Distribution modelling of the Short-toed Eagle in relation to potential food availability

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By

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Disclaimer

This thesis is an outcome of the *Biodiversity in fragmenting landscapes (BIOFRAG)* ITC internal research project in collaboration among:

- *International institute for Geo-information Science and Earth Observation* (ITC), Enschede, Netherlands
- *University of Malaga*, Malaga, Spain
- *Fundación Migres*, Algeciras, Spain

Abstract

The main objectives of this research are (1) to predict and explain the distribution of the Short-toed Eagle in Malaga province, Southern Spain, (2) to generate maps of preferred hunting sites and potential available prey for the Eagle and (3) to infer the contribution of prey availability in the Short-toed Eagle distribution model.

The spatial distribution of the prey snake species were modelled using multivariate statistical techniques and GIS (Geographic Information System). To select the explanatory environmental variables affecting the species distribution and to find out where the suitable habitat for the selected snake species in Malaga province are, predictive distribution models were created using logistic regression and the environmental favourability function, absence/presence data of the species and a set of independent variables related to bioclimatic, topographic and anthropogenic conditions.

A map showing Eagle's preferred hunting areas was generated by ranking the Corine land cover map using expert knowledge and interviews with local ornithologists. A potential food availability map was generated based on snake prey species distribution, combined with the Short-toed Eagle preferred hunting areas.

To assess the predictor variables affecting the Short-toed Eagle distribution in Malaga province, predictive distribution models were created using Maximum Entropy functions, presence data of the species, potential food availability and a set of 7 independent variables related to climatic conditions, topography and NDVI (Normalized Difference Vegetation Index). Presence data (observed nest-locations) were collected during fieldwork in September and October 2008.

To indentify a model with the fewest predictors that explained the data satisfactorily, five variables model were selected; minimum temperature in the wettest quarter, NDVI for mid August, precipitation in September, slope and the southness of aspect. This research also revealed that inclusion of the potential available prey in the distribution models did not result in significantly increased AUC (Area Under Curve) compared to the food excluded models. The final predictive model satisfactorily describes the Short-toed Eagle distribution in the Malaga province.

This research suggests re-testing the hypothesis using hyper spatio-temporal species distribution data and/or new potential food availability indices.

Key words: Short-toed Eagle, *Circaetus gallicus*, spatial predictive models, Maxent, environmental favourability function, potential food availability, *Malpolon monspessulanus, Hemorrhois hippocrepis, Rhinechis scalaris*, Malaga province

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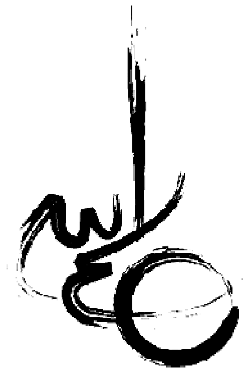

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1. Introduction

Exploring the relationship between a species and the features of the ecosystem in which it occurs is fundamental in conservation and biodiversity management. Sustaining biodiversity requires knowledge about its geographical distribution and pattern, as well as an understanding of the processes which are driving biodiversity at different scales (Skidmore et al., 2006). Decision makers and resource managers need to have a clear and reliable view of distribution of species and their abundance in the landscape as well as knowledge of relative suitability of habitats for a given species. Predictive modelling and mapping that is based on these relationships forms an analytical foundation for informed conversation planning, mapping patterns of biodiversity, detecting distributional changes from monitoring data and quantifying how variation in species performance related to on or more controlling factors (Guisan and Hofer, 2003, Phillips et al., 2006, Yost et al., 2008).

To create conservation strategies for a species such as the Short-toed Eagle (*Circaetus gallicus*), a migratory raptor whose distribution throughout north and west and central Europe has seriously declined (Gensbol, 2004, Bakaloudis et al., 2005, Agostini et al., 2002, Birdlife-International, 2008), wildlife managers need to know environmental requirements and geographical distributions. Several studies have been conducted to describe the habitat attributes of the Short-toed Eagle in the local level and its nest features, (Agostini et al., 2002, Bakaloudis et al., 2001, Bakaloudis et al., 1998, Bakaloudis et al., 2000, Bakaloudis et al., 2005, Gensbol, 2004, Gil and Pleguezuelos, 2001, Rocamora, 1994, Vlachos and Papageorgiou, 1994) however, few studies have evaluated the attributes at landscape level. Snakes distribution and their correlation with the Short-toed Eagle occurrences were minimally studied.

Advancements in computer technology, statistical modelling and Geographic Information System (GIS) software allow the knowledge of species/habitat relationship to be used for prediction the geographic distribution of individual population of wildlife species (Yost et al., 2008). Predictive species mapping is founded in ecological niche theory and predictor analysis and rests on the premise that species distribution can be predicted from the spatial distribution of environmental variables that correlated with or control the occurrence of a species (Yost et al., 2008, Phillips et al., 2006). Generally, there are three major steps involved with predictive modelling and mapping; (1) collect species level occurrence data and biophysical attributes of the landscape, (2) build the model to determine the best subset of predictors and their parameter coefficient and (3) application of the models to GIS data to predict probability of occurrence for un-sampled location (Yost et al., 2008, Corsi et al., 2000).

1.1. Research Problem

Available and published distribution maps in reference books and atlases have traditionally been compiled from records of localities where a species has been known to be present. A certain degree of interpolation, expert knowledge and guess is usually also involved in the compilation of these maps (Bustamante and Seoane, 2004). Predictive models provide an alternative way to build distribution, abundance and/or habitats suitability maps for a species (Guisan and Zimmermann, 2000). They are developed based on logic and knowledge that species are habitat selective (Cody, 1985) and there are correlations between environmental parameters and their distribution or abundance (Buckland and Elston, 1993). Atlases are costly to produce because they require much fieldwork and are not necessarily detailed enough for all applications. Logical and dynamic models could compensate for this by predicting the distribution as well as abundance of species using presence occurrences. It should be noted that detailed presence/absence occurrence data are available for some species; however, absence data are not available for most species (Phillips et al., 2006).

The European population of the Short-toed Eagle is approximately 8000 – 12,600 pairs (Gensbol, 2004). The densest population in western and southern Europe are on the Iberian Peninsula, in France, Croatia and Greece (Gensbol, 2004). Rocamora (1994) reported that the Iberian Peninsula has the largest breeding population in Europe, and perhaps in the whole Western Palaearctic. The breeding range has contracted considerably over the last hundred years (Rocamora, 1994, Birdlife-International, 2008). In the 19th century it ranged as far as north Germany, where the last breeding recorded was in 1877. Landscape changes and the fanatical campaign against birds of prey hit this species particularly hard, with the result that it died out completely in central Europe (Gensbol, 2004). The Short-toed Eagle uses mainly soaring flight during migration and avoids long water crossings by crossing at the Strait of Gibraltar (Agostini et al., 2002, Agostini and Mellone, 2008).

Some ornithologists believe that the main reason for the Short-toed Eagle population decline lies in the reduced availability of food. Reptiles do not thrive in intensely cultivated landscapes and they are very sensitive to pesticides and fertilisers used in farmlands. Resent research shows that the cumulative effect of Organochlorine residue in the liver of raptors which mainly feed on reptiles and amphibians were

quite high (van Drooge et al., 2008). Bakaloudis (1998) stated that "It is important to know how reptiles respond to land use activities to predict how any changes might affect the abundance and diversity of reptiles, which would have a knock-on effect on many groups of animals, including the Short-toed Eagle."
Bustamante and Seoane (2004) found that the statistical models yield better results than existing maps and atlases. They implemented generalised linear models of 10 x 10 km squares surveyed for the presence/absence of the species by road census. The results of the statistical models for the Short-toed Eagle were fairly accurate and predicted better than recordings of the atlas and the distribution maps. However, their customised model was still difficult to interpret from the point of view of the ecology of the species.

1.1.1. Short-toed Eagle

Circaetus gallicus (Gmelin, 1788) is a medium-sized bird of prey in the family Accipitridae and the order Falconiformes. The European population migrate mainly to sub-Saharan Africa north of the equator, leaving in September/October and returning in April/May. In Europe it is most numerous in Spain where it is fairly common but elsewhere it is rare in many parts of its range. In English this species is called Short-toed Eagle or some times Snake Eagle. Short-toed Eagle was classified as the LC[1] in the IUCN red list and Birdlife International (IUCN, 2009, Birdlife-International, 2008).

Short-toed Eagle founds in open cultivated plains, arid stony deciduous scrub areas and foothills and semi-desert areas. It requires trees for nesting and preys on reptiles, mainly snakes, but also some big lizards. The Short-toed Eagle is an accomplished flyer and spends more time on the wing than do most members of its genus. It favours soaring over hill slopes and hilltops on up draughts, and it does much of its hunting from this position at heights of up to 500 - 1000 meters (Birdlife-International, 2008).

Figure 1-1: Picture of Short-toed Eagle

[1] Least Concern

1.1.2. Selected Snake Species

There are three snake species that were studied in this research. Following the published papers it is assumed that these snake species are the only food for the Short-toed Eagle (Gil and Pleguezuelos, 2001, Moreno-Rueda and Pizarro, 2007).

– *Rhinechis scalaris* (Schinz, 1822)

It was identified taxonomically by *Elaphe scalaris* before. Common name in English is Ladder Snake because of ladder form of pattern. The ladder snake is one of the smaller European rat snakes. It can reach about 150 cm, but is normally 100-120 cm in length. The ladder snake inhabits many different habitats, prefers warm south turning and sunny places in the vicinity of escape possibilities in form of bushes or stonewalls. They love the heat and can be found hunting in the middle of the day even in midsummer. This species is listed as a Least Concern species in view of its wide distribution, tolerance of a broad range of habitats and presumed large population (IUCN, 2009).

– *Malpolon monspessulanus* (Hermann, 1804)

This snake is one of the back-fanged Colubrids. Owing to its prey preferences it inhabits in dry stony areas heavily populated by lizards, such as piles of stones on the edges of fields or near ruined buildings. When hunting it will occasionally rear up and look around, making it somewhat resemble the cobra. If it feels threatened it hisses loudly and attacks with the mouth closed. Unusually for a snake, this Colubrid possesses good vision. One of its distinguishing features is in fact the prominent ridge above its eyes, giving it a frowning appearance. Common English name for this species is Montpellier Snake (Lloyd, 2007). It is listed on Annex III of the Bern Convention on the Conservation of European Wildlife and Natural Habitats and it is present in many protected areas (IUCN, 2009).

– *Hemorrhois hippocrepis* (Linnaeus, 1758)

This classic Mediterranean species was also taxonomically named *Coluber hippocrepis* and its common name is Horseshoe Whip Snake. It takes its name from the horseshoe pattern along its body (Lloyd, 2007). This species occurs in a wide variety of arid, dry, rocky or sandy habitats. It may be found in scrubland, coastal plains, arable land, pastures, vineyards, almond and olive groves, rural gardens, villages and cities in and around buildings. This species is listed as Least Concern in view of its wide distribution, tolerance of a degree of habitat modification, presumed large population (IUCN, 2009).

1.2. Research Objectives

Despite the previous findings, there is however limited information on the relationship between environmental parameters and the occurrence of the raptors.

Since there is an impact of the loss of biodiversity on the environment, it is assumed that there should be a feed back relationship between the environment and loss of biodiversity, in this case, on the population of the Short-toed Eagle. This research therefore aims to develop a model of the probability of occurrence of the Short-toed Eagle in relation to environmental parameters and potential food availability.

1.2.1. General Objective

The general objective of this study is to investigate the relationship of habitat suitability of prey species and probability of occurrence of the Short-toed Eagle in Malaga province, southern Spain. Then depict the habitat suitability map of the Short-toed Eagle considering the potential available prey and other explanatory environmental variables in the study area.

1.2.2. Specific Objectives

- Generate a habitat suitability models for each of the prey snake species of the Short-toed Eagle based on the explanatory environmental variables.
- Depict a map of hunting preference area for the Short-toed Eagle based on the Corine land cover classes and hunting behaviour.
- Produce a potential available prey distribution map for the Short-toed Eagle based on the prey snake species distribution and hunting preference maps.
- Generate a habitat suitability model for the Short-toed Eagle based on the all environmental variables and potential food availability.
- Generate a habitat suitability model for the Short-toed Eagle based on the all environmental variables, except food.
- Measure the goodness of fit and compare the predictive ability of the both (all-inclusive and food excluded) distribution models.

1.3. Research Questions

Using the knowledge of the unique hunting behaviour of the Short-toed Eagle, does considering the potential available prey distribution, significantly increases the AUC, in the habitat distribution model of the Short-toed Eagle?

- Which subset of the explanatory environmental factors, significantly contributes to increase the predictive power of the each of the prey species probability of occurrence?
- Which land cover classes are preferred to be foraged by the Short-toed Eagle?

- Which subset of the explanatory environmental factors, significantly contributes to increase the predictive power of the Short-toed Eagle probability of occurrence?
- Whether considering potential prey availability map increases the predictive power of the probability of occurrence model of the Short-toed Eagle significantly?

1.4. Research Hypotheses

Hypothesis 1: Testing the concept that the selected subset of predictors, significantly contribute in a predictive multiple logistic regression model of the prey species?

> H0 = The selected subset of predictors do not significantly contribute in a predictive model of the prey species?

Hypothesis 2: Testing the concept that the Short-toed Eagle selects the foraging and hunting sites intentionally?

> H0 = Short-toed Eagle selects the foraging sites randomly.

Hypothesis 3: Testing the concept that the selected subset of predictors, significantly contribute in a predictive model of the Short-toed Eagle?

> H0 = The selected subset of predictors do not contribute significantly in a predictive model of the Short-toed Eagle?

Hypothesis 4: Testing the concept that considering the potential prey availability increased the predictive power of the Short-toed Eagle's distribution model?

> H0 = There is no significant difference in AUC between the model which does not take into account potential prey hotspots map, and the model which does take into account potential prey hotspots map.

1.5. Research Outputs

- Spatial distribution regression equation and correspondent distribution map for the Montpellier snake (*Malpolon monspessulanus*) in Spain.
- Spatial distribution regression equation and correspondent distribution map for the Ladder snake (*Rhinechis scalaris*) in Spain.
- Spatial distribution regression equation and correspondent distribution map for the Horseshoe Whip Snake (*Hemorrhois hippocrepis*) in Spain.
- Foraging preference map of the Short-toed Eagle in Malaga province.
- Distribution map of the potential available prey for the Short-toed Eagle in Malaga province
- Spatial distribution models and correspondent distribution maps for the Short-toed Eagle (*Circaetus gallicus*) considering potential available prey and explanatory environmental variables in Malaga province.

2. Materials and Methods

There were two different scales of modelling set in this research. (1) Broad scale modelling, to generate the habitat suitability models and maps of three prey snake species of the Short-toed Eagle, based on the available species presence/absence data and explanatory environmental predictors. (2) Local scale modelling, to generate the habitat suitability models of the Short-toed Eagle, based on the collected nest locations, explanatory environmental predictor and the downscaled prey species habitats. Figure 2.1 illustrates the general approach of this study.

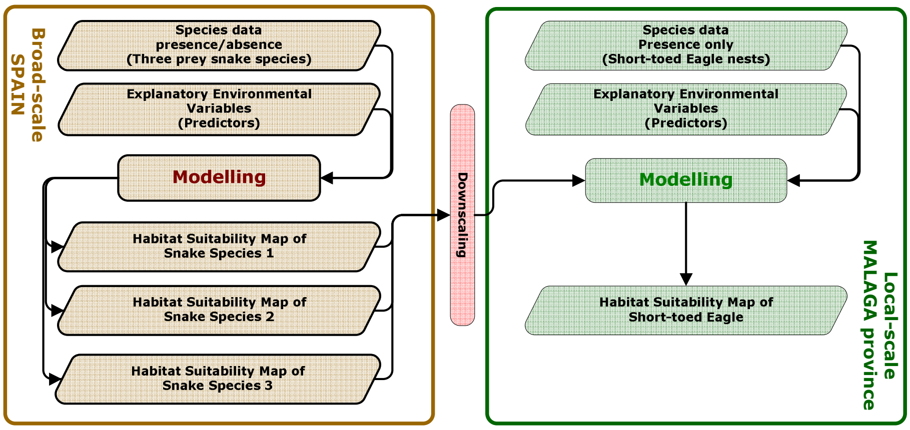

Figure 2-1: General Approach of the Study

This chapter describes the materials and methods of the research and these are presented as follows;

- Research workflow and steps
- Study area
- Species distribution data
- Predictor variables and ancillary data
- Statistical analysis and spatial modelling
- Assumptions and sources of errors
- Employed Software and Instruments

2.1. Reseach workflow

There were 13 steps accomplished to approach the research objectives and to answer the research questions. (1) Data preparations and point value extraction for three snake species from Spain geo-database, (2) multicollinearity diagnoses, (3) performing multiple logistic regressions and environmental favourability function (Real et al., 2008) based on the species presence/absence and explanatory environmental predictors, (4) downscaling the model and generating habitat suitability maps of three prey species in the local scale, (5) validating the local-scale habitat suitability of three snake species by the field collected data, (6) defining the favourable hunting land covers, (7) generating the potential available prey map base on the results of the 4th and 6th steps, (8) Data preparations and point value extraction for the Short-toed Eagle nests from Malaga province geo-database, (9) multicollinearity diagnoses, (10) distribution modelling by Maxent® (Phillips et al., 2006) based on the nest locations and explanatory environmental predictors, (11) distribution modelling by Maxent® based on the nest locations and potential food availability resulted in the 7th step, (12) validating the local-scale habitat suitability models resulted in the 10th and 11th steps and (13) comparison the predictive ability and measure the goodness of fit of models. (figure 2-2.)

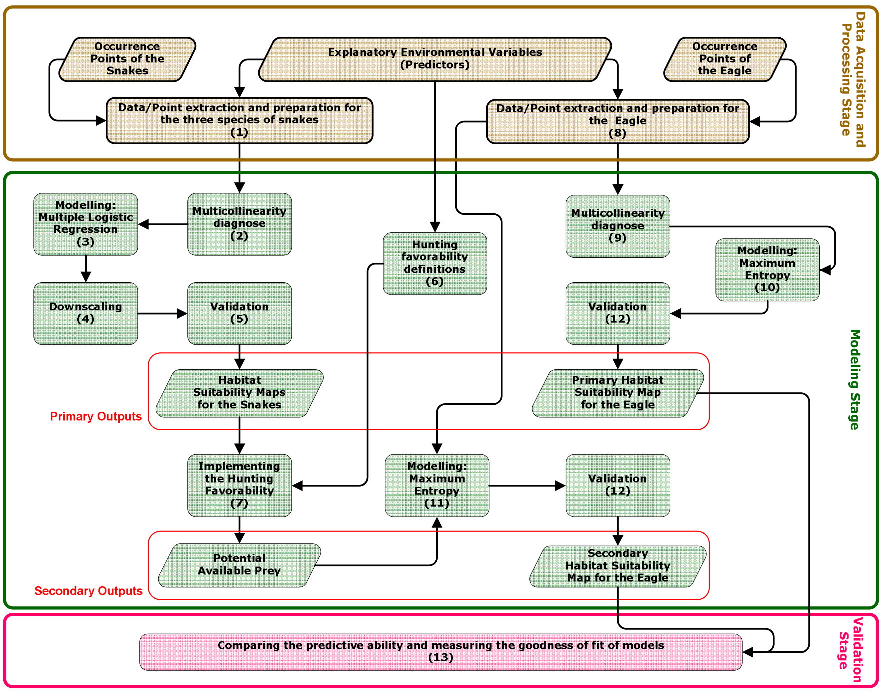

Figure 2-2: Research workflow and steps

2.2. Study Area

There were two different study areas set for this research as well as two different spatial scales; (1) Malaga Province as the study area of the Short-toed Eagle to compare the models and test the main hypothesis and (2) Spain as a study area to model habitat suitably of three prey snake species.

The Malaga province is located on the southern coast of Spain in the autonomous community of Andalusia. It is bordered by the Mediterranean Sea to the South, and by the provinces of Cadiz, Seville, Cordoba and Granada. The Malaga province is extended from 3˚45´50˝W about 165 kilometres to 5˚36´40˝W and from 36˚18´42˝N about 100 kilometres to 37˚17´5˝N. Its area is 7308 square kilometres. Figure 2-1 shows the geographical location of the study area. The prevailing climate of Malaga province is a warm Mediterranean with dry and warm long summers with short mild winters. Annual average temperature varies between 13 degree Celsius and 19 degree Celsius. Precipitation varies greatly form 400 millimetres in northern plains to 1700 millimetres in western forests, generally in form of rain (Font, 2000). Wind regimes and other meteorological phenomena in Malaga province are analogous to the strait of Gibraltar and Mediterranean Sea. The geographical relief varies greatly from sea level to almost 2000 meter above (USGS, 2003). Sclerophyllous vegetations and non-irrigated arable lands cover one third of study area. Olive groves are widespread in Malaga province followed by other principally occupied land by agriculture (EEA, 2000).

Spain lies in the Iberian Peninsula and occupies a considerable part of the Mediterranean basin. It borders to the North on the Bay of Biscay, France and Andorra; to the East, on the Mediterranean; to the South, on the Mediterranean and the Atlantic, and to the West on the Atlantic and Portugal. Spain is characterised by mild wet winters and by warm to hot/dry summers. It is situated in a temperate area, between latitudes 43 47' 24"N. and 36 00' '3" S. and between longitudes 7 00' 29" E. and 5 36' 40" W (Bario, 2006). With only 26% of the land arable, olive growing features is the main agricultural output of the region followed by other perennial crops such as citrus, almond and more recently, vines. Since Spain’s incorporation in the European Union, agriculture has been boosted by subsidies, with citrus and olive production being promoted. (ITC_report, 2002) Figure 2-3 shows the geographical location of the study area.

Malaga province has a well studied breeding population of the Short-toed Eagle in Andalusia, Southern Spain, compared to other provinces. Apart from that, inter-institutional interests between ITC and Malaga University facilitated the study of these areas.

Figure 2-3: Study Area – Spain (top) and the Malaga Province (bottom)

2.3. Species Distribution Data

Species data were collected in two different scales; broad national scale based on the available atlases and referenced and local province scale based on the fieldwork and sampling. This section describes the specification of the Short-toed Eagle breeding locations and the prey snake species presence/absence data.

2.3.1. Short-toed Eagle Species Occurrence Data

To obtain the Short-toed Eagle's nests location, the intensive field visits was conducted from 12th September to 15th October 2008 in Malaga province. Nongovernmental organisations and local ornithologists were asked to help and participate by pointing the nests location and drawing the territories at the given orthophoto images. Ornithologists of *SEO de Mijas/Ekologista* and *SEO de Ronda* indicated monitoring nests on the maps, as well as unsure nest-locations. After the field visit and positioning the nest, all the positions (n=32) were confirmed by the research field advisor *Dr. Antonio Román Munoz Gallego*[2] finally. Geographical positions of the raptor nests were requested not to be published. They are archived on the ITC intranet, under the *BioFrag-ITC*[3] project data security rules. Figure 2-4 shows the distribution of the collected Short-toed Eagle nests in the Malaga province. These presence-only data were used to generate the distribution models in Malaga province.

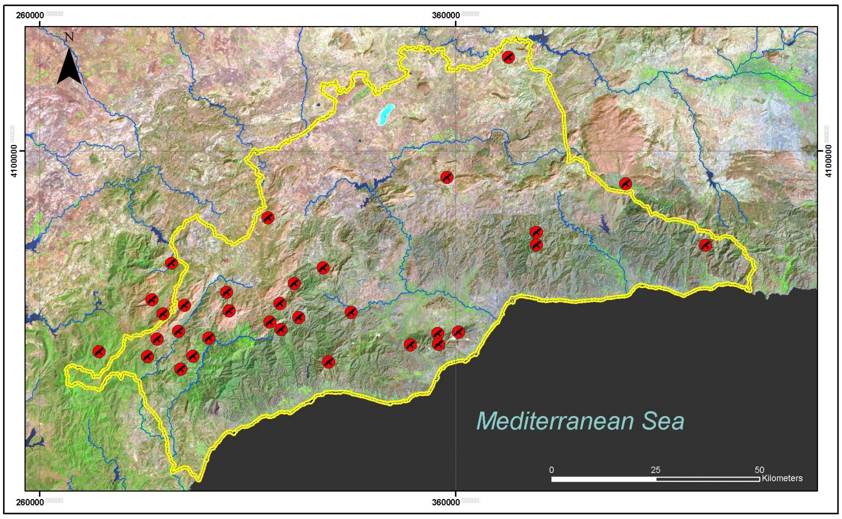

Figure 2-4: Distribution of the collected Short-toed Eagle nests in Malaga province

Long–term absence/presence data of the Short-toed Eagle was downloaded from the *Atlas of the breeding birds of Spain* (Marti and Del Moral, 2003) in Portable Document Format (PDF) format, were digitized and entered into the Spain geo-

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[2] http://www.fundacionmigres.org/

[3] http://www.itc.nl/research/themes/biofrag/default.asp

database. Data for this collective work has been gathered by volunteers with field work in the period 1998–2001 and can be considered as a reliable source of distribution information completely independent from published maps. The presence/absence 10 x 10 kilometres UTM squares (n=4930) were converted randomly to the presence/absence points. The Short-toed Eagle breeds in 2638 peninsular Spanish grid cells. These presence/absence data were employed to assess the validation of the final model resulted in local-scale (Malaga) on broad-scale (Spain).

2.3.2. Snake Species Occurrence Data

Long–term absence/presence data of the three snake species was downloaded from the *Red list of Amphibians and Reptiles of Spain* (Pleguezuelos, 2003) and entered in the Geo-database. Same as the Atlas of breeding birds of Spain, this atlas is based on the data that has been gathered in the period 1998–2001. The presence/absence 10×10 kilometres UTM squares (n=4930) were converted randomly to the presence/absence points. *Malpolon monspessulanus* is present in 2481, *Rhinechis scalaris* is present in 2272 and *Hemorrhois hippocrepis* is present in 992 out of 4930 peninsular Spanish grid cells. Based on these data presence/absence data, distribution models and maps of the mentioned snake species were generated.

To validate the national broad-scale models on local scale modelling, snake species presence points were collected during field work. Random sampling rules were set to cover Malaga province. Weather conditions for instance rain, wind and low temperatures, forced to "drive more" strategy to collect road killed snakes, as well as time limitation. Beside the spatial resolution of the studies (1km) and vast study area all the asphalt roads were covered in Malaga province. Each snake has recorded with a brief description of the land cover, time and weather condition as well as species, gender and age. Totally 124 sampling points were select. *Hemorrhois hippocrepis, Rhinechis scalaris* and *Malpolon monspessulanus* were found in 18, 13 and 23 sampling stations respectively. Figure 2-5 shows the distribution of the sampling points in Malaga province

2.4. Predictor Variables and Ancilliary Data

Four groups of explanatory environmental variables (predictors) were managed into the structure of personal geo-database for Spain in national scale, so did for Malaga province in large scale. Climatological variables, Topographic variables, Biological variables and anthropogenic variables were organised in the same extend and resolution. All the layers in the scale of Spain were defined in *GCS WGS 84* projections. The layers in the scale of Malaga were defined in *ED50 UTM 30N* projection. All the predictor maps were converted to ASCII format to communicate with other software.

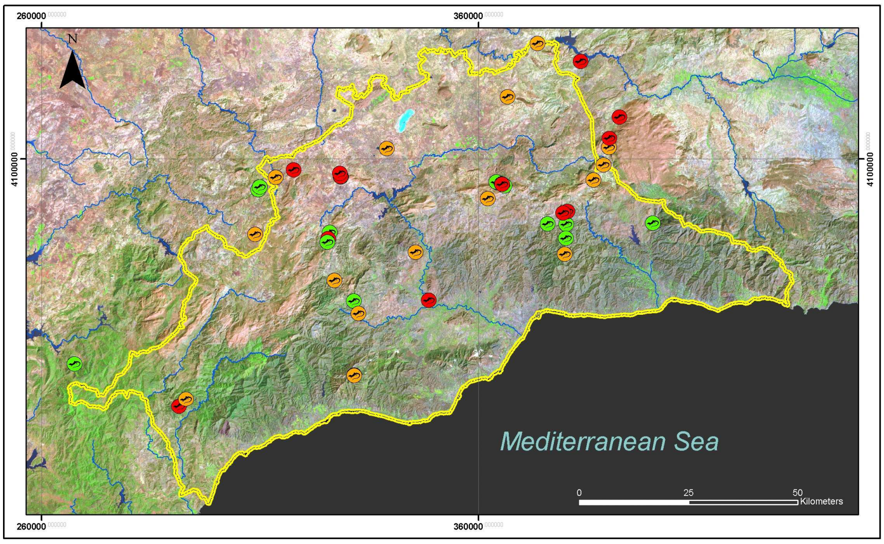


Figure 2-5: Distribution of the sampling points for prey snake species in Malaga province. *Hemorrhois hippocrepis, Rhinechis scalaris* and *Malpolon monspessulanus* are shown by orange, red and light green circles respectively.

2.4.1. Climatological Variables

Climatological variables were downloaded directly from WorldClim (Wordclim, 2008) online datasets. WorldClim is a set of global climate layers (climate grids) with a spatial resolution of a square kilometre. They can be used for ecological mapping and spatial environmental modelling. Temporal resolution of the WorldClim variables is monthly average from 1950 to 2000. (Hijmans et al., 2005) Variables included are monthly total precipitation, and monthly mean, minimum and maximum temperature, and 19 derived bioclimatic variables. Bioclimatic variables are derived from the monthly temperature and rainfall values in order to generate more biologically meaningful variables. The bioclimatic variables represent annual trends, seasonality and extreme or limiting environmental factors (Beaumont et al., 2005). There are 67 predictors listed in the climatological group of variables. Appendix I shows the table of predictor variables and their specifications.

2.4.2. Topographic Variables

Topographic variables were derived from the SRTM (USGS, 2003) data which is available online. The Shuttle Radar Topography Mission (SRTM) obtained elevation data on a near-global scale to generate the most complete high-resolution digital topographic database of Earth. SRTM consisted of a specially modified radar system that flew onboard the Space Shuttle Endeavour during an 11-day mission in February of 2000. (Rodriguez and Daffer, 2005) Slope and aspect of slope were calculated using the spatial analyst toolbox of ArcMap. The aspect degree was converted to "*Southness*" value in which instead of pixel value from -1 to 360 degree (N to N!), they were converted to 1 to 180 scale measures (N to S). The highest the value was the more south direction slope facing at. Also approximate distance to main rivers and approximate distance to the Mediterranean Sea (coastline) was calculated as additional the raster layer to this group of variables. There are 5 predictors listed in the topographic group of variables. Appendix I shows the table of predictor variables and their specifications.

2.4.3. Biological Variables

Biological variables in this research are limited to average scaled NDVI per every 10 days obtained and analysed from the *Vegetation Program (Vegetation-Programme, 2008)*. The Vegetation Programme is conceived to allow daily monitoring of terrestrial vegetation cover through remote sensing, at regional to global scales. The instrument and associated ground services for data archival, processing and distribution are operational since April 1998. The first *vegetation* instrument was part of the SPOT 4 satellite and a second payload, *vegetation 2*, is now operationally operated onboard SPOT 5. There are 36 predictors listed in the biological group of variables. Appendix I shows the table of predictor variables and their specifications.

2.4.4. Anthropogenic Variables and Land Cover

The *Corine* land cover map, (EEA, 2000) has been classified into 2 classes of suitability based on expert knowledge to form one of the important predictor variables. Finally, approximate distance to highways, approximate distance to railroad, and approximate distance to urban and industrial areas were derived from 1:1000000 national topographic maps and categorized as anthropogenic variables. There are 4 predictor variables listed in the anthropogenic group of variables. Appendix I shows the table of predictor variables and their specifications

2.4.5. Ancillary data

Quikbird (DigitalGlobe, 2004) orthophoto images were employed to facilitate the public participatory during fieldwork. NGOs and local ornithologist were asked to draw territories and location of the Short-toed Eagle nest on the hardcopies during field work and site visits. At the end all the nests points were visited by person and the accurate GPS positions were recorded. The territories were also digitized and saved on geo-database.

2.5. Statistical analysis and spatial modelling

Briefly, to select a subset of significant predictors and to avoid multicollinearity effects of correlated predictors, *Variance Inflation Factors (VIF)* was calculated and the collinear predictors were eliminated one by one in each of the iteration for dataset; (1) broad-scale Spain and (2) local-scale Malaga province explanatory environmental variables. Then a *Multiple Logistic Regression* of presence/absence three snake species data was preformed on the subset of the resulting significant broad-scale predictor variables, using backward stepwise procedures to obtain models, where all predictors are significant. Meanwhile a probability of occurrence of the Short-toed Eagle nesting sites has been computed by *Maximum Entropy* method based on the presence-only data in Malaga province and independent variables. This section describes the statistical methods that have been performed in this research.

2.5.1. Multicollinearity Diagnoses

A high degree of multicollinearity among the predictors results the disproportionately large standard deviation of the regression coefficients which leads to Type II error in term of accepting the hypothesis that the coefficients are zero even when the associated variable is important in explaining variation in y (ITC_handouts, 2008). Sets of environmental variables often exhibit varying amounts of linear dependencies which results in a form of ill-conditioning in the correlation matrix. Subsequently, the usual least squares analysis of a regression model can dramatically become inadequate (Owen, 1988). Since linear dependencies may not be restricted to only two predictors analysis of pair wise correlations between variables may not be sufficient. Variance Inflation Factor (VIF) is a common indicator used to detect multicollinearity (Montgomery, 1982) and is calculated by the following mathematical expression;

$$VIF = \frac{1}{1 - R^2_i} \qquad (2\text{-}1)$$

Myers (1990) suggests that values above 10 are aversion for concern (Bowerman and O'Connell, 1990, Myers, 1990).

2.5.2. Multiple Logistic Regression

Logistic regression is a model used for the prediction of the probability of occurrence of an event by fitting data to a logistic curve. It is a generalized linear model used for binomial regression. It makes use of several predictor variables that may be either numerical or categorical (Agresti, 2002). For example, the probability of absence or presence of a species might be predicted from knowledge of its habitat and ecological behavior. In logistic regression, instead of prediction the value of a variable *Y* from a predictor variable X_1 or several predictor variables X_n in multiple linear regression, the probability of *Y* occurring is predicted by given known values of X_1 or X_n.

$$P(y) = \frac{1}{1+e^{-y}} \qquad (2\text{-}2)$$

P(Y) is the probability of *Y* occurring, *e* is the base of natural logarithms. The *P(y)* can take as an input any value from negative infinity to positive infinity, whereas the output is confined to values between 0 and 1. The variable *y* represents the exposure to some set of predictor – here are explanatory environmental variables- , while *P(y)* represents the probability of a particular outcome – here is occurrence of species- , given that set of predictors. The variable *y* is a measure of the total contribution of all the predictors used in the model and is defined as:

$$y = \beta_0 + \beta_1 x_1 + \beta_1 x_2 + ... + \beta_k x_k \qquad (2\text{-}3)$$

β_0 is called the *constant* and β_1, β_2, β_3, and so on, are called the *regression coefficients* of x_1, x_2, x_3 respectively.

To assess whether a model fits the data, comparison of the observed and predicted values are used. The log-likelihood (ℓ) is used as a measure. The log-likelihood is therefore based on summing the probabilities associated with the predicted and actual outcomes. The large values of the log-likelihood statistics indicate poorly fitting statistical models (Field, 2006). By adding one or more predictors to the model, the improvement of the model can be computed. Note that multiplying this value by 2 gives the result a chi-square (χ^2) distribution and so makes it easy to calculate/estimate the significance of the value (Moore, 1998).

The *R*-statistic is the partial correlation between the outcome variable and each of the predictor variables and it can vary between -1 and 1. A positive value indicates that as the predictor variable increases so does the likelihood of the even occurring and vice versa. If a variable has a small value of *R* then it contributes only a small amount to the model (Field, 2006).

Like *t*-test in linear regression the Wald statistics explains whether the *β*-coefficient for that predictor is significantly different from zero. Then we can assume that the predictor is making a significant contribution to the prediction of the outcome (*Y*). The Wald statistics should be used cautiously when the regression coefficient (*β*) is large and so inflated the standard error. The inflation of the standard error increase the probability of rejecting a predicator as being significant when in reality it is making a significant contribution to the model (Type II error) (Field, 2006). Multiple logistic regression of presence/absence species distribution (section 2-3-2) has been performed on the subset of resulting significant predictors using backward stepwise procedure to obtain models where all variables added significant predictive power.

2.5.3. Environmental Favourability Functions

The number of presences and absences in the study area was not equal, so the probability values from multiple logistic regressions potentially were biased to the group with the greatest number. To overcome this issue, environmental favourability function performed (Real et al., 2006). Castro et al. (2008) described that this function assesses the local variation in presence probability with respect to the overall species prevalence, and that therefore yields geographical favourability values for the species independently of the proportion of the initial presence/absence rate in the study area (Castro et al., 2008).

Environmental favourability could obtain directly from the multiple logistic regression probability values using the following formula

$$F = \left(\frac{P(y)}{1-P(y)}\right) / \left(\frac{n_p}{n_a} + \frac{P(y)}{1-P(y)}\right) \qquad (2\text{-}4)$$

n_p is number of presences, n_a is number of absences and $P(y)$ is the probability of occurrence form the equation 2-3.

2.5.4. Model Building with Maxent®

The estimated Maxent probability distribution is exponential in a weighted sum of environmental features divided by a scaling constant to ensure that the probability values range from 0 to 1 and sum to 1 (Yost et al., 2008). The Maxent probability distribution takes the form

$$q_\lambda(x) = \frac{e^{\lambda . f(x)}}{Z_\lambda} \qquad (2.5)$$

λ is a vector of n real-valued coefficients or feature weights, f denotes the vector of all n features, and z_λ is a normalizing constant that ensures that q_λ sums to 1. Maxent is a maximum-likelihood method that generates the probability distribution over the pixels in a grid of the modelling area. The program starts with a uniform distribution, and performs a number of iterations, each of which increases the probability of the sample locations for the species. The probability is displayed in terms of "gain", which is the log of the number of grid cells minus the log loss (average of the negative log probabilities of the sample locations). The gain starts at zero (the gain of the uniform distribution) and increases as the program increases the probabilities of the sample locations. Phillips et al (2006) explained that the gain increases iteration by iteration, until the change from one iteration to the next falls below the convergence threshold, or until maximum iterations have been performed. The gain is a measure of the likelihood of the samples. For example, if the gain is 0.8, it means that the average sample likelihood is $exp(0.8)\approx 2.22$ times higher than that of a random background pixel. The uniform distribution has gain 0, so the gain can be interpreted as representing how much better the distribution fits the sample points than the uniform distribution does. The gain is closely related to "deviance", as used in generalized linear models. The sequential-update algorithm is guaranteed to converge to the optimum probability distribution and because the algorithm does not use randomness, the outputs are deterministic (Phillips et al., 2006).

To control over-fitting, Maxent constrains the estimated distribution so that the average value for a given predictor is close to the empirical average (within empirical error bounds) rather than equal to it. This smoothing procedure is called regularization and users can alter the parameters to potentially compensate for small sample sizes. The Maxent distribution is calculated over the set of pixels representing the study area that have data for all environmental variables. However, if the number of pixels is very large, processing time increases without a significant improvement in modelling performance. For that reason, when the number of pixels with data is larger than 10,000 (e.g. this research) a random sample of 10,000 "background" pixels is used to represent the variety of environmental conditions present in the data. The Maxent distribution is then computed over the union of the "background" pixels and the samples for the species being modelled. Maxent's predictions for each analysis cell are represented as cumulative values representing a percentage of the probability value for the current analysis cell and all other cells with equal or lower probability (Yost et al., 2008). The cell with a value of 100 is the most suitable, while cells close to 0 are the least suitable within the study area. The formulaic description of the Maxent modelling procedure applied to species occurrence data and a description of the Maxent program (version 3.2.1) used to perform the modelling in this study is given by Phillips et al. (2006).

As far as the presence-only distribution data for the Short-toed Eagle nests were available in Malaga province (section 2-3-1), Maxent methods were employed to perform analysis on the subset of resulting significant predictors. This analysis was accomplished by identifying which variables were most important in predicting that habitat. Maxent's Jackknife test of variable importance can be used to evaluate the relative strengths of each predictor variable (Yost et al., 2008). The training gain is calculated for each variable alone as well as the drop in training gain when the

variable is omitted from the full model (Phillips et al., 2006). Therefore, the modelling process started with a full model that contained all predictor variables (n=8). Then, the variable with the lowest decrease in the average training gain when omitted was removed and the remaining variables were used to build the model.
Functions were selected to automatic perform as it was recommended in user help. Model settings that train the algorithm to get close to convergence are the maximum number of iterations, set to 1000, the convergence threshold, set to 10^{-5} and the regularization multiplier was set to the value of 0.5 following Yost et al (2008). The full set of presence points (n=32) were used to build the final model to obtain the best estimate of the species distribution and for creating a GIS probability distribution map.

2.5.5. Model Evaluation

Two statistical measures were employed to compare individual species predictions with 'ground truth': (1) Kappa statistics (Cohen, 1960) by detecting the optimal threshold for cutting the probabilistic predictions into presence-absence on the calibration dataset and using this optimal threshold for calculating Kappa on the evaluation dataset (Guisan, 2000) and (2) the threshold-independent Receiver Operating Characteristic (ROC) approach, by calculating the area under the ROC curve (AUC) as the measure of the prediction success.
Cohen's *κ* provides a measure of the proportion of all possible cases of presence or absence that are correctly predicted after accounting for chance effects. It is thus considered as a simple, effective, standardised and appropriate statistic for evaluating or comparing presence-absence models (Manel et al., 2001). The equation for *κ* is:

$$\kappa = \frac{\Pr_a - \Pr_e}{1 - \Pr_e} \tag{2-6}$$

$\Pr_a$ is the relative observed agreement among raters (observed and ground truth), and $\Pr_e$ is the hypothetical probability of chance agreement, using the observed data to calculate the probabilities of each observer randomly saying each category. If the raters are in complete agreement then κ = 1 and if there is no agreement among the raters then κ ≤ 0.
The receiver operating characteristic (ROC) analysis was employed to evaluate how well the model performances compared to random predictions. The area under the ROC (AUC) is an index of performance because it provides a single measure of overall accuracy that is independent of any particular threshold (Deleo, 1993). The ROC curve is therefore a graphical representation of the trade-off between the false

negative and false positive rates for every possible probability cut-off (Zarri et al., 2008). The ROC plot was generated using SPSS® and the AUC and its standard error were calculated. The results are reported as AUC ± its standard error along with the significance of a test that the area = 0.5, i.e. that the model result does not differ from chance.

"However, When ROC analysis is used on presence-only data, the maximum AUC is less than one (Wiley et al., 2003), and is smaller for generalist (wider ranging) species. The maximum achievable AUC can be shown to be equal to *1- a/2,* where *a* is the fraction of pixels covered by the species' distribution." (Yost et al., 2008)

Model performances evaluated by keeping out a subset of the presence points for training and use the remaining records to test the resulting model. Performance can vary depending upon the particular set of data withheld from building the model for testing, therefore, 10 random partitions of the presence records were made to assess the average behaviour of Maxent, following Phillips et al. (2006). Each partition was created by randomly selecting 85% of the total presence points (n=27) and 1000 random background points selected as negative instances (pseudo-absence) as training data. The remaining 15% of presence points (n=5) were used for testing the model.

The Maxent models were also evaluated with the binomial test to determine whether a model predicted the test localities significantly better than random (Phillips and Dudik, 2008). The binomial test requires that thresholds be used in order to convert continuous predictions into suitable and unsuitable areas for the Short-toed Eagle. After applying a threshold, model performance can be investigated using the extrinsic omission rate, which is the fraction of test localities that fall into pixels that are predicted as not suitable for the Short-toed Eagle, and the proportional predicted area, which is the fraction of all the pixels that are predicted as suitable. The p-values associated with a cumulative threshold of one, five and ten are reported to show trend as the threshold varied.

Finally the success of the model was evaluated by visual inspection as well. A good model should produce regions of high probability that cover the majority of presence records and areas of low probability should contain few to no presence points.

2.5.6. Model Comparison

The Akaike information criterion (AIC) and the Schwartz information criterion (SIC) are two objective measures of a model's suitability and goodness of fit (Koehler and Murphree, 1988). "They are grounded in the concept of entropy, in effect offering a relative measure of the information lost when a given model is used to describe reality and can be said to describe the trade-off between bias and variance in model construction" (Burnham, 1998). The AIC and SIC are not just tests on the model in the sense of hypothesis testing, rather they are tools to select the proper models. Given a data set, several competing models may be ranked according to their AIC or SIC, with the one having the lowest value being the best (Burnham, 1998).

$$AIC = \log\left(\frac{SSE}{n}\right) + \frac{2K}{n} = \frac{-2\ell}{n} + \frac{2K}{n} \tag{2-7}$$

$$SIC = \log\left(\frac{SSE}{n}\right) + \log\frac{n \times K}{n} = \frac{-2\ell}{n} + \frac{K \times \log n}{n} \tag{2-8}$$

In which K is the number of estimated coefficients, n is the number of observations, SSE stands for error sum of squares and ℓ is the log-likelihood of the models. Koehler and Murphree (1988) discussed that it is preferable to apply the SIC test which leads to lower order models for prediction (Koehler and Murphree, 1988).

2.6. Assumptions and source of errors

It is assumed that the three selected snake species are the only source of food for the Short-toed Eagle and they are fully active during breeding session in Malaga province. Also breeding site and hunting sites of the Short-toed Eagle were considered the same habitat. Territorial behaviours of the Short-toed Eagle are not taken into the account. Operational source of errors goes to the field work, using GPS and digitizing steps. Accuracy of predictors and even the species distribution atlases which are available on the corresponding websites should be take into the account. Biases have already discussed in above methods sections and more in discussion chapter. So some spurious significance is likely, but the results seem reasonable and consistent with theory and field observations.

2.7. Employed Software and Field Instruments

The following technical software applications were employed in this research under the ITC authorized licences, as well as the general office utilities on Window XP® platform; SPSS® version 15.0, ESRI® ArcMap® ArcInfo® 9.3, ESRI® ArcPad® 8.0 and MaxEnt® 3.2.1 [4].

HP iPAQ PDA Classic Handheld and 12 parallel channels Bluetooth GPS receiver recorded the field data position with 15 meters accuracy in 2 dimensions (x,y).

[4] Maximum entropy modelling of species geographic distributions

3. Results

This chapter describes the main findings of the research and discuses them briefly. These are presented as 3 sections:

- Environmental favourability of the snake species
- Potential food availability
- Habitat suitability modelling of the Short-toed Eagle

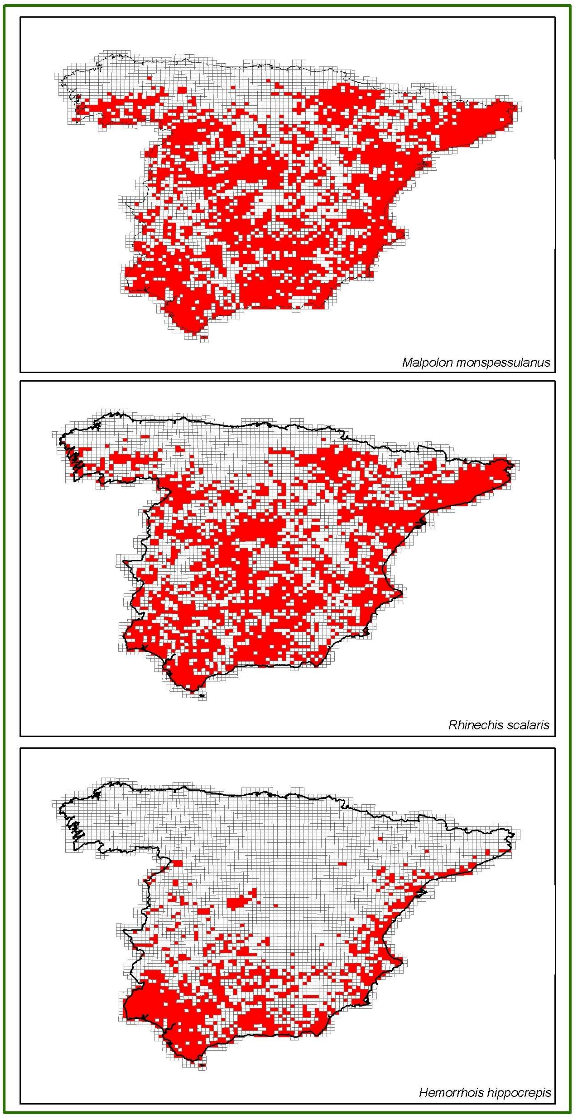
3.1. Environmental Favourability of the Snake Species

As explained in the first chapter the Short-toed Eagle proved to be a specialist feeder in southern Spain, as snake prey comprised almost 95% of the diet, of which most of them belong to only three species *Malpolon monspessulanus, Rhinechis scalaris* and *Hemorrhois hippocrepis* (Gil and Pleguezuelos, 2001, Vlachos and Papageorgiou, 1994). This section explains the outcome of the data processing to obtain the predictive spatial distribution models and environmental favourability maps for each of the three prey snake species in Spain. The following abbreviations were used to make the addressing to the species more simple; *Smn* for *Malpolon monspessulanus, Srs* for *Rhinechis scalaris* and *Shh* for *Hemorrhois hippocrepis.*

The three snake species presence/absence data for the Spanish 10 km UTM grids ($n_{total} = 4930$) were obtained from the *Atlas of the Red List Reptiles and Amphibians of Spain* (Pleguezuelos, 2003). Table 3-1 shows the number of UTM grids with recorded snake species presence or absence and also the percentage of cells which contained the species. The snake occupancy for *Smm* and *Srs* were 50.2% and 46.1% respectively. This means that they are present in almost half of the Spanish 10km UTM grid cells.

Table 3-1: Number of Absences/Presences of Snake Species in Spain UTM grids (*n=4930*)

	Malpolon monspessulanus (Smm)	*Rhinechis scalaris (Srs)*	*Hemorrhois hippocrepis (Shh)*
Number of Cells tagged as “Presence”	2481	2272	992
Number of Cells tagged as “Absence”	2449	2658	3938
Snake occupancy %	50.3	46.1	20.1



The distribution maps of presence UTM grid (figure 3-1) illustrate that they are distributed in a wide range. The *Shh* species mainly concentrates its niche to southern areas. By visual interpretation it is clear that the distribution of snake species significantly decreases in the north-west of Spain, mainly the coastal zone of Atlantic Ocean and the Bay of Biscay. Figure 3.1 shows the distribution of snake species in Spain.

Compiling the distribution maps with some climatic layer shows that these species are widely thrive climatologically as well as spatial distribution. (Table 3-2)

Figure 3-1: Spatial distribution of the three snake species in Spain. *Malpolon monspessulanus (top), Rhinechis scalaris (middle), and Hemorrhois hippocrepis (bottom).* The red grids represent observed occurrence/presences (Pleguezuelos, 2003).

3.1.1. Independent Predictor Variable for the Snake Species

Multicollinearity diagnoses were performed on the explanatory environmental variables dataset of whole Spain for each snakes based on presences/absences, as described in section 2-2-1. From the resulting VIFs (equation 2-1), it was concluded that the existence of multicollinearity was not significantly high since none exceeded 10 as the rule of thumb. (Montgomery and Peck, 1982) and hence all the variables could be used in subsequent analysis. Appendix II shows the significantly independent sets of predictors and the corresponding VIF values after multicollinearity diagnoses for each snake species in Spain.

Table 3-2: Brief summary of environmental variables of the observed snake species

		Minimum temperature of the wettest quarter (°C)	Maximum temperature of warmest month (°C)	Annual mean temperature (°C)	Precipitation of driest quarter (mm)	Precipitation of warmest quarter (mm)	Precipitation of coldest quarter (mm)
Malpolon monsepessulanus	Mean	3	29	13	67	76	166
	Minimum	0	13	7	10	15	64
	Maximum	87	36	18	311	311	646
Rhinechis scalaris	Mean	3	30	14	65	73	165
	Minimum	0	18	50	12	17	65
	Maximum	86	36	18	259	274	645
Hemorrhois hippocrepis	Mean	4	31	16	38	45	182
	Minimum	0	22	52	10	15	65
	Maximum	85	36	18	180	216	404

3.1.2. Statistical Analysis and Spatial Modelling

Multiple logistic regressions of presence/absence data using backward stepwise procedure were performed on the subset of the resulting significant predictor variable (table 3-3) to obtain models where all variables added significant predictive power. The parameters in the logistic regression equation were estimated by maximum likelihood and tested by the test of Wald (section 2-2-1).

To establish differences between favourable and unfavourable pixels, the favourability values were assigned into three classes. Thus, pixels with predicted favourability values higher than 0.8 were considered as favourable areas for the species, while those with values lower than 0.2 were considered as unfavourable (Munoz et al., 2005, Corsi et al., 2004). Remaining squares were assessed as intermediate favourability areas (Real et al., 2005).

3.1.2.1. *Malpolon monspessulanus*

Statistical procedure resulted in a final model for *Smn* (*Malpolon monspessulanus*) species in the 16th backward Wald step as below. Table 3-3 shows the summary results of the logistic regression analysis carried out on GIS data layers for *Smn* species. Figure 3.2 illustrates the environmental favourability of *Smn* Species in Spain.

Y_{Smn} *~ Constant + B1 × (NDVI mid March) + B2 × (Precipitation in March) +B3 × (Precipitation in October) + B4 × (Maximum temperature in February) + B5 × (Mean temperature in January) + B6 × (Mean temperature in December) + B7 × (Mean temperature in May) + B8 × (Minimum temperature in March) + B9 × (Minimum temperature in February) + B10 × (Precipitation Seasonality) + B11 × (Annual mean temperature) + B12 × (Annual precipitation) + B13 × (Isothermality) + B14 × (Elevation) + B15 × (Slope)*

Then:

$P(Y_{Smn}) \sim logit\ (Y_{Smn}) = log\ (1/(1+exp(-Y_{Smn})))$

And:

$F_{Smm} \sim P(Y_{Smn})^a$

[a] *Number of presences and absences are equal.*

Table 3-3: Summary results of the logistic regression analysis for *Malpolon monspessulanus*

Variables		*B*	SE (*B*)	Wald	*P*
Constant		-7.93621	1.672	22.524	
NDVI mid March	*B1*	0.00301	0.001	8.094	0.004
Precipitation in March (mm)	*B2*	-0.02065	0.003	48.558	0.000
Precipitation in October (mm)	*B3*	0.02016	0.004	27.753	0.000
Maximum temperature in February (°C × 10)	*B4*	-0.00002	0.000	4.361	0.037
Mean temperature in January (°C × 10)	*B5*	-0.00002	0.000	7.900	0.005
Mean temperature in December (°C × 10)	*B6*	0.00002	0.000	6.133	0.013
Mean temperature in May (°C × 10)	*B7*	0.16461	0.014	137.362	0.000
Minimum temperature in March (°C × 10)	*B8*	-0.00001	0.000	8.269	0.004
Minimum temperature in February (°C × 10)	*B9*	-0.00001	0.000	13.708	0.000
Precipitation Seasonality	*B10*	0.02273	0.006	15.732	0.000
Annual mean temperature (°C)	*B11*	-0.09784	0.011	81.304	0.000
Annual precipitation (mm)	*B12*	-0.03692	0.005	45.243	0.000
Isothermality	*B13*	-0.10116	0.029	12.178	0.000
Elevation (m)	*B14*	0.00477	0.000	134.588	0.000
Slope (%)	*B15*	0.02907	0.007	16.571	0.000

The AUC (*=0.717*) and its standard error (*=0.007 confident level 95%*) for the performed model were calculated using non-parametric approaches. Cohen's Kappa was 0.457 (*cut value= 0.5*) which showed slight agreement. Overall accuracy was 72.0%, expected accuracy was 49.0% so the model performed 23.0% better than a random model.

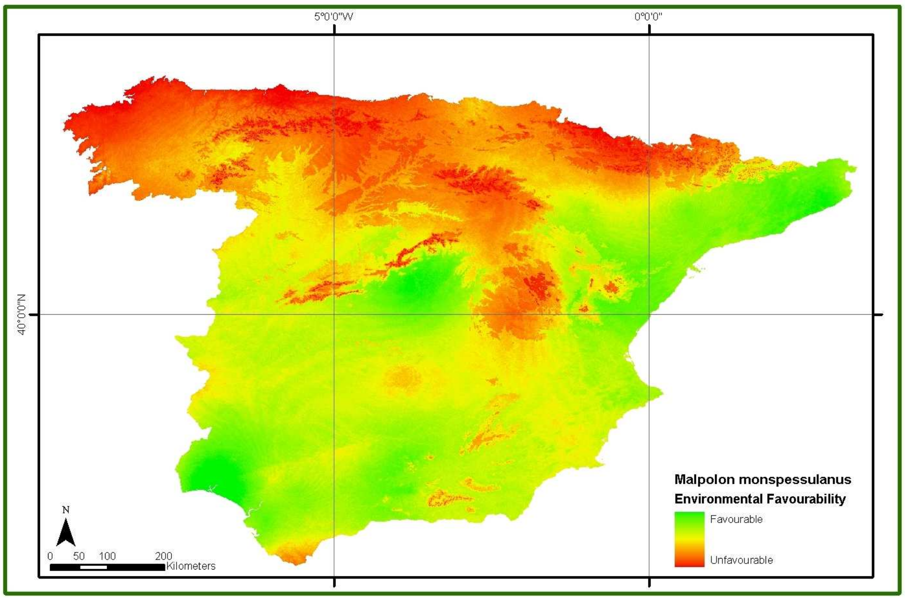


Figure 3-2: Environmental Favourability map of *Malpolon monspessulanus* in Spain

Table 3-4: Cross tabulation of field collected (Sep. and Oct. 2008) samples of *Malpolon monspessulanus* and environmental favourability values generated by the model.

Sample point ID	Date	*X*	*Y*	Note	Favourability value from map
Smn 1	Sep-08	267516	4052926	Road killed, Afternoon, Cloudy	0.68
Smn 2	Sep-08	399888	4085313	Evening, Cloudy	0.75
Smn 3	Sep-08	309576	4092942	Road killed, Afternoon, Cloudy	0.59
Smn 4	Oct-08	309899	4093590	Road killed, Noon, Rainy	0.79
Smn 5	Oct-08	375787	4085065	Road killed, Afternoon, Cloudy	0.69
Smn 6	Oct-08	380061	4085008	Noon, Partly cloudy	0.69
Smn 7	Oct-08	379968	4081858	Afternoon, Sunny	0.72
Smn 8	Oct-08	328478	4095861	Road killed, Afternoon, Cloudy	0.65
Smn 9	Oct-08	325908	4083134	Road killed, Evening, Cloudy	0.63
Smn 10	Oct-08	325373	4080943	Road killed, Afternoon, Rainy	0.67
Smn 11	Oct-08	331443	4067373	Road killed, Afternoon, Cloudy	0.63
Smn 12	Oct-08	364029	4094745	Road killed, Morning, Rainy	0.71
Smn 13	Oct-08	365300	4094243	Afternoon, Sunny	0.72
Smn 14	Oct-08	365597	4094093	Road killed, Afternoon, Partly	0.72
Smn 15	Oct-08	365965	4093855	Road killed, Afternoon, Rainy	.72

To downscale the national scale model to local scale, the final equation was applied on the Malaga province geo-databank to obtain the environmental favourability map for *Malpolon monsepessulanus* at a higher spatuial resolution for the Malaga province. To validate the downscaled map, collected points (*n=15*) during field work were cross tabulated by the favourability values of the corresponding pixels. All the sampling points (*n=15*) were located in intermediate favourable areas (F_{Smm} > 0.2). Table 3-4 shows the sample points and corresponding favourability values. Figure 3-3 illustrates the distribution of the observed species points on the environmental favourability map.

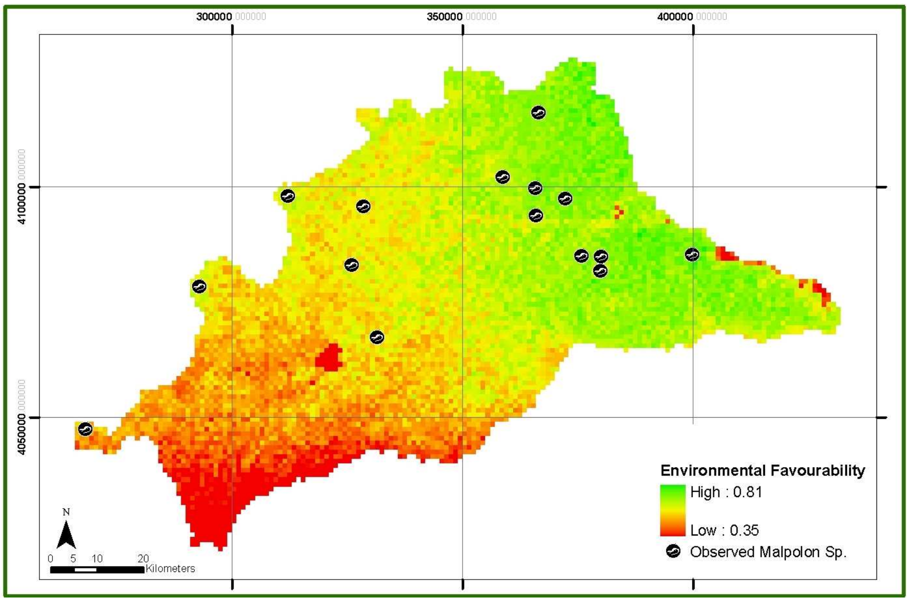


Figure 3-3: Observation points and downscaled environmental favourability map of *Malpolon monspessulanus* in Malaga province.

3.1.2.2. *Rhinechis scalaris*

Statistical procedure resulted in the final model for *Srs* (*Rhinechis scalaris*) species. Table 3-5 shows the summary results of the logistic regression analysis carried on GIS data layer for *Srs* species.

> Y_{Srs} *~ Constant + B1 × (NDVI late May) + B2 × (NDVI early July) + B3 × (NDVI late August) + B4 × (NDVI late November) + B5 × (Maximum temperature in February) + B6 × (Maximum temperature in March) + B7 × (Minimum temperature in April) + B8 × (Minimum temperature in February) + B9 × (Minimum temperature in November) + B10 × (Minimum temperature in October) + B11 × (Annual mean temperature) + B12 × (Minimum temperature of the wettest quarter) + B13 × (Southness) + B14 × (Slope)*

Then:

$$P(Y_{Srs}) \sim logit\,(Y_{Srs}) = log\,(1/(1+exp(-Y_{Srs})))$$

And:

$$F_{Srs} = \left(\frac{P(Y_{Srs})}{1-P(Y_{Srs})}\right) / \left(\frac{2272}{2658} + \frac{P(Y_{Srs})}{1-P(Y_{Srs})}\right)$$

The AUC (=*0.678*) and its standard error (=*0.008 confident level 95%*) for the performed model were calculated using non-parametric approaches. Cohen's Kappa was 0.395 (*cut value= 0.5*). Overall accuracy was 71.0%, expected accuracy was 52.0% so the model performed 19.0% better than a random model. Figure 3.4 illustrates the environmental favourability of *Srs* Species in Spain.

Table 3-5: Summary results of the logistic regression analysis for *Rhinechis scalaris*

Variables		*B*	SE (*B*)	Wald	*P*
Constant		-0.30100	0.327	0.851	0.356
NDVI late May	*B1*	0.01000	0.002	22.354	0.000
NDVI early July	*B2*	-0.00500	0.002	3.882	0.049
NDVI late August	*B3*	-0.00600	0.002	7.858	0.005
NDVI late November	*B4*	-0.00600	0.001	18.859	0.000
Maximum temperature in February (°C × 10)	*B5*	-0.05200	0.008	41.075	0.000
Maximum temperature in March (°C × 10)	*B6*	-0.03700	0.009	16.296	0.000
Minimum temperature in April (°C × 10)	*B7*	-0.00021	0.000	7.774	0.005
Minimum temperature in February (°C × 10)	*B8*	-0.00011	0.000	10.345	0.001
Minimum temperature in November (°C × 10)	*B9*	-0.00009	0.000	3.831	0.050
Minimum temperature in October (°C × 10)	*B10*	-0.0091	0.005	3.168	0.075
Annual mean temperature (°C)	*B11*	0.09901	0.012	66.945	0.000
Minimum temperature of the wettest quarter (°C)	*B12*	-0.00012	0.000	3.514	0.061
Southness (°)	*B13*	0.00102	0.001	3.713	0.054
Slope (%)	*B14*	0.03700	0.007	30.851	0.000

To downscale the national scale model to local scale, the final equation were applied on the Malaga province geo-databank to obtain the environmental favourability map for *Srs* Species in Malaga province. To validate the downscaled map, collected points (*n=14*) during field work were cross tabulated by the favourability values of the corresponded pixels. All 14 observed sampling points were located in intermediate favourable area ($F_{Srs} > 0.2$).

Table 3-6 shows the sample points and corresponding favourability values. Figure 3-5 illustrates the distribution of the observed species points on the environmental favourability map in Malaga province.

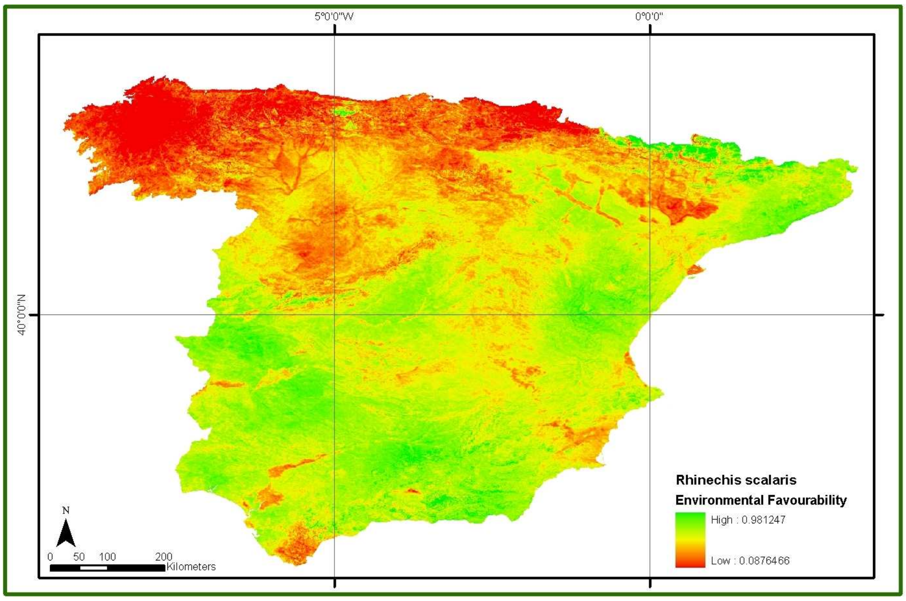


Figure 3-4: Environmental Favourability map of *Rhinechis scalaris* in Spain

Table 3-6: Cross tabulation of field collected (Sep. and Oct. 2008) samples of *Rhinechis scalaris* and environmental favourability values generated by model.

Sample point ID	Date	*X*	*Y*	Note	Favourability value from map
Srs 1	Sep-08	383322	4122328	Noon, Partly cloudy	0.66
Srs 2	Sep-08	253560	4006120	Evening, Cloudy	0.59
Srs 3	Sep-08	291438	4043153	Road killed, Afternoon, Cloudy	0.52
Srs 4	Sep-08	392197	4109598	Road killed, Noon, Rainy	0.64
Srs 5	Sep-08	317712	4097425	Road killed, Afternoon, Cloudy	0.44
Srs 6	Oct-08	380355	4087933	Noon, Partly cloudy	0.43
Srs 7	Oct-08	379303	4087575	Afternoon, Sunny	0.47
Srs 8	Oct-08	389910	4104702	Road killed, Afternoon, Cloudy	0.63
Srs 9	Oct-08	348561	4067526	Evening, Cloudy	0.59
Srs 10	Oct-08	328424	4095977	Road killed, Afternoon, Cloudy	0.63
Srs 11	Oct-08	328206	4096619	Road killed, Afternoon, Cloudy	0.66
Srs 12	Oct-08	325566	4081692	Afternoon, Sunny	0.75
Srs 13	Oct-08	365395	4094199	Road killed, Afternoon, Cloudy	0.54
Srs 14	Oct-08	383322	4122328	Evening, Cloudy	0.64

3.1.2.3. *Hemorrhois hippocrepis*

Statistical procedure resulted to the final model for *Shh* (*Hemorrhois hippocrepis*) species in the 12th step. Table 3-7 shows the summary results of the logistic regression analysis carried on GIS data layer for *Shh* species.

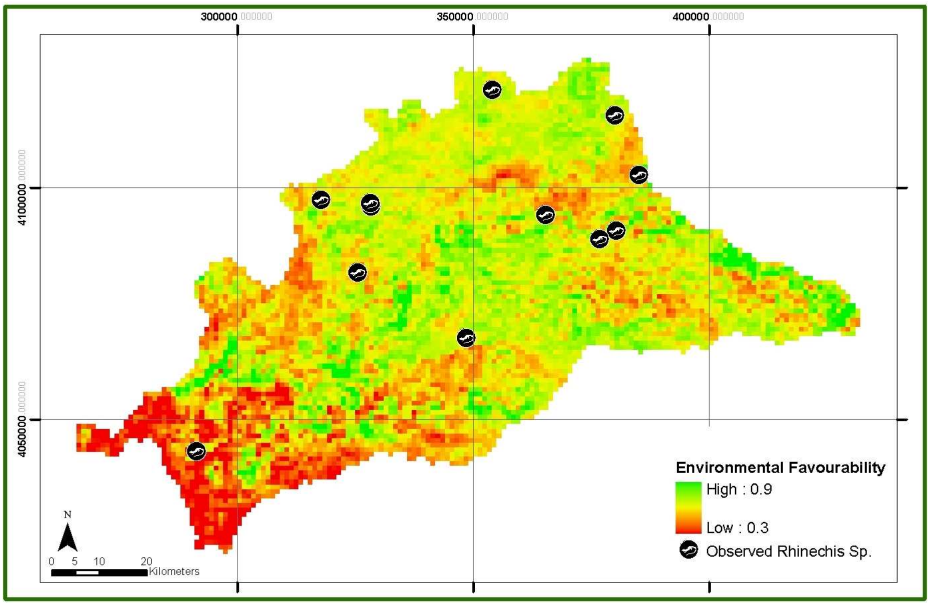


Figure 3-5: Observation points and downscaled environmental favourability map of *Rhinechis scalaris* in Malaga province.

Y_{Shh} *~ Constant + B1 × (NDVI early July) + B2 × (NDVI late August) + B3 × (NDVI early November) + B4 × (NDVI mid March) + B5 × (Precipitation in January) + B6 × (Precipitation in June) + B7 × (Precipitation in October) + B8 × (Maximum temperature in March) + B9 × (Mean temperature in January) + B10 × (Mean temperature in December) + B11 × (Mean temperature in May) + B12 × (Minimum temperature in March) + B13 × (Mean Diurnal temperature range) + B14 × (Isothermality) + B15 × (Minimum temperature of wettest quarter) + B16 ×(Mean temperature of the driest quarter) + B17 ×(Slope)*

Then:

$$P(Y_{Shh}) \sim logit\,(Y_{Shh}) = log\,(1/(1+exp(-Y_{Shh})))$$

And:

$$F_{Shh} = \left(\frac{P(Y_{Shh})}{1-P(Y_{Shh})}\right) / \left(\frac{992}{2938} + \frac{P(Y_{Shh})}{1-P(Y_{Shh})}\right)$$

The AUC (*=0.901*) and its standard error (*=0.005 confident level 95%*) for the performed model were calculated using non-parametric approaches. Cohen's Kappa was 0.81 (*cut value= 0.5*). Overall accuracy was 87.0%, expected accuracy was 32.0% so the model performed 55.0% better than a random model. Figure 3.6 illustrates the environmental favourability of *Shh* Species in Spain.

Table 3-7: Summary results of the logistic regression analysis for *Hemorrhois hippocrepis*

Variables	*B*		SE (*B*)	Wald	*P*
Constant		0.13837	1.782	0.006	0.938
NDVI early July	B1	-0.01569	0.003	23.457	0.000
NDVI late August	B2	0.01330	0.004	11.884	0.026
NDVI early November	B3	-0.00571	0.003	4.938	0.000
NDVI mid March	B4	0.01549	0.002	43.240	0.000
Precipitation in January (mm)	B5	-0.02873	0.004	57.170	0.000
Precipitation in June (mm)	B6	-0.18202	0.011	285.003	0.000
Precipitation in October (mm)	B7	0.05902	0.006	92.655	0.000
Maximum temperature in March (°C × 10)	B8	-0.11106	0.016	45.346	0.000
Mean temperature in January (°C × 10)	B9	-0.05786	0.012	24.338	0.000
Mean temperature in December (°C × 10)	B10	0.05791	0.012	24.378	0.000
Mean temperature in May (°C × 10)	B11	0.09831	0.015	40.804	0.019
Minimum temperature in March (°C × 10)	B12	0.00002	0.000	5.478	0.016
Mean Diurnal temperature range (°C)	B13	-0.01201	0.005	5.775	0.003
Isothermality	B14	0.11730	0.040	8.746	0.001
Minimum temperature of wettest quarter	B15	-0.00001	0.000	9.951	0.003
Mean temperature of the driest quarter (°C)	B16	-0.00518	0.002	8.517	0.003
Slope (%)	B17	0.03871	0.011	12.664	0.000

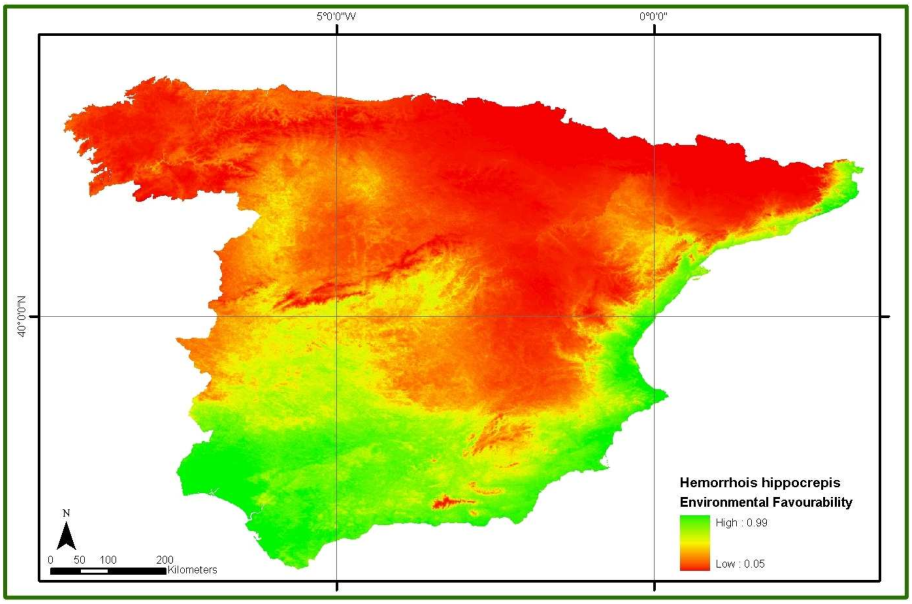


Figure 3-6: Environmental Favourability map of *Hemorrhois hippocrepis* in Spain

Table 3-8: Cross tabulation of field collected (Sep. and Oct. 2008) samples of *Hemorrhois hippocrepis* and environmental favourability values generated by model.

Sample point ID	Date	*X*	*Y*	Note	Favourability value from map
Shh 1	Sep-08	293034	4044852	Noon, Partly cloudy	0.90
Shh 2	Sep-08	338986	4102306	Evening, Cloudy	0.64
Shh 3	Sep-08	364398	4094515	Road killed, Afternoon, Cloudy	0.74
Shh 4	Sep-08	362069	4090863	Road killed, Noon, Rainy	0.69
Shh 5	Sep-08	362101	4090862	Road killed, Afternoon, Cloudy	0.69
Shh 6	Oct-08	389808	4102588	Noon, Partly cloudy	0.92
Shh 7	Oct-08	366618	4114222	Afternoon, Sunny	0.78
Shh 8	Oct-08	373462	4126417	Road killed, Afternoon, Cloudy	0.78
Shh 9	Oct-08	331541	4050315	Evening, Cloudy	0.87
Shh 10	Oct-08	331538	4050241	Road killed, Afternoon, Cloudy	0.87
Shh 11	Oct-08	308871	4082686	Road killed, Afternoon, Cloudy	0.89
Shh 12	Oct-08	313631	4095778	Afternoon, Sunny	0.76
Shh 13	Oct-08	379744	4078140	Evening, Cloudy	0.86
Shh 14	Oct-08	386301	4095117	Road killed, Afternoon, Cloudy	0.73
Shh 15	Oct-08	388628	4098646	Road killed, Afternoon, Cloudy	0.74
Shh 16	Oct-08	345567	4078616	Noon, Partly cloudy	0.81
Shh 17	Oct-08	327030	4072024	Evening, Cloudy	0.74

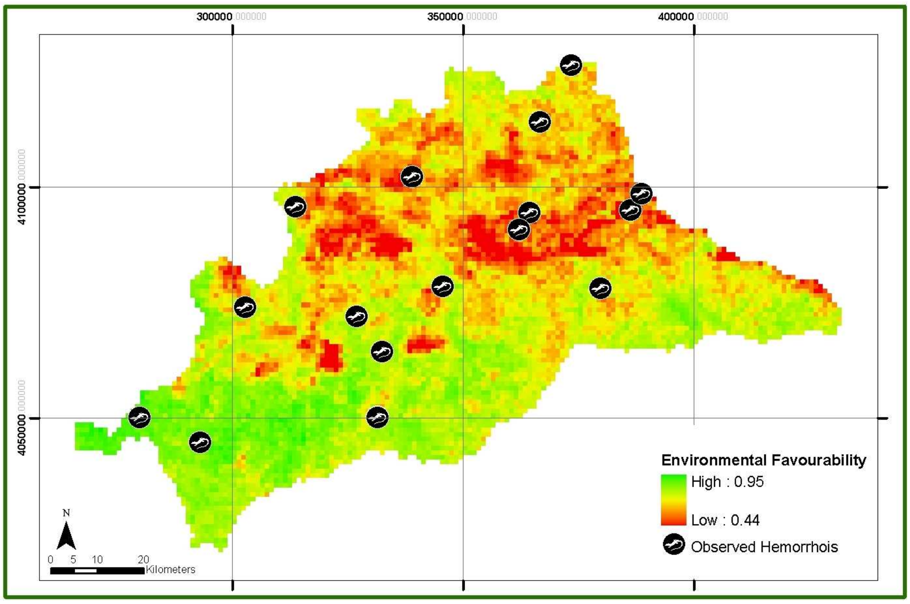


Figure 3-7: Observation points and downscaled environmental favourability map of *Hemorrhois hippocrepis* in Malaga province.

To downscale the national scale model to local scale, the final equation were applied on the Malaga province geo-databank to obtain the environmental favourability map for *Hemorrhois hippocrepis* in Malaga province. To validate the downscaled map, collected points (*n=17*) during field work were cross tabulated by the favourability values of the corresponded pixels. All the sampling points (*n=17*) located in intermediate favourable area ($F_{Srs} > 0.2$). Table 3-8 shows the sample points and corresponding favourability values. Figure 3-7 illustrates the distribution of the observed species points on the environmental favourability map in Malaga province.

3.1.3. Snake Species Models comparison

Comparison the method and expected accuracy of three snake species models revealed that although the method accuracy in *Smm* and *Srs* show fair agreements but the generated models improved a 50% expected accurate species models. The distribution model for Shh performs better than the two other species by improving 55% overall accuracy (figure 3-8)

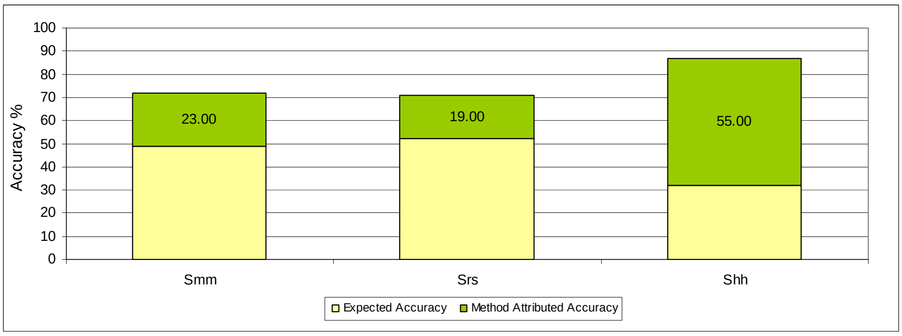


Figure 3-8: Overall, expected and method attributed accuracy of three snake species; (Smm: Malpolon monsepessulanus, Srs: Rhinechis scalaris and Shh: Hemorrhois hippocrepis)

3.2. Snakes Distribuion vs Eagle Foraging

Although the previous step generated a clear view of how the three snake species are distributed in the study area, they have not an equal chance of being hunted by the Short-toed Eagle. The snakes in the Short-toed Eagle foraging habitat are more likely to be catch than the other snakes.

3.2.1. Hunting Preference Areas

Preference of snake eagles to hunt in different landscape types was obtained by combining the Corine land cover classes (EEA, 2000) with results from field interviews. During field work in September and October 2008, 8 ornithologists were asked to rank the land cover classes from 0 to 5 in order of suitability for snake eagle hunting. To minimise the bias the ranked values were converted to Boolean dummy variable. Therefore, the land cover classes which were ranked more than 2 by at least by 4 ornithologists were assumed preferred foraging areas. Table 3-9 shows a summery of the results of the interviews and the final ranks that were assigned to each land cover classes. Figure 3-9 illustrates the preferred foraging areas of the Short-toed Eagle on the LandSat ETM+ 2002 images. Foraging areas cover 54.3% of the Malaga province and are mainly located in south west (*Sierra de Ronda*) and south (*Sierra de Mijas*, *Sierra de Malaga*), followed by some fragmented areas on east and central parts.

Table 3-9: Foraging preference of land cover classes for the Short-toed Eagle

Corine Code	Land Cover Description	Interviewees (ranks 0-5)								Boolean ranks
		I1	I2	I3	I4	I5	I6	I7	I8	
111	Continues Urban Fabric	0	0	0	0	0	0	0	0	0
112	Discontinues urban fabric	0	0	0	0	0	1	0	0	0
121	Industrial or commercial units	0	0	0	0	0	0	0	0	0
123	Port areas	0	0	0	0	0	1	0	0	0
124	Airports	0	0	0	0	1	1	0	0	0
131	Mineral extraction sites	0	1	0	2	1	1	1	0	0
133	Construction sites	0	0	0	0	0	0	1	0	0
142	Sport and leisure facilities	1	0	0	0	0	0	0	1	0
211	**Non-irrigated arable land**	5	4	5	5	5	4	5	5	1
212	**Permanently irrigated facilities**	2	4	3	4	4	3	1	2	1
221	**Vineyards**	1	0	2	2	2	0	0	2	1
222	**Fruit trees and berry plantations**	1	0	3	3	2	0	0	2	1
223	Olive groves	1	0	0	0	1	0	0	0	0
241	**Annual crop associated with permanent crop**	1	0	3	2	3	0	2	2	1
242	**Complex cultivation patterns**	1	0	3	3	2	0	0	2	1
243	**Principally occupied agriculture**	4	4	3	5	3	4	3	5	1
244	**Agro-forestry areas**	1	0	3	3	2	0	0	2	1
311	Broad-leaved forest	1	0	0	0	1	0	0	0	0
312	Coniferous forest	1	0	0	0	1	0	0	0	0
313	Mixed forest	1	0	0	0	1	0	0	0	0
321	**Natural grassland**	5	4	5	5	5	4	5	5	1
323	**Sclerophyllous vegetation**	5	4	5	5	5	4	5	5	1
324	**Transitional woodland shrub**	4	3	4	5	3	4	3	5	1
332	**Bare rock**	4	4	3	5	3	4	3	5	1
333	**Sparsely vegetated areas**	4	5	5	5	5	4	5	5	1
334	**Burnt areas**	4	4	3	5	3	4	3	5	1
511	Water courses	0	0	0	0	0	0	0	0	0
512	Water bodies	0	0	0	0	0	0	0	0	0

Arable lands such as non-irrigated arable land or irrigated facilities as well as vineyards and semi dense fruit trees and berry plantations were ranked as foraging area for the Short-toed Eagle in Malaga province. Heterogeneous agricultural and agro-forestry areas were also reported by Bakaloudis et al (2001) and Tapia et al (2008). Natural grassland, Sclerophyllous vegetation, transitional woodland shrub, bare rock, sparsely vegetated areas and burnt areas were reported as the favourite foraging sites in published papers. (Bakaloudis et al., 2001, Bakaloudis et al., 1998, Bakaloudis et al., 2000, Bustamante and Seoane, 2004, Gil and Pleguezuelos, 2001, Moreno-Rueda and Pizarro, 2007, Rocamora, 1994, Sanchez-Zapata and Calvo, 1999, Tapia et al., 2008, Vlachos and Papageorgiou, 1994)

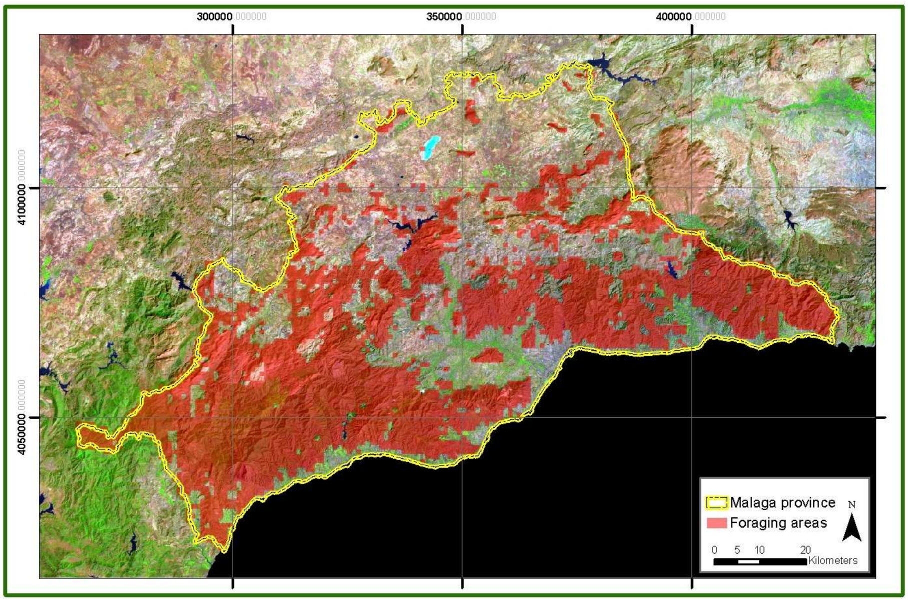


Figure 3-9: Areas considered as suitable for foraging for the Short-toed Eagle in Malaga province on ETM 2002

3.2.2. Potential Food Availability

By combining the preferred foraging areas and predicted distribution of snake species a potential prey distribution map has been resulted. In other word, the snake is not necessarily a potential prey for the Short-toed Eagle if the land cover is not suitable for hunting and foraging. For instance one snake is potentially a perfect prey in Sclerophyllous vegetation, however in mixed forest it would not be seen by Short-toed Eagle.

Using the knowledge of feeding and diet preference of the Short-toed Eagle, following weights (equation 3-1) were applied to generate a potential food availability map consist of three individual prey species maps (Gil and Pleguezuelos, 2001). The weights were estimated by summarizing the probability of occurrence from the logistic values in the study area also they were cross checked by the published paper (Vlachos and Papageorgiou, 1994). Figure 3-10 illustrates potential food availability map for the Short-toed Eagle in Malaga province.

$$\sum Z = \left(0.5 \times Z_{Smm}\right) + \left(0.3 \times Z_{Srs}\right) + \left(0.2 \times Z_{Shh}\right) \qquad (3.1)$$

where Z is a summarized probability of occurrence of each snake species

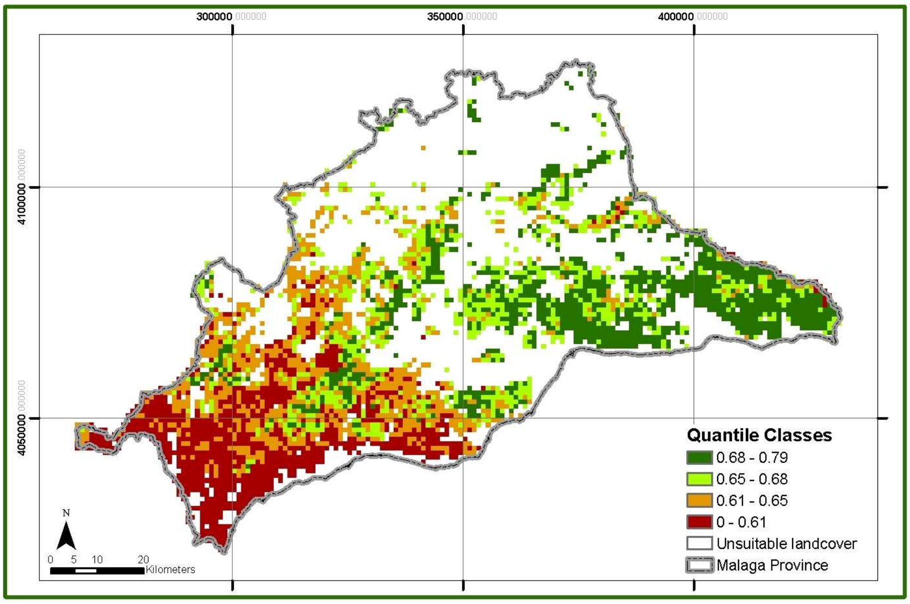


Figure 3-10: Potential food availability map for the Short-toed Eagle in Malaga province

3.3. Distribution Modelling of the Short-toed Eagle

Based on the collected nest positions (*n=32*) (figure 2-4) the Maximum Entropy Model was employed to generate a prediction models. In brief, the approach of Maxent is to find the probability distribution of maximum entropy (closest to the uniform) subject to the constraints imposed by the information available regarding the observed distribution of the species and the environmental conditions across the study area (Suarez-Seoane et al., 2008). The method assigns a probability of occurrence to each cell grid in this area. The Maxent output (model predictions) is presented as cumulative probabilities, where the value of a given pixel is the sum of that pixel and all others with equal or lower probability, multiplied by 100 to give a percentage. Note that using presence-only data, it is generally not possible to calculate probabilities of presence; instead, outputs are relative likelihood of presence (Pearce and Boyce, 2006).

3.3.1. Predictor Variable in Malaga Province

Multicollinearity a diagnosis was performed on the Malaga province explanatory environmental variables dataset for the Short-toed Eagle, as described in section 2-2-1. From the resulting VIFs (equation 2-1), it was concluded that the existence of multicollinearity was not significantly high since none exceeded 10 as the rule of thumb. (Montgomery and Peck, 1982) and hence all the variables could be used in subsequent analysis. Table 3-10 shows the significantly independent sets of predictors and the corresponding VIF values after multicollinearity diagnoses for the Short-toed Eagle in Malaga province. NDVI for mid August, precipitation in September, minimum temperature in March, minimum temperature of the wettest quarter, elevation, south direction, slope, and potential food availability were set as inputs to the modelling phase.

Table 3-10: Explanatory environmental variables used to model the Short-toed Eagle distribution in Malaga province (Sources and references explained in section 2.2 in details, check Appendix I for list of variables)

ID	Predictors	Description	VIF
Ecg1	NDVI14	NDVI value mid August	5.75
Ecg2	PER9	Precipitation in September	3.16
Ecg3	TMIN3	Minimum temperature in March	1.73
Ecg4	BIO6_CL	Minimum temperature of wettest quarter	1.15
Ecg5	ALT_CLIP	Elevation	2.93
Ecg6	SOUTHNESS	South direction	3.90
Ecg7	SLOPE	Slope of steeps	2.81
Ecg8	food	Potential Food Availability	1.72

3.3.2. All-inclusive Model

The regularized training gain for the all-inclusive model (environmental variables and potential food availability) generated with all presence records (n=32) was 0.832. From the Jackknife test of variable importance the single most important predictor in terms of the gain produced, was altitude (*alt_clip*) followed closely by precipitation in September (*per9*) and minimum temperature in March (*tmin3*). NDVI for mid August (*NDVI14*) decreased the gain the most when it was omitted from the full model, which means it contained information that was not present in the other predictors (figure 3-11).

According to the amount of decrease in model gain when a variable was omitted, the order of excluded variable for the all inclusive model was 1) minimum temperature in March (*tmin3*), 2) altitude (*alt_clip*), 3) potential food availability (*food*), 4) precipitation in September (*per9*), 5) slope, 6) south direction and 7) NDVI for mid August (*NDVI14*).

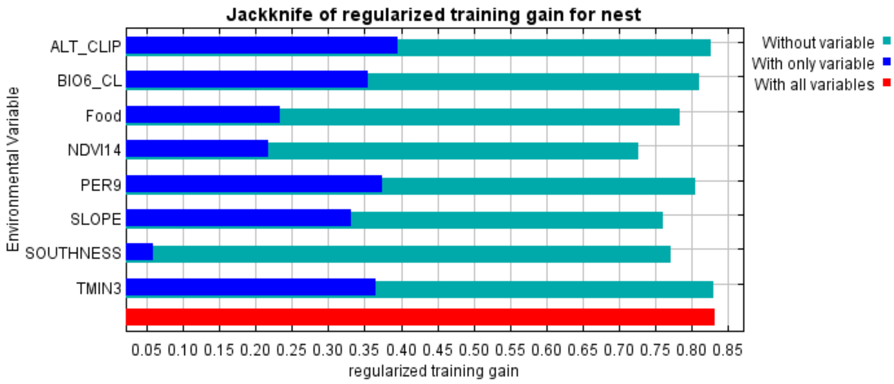


Figure 3-11: Jackknife of training gain for all-inclusive model built with all presence data

Following Philips (2006) and Yost (2008) binomial test resulted that some of the *p*-values from threshold categories of fixed cumulative values 5 and 10 were less than 0.025 (*a=0.5*) indicating that predictions were significantly better than random regardless of the number of predictor variables. Binomial test *p*-values decreased substantially when the threshold changed from one to ten, meaning a higher probability of rejecting the null hypothesis as threshold increased to 10. (table 3-11)

Table 3-11: *p*_values from the binominal test for all-inclusive model

Number of Variables	Binominal test p-value for threshold			Excluded variables
	1	5	10	
8	0.07587	0.00154	0.00005	
7	0.04212	0.00035	0.00717	Tmin3
6	0.19500	0.00396	0.00531	Altitude
5	0.10290	0.00381	0.00016	Food
4	0.06663	0.00210	0.00127	Per9
3	0.34040	0.06711	0.00666	Slope
2	0.20850	0.01347	0.00086	Southness
1	0.23270	0.03953	0.16360	NDVI14

The average test AUC values were relatively the same as model size decreased. It increased slightly when altitude was omitted and dropped with the one-variable model containing *Bio06* (minimum temperature of the wettest quarter). The average training gain declined gradually as variables were removed. There was an average ascent in the standard deviation (0.025 to 0.075) of the test AUC values from the eight-variable to the one variable. The variability was lower in the behaviour of the average test gain as model size decreased (figure 3-12).

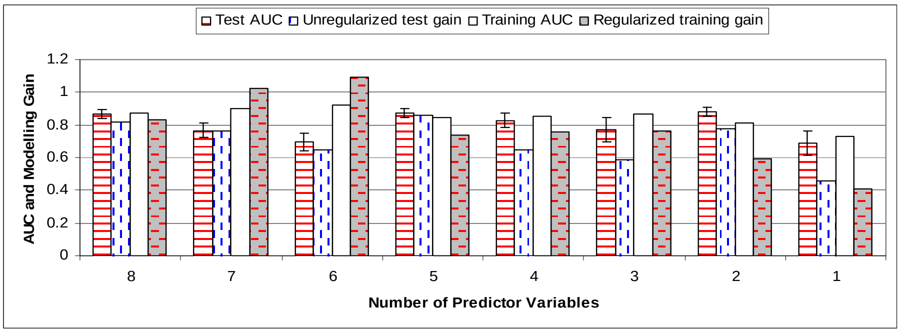


Figure 3-12: Values for the test AUC, unregularized test gain, training AUC and regularized training gain in all-inclusive model.

Following Yost et al (2008) and Seoane et al (2008), given the higher sensitivity of the average training gain relative to the average AUC value, the former metric was employed to detect which of the performing models should be used for mapping. Therefore, the logical choice of best model was the one that had the fewest predictors with an average training gain not significantly different than the full model or the model with highest training gain (Yost et al., 2008, Suarez-Seoane et al., 2008).

Using the overlap between 95% confidence intervals for test gain as the criteria for significance the five-variable model containing the minimum temperature in the wettest quarter, NDVI for mid August, precipitation in September, slope and south direction was not significantly different than the tree larger models but was performing better than the remaining smaller models. Finally the five-variable model was used to create the distribution of the Short-toed Eagle in the Malaga province (figure 3-13).

3.3.3. Food Excluded Model

The regularized training gain for the seven-variable model using all presence records but without the potential food availability was 0.842. The relative importance of the predictor variables, according to the training gain was closely the same as when the potential food availability was included in the model.

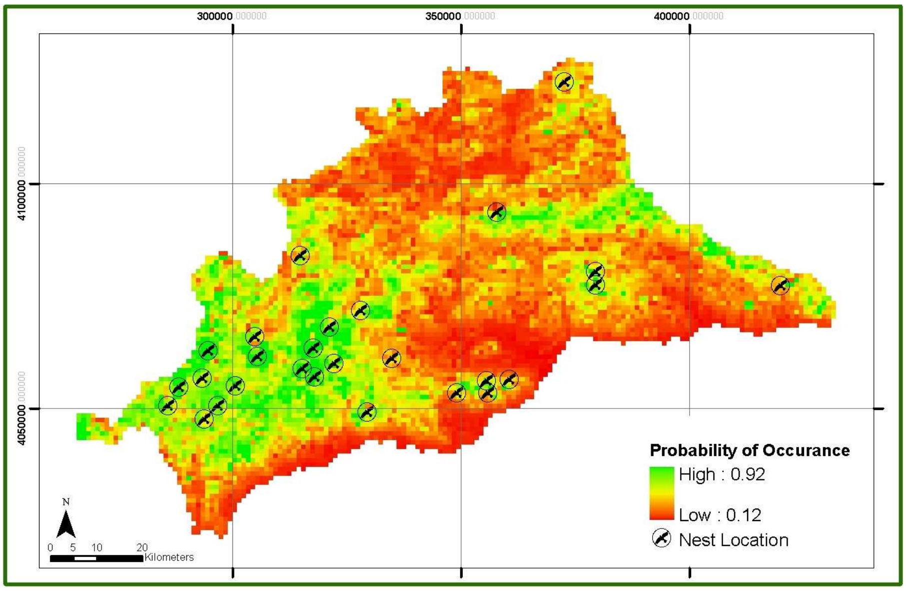


Figure 3-13: Nest locations on the distribution map of the Short-toed Eagle based on five-variable model in Malaga province

NDVI for mid August and southness increase the gain the most when eliminated, indicating it contained the most information not contained in the other variables (figure 3-14). The order of variable elimination from the full model (food excluded) was 1) minimum temperature in March, 2) minimum temperature in the wettest quarter, 3) altitude, 4) slope, 5) southness, 6) NDVI for mid August and precipitation in September.

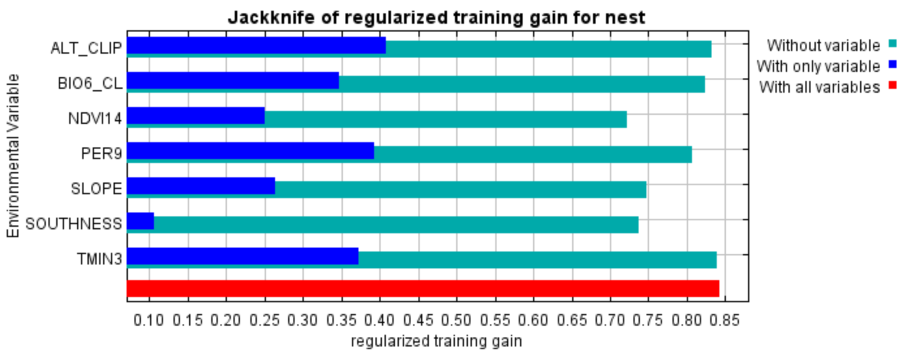


Figure 3-14: Jackknife of training gain for food excluded model built with all presence data

The interpretation of the binomial test showed that, on average, all of the models performed better than a random model (table 3-12). Note that the average test AUC values were slightly higher than those for the models with potential food availability and the decrease in value as variables were removed was small (figure 3-15).

Unlike the test AUC values the average test gain was sensitive to the removal of the predictors. There was a sharp decline in the average test gain for the six, four and two-variable model as well as increase in average training gain for the three-variable model followed by a steep ascent for the smaller models. The standard deviation of the seven training gain averages ranged between 0.047 and 0.068.

Table 3-12: *p*-values from the binominal test for food-excluded model

Number of Variables	Bionominal test p-value for threshold			Excluded variables
	1	5	10	
7	0.08523	0.01510	0.00091	
6	0.23220	0.01326	0.00653	Tmin3
5	0.37590	0.01949	0.00896	Bio6
4	0.09051	0.01317	0.00047	Altitude
3	0.14400	0.00741	0.00509	Slope
2	0.27850	0.01035	0.07055	Southness
1	0.19500	0.06066	0.06445	NDVI14

Using the overlap between 95% confidence intervals for test gain averages as the criteria for significance it appears that the model containing NDVI for mid August, south direction and precipitation in September was statistically different from the models with more variable predictors (figure 3-15).

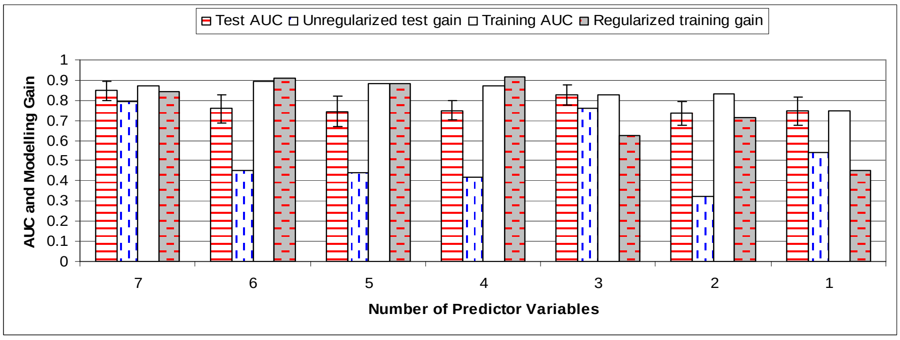


Figure 3-15: Values for the test AUC, unregularized test gain, training AUC and regularized training gain in food excluded model.

3.3.4. Predictor Variables

Although potential food availability produced positive linear response profiles, the information given to model from this layer were already present in other variable predators. By increasing the potential food availability, the probability of occurrence increased form 0.25 to almost 0.6 (figure 3-16). Generally an increase in precipitation in September increases the probability of occurrence. Pixels with precipitation more than 30 millimetres in September gain 0.6 onward. These results were consistent with what could ecologically be expected.

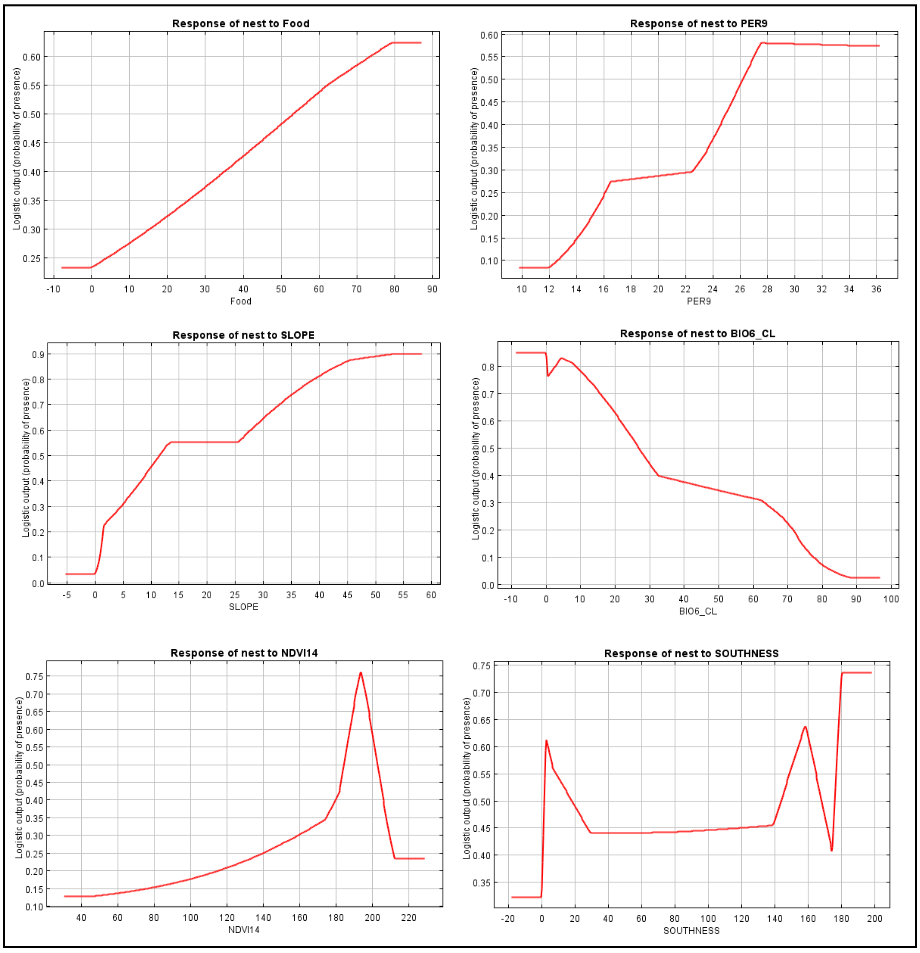


Figure 3-16: Response curves of environmental variable when all presence point were used in all-included model.

Response curves show that the exponent value will be close to zero when a minimum temperature in the wettest quarter is close to 10˚ Celsius. The value of the logistic output started at 0.15 for the lowest values of NDVI in mid August (40), then increased to a little over 0.75 at the NDVI value of 190. Practically south direction was a difficult landscape feature to create a reliable predictor variable, as far as generalization to 1km pixel size. The pattern suggests that the Short-toed eagle show a slight avoidance of west and east facing slopes for nest sites. The thermal benefit of early morning solar radiation to nest was not clear from curves. The slope predictor variable performed poorly in the models and the response of the exponent across the range of values was positive.

The analysis suggests that potential food availability for snake eagles is not a powerful predictor variable in this dataset. In fact, the average training gain for the model containing just the potential food availability (0.196) alone was significantly lower than the other predictors. Nonetheless, minimum temperature in early migration session and NDVI in mid August emerged as important ecological features for the habitat suitability of the Short-toed Eagle in Malaga province. A five-variable model built from the full set of 32 nests locations was used to create the distribution map of the Short-toed eagle in Malaga province. The predictor variables in this model included the minimum temperature in the wettest quarter, precipitation in September, south direction, NDVI for mid August and Slope. (Figure 3-12). Visual inspection indicates strong agreement between nests and the probability distribution map. The regions of highest nest locations were accurately associated with regions of high probability predicted by the model. However, even though Maxent predicted a relatively compact area of high nesting potential there were still a few nests placed in areas quantified as low nesting potential.

3.3.5. More Measures to Compare the Models

According to the explanation of section 2-5-6, the Akaike information criterion (AIC) and the Schwartz information criterion (SIC) were employed to measures a model's suitability and goodness of fit (Koehler and Murphree, 1988). Here the all-inclusive model (explanatory environmental variables and potential food availability) and the food excluded model (Only environmental variables) were compared. Table 3-13 shows the summery of comparison.

Maxent defined a value of 0.422 as the logistic threshold value for the all-inclusive model when training sensitivity and specify were equal. Corresponded value in food excluded model was 0.377. The food-excluded model generated a habitat suitability map with 5197 suitable pixel versus 2274 unsuitable pixels and 4 nest-locations out of 32 located in unsuitable areas. The all-inclusive model generated a habitat suitability map with 5865 suitable pixels versus 1606 pixels and 29 nests were located in suitable area. Both AIC and SIC assigned to the food excluded model were smaller than the all-inclusive model. The lower AIC and SC are, the better the specification. This result is consistent with the Maxent binominal test results that potential food availability did not improve the predictive power of the model in this case of study.

Table 3-13: Summary result of model comparison

Measures	All inclusive	Food excluded
Predictors #	**8** Minimum temperature in the wettest quarter, NDVI for mid August, Precipitation in September, Slope, South directions, Altitude, Minimum temperature in Mach & Potential food availability	**7** Minimum temperature in the wettest quarter, NDVI for mid August, Precipitation in September, Slope, South directions, Altitude & Minimum temperature in Mach
Presence Points #	32	32
Akaike information criterion (AIC)	0.31	**0.25**
Schwartz information criterion (SIC)	0.27	**0.19**

Figure 3-17 shows how the probability of occurrence changed by omitting the potential food availability form all-inclusive model. Nests number 3, 7 and 29 were located in an unsuitable zone based on the all-inclusive model. Food-excluded model tagged nests number 2, 7, 11, 27 in unsuitable zone. Corresponded pixels of the nest-locations 3, 6, 7, 11, 27 and 29 had more than 5% changes in probability of occurrences by omitting potential availability from the set of predictors.

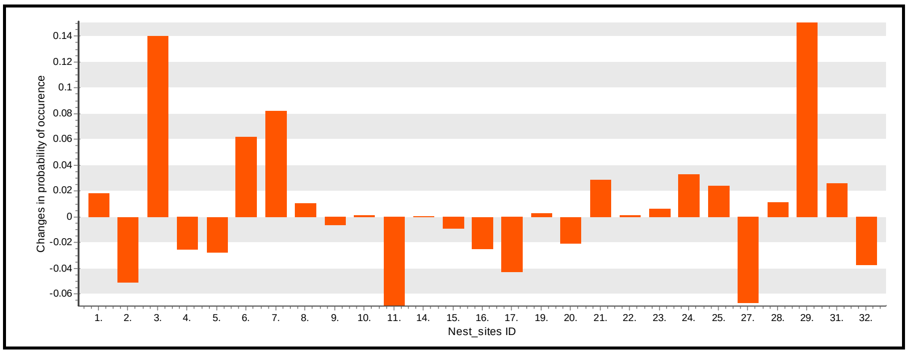


Figure 3-17: Changes in probability of occurrence extracted from suitability map to nest-sites locations by omitting the potential food availability from all-inclusive model.

4. Discussion

4.1. Generalist Species

The results from section 3-1 of this study - environmental favorability (Real et al., 2006) of snake species in Spain - revealed that although there are several environmental parameters characterising ecological preferences of the three snake species, the contribution level of predictor variables are very small. These generalist species are able to thrive in a wide variety of ecological conditions and can make use of a variety of different resources. Overlaying the distribution datasets of *Malpolon monsepessulanus* and *Rhinechis scalaris* on explanatory environmental variables (table 3-2) revealed that they widespread geographically compared to *Hemorrhois hippocrepis* in Spain (Moreno-Rueda and Pleguezuelos, 2007). This concurs with, Hernandez et al. (2006) who confirmed the results of other researchers that the ecological characteristics of species affects modelling accuracy, where species that are widespread in both geographic and environmental space, as is the case with the all three selected snake species data, are generally more difficult to model than species with more specific spatial distributions. They also confirmed that the ability to model species effectively is strongly influenced by species ecological characteristics independent of sample size (Araújo and New, 2007, Hernandez et al., 2006, Araujo and Guisan, 2006).

Cohen's Kappa test revealed that *Malpolon monsepessulanus* and *Rhinechis scalaris* are expected to be observed in almost 50% of pixels and the distribution models improved 23 and 19 percent method attributed accuracy respectively. The probability of observation in random pixels for *Hemorrhois hippocrepis* is 32% which were improved by methods to 87% overall accuracy (figure 3-8). Note that the complicated predictive models with 15, 14 and 17 independent predictors for each of these species were statistically significant but very difficult to interpret from ecological point of view.

Presence/absence distribution datasets of snake species with more temporal and spatial resolutions may improve the modelling quality. These species are listed as Least Concern in view of their wide distribution, tolerance to a broad range of habitats and presumed large population. They are unlikely to decline fast enough to qualify for listing in a more threatened category (IUCN, 2009). As far as these species are listed as least concerned, eco-geographers and herpetologists were less interested in them as well.

4.2. Snakes Distribution To Prey Availability

The Short-toed Eagle has a highly specialized diet, preying almost exclusively on ophidians (Moreno-Rueda and Pizarro, 2007, Vlachos and Papageorgiou, 1994). Three snake species; *Malpolon monsepessulanus, Rhinechis scalaris* and *Hemorrhois hippocrepis* comprise almost 95% of the diet, in both frequency and biomass (Gil and Pleguezuelos, 2001). Generally speaking, snakes are usually very elusive and therefore it could be assumed that the distribution of the Short-toed eagle is related to the accessibility to its primary prey. This raptor forages among shrub, herbaceous vegetation associations, open spaces and heterogeneous agriculture areas, avoiding forest, probably because snake detection is easer in open lands (Bakaloudis et al., 1998, Moreno-Rueda and Pizarro, 2007). It was assumed that presence of the three above mentioned snake species might favour the distribution of the Short-toed Eagle. Snake species distribution maps and foraging preference map were compiled to generate the potential food availability of the Short-toed Eagle.

As it has discussed in section 3-1-3, two of three predicted distribution maps of snake species had high level of uncertainties. Although the downscaled map to Malaga province was evaluated successfully by the fieldwork presence points, there might be contradicting results if absence data would have been available. Note that 93%, 88% and 94% of the Malaga province were classified as suitable for *Malpolon monsepessulanus*, *Rhinechis scalaris* and *Hemorrhois hippocrepis* respectively (figures 3-3, 3-5 and 3-7 also tables 3-4, 3-6 and 3-8).

Preferred foraging/hunting areas/sites of the Short-toed eagle were minimally studied. However, the published studies show that this raptor prefers open spaces in general (Tapia et al., 2008, Bakaloudis et al., 2001, Bakaloudis et al., 1998, Bakaloudis et al., 2000, Moreno-Rueda and Pizarro, 2007, Sanchez-Zapata and Calvo, 1999, Vlachos and Papageorgiou, 1994, Agostini et al., 2002, Bustamante and Seoane, 2004, Kumar, 1996, Rocamora, 1994) and local ornithologist confirmed this general statement, but there were no clear definition of open space from the Short-toed Eagle point of view. Given questionnaires to local NGOs and ornithologists were designed to cover up this gap by ranking the Corine land cover (EEA, 2000) classes, but the uncertainties are still high. Overlaying the nest-site locations and final foraging maps shows that all the nests were located completely within “forage-suitable” areas.

4.3. Indirect predictors

It is desirable to predict the spatial distribution of species based on ecological parameters that are believed to be causal, driving forces for their distribution and abundance (Guisan, 2000). However these parameters are often sampled from digital maps as they are difficult or expensive to measure and tend to be less precise (Omolo, 2006). Bioclimatic parameters those used in this research were developed by elevation-sensitive spatial interpolations of climate station data (Hijmans *et al*., 2004) which introduce spatial uncertainties. Austin and his colleagues (2007) consider climate as a direct predictor thus posing strong distributional limits whereas vegetation/habitat type (NDVI , Prey distribution) could be considered as an indirect predictor since it does not have direct physiological relevance for a specie's performance (Austin, 2007). In some cases of study climatic models have been shown to predict the Short-toed Eagle and three prey snake species distributions more accurately (Guisan and Hofer, 2003, Beaumont et al., 2005, Carter et al., 2006). The results of this research are consistent with these studies as the selected eco-climatic parameters explained the Short-toed Eagle distribution more efficiently than prey distribution or NDVI in scale of current research. In addition, potential food availability explained less deviance than bio-climate variables. It is plausible that relative to climate, snake species distributions are of secondary importance to the Short-toed Eagle species considered.

Yost and his colleagues (2008) discussed that the set of modelling variables might be insufficient to describe all the parameters of a species fundamental niche relevant to its distribution at the grain of the modelling task (Yost et al., 2008). Therefore, errors within the explanatory environmental predictor variables (e.g. potential food availability) will directly affect model accuracy. The results of this study would be different, if presence/absence data with more accurate location information had been used.

4.4. Scale Issue

Questions on species distribution must adequately take into the account the issue of resolution and scale referring to the extent of the study area (Guisan and Hofer, 2003, Murwira et al., 2003). Integrity of the variable predictors and their possible combinations might not have been retained when aggregated to 10×10 kilometre absence/presents resolution. It could possibly explain why both food-excluded and all-inclusive models were not gain very high AUC values. Patthey (2003) discussed in his work that a modelling study conducted at a small scale (large extent) can disclose environmental variables that best characterise the overall species range whereas, a second nested analysis at a large scale (small extent) can disclose other environmental predictors that best characterise habitat at population or home range level (Patthey, 2003). Nevertheless, it is important to consider that some predictors could remain important at all scales. Multi-scale models comparison perspectives were not considered in the scope of this study; however, results clear it meantime.

4.5. Different Habitats.

This research employed the application of predictive modelling and mapping to the Short-toed Eagle habitat with Maximum Entropy (Phillips et al., 2006). The relationships between the Short-toed Eagle nest-sites locations and a set of explanatory environmental variables were quantified using the Maxent software and a probability distribution map was created that locates the likelihood of the suitable habitat. The objective was to identify a model with the fewest predictor variables that explained the data satisfactorily based on *the principle of parsimony and the philosophy that models are only estimates of reality and that no single model is ever "true" or likely to perform well in all applications* (Hilborn and Mangel, 1997).

The statistical analysis and spatial modelling included creating a full model containing all the predictors, identifying the least informative predictor, omitting that predictor, and repeating this process until only one variable remained. At the end, the model with the fewest predictors and an average training gain - not significantly less than the model with highest training gain - was selected as the best model (sections 3-3-2 and 3-3-3). The Maximum entropy models conveyed through the differences in training and test gain between models containing the potential food availability and those without them, indicate that the full set of explanatory environmental variables (all-inclusive model) contributing the habitat modelling within the study area were sufficiently represented with the seven other predictor variables (food excluded model).

This concurs with Moreno-Rueda (2007) who found no significant effect of snake species richness on the distribution of the Short-toed Eagle. Their report also indicated that the effect of snake species was not due to the presence of these species consumed by the eagle (Moreno-Rueda and Pizarro, 2007). The diet of the Short-toed eagle, although based on snakes, possibly varies considerably among study zones (Gil and Pleguezuelos, 2001). It suggests that this raptor is a tropic generalist within the order ophidians and this might explain why the three snake species did not affect its distribution. It could be that different snake species are distributed structurally in time (throughout the day or throughout the year) and that higher snake species richness (several active snakes at a time) creates a larger window of opportunity to hunt for the eagle (Moreno-Rueda and Pizarro, 2007). Also it is possible that in the zones with low potential availability of the prey, eagles prey on alternative snakes or even alternative sources of food (e.g. *Timon lepidus*). Although these possibilities and ecological interpretations did not test in this research and final distribution map of the Short-toed Eagle concurs with currently published *Atlas of Raptor of Malaga province* (Muñoz and Jiménez, 2008), the models predictors and their contribution might change by considering above mentioned factors.

4.6. Specifity of Models

All nest-site locations have some level of error that can be biased by accessibility, sampling barriers and variation in sampling effort over space and time. The choice of environmental explanatory predictors as inputs for models affects the level of precision to which a model can be generalized to other areas and time periods.

Maximum Entropy as well as logistic regression effectively model ecological rather than fundamental niches due to its intrinsic entropy and empirical nature. This can vary spatially and temporally hence models fitted for the same species but in different areas and/or at different resolutions can be difficult to compare (Guisan, 2000, Pearce and Ferrier, 2000, Phillips et al., 2006). Therefore the models of this research are only valid for the study scale, temporal and spatial resolution under which they have been developed.

5. Conclusions and Recommandations

Understanding the quantitative relationship between species and their surrounding environment is fundamental to understand the general ecological requirements of species and their assemblages (Skidmore, 2002). Predicting their potential distributions in weak-sampled locations may lead to their discovery or reveal factors that might explain their absence (Omolo, 2006). More importantly from a conservation and biodiversity management point of view, it provides the opportunity to assess the possible barriers that may keep species away from the area and thus plan appropriate conservation tasks. As Omolo (2006) concluded the relevance and disparate methodologies for species distribution modelling are not in doubt, intrinsic species-environment relationships still remain contentious. A key debate amongst eco-geographers has been the notion that at generalist species, secondary predictors such as food availability are better predictors of potential species distributions when compared to other primary predictors such as climate and topography (Thomson et al., 2007). Using snake species occurrence records in Spain, nest-sites locations in Malaga province and statistical predictive techniques (Logistic regression and Maximum Entropy), the specific objectives for this study were as outlined below;

The first objective aimed at establishing if there were significant relationships between the three prey snake species distributions and eco-geographic parameters; climatic- and topographic conditions, and NDVI. This research revealed that through significance tests and proportions of explained deviance, sets of independent predictors were significantly correlated with species distributions. The results indicated that climatic parameters explained a higher proportion of consistence for species distributions compared to other predictors.

The second and third objectives tried to generate a representative map for prey availability based on prey snake species distribution and foraging site. This research concluded that the generated map was not elucidating food availability and suffered substantial biases.

The forth and fifth objectives, which formed the crux of this research, were to compare the relative predictive powers of potential food availability versus other explanatory environmental variables. These objectives were to make spatial predictions of the Short-toed Eagle based on the ‘best-fit’ models and parsimony philosophy in science and assess their accuracies. Overall, using Cohen’s Kappa, AUC statistics, Akaike and Schwartz information criterion, it is concluded that spatial distribution map derived from all-inclusive model performed better than those derived from food-excluded model with the same number of predictors. In summary, these results are contrary to our expectations and do not support established ecological theory that potential food availability is a critical issue and limiting factor. Nonetheless, some key perspectives from this research are offered as follows;

5.1. Specific Conclusions

1. At the study scale, potential food availability dose not improve the predictive power of the Short-toed Eagle distribution models compared to the food-excluded models. Although there were not any multicollinearity defined between potential food availability and other independent variables, it seems that minimum temperature in March, southness, slope and precipitation in August contained the most information contain in food predictor.

2. Overall, five-variable models (minimum temperature in the wettest quarter, precipitation in September, NDVI in mid August, slope and southness) better relates to actual nest-site location distributions than those based on food availability or other predictors. These results suggest that the distributional limits of this migratory species and their respective assemblages in the Malaga province may be largely set by climatic parameters in the beginning and end of migration session.

3. On a national scale, 10km spatial and annual temporal resolution of the snake species presence/absence data is not sufficient to be used in distribution modelling of selected snake species. Distribution modelling of widespread species in both geographic and environmental space, as is the case the *Malpolon monspessulanus* and *Rhinechis scalaris* species, are generally more difficult and complicated than species with more specific spatial distributions such as *Hemorrhois hippocrepis*.

4. The applied method to generate potential food availability did not result in satisfactory representative. Bias and uncertainties were high in both, snake specie distribution and allocating foraging areas.

5. The above mentioned issues leads to the conclusion that hypothesis of species-food distribution, at least as here interpreted between the Short-toed Eagle and three selected snake species, is impermanent until fundamental issues of scale and resolution are adequately take into consideration and resolved.

6. The methodological framework employed in this study was simple, robust and replicable. Environmental favourability function and Maximum Entropy Models provided a powerful basis for testing hypothesis and assessed possible impacts of considering the potential food availability on the Short-toed Eagle distributions.

5.2. Recommandations

1. Re-test the hypothesis using hyper temporal resolution species distribution datasets and/or new potential food availability indices (e.g. snake richness/abundance) that may have physiological relevance for the Short-toed Eagle and/or their assemblages.

2. Test the hypothesis that there is a spatio-temporal relationship between diurnal activities of the prey species and the Short-toed Eagle.

3. Test the hypothesis that the critical parameter of the ecosystem in breeding habitat (nest-site location) may differ from foraging/hunting habitat of the Short-toed Eagle.

4. In addition, a second nested analysis for the prey snake species at a local scale (Malaga province extent) can reveal other features that characterise habitat (species distribution) at a national level. A multi-scale perspective may add new discernment to the current knowledge of inter-species (prey and predator) relationships.

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7. Appendices

7.1. App. I – List of Variables

ID	Layer Name	Definition	Unit	References
1	Tmin1	Minimum Temperature in January	(ºCx10)	11
2	Tmin2	Minimum Temperature in February	(ºCx10)	11
3	Tmin3	Minimum Temperature in March	(ºCx10)	11
4	Tmin4	Minimum Temperature in April	(ºCx10)	11
5	Tmin5	Minimum Temperature in May	(ºCx10)	11
6	Tmin6	Minimum Temperature in June	(ºCx10)	11
7	Tmin7	Minimum Temperature in July	(ºCx10)	11
8	Tmin8	Minimum Temperature in August	(ºCx10)	11
9	Tmin9	Minimum Temperature in September	(ºCx10)	11
10	Tmin10	Minimum Temperature in October	(ºCx10)	11
11	Tmin11	Minimum Temperature in November	(ºCx10)	11
12	Tmin12	Minimum Temperature in December	(ºCx10)	11
13	Tmax1	Maximum Temperature in January	(ºCx10)	11
14	Tmax2	Maximum Temperature in February	(ºCx10)	11
15	Tmax3	Maximum Temperature in March	(ºCx10)	11
16	Tmax4	Maximum Temperature in April	(ºCx10)	11
17	Tmax5	Maximum Temperature in May	(ºCx10)	11
18	Tmax6	Maximum Temperature in June	(ºCx10)	11
19	Tmax7	Maximum Temperature in July	(ºCx10)	11
20	Tmax8	Maximum Temperature in August	(ºCx10)	11
21	Tmax9	Maximum Temperature in September	(ºCx10)	11
22	Tmax10	Maximum Temperature in October	(ºCx10)	11
23	Tmax11	Maximum Temperature in November	(ºCx10)	11
24	Tmax12	Maximum Temperature in December	(ºCx10)	11
25	Tmean1	Mean Temperature in January	(ºCx10)	11
26	Tmean2	Mean Temperature in February	(ºCx10)	11
27	Tmean3	Mean Temperature in March	(ºCx10)	11
28	Tmean4	Mean Temperature in April	(ºCx10)	11
29	Tmean5	Mean Temperature in May	(ºCx10)	11
30	Tmean6	Mean Temperature in June	(ºCx10)	11
31	Tmean7	Mean Temperature in July	(ºCx10)	11
32	Tmean8	Mean Temperature in August	(ºCx10)	11
33	Tmean9	Mean Temperature in September	(ºCx10)	11
34	Tmean10	Mean Temperature in October	(ºCx10)	11
35	Tmean11	Mean Temperature in November	(ºCx10)	11
36	Tmean12	Mean Temperature in December	(ºCx10)	11
37	Pre1	Mean Precipitation in January	(mm)	11

ID	Layer Name	Definition	Unit	References
38	Pre2	Mean Precipitation in February	(mm)	11
39	Pre3	Mean Precipitation in March	(mm)	11
40	Pre4	Mean Precipitation in April	(mm)	11
41	Pre5	Mean Precipitation in May	(mm)	11
42	Pre6	Mean Precipitation in June	(mm)	11
43	Pre7	Mean Precipitation in July	(mm)	11
44	Pre8	Mean Precipitation in August	(mm)	11
45	Pre9	Mean Precipitation in September	(mm)	11
46	Pre10	Mean Precipitation in October	(mm)	11
47	Pre11	Mean Precipitation in November	(mm)	11
48	Pre12	Mean Precipitation in December	(mm)	11
49	Bio1	Annual Mean Temperature	(ºC)	11
50	Bio2	Mean Diurnal Range (Mean of monthly (max temp - min	(ºC)	11
51	Bio3	Isothermality (P2/P7) (* 100)	(ºC)	11
52	Bio4	Temperature Seasonality (standard deviation *100)	(ºC)	11
53	Bio5	Max Temperature of Warmest Month	(ºC)	11
54	Bio6	Mean Temperature of Wettest Quarter	(ºC)	11
55	Bio7	Temperature Annual Range (P5-P6)	(ºC)	11
56	Bio8	Mean Temperature of Wettest Quarter	(ºC)	11
57	Bio9	Mean Temperature of Driest Quarter	(ºC)	11
58	Bio10	Mean Temperature of Warmest Quarter	(ºC)	11
59	Bio11	Mean Temperature of Coldest Quarter	(ºC)	11
60	Bio12	Annual Precipitation	(mm)	11
61	Bio13	Precipitation of Wettest Month	(mm)	11
62	Bio14	Precipitation of Driest Month	(mm)	11
63	Bio15	Precipitation Seasonality (Coefficient of Variation)	(mm)	11
64	Bio16	Precipitation of Wettest Quarter	(mm)	11
65	Bio17	Precipitation of Driest Quarter	(mm)	11
66	Bio18	Precipitation of Warmest Quarter	(mm)	11
67	Bio19	Precipitation of Coldest Quarter	(mm)	11
68	NDVI1	NDVI in early April	Scaled 1-255	12
69	NDVI2	NDVI in mid April	Scaled 1-255	12
70	NDVI3	NDVI in late April	Scaled 1-255	12
71	NDVI4	NDVI in early May	Scaled 1-255	12
72	NDVI5	NDVI in mid May	Scaled 1-255	12
73	NDVI6	NDVI in late May	Scaled 1-255	12
74	NDVI7	NDVI in early June	Scaled 1-255	12
75	NDVI8	NDVI in mid June	Scaled 1-255	12
76	NDVI9	NDVI in late June	Scaled 1-255	12
77	NDVI10	NDVI in early July	Scaled 1-255	12
78	NDVI11	NDVI in mid July	Scaled 1-255	12
79	NDVI12	NDVI in late July	Scaled 1-255	12
80	NDVI13	NDVI in early August	Scaled 1-255	12
81	NDVI14	NDVI in mid August	Scaled 1-255	12
82	NDVI15	NDVI in late August	Scaled 1-255	12
83	NDVI16	NDVI in early September	Scaled 1-255	12

ID	Layer Name	Definition	Unit	References
84	NDVI17	NDVI in mid September	Scaled 1-255	12
85	NDVI18	NDVI in late September	Scaled 1-255	12
86	NDVI19	NDVI in early October	Scaled 1-255	12
87	NDVI20	NDVI in mid October	Scaled 1-255	12
88	NDVI21	NDVI in late October	Scaled 1-255	12
89	NDVI22	NDVI in early November	Scaled 1-255	12
90	NDVI23	NDVI in mid November	Scaled 1-255	12
91	NDVI24	NDVI in late November	Scaled 1-255	12
92	NDVI25	NDVI in early December	Scaled 1-255	12
93	NDVI26	NDVI in mid December	Scaled 1-255	12
94	NDVI27	NDVI in late December	Scaled 1-255	12
95	NDVI28	NDVI in early January	Scaled 1-255	12
96	NDVI29	NDVI in mid January	Scaled 1-255	12
97	NDVI30	NDVI in late January	Scaled 1-255	12
98	NDVI31	NDVI in early February	Scaled 1-255	12
99	NDVI32	NDVI in mid February	Scaled 1-255	12
100	NDVI33	NDVI in late February	Scaled 1-255	12
101	NDVI34	NDVI in early March	Scaled 1-255	12
102	NDVI35	NDVI in mid March	Scaled 1-255	12
103	NDVI36	NDVI in late March	Scaled 1-255	12

References:
11- WorldClim http://www.worldclim.org/current.htm
12- Spot Vegetation http://www.spot-vegetation.com/
13- Shuttel Radar Topography Mission http://www2.jpl.nasa.gov/srtm/
14- Europian Environmental Agency, CORINE land cover http://www.eea.europa.eu/themes/landuse/clc-download

7.2. App. II – Independent preditors for *Malpolon monspessulanus*

ID	Predictors	Description	VIF
Smm01	ndvi06	Average NDVI in late May	8.190
Smm02	ndvi10	Average NDVI in early July	6.729
Smm03	ndvi15	Average NDVI in late August	6.015
Smm04	ndvi21	Average NDVI in late October	4.771
Smm05	ndvi35	Average NDVI in mid March	5.413
Smm06	per3	Average precipitation in March	5.347
Smm07	per10	Average precipitation in October	7.119
Smm08	tmax2	Maximum temperature in February	3.987
Smm09	tmax3	Maximum temperature in March	1.889
Smm10	tmean1	Mean temperature in January	5.517
Smm11	tmean12	Mean temperature in December	7.059
Smm12	tmean3	Mean temperature in March	4.327
Smm13	tmean5	Mean temperature in May	8.389
Smm14	tmin4	Minimum temperature in April	5.486
Smm15	tmin3	Minimum temperature in March	3.210
Smm16	tmin2	Minimum temperature in February	4.267
Smm17	tmin12	Minimum temperature in December	3.312
Smm18	tmin11	Minimum temperature in November	4.076
Smm19	tmin10	Minimum temperature in October	2.579
Smm20	bio11_cl	Mean temperature of coldest quarter	7.518
Smm21	bio15_cl	Precipitation seasonality (Coefficient of variation)	4.562
Smm22	bio1_cl	Annual mean temperature	1.404
Smm23	bio2_cl	Mean diurnal temperature range	2.850
Smm24	bio3_cl	Isothermality	1.573
Smm25	bio6_cl	Minimum temperature of coldest Month	3.834
Smm26	bio8_cl	Mean temperature of wettest quarter	1.903
Smm27	bio9_cl	Mean temperature of driest quarter	1.629
Smm28	alt_clip	Elevation	1.096
Smm29	slope	Slope	1.450
Smm30	south_deg	South direction, "southness"	1.012
Smm31	Corine	Corine land cover	1.011

7.3. App. III – Independent preditors for Rhinechis scalaris

ID	Predictors	Description	VIF
Srs01	ndvi06	Average NDVI in late May	7.313
Srs02	ndvi10	Average NDVI in early July	6.909
Srs03	ndvi15	Average NDVI in late August	5.323
Srs04	ndvi21	Average NDVI in late October	3.568
Srs05	ndvi35	Average NDVI in mid March	5.101
Srs06	tmax2	Maximum temperature in February	5.478
Srs07	tmax3	Maximum temperature in March	3.234
Srs08	tmax9	Maximum temperature in September	2.029
Srs09	tmean1	Mean temperature in January	6.989
Srs10	tmean12	Mean temperature in December	6.047
Srs11	tmean3	Mean temperature in March	2.994
Srs12	tmin4	Minimum temperature in April	7.177
Srs13	tmin3	Minimum temperature in March	3.217
Srs14	tmin2	Minimum temperature in April	4.183
Srs15	tmin12	Minimum temperature in December	3.162
Srs16	tmin11	Minimum temperature in November	4.146
Srs17	tmin10	Minimum temperature in October	5.833
Srs18	bio11_cl	Mean temperature of coldest quarter	8.147
Srs19	bio1_cl	Annual mean temperature	2.007
Srs20	bio6_cl	Minimum temperature of wettest quarter	3.147
Srs21	bio8_cl	Maximum temperature of wettest quarter	1.307
Srs22	bio9_cl	Mean temperature of driest quarter	1.560
Srs23	alt_clip	Elevation	1.137
Srs24	South_deg	South direction, "southness"	1.012
Srs25	slope	Slope	1.326
Srs26	Corine	Corine land cover	1.011

7.4. App. IV –Independent preditors for *Hemorrhois hippocrepis*

ID	Predictors	Description	VIF
Shh01	ndvi06	Average NDVI in late May	7.840
Shh02	ndvi10	Average NDVI in early July	7.580
Shh03	ndvi15	Average NDVI in late August	6.897
Shh04	ndvi22	Average NDVI in early November	4.718
Shh05	ndvi35	Average NDVI in mid March	4.553
Shh06	per1	Average precipitation in January	5.759
Shh07	per4	Average precipitation in April	7.612
Shh08	per6	Average precipitation in June	6.494
Shh09	per10	Average precipitation in October	6.348
Shh10	tmax1	Maximum temperature in January	8.402
Shh11	tmax3	Maximum temperature in March	2.001
Shh12	tmean1	Mean temperature in January	4.724
Shh13	tmean12	Mean temperature in December	6.031
Shh14	tmean4	Mean temperature in April	8.991
Shh15	tmean5	Mean temperature in May	8.806
Shh16	tmin4	Minimum temperature in April	5.012
Shh17	tmin3	Minimum temperature in March	2.706
Shh18	tmin2	Minimum temperature in February	4.737
Shh19	tmin12	Minimum temperature in December	3.361
Shh20	tmin11	Minimum temperature November	3.253
Shh21	tmin10	Minimum temperature in October	3.991
Shh22	bio2_cl	Mean diurnal tempreture range	2.531
Shh23	bio3_cl	Isothermality	1.388
Shh24	bio6_cl	Minimum temperature of wettest quarter	4.406
Shh25	bio8_cl	Maximum temperature of wettest quarter	1.865
Shh26	bio9_cl	Mean temperature of driest quarter	1.401
Shh27	alt_clip	Elevation	1.096
Shh28	south_log	Logarithmic South direction, "southness"	1.018
Shh29	slope	Slope	1.481
Shh30	Corine	Corine land cover	1.131