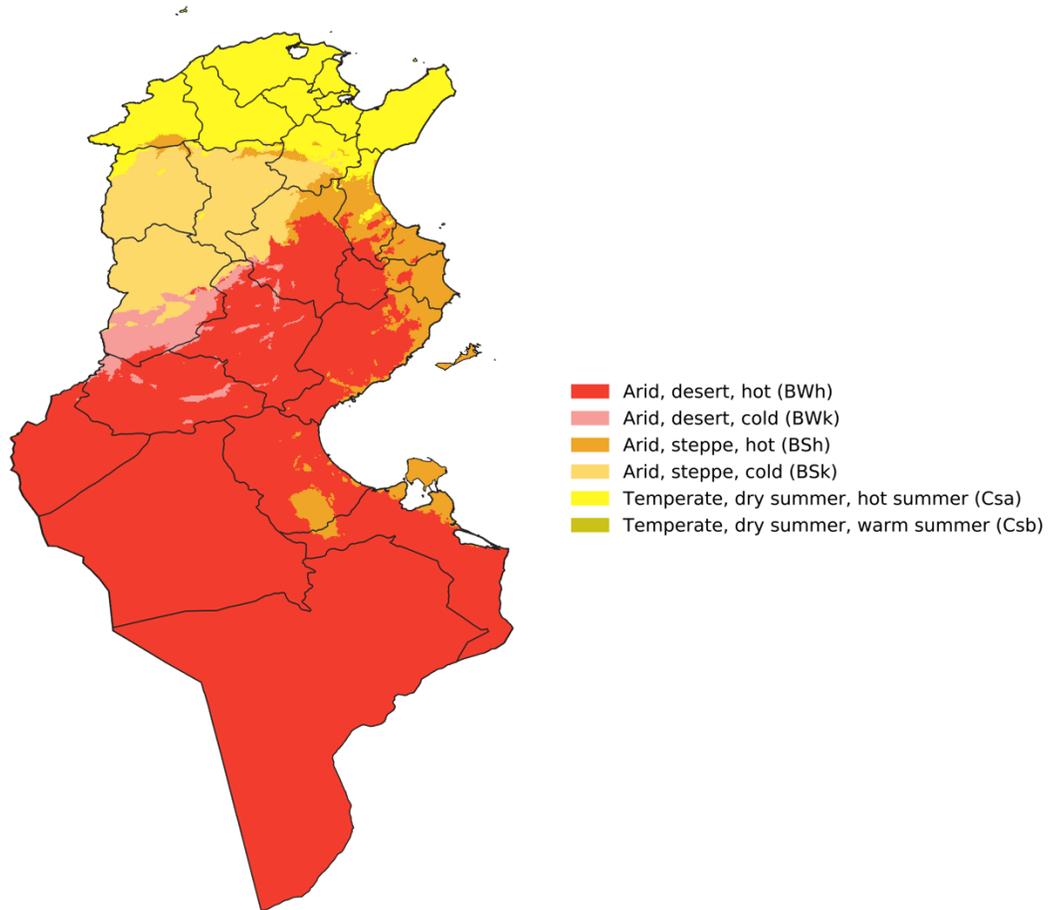
698 **FIGURE 3. Calibration result and best selected models used for modelling the potential**  
699 **geographic distribution of *Rhipicephalus sanguineus* s.l. in Tunisia**

700 **FIGURE 4: Mean responses of *Rhipicephalus sanguineus* s.l. to the Bio2, Bio10, Bio11, Bio16,**  
701 **and Bio17 predictors in the 7 models after 10 replicates**

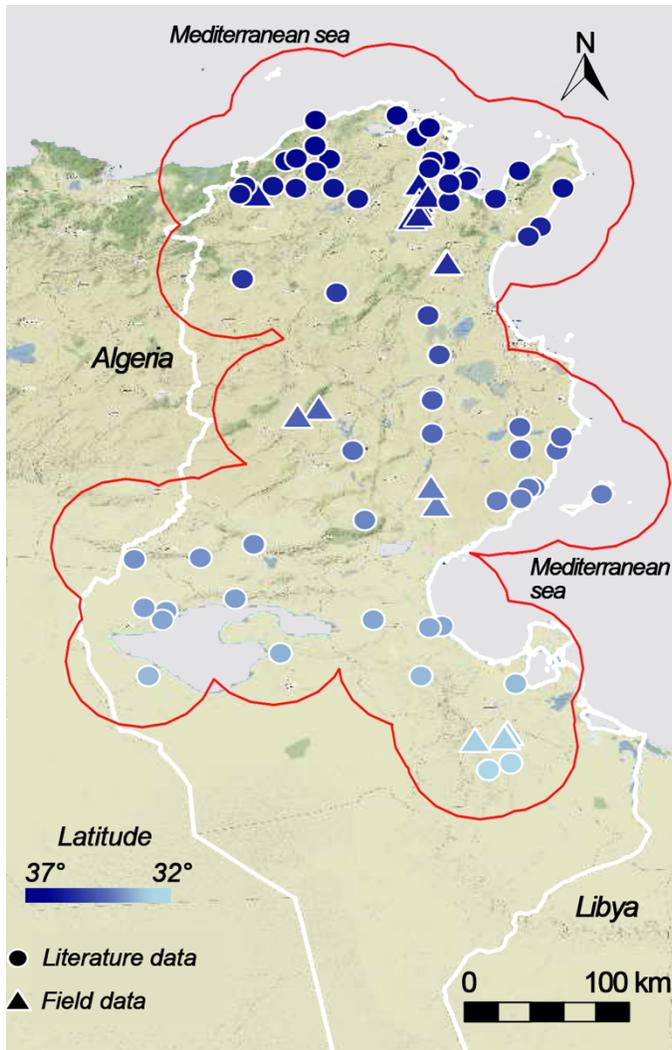
702 **FIGURE 5. Potential distribution of *Rhipicephalus sanguineus* s.l. in Tunisia based on MaxEnt**  
703 **modelling**

704

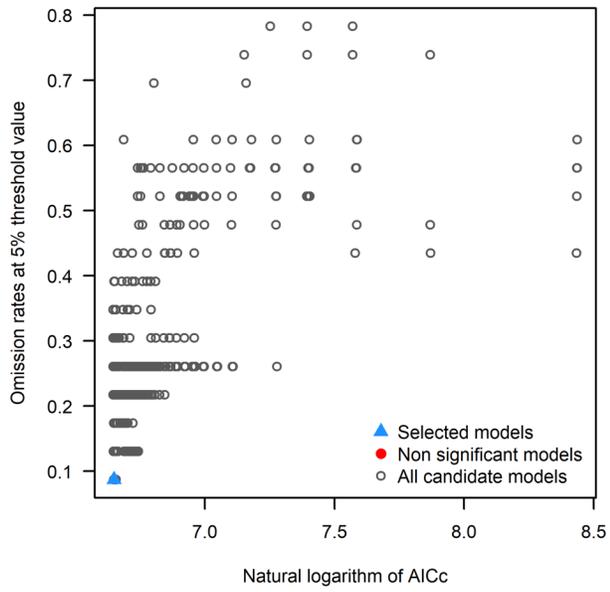
*Figures*



**FIGURE 1.**



**FIGURE 2.**



**FIGURE 3.**

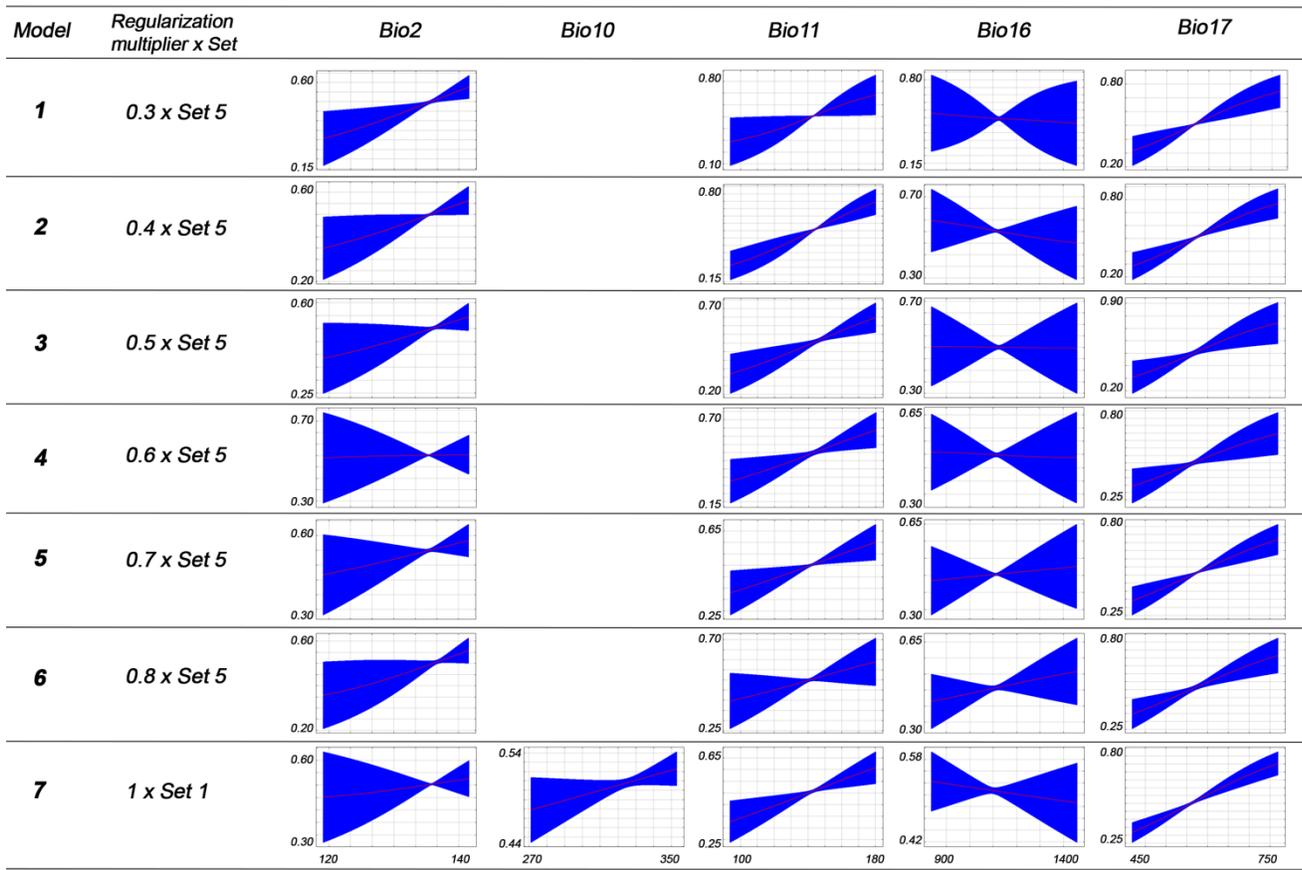


FIGURE 4

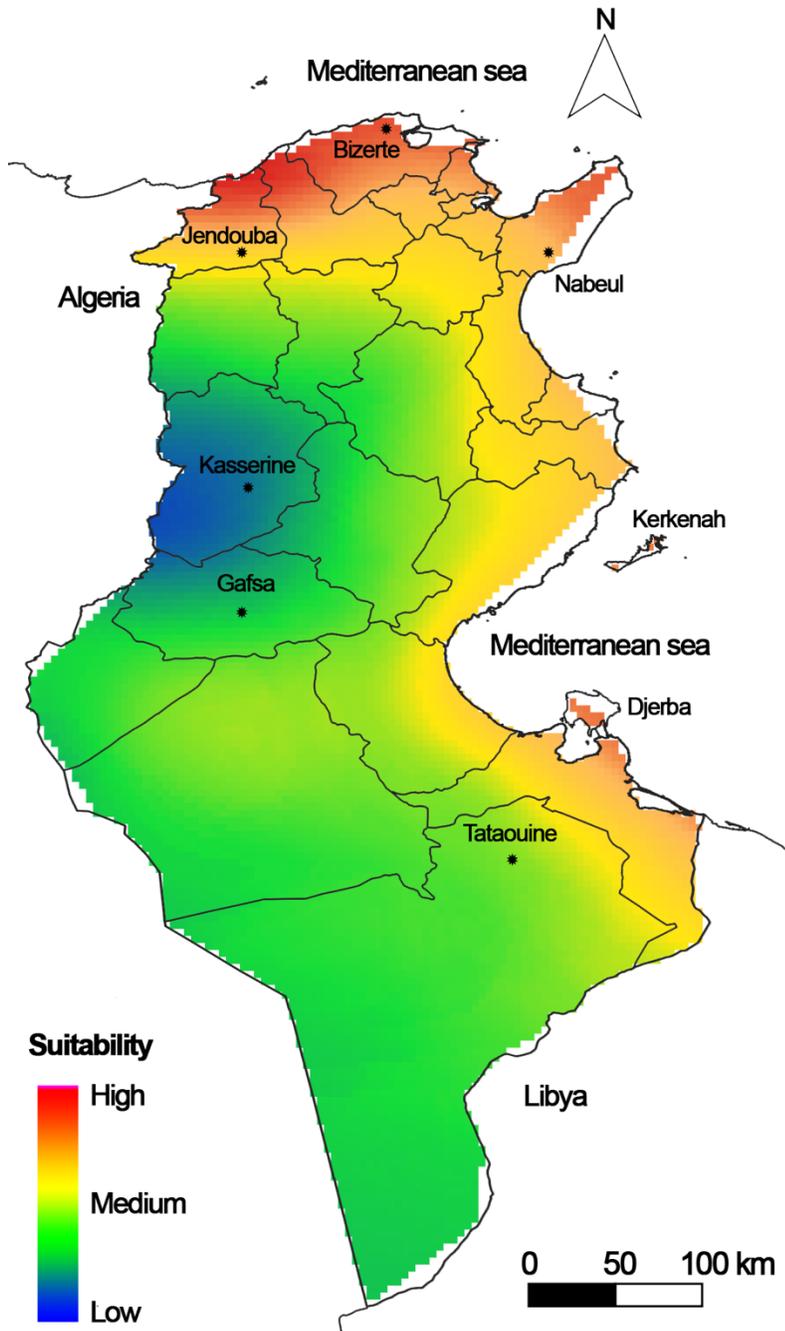


FIGURE 5.