Proceedings

Climatic Suitability for *Haplodrassus rufipes* in a Mediterranean Area: Linking a Predaceous Species to the Olive Grove [†]

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Abstract: The use of natural enemies against crop pests has been promoted during the last decades. Efficient pest limitation relies on the overlap of the predator and the pest in time and space. In Portugal, the cultivation of the olive tree (*Olea europaea* L.) represents a key economic and cultural activity. Previous works highlighted the ground hunter spider *Haplodrassus rufipes* as a promising natural enemy against the olive fruit fly *Bactrocera oleae*, the main pest of the olive tree in northeastern Portugal. The objectives of this work were to approximate the distribution of *H. rufipes* throughout the whole Iberian Peninsula using its climatic suitability and compare it with the distribution of *O. europaea*. For this, a maximum entropy model at a 1 km resolution was developed. The distribution of O. europaea was visualized using a chorological map. The most contributing bioclimatic variable to the maxent model was the mean diurnal range. The distribution of *O. europaea* fairly overlapped the highest values of the bioclimatic suitability of *H. rufipes* throughout the Iberian Peninsula.

Keywords: maxent; species distribution; natural enemies; Iberian Peninsula

1. Introduction

The olive grove agroecosystem is a relevant activity with a social and economic impact in Mediterranean areas threatened by pressures of the socioeconomic current situation [1]. Although this ecosystem is usually considered somehow stable due to the stability of the environment, the tolerance of pest damage, a complex network of insects inhabiting the crop, and abundant natural enemies [1], the crop is not free of threats such as the attack of important pests. Among these, the monophagous frugivorous pest *Bactrocera oleae* (Rossi, 1790) (Diptera: Tephritidae), the olive fly, is one of the most pernicious causing significant losses every year [2]. On the other hand, among the natural enemies of the olive fly, the spiders raised interest as potential predators that could play a role in pest limitation e.g., [3].

In the light of the diversity and ubiquity of spiders, efforts must be made in targeting those species or guilds (e.g., groups of species using the same hunting strategy) with the potential to successfully prey on the olive fly. In this context, the first condition to meet is that the species coincides in space with the crop range. To assess this relationship at a broad geographical scale, the use of species distribution models (SDM) represents a useful approach.

Species distribution models allow linking occurrence data to environmental drivers through measures of the relationship between species and the environment [4]. The resulting maps represent habitat suitability values or probability values depending on the underlying occurrence data see [5].

Haplodrassus rufipes (Lucas, 1846) (Araneae: Gnaphosidae) is a medium-sized active ground hunting spider (prosoma length 3.5 mm) [6]. Both sexes have been observed preying on adults and pupae of *B. oleae* in laboratory [7]. Although it has been observed inhabiting the olive crop in Portugal [7], the number of occurrence records reported for the Iberian Peninsula is still low. In this work, we aimed at developing an SDM able to predict the habitat suitability of *H. rufipes* throughout the Iberian Peninsula and compare it with the range of *O. europaea*.

2. Experiments

The model was developed using R [8] using the machine-learning method maxent. This modelling procedure uses the maximum entropy to approximate the distribution of a species based on presence-only data [9]. We used the R implementation of maxent of {dismo} package [10].

The bioclimatic variables used were obtained from the WorldClim database [11], a gridded climate database derived from monthly temperature and rainfall. The bioclimatic data was used at 0.5 min spatial resolution (~1 km^2) (Table 1).

Table 1. Description of bioclimatic variables provided by the WorldClim database.

| Code in Database	Bioclimatic Variable
bio1	Annual mean temperature
bio2	Mean diurnal range (mean of monthly (max temp − min temp))
bio3	Isothermality (bio2/bio7) (×100)
bio4	Temperature seasonality (standard deviation × 100)
bio5	Max temperature of warmest month
bio6	Min temperature of coldest month
bio7	Temperature annual range (bio5-bio6)
bio8	Mean temperature of wettest quarter
bio9	Mean temperature of driest quarter
bio10	Mean temperature of warmest quarter
bio11	Mean temperature of coldest quarter
bio12	Annual precipitation
bio13	Precipitation of wettest month
bio14	Precipitation of driest month
bio15	Precipitation seasonality (coefficient of variation)
bio16	Precipitation of wettest quarter
bio17	Precipitation of driest quarter
bio18	Precipitation of warmest quarter
bio19	Precipitation of coldest quarter

No selection of variables was done a priori see [12]. However; the model was refitted using the three most contributing drivers after a first tunning procedure. The tuning of the maxent model followed Muscarella et al. (2014) [13] towards a balance of goodness-of-fit with model complexity and evaluation of models with spatially independent data. The "checkerboard1" method for partitioning occurrence data was used to build a pool of 40 models corresponding to five combinations of feature classes (linear, quadratic, product, threshold, and hinge) and eight regularisation multipliers (β) (0.5, 1, 1.5, 2, 2.5, 3, 3.5, and 4). The selected optimal model was the one

that achieved the lowest AIC (Akaike Information Criterion). For the optimal model, the AUC (area under the curve) was calculated and used as a measure of the predictive potential of the model [14]. The occurrence data was obtained from the GBIF database [15,16] and the chorological map of O. europaea from Caudullo, et al. (2017) [17].

3. Results

The model that best performed was the one combining the linear, quadratic, hinge, and product features (LQHP) with a regularisation multiplier $\beta = 2$ (Table A1). The model was developed using 1000 background points, 24 presence records for training, and 7 for testing. This model gave an AIC = 978.37 and resulted in three parameters. The AUC was 0.69 ± 0.07 (SD). The percent contribution of the three bioclimatic drivers used was 71.10, 23.90, and 5.0% for the precipitation of the driest month, the temperature annual range, and mean diurnal range, respectively.

The most suitable area for *H.rufipes* was found to correspond to the main Mediterranean climate areas throughout the Iberian Peninsula and mostly overlapped with the distribution of *O. europaea* (Figure 1). The response curve obtained for the most contributing bioclimatic variable, the precipitation of the driest month, decreased as the amount of precipitation increased (Figure 2).
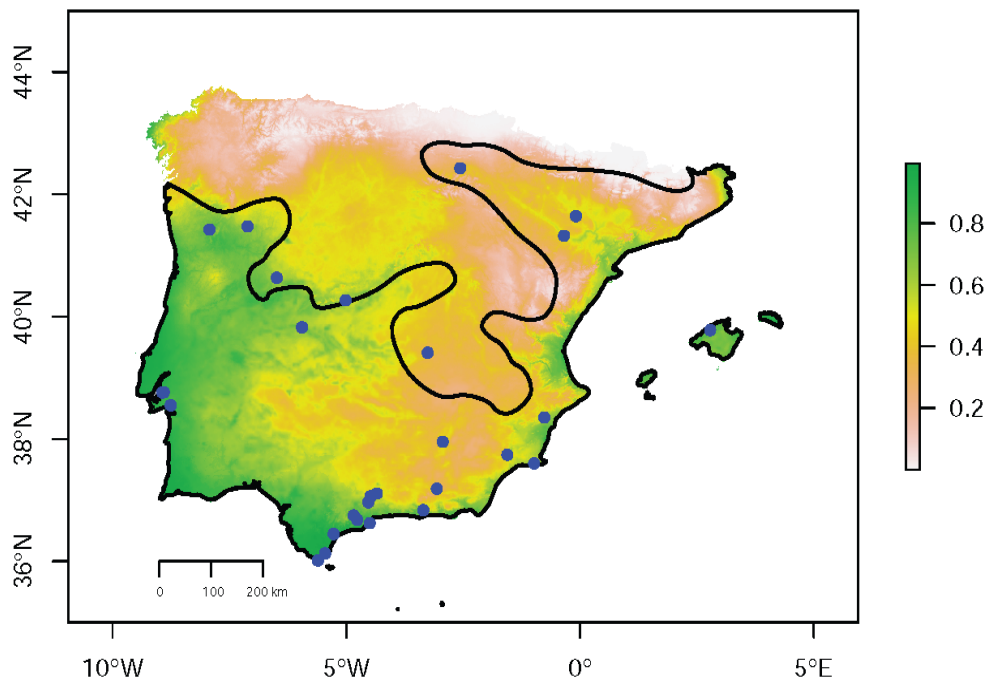
Figure 1. Biolclimatic suitability map for *Haplodrassus rufipes* in the Iberian Peninsula. Blue dots represent occurrence records. Black line represents the contour of the chorlogical map of *Olea europaea*.
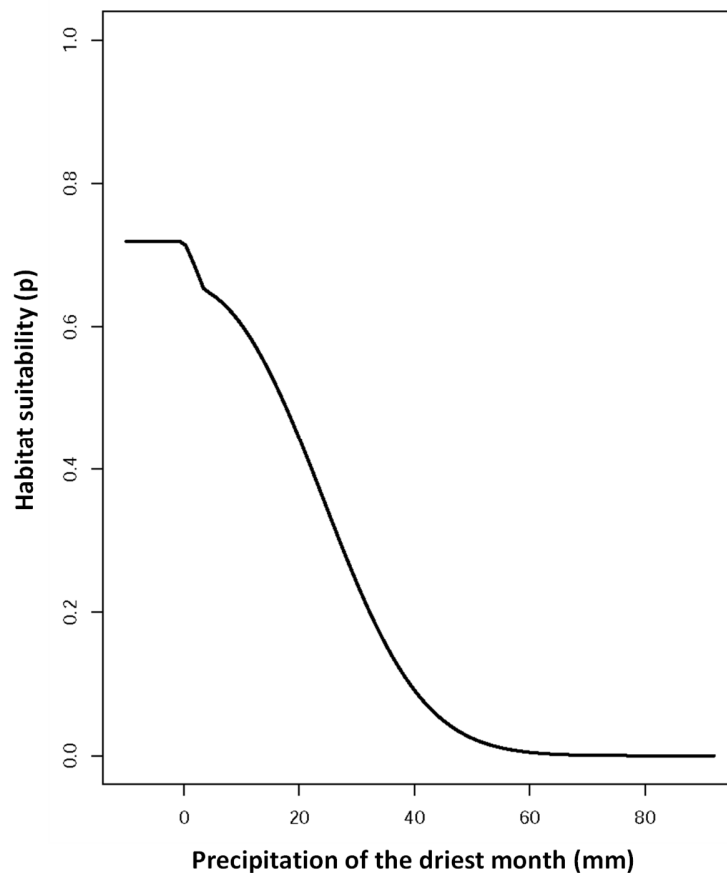
Figure 2. Response curve (habitat suitability) of *Haplodrassus rufipes* according to the precipitation of the driest month in the Iberian Peninsula.

4. Dicussion

Species distribution models proved to be useful to evaluate the predicted range of potential natural enemies. Comparing this range with the geographical distribution of a crop can help to assess the feasibility of considering different species as potential natural enemies. In this work, The high amount of overlap of the distribution of the spider and the crop suggest that further studies on the role of *H. rufipes* as a potential natural enemy in the olive grove agroecosystem are worthy. The amount of contribution of the precipitation of the driest month to the model suggests that this driver may significantly affect the life-cycle of *H. rufipes*. The strong decreasing pattern of habitat suitability as the precipitation increases suggests that this could be a species adapted to dry environments such as the mediterranean ecosystem, especially during summer. This agrees with the adaptations of the olive grove to grow under dry conditions [18].

5. Conclusions

Research on the life-cycle and functional response of *H. rufipes* on *B. oleae* may allow parametrizing individual-based models and predict the rate of predation in the field thus allowing to evaluate the eficiency of the spider as agent of biological control.

agreed to the published version of the manuscript. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Outputs of the maxent model tuning for *Haplodrassus rufipes*. Bold text indicates the selected model with the lowest AIC. RM: Regularization multiplier.

Model	Features	RM	AIC	Parameters
1	L	0.5	982.3185	3
2	L	1	982.4030	3
3	L	1.5	982.5269	3
4	L	2	982.6856	3
5	L	2.5	982.8816	3
6	L	3	983.1131	3
7	L	3.5	983.3792	3
8	L	4	983.6834	3
9	LQ	0.5	978.8699	3
10	LQ	1	978.9590	3
11	LQ	1.5	979.1044	3
12	LQ	2	979.3069	3
13	LQ	2.5	979.5627	3
14	LQ	3	979.8737	3
15	LQ	3.5	980.2352	3
16	LQ	4	980.6515	3
17	LQH	0.5	991.0409	10
18	LQH	1	985.1734	7
19	LQH	1.5	986.7045	6
20	LQH	2	979.4320	3
21	LQH	2.5	979.6956	3
22	LQH	3	980.0127	3
23	LQH	3.5	980.3777	3
24	LQH	4	980.7951	3
25	LQHP	0.5	992.5499	10
26	LQHP	1	981.4068	5
27	LQHP	1.5	982.4808	5
28	**LQHP**	**2**	**978.3702**	**3**
29	LQHP	2.5	982.2892	4
30	LQHP	3	981.1815	3
31	LQHP	3.5	982.8461	3
32	LQHP	4	984.7757	3
33	LQHPT	0.5	1016.0185	17
34	LQHPT	1	984.6857	7
35	LQHPT	1.5	987.4957	7

36	LQHPT	2	979.7848	4
37	LQHPT	2.5	980.8471	4
38	LQHPT	3	982.1643	4
39	LQHPT	3.5	983.7439	4
40	LQHPT	4	985.5982	4

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