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RESEARCH ARTICLE

# Modeling spatial distribution of European badger in arid landscapes: an ecosystem functioning approach

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**Abstract** Understanding the factors determining the spatial distribution of species is a major challenge in ecology and conservation. This study tests the use of ecosystem functioning variables, derived from satellite imagery data, to explore their potential use in modeling the distribution of the European badger in Mediterranean arid environments. We found that the performance of distribution models was enhanced by the inclusion of variables derived from the Enhanced Vegetation Index (EVI), such as mean EVI (a proxy for primary production), the coefficient of variation of mean EVI (an indicator of seasonality), and the standard deviation of mean EVI (representing spatial heterogeneity of primary production). We also found that distributions predicted by remote sensing data were consistent with the ecological preferences of badger in those environments, which may be explained by the link between EVI-derived variables and the spatial and temporal variability of food resource availability. In conclusion, we suggest the incorporation of variables associated with ecosystem function into species modeling exercises as a useful tool for improving decision-making related to wildlife conservation and management.

**Keywords** Ecological niche modeling · MaxEnt · Remote sensing · EVI · Land use-land cover · Mediterranean ecosystems · Spain · *Meles meles*

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## Introduction

Understanding the factors determining the spatial distribution of species is a major challenge in ecology and conservation biology (Brown et al. 1995). The European badger (*Meles meles*) is medium-sized carnivore widely distributed across Europe. In Mediterranean arid landscapes the species is not abundant or is absent due to extreme aridity (Virgós et al. 2005). Current spatial distribution models for the European badger use occurrence data in conjunction with environmental variables derived from GIS data sources, such as topographic, climatic, and land cover/use (Virgós and Casanovas 1999a; Jepsen et al. 2005; Newton-Cross et al. 2007). These models have improved our understanding of badger distribution and abundance (Newton-Cross et al. 2007) by reducing limitations associated with field sampling (e.g., high economic cost and limited geographic range). However, data derived by GIS cartography could include limitations of ecological representativeness such as not representing relevant landscape features for the target species or inadequate spatial resolution (Pearce et al. 2001).

The use of ecosystem functioning variables could improve spatial distribution modeling due to their capacity to reflect spatial variability of landscape features and faster response to environment changes (Pettorelli et al. 2011). Ecosystem functioning variables can be extracted from remote sensing imagery, available continuously, both spatially and temporally. This allows the employment of standardized spectral indexes for monitoring species on different spatio-temporal scales (Nilsen et al. 2005) reducing extrapolations. An example of potentially useful ecosystem functioning variables are the functional attributes derived by the Enhanced Vegetation Index (EVI). The EVI has been used in mammal ecology by Wang et al. (2010), Meynard et al. (2012), and Bardsen and Tveraa (2012). The EVI is linearly related to ecosystem carbon gains, and therefore, to net primary productivity (NPP) (Monteith 1981), which is used as a surrogate of ecosystem functioning (Alcaraz et al. 2006; Cabello et al. 2012b). Thus, measures derived from EVI can describe ecosystem functional attributes (Pettorelli et al. 2005). These attributes include the mean annual EVI (i.e., surrogate of primary production) (Huete et al. 1997; Sims et al. 2006) and the coefficient of variation of mean annual EVI (i.e., indicator of seasonality) (Alcaraz-Segura et al. 2012).

The resource dispersion hypothesis posits that the size of badger territories is mainly linked to the dispersion of food resources (Macdonald 1983; Kruuk 1989; Macdonald and Carr 1999). This hypothesis emphasizes the key role of patchiness of food quality in determining how large badger territories are. For example, habitat productivity tends to drive body condition, ultimately influencing fitness (Woodroffe 1995). As a consequence, reproductive success of females is largely dependent on food conditions, which in badgers are mainly linked to climate factors mediating food abundance (e.g., productivity of habitats) (Woodroffe and Macdonald 1995). Therefore, badger demography, abundance and social life is mainly shaped by food availability and predictability (seasonality), which can be assessed by ecosystem functional attributes derived of spectral vegetation indices (e.g., Nilsen et al. 2005; Pettorelli et al. 2005, 2006).

The purpose of this study is to test the use of ecosystem functional variables derived from EVI (e.g., mean annual EVI, coefficient of variation of mean annual EVI, and spatial deviation of mean annual EVI) to improve spatial distribution modeling of the European badger. With this aim, we first sampled badger occurrence in a representative arid landscape located in the southeastern Iberian Peninsula (Fig. 1). Secondly, we designed a variety of spatial distribution models based on environmental variables, with and without including EVI-derived variables. We also explored their performance based on a subset of previously sampled presence data and the habitat preferences of badger as described by other authors. Finally, we discuss the role of ecosystem functional dimension in species ecological modeling and conservation.

## Methods

### Study area

We selected a representative area of arid landscapes in the southeastern Iberian Peninsula based on the

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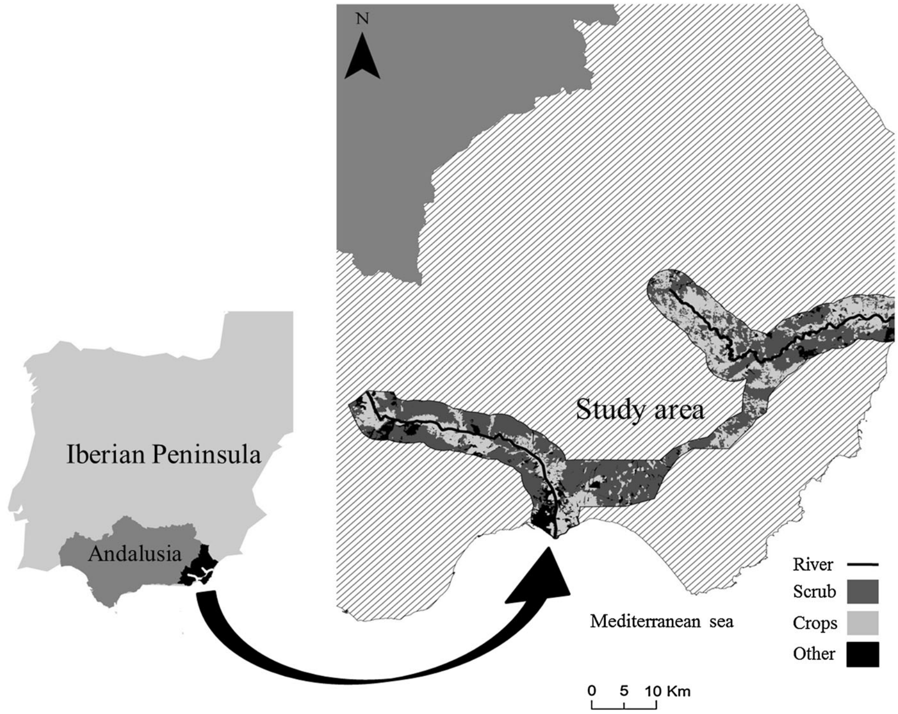



**Fig. 1** Study area location

Martonne aridity index (Martonne 1926) (Fig. 1), as it is easily calculated and mapped with GIS layers. Inside this area defined as Arid steppic by the Martonne index (range 5–15), we drew a 3.5 km-radius buffer zone on both sides of the two major rivers basins in the region, and then joined the two buffers (Fig. 1). In this form, we ensure inclusion of the potential home range estimated for European badgers in these environments (i.e., 9 km$^2$) (Lara-Romero et al. 2012). The study area comprised 835 km$^2$, with a temperature gradient (range of minimum mean temperatures: 7–12 °C, range of maximum mean temperatures: 23–28 °C) and an annual precipitation gradient (200–600 mm/m$^3$) associated with a wide altitudinal gradient (0–1,400 m). Evapotranspiration ranges from 93 to 945 mm/year. Another important feature of the area is the diversity of land cover/use: xerophytic scrubs represent 48 % of the area, where *Stipa tenacissima* is the most abundant. Forested habitat is very scarce, corresponding mostly to scattered pine forests (*Pinus halepensis*). Crops occupy 27 % of the study area and include fruit orchards (especially abundant near the rivers), arable crops and greenhouses, in similar proportions.

Field survey data

A field survey was conducted from September 2010 to February 2011. The study area was divided into 5 × 5 km UTM (Universal Transverse Mercator) plots (out of total 66 plots) to organize the field surveys and not as the sampling unit. A survey to identify signs of badgers (i.e., footprints, latrines and setts) was carried out for 6 h in each plot. To maximize the detection of the species with the least effort, we selected places for survey such as paths and catchments for footprints, hills for latrines and easy to dig sloping areas for setts. These places are known to be usually used by badgers. The GPS (UTM) coordinates of each sign were noted with a measurement error of up to 10 m using a GPSmap® 60CS×-Garmin. To avoid spatial autocorrelation of environmental variables (see below), no signs within 100 m from each other were considered (see Appendix 5).

Environmental data

The study area was characterized based on twenty predictor variables (Table 1 and Appendix

**Table 1** Groups of variables used for constructing models

| Variable | Short name | Groups of variables | | | |
|---|---|---|---|---|---|
| | | Group 1 | Group 2 | Group 3 | Group 4 |
| Mean slope | SLO | X | | | |
| Annual mean rainfall | MRAIN | X | | | |
| Mean value of the maximum temperatures | MMT | X | | | |
| Area of scattered scrub | SSCRUB | | X | | |
| Area of dense scrub | SDCRUB | | X | | |
| Area of woody crop | SWCROP | | X | | |
| Area of arable crop | SACROP | | X | | |
| Area of mixed crop | SMICROP | | X | | |
| Area of mosaic crop | SMOCROP | | X | | |
| EVI annual mean | EVIMEAN | | | X | |
| Standard deviation of EVI annual mean | EVISTD | | | X | |
| Coefficient of variation of EVI annual mean | EVICV | | | X | |
| EVI autumn mean | AEVI | | | X | |
| EVI spring mean | SEVI | | | X | |
| EVI annual mean of scattered scrub | SSCEVI | | | | X |
| EVI annual mean of dense scrub | DSCEVI | | | | X |
| EVI annual mean of woody crop | WCEVI | | | | X |
| EVI annual mean of arable crop | ACEVI | | | | X |
| EVI annual mean of mixed crop | MICEVI | | | | X |
| EVI annual mean of mosaic crop | MOCEVI | | | | X |

Group 1: topography and climate, group 2: Land cover and Land use, group 3: EVI variables, group 4: EVI of land cover. Each model contained group 1, the ALL model all four groups, LC & LU model groups 1 and 2, the EVI model groups 1 and 3, and the EVI LC model groups 1 and 4. Thus, three models included the ecosystem functional variables: EVI, EVI LC and ALL, and only LC & LU model did not include these variables

4). Nine of these variables are commonly used in European badger ecology studies (e.g., Virgós and Casanovas 1999a; Revilla et al. 2000; Macdonald and Newman 2002; Jepsen et al. 2005; Rosalino et al. 2008; Lara-Romero et al. 2012), and were comprised by two climate variables, one topographic variable and six variables related to habitat structure represented by different land cover/use. The eleven remaining variables were derived from remote sensing data.

Final resolution of environmental data sets was adjusted to 100 × 100 m pixel size (i.e., sample unit), to agree with the predominant smallest spatial resolution of data (Ferrier and Watson 1997; Elith and Leathwick 2009). Some variables (i.e., land cover/use variables) were scaled to the relevant scale for badgers (i.e., their home range).

*Topographic and climate variables*

Topographic and climate variables were derived from spatial data layers of the Environmental Information Network of Andalusia (http://www.juntadeandalucia.es/medioambiente/site/web/rediam). ESRI® ArcMap™ 9.3 was used for their handling and processing. The topographic variable was mean slope, which has been described as a factor relevant for sett digging (Jepsen et al. 2005). It was estimated from the digital elevation model of Andalusia with a spatial and elevation pixel resolution of 20 × 20 m. This layer was resampled to 100 × 100 m.

Climate variables (Virgós and Casanovas 1999a; Johnson et al. 2002; Macdonald and Newman 2002) were mean annual rainfall and the mean maximum temperature, acquired with a resolution of 100 x 100 m, so no transformation was made.

### *Land cover and land use variables*

The land cover and land use variables (Virgós and Casanovas 1999a; Revilla et al. 2000; Rosalino et al. 2008; Lara-Romero et al. 2012) were derived from Andalusian Land use/Land cover map (scale 1:25,000 from 2007), in vector format. This layer included the following classes: scattered scrub, dense scrub, woody crops, arable crops, mixed crops (woody and arable) and mosaic crops (crops and natural vegetation). The study area was first divided into 3 × 3 km plots. We estimated the area (km$^2$) of each class and then we rasterized to 100 × 100 m pixel size. These variables were scaled because the percent cover is relevant for badgers (Lara-Romero et al. 2012), instead of using the class of land cover/use as categorical variable. We considered a 9 km$^2$ area as the probable home range of the European badger in areas of low habitat suitability (Lara-Romero et al. 2012).

### *EVI variables*

The eleven variables derived from remote sensing data were estimated based on the MOD13Q1 EVI product, generated from images captured by the MODIS sensor aboard the NASA's TERRA satellite (www.modis.gsfc.nasa.gov) for a period of seven years. These images have the advantages of its high temporal resolution of 16 days (23 images/year) and spatial resolution appropriate to the scale of the study (231 × 231 m). The images were subjected to pixel quality filtering, in which those affected by heavy content of aerosols, clouds, shadows, snow or water were eliminated. The EVI is the index least affected by atmospheric conditions and presents fewer saturation problems for high levels of biomass (Huete et al. 2002).

The mean annual EVI is linearly related to total carbon gain (Running et al. 2000), and has been used as a surrogate of vegetation productivity (Alcaraz-Segura et al. 2012). The standard deviation of mean annual EVI is an indirect measure of spatial heterogeneity, so that a high standard deviation may indicate mixed patches, while a low standard deviation is common in homogeneous landscapes. This variable was estimated by calculating the standard deviation of mean annual EVI in the 3 × 3 km plots used to estimate the land cover/use variables. The coefficient of variation of mean annual EVI is a seasonal carbon gain descriptor (Alcaraz et al. 2006) that has been used as an indicator of ecosystem seasonality (Alcaraz-Segura et al. 2012). Furthermore, seasonality, although described by other variables, has proven decisive in modeling the habitat of several other species (Boyce 1978; Ferguson and McLoughlin 2000; Wiegand et al. 2008). In addition to these, the EVI autumn mean (September–November) and EVI spring mean (March–May) were also included as variables, because they represent the two growing seasons in Mediterranean arid landscapes (Cabello et al. 2012b).

EVI variables were resampled to 100 × 100 m by a bilinear resampling technique. It determines the new value of a cell based on a weighted distance average of the four nearest input cell centers. This is likely more realistic than using nearest-neighbor interpolation method (Phillips et al. 2006).

### *EVI of land cover and land uses variables*

Five variables were created by calculating mean EVI for each class of land cover/use referred to above. These variables were also resampled to 100 × 100 m by a bilinear resampling technique.

## Model building

### *MaxEnt*

We used MaxEnt (Phillips et al. 2006) to model the spatial distribution of the European badger. The MaxEnt algorithm uses presence-only data. This is an advantage when working with a very low density of target species at large scales, as we expected in the study area based on Lara-Romero et al. (2012), due to the uncertainty in absences. Although MaxEnt has been criticized on several occasions (see recently Veloz 2009; Yackulic et al. 2012), it is widely used for modeling the spatial distribution of species for various purposes, e.g., testing model performance against other methods (Elith et al. 2006) and using several types of variables (Buermann et al. 2008), predicting species richness or diversity (Graham and Hijmans 2006), or forecasting distributions to estimate variations with climate change/land transformation (Yates et al. 2010). Finally, given that (1) the main goal of this study is to test the performance of models using ecosystem functional variables, and (2) prediction maps generated by MaxEnt are of interest as assessment tools, but are not the goal itself, we considered MaxEnt a valid tool for achieving our objectives.

*Models*

To test the utility of environmental functional variables in modeling the spatial distribution of the badger, we combined the twenty variables into four groups, with and without including ecosystem functional variables (Table 1). We defined these four groups because they were the most ecologically reasonable and of interest for comparison in keeping with the objectives of this study. These groups of variables, along with the badger presence data, were input to compute models. We used 10-fold cross-validation of the occurrence locations. Each partition was made by randomly selecting 75 % of the occurrence locations as training data, and the remaining 25 % as test data. Then, each one of the partitions, along with each of the four combinations of variables, was run in MaxEnt to compute the models. We made 10 random partitions rather than a single one in order to assess the average model behavior, and to allow for statistical testing of observed differences in performance (Phillips et al. 2006).

## Model evaluation

*Threshold-independent evaluation*

We evaluated the performance of models created from different combinations of variables using all discriminating thresholds within the predicted area as suitable or unsuitable for badgers. We used (threshold-independent) receiver operating characteristic (ROC) analysis for this, as it uses a single measure, the area under the curve (AUC), to show model performance. With presence-only data, the $AUC_{PO}$ (i.e., AUC estimated with presence-only data) maximum was less than 1 (Wiley et al. 2003), so we do not know how close to optimal a given $AUC_{PO}$ was. Nevertheless, we were able to determine the statistical significance of the $AUC_{PO}$ and compare the performance of different models (Phillips et al. 2006). We employed a DeLong test (DeLong et al. 1998) to compare $AUC_{PO}$ values for each combination of variables. The DeLong test is designed to nonparametrically compare the difference between two AUCs from two correlated ROC curves. The $Z$ score is defined as the difference of AUC divided by its standard error. Under the null hypothesis (the difference in AUC is zero) $Z$ has a standard normal distribution (Chen et al. 2013). This test was computed in R (R Development Core Team 2008).

*Information criteria*

Following Warren and Seifert (2011), we implemented an Akaike information criterion corrected for small sample size (AICc) (Burnham and Anderson 2002) in the MaxEnt models. We standardized raw scores for each model, so that all scores within the study area added up to 1. Then we calculated the likelihood of the data in each model by taking the product of the suitability scores for each pixel showing presence. Both training and test data were used in calculating likelihood. The number of parameters was measured by counting all parameters with a nonzero weight in the *.lambda* file produced by MaxEnt. All AICcs were computed using ENMTools software (Warren et al. 2010).

*Variable relative importance and response curves*

We evaluated the relative importance of the variables using a jackknife test on the $AUC_{PO}$ found from test data. Thus $AUC_{PO}$ was estimated by (1) removing the corresponding variable, and then creating a model with the remaining variables, (2) creating a model using each variable alone, and (3) using all variables. Furthermore, we plotted the response curves for the variables which caused the widest variations in the $AUC_{PO}$. Curves were estimated by generating a model using only the corresponding variable and disregarding those remaining (Phillips et al. 2006).

# Results

## Occurrence of European badger

The field survey yielded 94 presence locations, mainly associated with the two main rivers in the study area (see Appendix 1). Landscapes near the rivers had a larger supply of food resources for the European badger, because crops are abundant there (Fig. 1). These presence records are enough for this study since MaxEnt algorithm has been proved to works well at different sample size (Hernández et al. 2006). 51 of the records were footprints, 26 latrines, 15 setts and 2 road casualties.

Threshold-independent test

In 6 of the 10 partitions, combinations with all variables (ALL) yielded the models with the highest $AUC_{PO}$ (Table 2). In 8 of the 10 partitions, the $AUC_{PO}$ was higher for EVI and EVI LC than for the Land cover & Land uses models, which were the lowest in most of the partitions.

Information criteria

Table 3 shows Akaike weights found by models. It is accepted that models with AICc differences (ΔAICc) <2 are plausible while models with ΔAICc values >10 are rejectable (Burnham and Anderson 2002). Thus, 6 of the 10 data partitions accepted EVI and LC & LU as the most parsimonious models, while one of the partitions accepted the EVI LC model. ALL models were not plausible in any of the partitions.

Relevant variables and their effects

We only analyzed the relative importance of variables from the ALL model, with the maximum $AUC_{PO}$ value. Area of mosaic crop (*SMOCROP*) caused a 2 % reduction in $AUC_{PO}$ (Fig. 2b). Therefore, this variable, along with others that caused a reduction of over 1 % (Area of scattered scrub (*SSCRUB*), EVI of mosaic crop (*MOCEVI*), mean maximum temperature (*MMT*) and coefficient of variation of mean EVI (*EVICV*)), provided the most useful information not present in the other variables. We considered reductions about 2 and 1 % as relevant, because these percentages were above the third quartile (0.84 %) of reduction values percentage. *EVIMEAN* alone had the highest $AUC_{PO}$ (87.4 % $AUC_{PO}$ with all variables) (Fig. 2a) and therefore, this variable provided the most useful information by itself. Apart from this, others like EVI spring, EVI autumn, EVI scattered scrub and standard deviation of mean EVI, were over 79 %.

Variables such as scattered scrub area, mean maximum temperature, standard deviation of mean EVI and EVI of scattered scrub exerted a nonlinear effect on European badger habitat suitability, as predicted by MaxEnt (Appendix 2). On the contrary, mosaic crop area and mean annual EVI, exerted a positive linear effect, while EVI crop mosaic and coefficient of variation of mean EVI had a negative linear effect.

**Table 2** Comparison of threshold-independent receiver operating characteristic (ROC) results for European badger using LC & LU, EVI, EVI LC and ALL models

| Data partition | LC & LU $AUC_{PO}$ | EVI $AUC_{PO}$ | EVI LC $AUC_{PO}$ | ALL $AUC_{PO}$ |
|---|---|---|---|---|
| 1 | 0.722 | *0.669* | **0.725** | 0.722 |
| 2 | *0.63* | **0.701** | 0.634 | 0.674 |
| 3 | *0.644** | 0.705 | **0.745** | 0.658 |
| 4 | *0.753** | 0.756* | 0.761 | **0.816** |
| 5 | *0.625** | **0.785** | 0.69 | 0.69* |
| 6 | *0.742** | 0.793* | 0.746* | **0.808** |
| 7 | 0.734 | 0.726 | *0.707* | **0.741** |
| 8 | *0.673** | 0.711 | 0.682 | **0.735** |
| 9 | 0.772 | 0.788 | *0.753* | **0.831** |
| 10 | *0.718** | 0.758* | 0.77 | **0.82** |
| Average | 0.701 | 0.739 | 0.721 | 0.749 |
| Standard deviation | 0.053 | 0.042 | 0.042 | 0.065 |
| Maximum | 0.772 | 0.793 | 0.770 | 0.831 |
| Minimum | 0.625 | 0.669 | 0.634 | 0.658 |

For each random partition of occurrence records, the maximum $AUC_{PO}$ is marked in bold, the minimum italicized, and if the observed difference between the maximum $AUC_{PO}$ and the rest is statistically significant (under a null hypothesis that true $AUC_{POs}$ are equal), it is marked with an asterisk

*LC & LU* Land cover and Land uses, *$AUC_{PO}$* AUC estimated with presence-only data

## Discussion

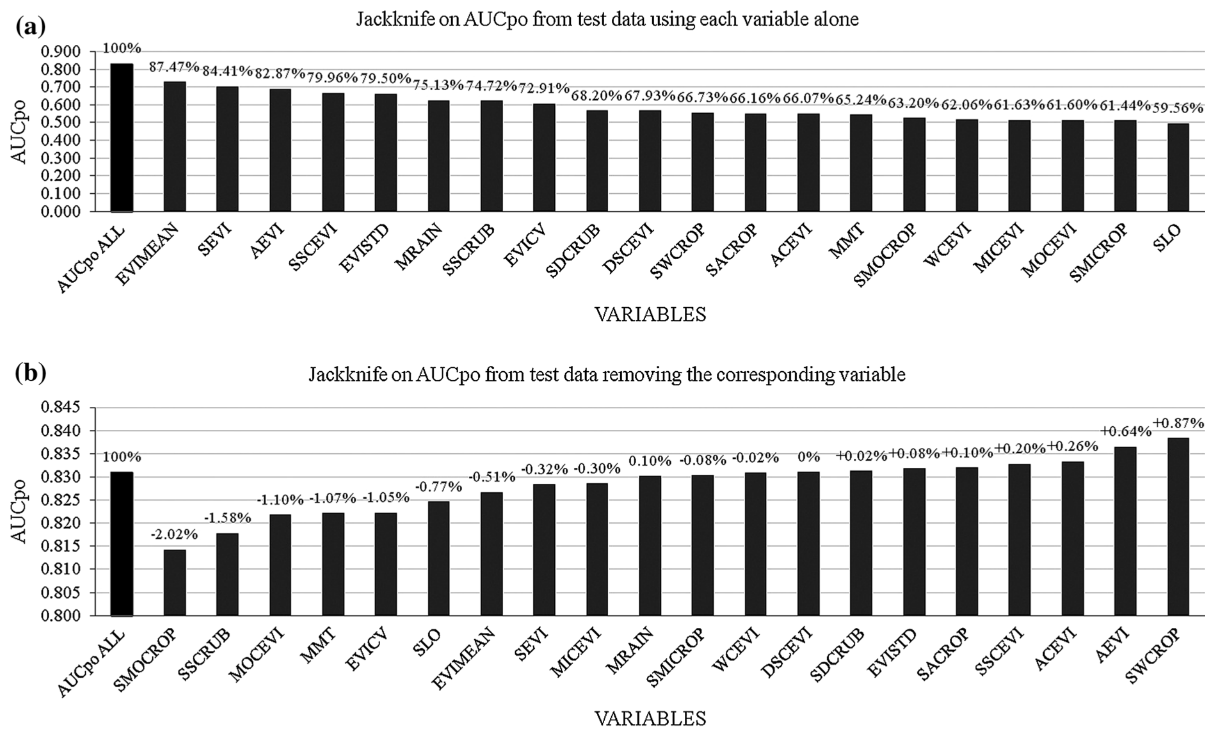
Did the EVI-derived variables improve ecological niche modeling of the European badger in arid landscapes?

EVI variables provided useful information that improved the ecological niche modeling of European badger in arid Mediterranean landscapes. Based on the $AUC_{PO}$ and AICc criteria, models built with EVI variables, performed well in predicting the spatial distribution, while models without them were inferior (based on $AUC_{PO}$). We suggest that the variables included in the EVI models underlie the spatiotemporal dynamic of badger food resources by describing vegetation productivity (*EVIMEAN*), seasonality

**Table 3** Number of estimated parameters (*K*), AICc differences (ΔAICc) and Akaike weights ($W_i$). The maximum $W_i$ for each random partition of occurrence records is marked in bold

| Partition data | LC & LU | | | EVI | | | EVI for LC | | | ALL | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | K | ΔAICc | Wi | K | ΔAICc | Wi | K | ΔAICc | Wi | K | ΔAICc | Wi |
| 1 | 24 | 0.00 | **0.73** | 30 | 1.98 | 0.27 | 33 | 29.28 | 0.0 | 46 | 40.63 | 0.0 |
| 2 | 26 | 17.72 | 0.00 | 27 | 0.00 | **1.00** | 28 | 35.18 | 0.0 | 49 | 91.35 | 0.0 |
| 3 | 27 | 29.05 | 0.00 | 28 | 0.00 | **1.00** | 37 | 58.81 | 0.0 | 51 | 107.23 | 0.0 |
| 4 | 28 | 0.00 | **0.55** | 33 | 0.41 | 0.45 | 37 | 44.61 | 0.0 | 47 | 34.45 | 0.0 |
| 5 | 25 | 0.00 | **1.00** | 34 | 15.58 | 0.00 | 29 | 11.82 | 0.0 | 47 | 53.23 | 0.0 |
| 6 | 29 | 13.74 | 0.00 | 30 | 0.00 | **1.00** | 34 | 38.57 | 0.0 | 54 | 108.75 | 0.0 |
| 7 | 27 | 15.15 | 0.00 | 26 | 0.00 | **1.00** | 31 | 39.43 | 0.0 | 43 | 27.42 | 0.0 |
| 8 | 30 | 0.00 | **0.94** | 33 | 5.39 | 0.06 | 35 | 25.30 | 0.0 | 47 | 34.13 | 0.0 |
| 9 | 25 | 0.00 | **0.69** | 34 | 14.69 | 0.00 | 27 | 1.61 | 0.3 | 53 | 94.24 | 0.0 |
| 10 | 25 | 0.00 | **1.00** | 34 | 19.93 | 0.00 | 28 | 12.72 | 0.0 | 50 | 66.34 | 0.0 |

*LC & LU* Land cover and Land uses




*MRAIN*: Mean annual rainfall; *SLO*: Mean slope; *MMT*: Mean maximum temperature; *SSCRUB*: Area of scattered scrub; *SDCRUB*: Area of dense scrub; *SWCROP*: Area of woody crops; *SACROP*: Area of arable crops; *SMICROP*: Area of mixed crops; *SMOCROP*: Area of mosaic crops; *EVIMEAN*: Mean annual EVI; *AEVI*: Mean autumn EVI; *SEVI*: Mean spring EVI; *EVICV*: Coefficient of variation of mean annual EVI; *EVISTD*: Standard deviation of mean annual EVI; *SSCEVI*: Mean annual EVI of scattered scrub; *DSCEVI*: Mean annual EVI of dense scrub; *WCEVI*: Mean annual EVI of woody crop; *ACEVI*: Mean annual EVI of arable crop; *MICEVI*: Mean annual EVI of mixed crop; *MOCEVI*: Mean annual EVI of mosaic crop. AUCpo: AUC estimated with presence-only data.

**Fig. 2** Jackknife test of variable importance for European badger in the ALL model with maximum $AUC_{PO}$. **a** *Bars* show the $AUC_{PO}$ with each variable modeled separately. *Ratios above the bars* show the $AUC_{PO}$ percentage of the reference value (0.831); **b** *Bars* show the $AUC_{PO}$, when each variable is extracted from the model. The *ratios above the bars* show the ratio decreased by the $AUC_{PO}$ with respect to the reference value (0.831)

(*EVICV*) and spatial heterogeneity (*EVISTD*). Thus, areas with high EVI mean and EVI spatial heterogeneity represented more suitable habitats for the European badger, while they rejected areas with high EVI seasonality.

Our study showed that despite the fact that rainfall (expressed here as mean annual rainfall, *MRAIN*) is considered the main driver of vegetation growth in Mediterranean environments (Nemani et al. 2003), it did not prove to be as good a predictor as the mean EVI (as proxy of primary productivity) for European badger distribution. The higher performance of EVI mean can be explained by the findings of Cabello et al. (2012b), in which productivity derived from EVI in drylands reflects the variation of the water use efficiency and its availability due to the features of vegetation and lithology. In addition, EVI mean also reflected the NPP for irrigated crops, which do not depend directly on rainfall (33 % of crops in the study area are irrigated).

Additionally, more seasonal environments in the study area (i.e., with high *EVICV* values) represented zones with low habitat quality for European badger. Johnson et al. (2002), suggested that badger densities across Europe are associated with seasonal constraints, or some other constraint(s) that covary with seasonality. EVI models predicted as suitable, landscapes with little annual variation in EVI values, corresponding with sites where the availability of food may be assured even in summer, the season experiencing the most extreme shortages in food. Similarly, Virgós and Casanovas (1999a) showed that a decrease in summer rainfall reduces badger occurrence in Mediterranean mountains.

We also found that badgers selected areas with high EVI spatial heterogeneity. Pita et al. (2009) described the Mediterranean rural landscape as a shifting mosaic that benefits diversity and presence of species as the European badger. The different types of traditional crops, along with patches of semi-natural vegetation, especially scrub and/or forest, yield a wide variety of food resources. We argue that the *EVISTD* variable might detect these mosaic landscapes. However, although this variable contributed positively to European badger habitat suitability, its effect was nonlinear, suggesting that badgers would not need such heterogeneity to survive in certain landscapes.

Both *EVICV* and *EVISTD* might depict variability of resources availability. *EVICV* represents temporal variability in the availability of resources because it is the dispersion of mean EVI throughout the year. In this sense, if EVI in summer and winter are significantly different, the annual temporal variability of EVI will be large. On the other hand, *EVISTD* represents spatial variability because it is the standard deviation of mean EVI into the potential territories of badgers. In consequence, high values indicate that a landscape will be more heterogeneous.

### Was the predicted spatial distribution across arid lands consistent with the ecological preferences of the European badger?

The distribution predicted by the EVI models was coherent with the habitat preferences described for the European badger (see Appendix 3 for further details of predicted distributions by models). Our results reveal that badger′s presence in the study area was mainly associated with sites near rivers where there were several different types of crops and patches of natural vegetation. According to Lara-Romero et al. (2012), in Mediterranean drylands the European badger prefers mosaic landscapes consisting of fruit orchards and natural vegetation, which provide shelter and food resources. In these environments, the diet is diversified, with consumption of fruit increasing in some seasons (Barea-Azcón et al. 2010). Fruits, insects and vertebrates have also been described as relevant food resources for European badger in Mediterranean environments (Rodríguez and Delibes 1992; Revilla and Palomares 2002). Likewise, other authors have related the occurrence or abundance of these items with satellite-derived vegetation indices, such as EVI or Normalized Difference Vegetation Index (NDVI) (see Willems et al. 2009; Lafage et al. 2013; Tapia et al. 2013).

EVI and EVI for Land cover models discriminated better between suitable (i.e., mosaic landscapes with crops) and unsuitable areas (homogeneous patches of dense xerophytic scrubs) than the LC & LU models (see Table 2 and Appendix 3). EVI variables provided information for discriminating between two patches with the same type of land use and cover, but with different primary production, seasonality and spatial heterogeneity. The EVI for Land cover models exhibited an intermediate performance (Table 2). These models also used variables related to primary productivity. However, such variables were averaged based on the spatial classification derived by GIS cartography. These maps may not represent relevant landscape features for the target species or inadequate spatial resolution (Pearce et al. 2001).

Sites with high *EVIMEAN* and *SMOCROP* (area of mosaic crops) values represented the most suitable habitats for the European badger. However, the variable EVI mean of mosaic crops (*MOCEVI*) showed a negative effect on badger presence, which could be explained by the fact that 1—mosaic crop variable, in turn, encompasses different types of crops, and 2—badger presence records with high EVI values, are associated with non-irrigated almond crop, which would not favor badger presence in those areas. This suggests that in particular landscapes, the type of land use would be more decisive for badger than its associated productivity.

Removal of variables such as *SWCROP* (area of woody crop) and *AEVI* (EVI autumn), did increase performance, meaning that such variables reduced the generality of the model. This is, models made with these variables appear to be less transferable to other geographic areas or to projected future distributions by applying future conditions (Phillips 2006).

Regarding the potential bias of the selected study area on results, we consider that the study area contained enough variability to ensure that its effect was minimized. Probably, a larger buffer would provide similar results because the area between both rivers has not crops. In Mediterranean arid landscapes, the major landscape variability is generally associated with areas near rivers (Corbacho et al. 2003) and along altitudinal gradients, just what we defined with our study area.

## Ecosystem functional dimension in species ecological modeling and conservation

The incorporation of remotely sensed characterization of the ecosystem functional dimension in management and monitoring of species and populations is gaining attention in conservation biology (Cabello et al. 2012a). Ecosystem functional dimension provides proxies showing biodiversity patterns and new tools and criteria that can assist in designing conservation planning and actions. Some examples are shown by Bardsen and Tveraa (2012), who used vegetation productivity estimated by EVI to advance knowledge of the reproductive biology of reindeer (*Rangifer tarandus*) in Norway; Oindo (2002) who predicted mammal species richness and abundance using multi-temporal NDVI data; or Wiegand et al. (2008), who studied the relationship between brown bear (*Ursus arctos*) habitat quality and the seasonal course of NDVI as a proxy for ecosystem functioning in the northern Iberian Peninsula.

Ecological modeling of the European badger in the Iberian Peninsula has to date been addressed mainly using landscape structural variables estimated from visual field observation (transect scale) (Virgós and Casanovas 1999b) and by GIS information (regional scale) (Rosalino et al. 2004). Even though these variables that reflect landscape structure are essential to modeling the species distribution (Rosalino et al. 2008), they do not reflect the role of ecosystem functioning indicators or their bidirectional relationship with the conservation of biodiversity and ecosystem processes (Cabello et al. 2012a). However, Pettorelli et al. (2005) and García-Rangel and Pettorelli (2013) point out some constrains of remote sensing data to wildlife studies such as select the most suitable processing to eliminate noise in the data, insufficient temporal resolution to precisely date phenological phenomena, and economic disadvantages due to many satellites still produce data that are not free.

Our study is the first to show that incorporation of ecosystem functional variables (EVI-derived) improves the prediction of spatial distribution modeling of the European badger in arid landscapes, considered especially sensitive to Global Change (Lavorel et al. 1998). In this sense, Pettorelli et al. (2005) suggested that satellite-derived indexes, such NDVI or EVI, could be used to predict the ecological effects of environmental change on ecosystems functioning and animal population dynamics and distributions, due to their correlation with vegetation biomass and relationship with climate variables.

Finally, we found that EVI variables represented relevant ecological parameters for the description of the distribution of the European badger as they can indicate (1) a high NPP associated with orchards or fruit crops, very important for its survival in Mediterranean arid landscapes (Rodríguez and Delibes 1992; Lara-Romero et al. 2012), (2) seasonality in the primary production, which can be seen as a surrogate of habitat quality (Johnson et al. 2002), and (3) spatially heterogeneous landscapes which provide different food resources (Pita et al. 2009). However, these variables should be tested in other areas of its distribution range. Models including EVI variables perform better (based on $AUC_{PO}$) than models not including these variables. Additionally, continuous availability, both spatially and temporally, of remote sensing data can improve the accuracy of monitoring and modeling wildlife for conservation purposes in arid ecosystems throughout the world.

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