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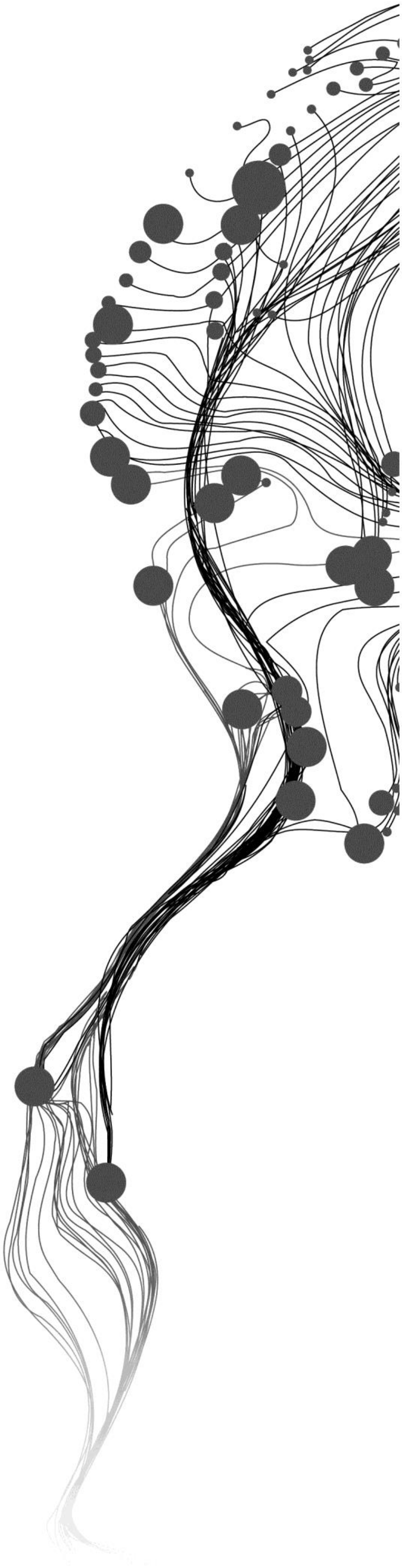

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ABSTRACT

Long eared owls (*Asio otus*) in Crete are common agricultural species affected by the recent changes in agro-forestry systems. Therefore concrete studies of habitat selection are needed to improve the knowledge about the behaviour of the species inside intensively managed landscapes. We analyzed animal home range size and habitat selection of Long-eared owl inside the agricultural area of Crete using radio tracking data and ASTER VNIR images. Land cover classification of the area was produced and landscape contextual information was extracted for two different scales – nominal scale predictors derived from ASTER VNIR images and landscape scale predictors derived from the land cover map. These were used to predict habitat selection at two different scales using maximum entropy approach. At nominal scale distance to potential roost sites was most important contributor to model performance, followed by NDVI heterogeneity. Furthermore, local heterogeneity of primary productivity was better predictor than simply primary productivity at presence location. At landscape scale the amount of open areas improved model performance significantly. Again, incorporating landscape contextual information improved habitat selection prediction compared to using only discrete land cover classification. Home range size was between 337 and 1768 ha (kernel methods). Considerable degree of segregation of home ranges was observed suggesting animals defend hunting territories. Results of our study confirm finding from similar research in other parts of the Mediterranean – Long-eared owls have a wide range of habitat tolerance preferring mixed habitat conditions but avoiding too open areas or dense olive plantations. The research has implication in the face of new reforms of European common agricultural policy which emphasized the importance of landscape structure in preserving biodiversity inside the agricultural areas of Europe.

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1. INTRODUCTION

1.1. Background

Mediterranean island ecosystems have rich biodiversity determined by their unique historical development, small size, and relative isolation from mainland Europe (Rigueiro-Rodróguez et al, 2008). However, the same factors also make them vulnerable to rapid land development (Vogiatzakis & Rockham, 2008). In Crete island, for example, significant land use changes occurred after Greece's inclusion in the EU (Yassoglou & Kosmas, 2000). Improvements in agricultural technology and better trade have led to abandonment of traditional agricultural practices and intensification of olive tree cultivation in accessible lowlands. These changes resulted in biodiversity loss and lowered ecosystem resilience (Papanastis et al., 2009).

At the same time these areas are important biodiversity and research hotspots (Vogiatzakis & Rockham, 2008). Crete is the final European stop over along the migration path of European migratory birds (e.g. Oppel et al., 2015), while lowland areas provide mild winter climate for short distance migrants (Tzortzakaki, Simaiakis, & Xirouchakis, 2012). Therefore, scientist emphasized the importance of conserving the areas in an effort to stop the ongoing landscape degradation and preserve the rich biodiversity present on the islands (Tzatzanis, Wrbka, & Sauberer, 2003). In line with this call, the second major revision of the EU's Common Agricultural Policy (CAP) sets a long term objective to shift land use practices towards more sustainable forms of use. To achieve this goal, policy makers in the EU will have to rely on accurate assessments of the impact of current policy measures through active research and monitoring of these systems.

Assessment of the efficiency of agricultural policy can be inferred through long term monitoring studies of focal animal groups (Carignan & Villard, 2002). Long-eared owl (*Asio otus* Linnaeus, 1758) has been extensively studied in other parts of its geographical range, which makes it ideal focal species for comparative research. It is typical farmland species relying both on open areas for hunting but also forest edges and coniferous tree groups for nest sites. Current dynamic changes in agro-forestry systems in Crete (Papanastasis, 2004) will likely affect this species. Therefore, research is needed to identify its preferred habitats inside intensively managed landscapes of Crete. Indeed, there is lack of concrete habitat

Figure 1.1 Messara plain. Flat alluvial plain in southern Crete is mainly used for olive production

preference studies for the species inside Crete Island. Research in other parts of the Mediterranean region have shown that owls hunt mainly along the field or forest edges (Galeotti, Tavecchia, & Bonetti, 1997; Cecere, Bombino, & Santangeli, 2013; Bartolommei, Mortelliti, Pezzo, & Puglisi, 2013).

In the lowland agricultural area of Messara plain Long-eared owls gather at communal roost during the winter with as much as 60 individuals present inside a small group of pine trees (Xirouchakis, personal communication). They also use pine trees and small groupings as daily roost sites, while mostly hunt by flying over open areas (Glutz von Blotzheim & Bauer, 1980). The plain is an intensively managed agricultural area in the island dominated by olive-tree plantations, vineyards, and citrus plantations. Land ownership is divided into small parcels creating significant heterogeneity within the plain. It has been shown that cultivation and management methods may have effect on wintering raptors in the area (Tzortzakaki et al., 2012).

In order to survive in certain area, the main habitat requirements of Long-eared owls such as food rich open patches of grasslands, and nest and roost site availability should be met at least in the minimum level. Therefore, it is likely that configuration of such landscape elements will determine the availability of breeding and hunting grounds, thus affecting habitat selection of Long-eared owl. What are the exact habitat requirements, and the extent of the habitat relevant for Long-eared owl when making decisions for movement, are unknown. More detailed look into the apparent range of perception and habitat preference inside its breeding home range should help to identify what is the appropriate scale to study landscape structure and which properties of landscape are important for Long-eared owl survival inside Messara plain. This in turn can guide future management decisions.

1.2. Research objectives

The aim of this work is to analyse home range size and habitat selections of this medium sized nocturnal bird inside intensively managed Mediterranean agricultural landscape. Medium resolution remote sensing images were used to classify the agricultural landscape and produce a detailed land cover map of the study area. Then landscape structure characteristics were derived and were used to study habitat preference using non-parametric statistical algorithm (Phillips et al., 2006)(Figure 1.2). The three main research objectives were:

(1) Mapping highly heterogeneous landscape of Messara plain using ASTER VNIR images,

(2) Analysing individual Long-eared owls home range,

(3) Modelling habitat selection strategy of Long-eared owl in response to landscape characteristics.

1.3. Research questions

What is the average home range size of Long-eared owls in Messara plain?

Do long-eared owls prefer open habitats for hunting?

What is Long-eared owl selection towards of heterogeneous habitat?

At what scale is the effect of heterogeneity perceived by the animals?

1.4. Research hypothesis

H_0: Average home range size is equal to sizes in other regions.
H_1: Average home range size is smaller than other regions.

H_0: Long-eared owls in Messara prefer uniform habitat conditions.
H_1: Long-eared owls in Messara prefer more heterogeneous habitats.

H_0: Probability of Long-eared owls using a location does not depend on degree of openness of surrounding habitat.
H_1: Probability of Long-eared owls using a location increases with increase of openness of surrounding habitat.

H_0: Heterogeneity of NDVI calculated for different window sizes contribute equally to model gain.
H_1: There is certain window size of NDVI heterogeneity which maximizes gain.

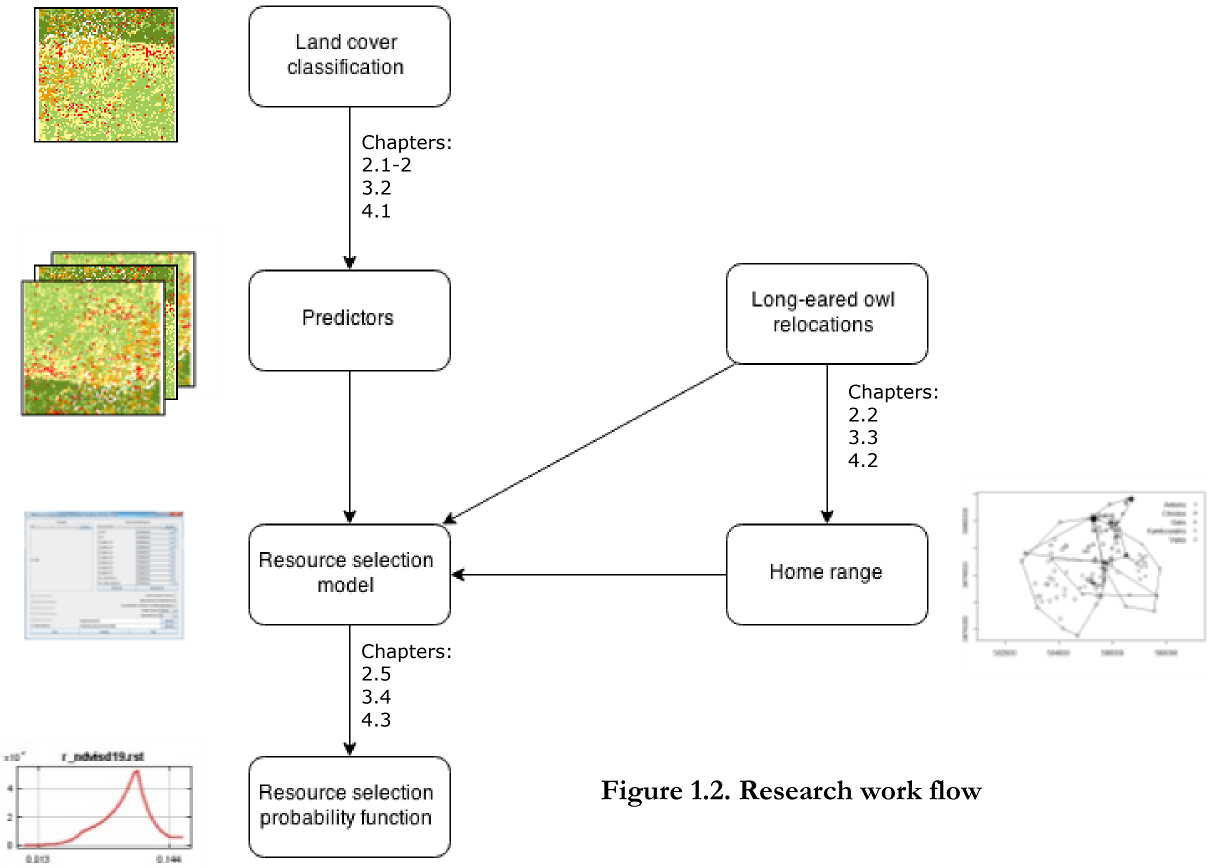


Figure 1.2. Research work flow

2. LITERATURE REVIEW

The following section previews studies and concepts relevant to this thesis. First, a background on Long-eared owl biology is given to make us familiar with the animal under study. Then, a short review focuses on the importance of deriving good estimation of land cover. Finally, a summary of the resource selection framework is tried with the intention to give an overview of main concepts in such studies and challenges associated with analysis of animal resource use. More in depth discussion on some relevant points is placed in grey boxes in order to make reading easier.

2.1. Long-eared Owl behavior and studies in the Mediterranean

Long-eared Owl (*Asio otus* L., 1758) is a bird species from family typical owls (Strigidae) distributed across most of the Holarctic region. In Europe owls reach northern Scandinavia and Russian taiga region. It is mostly sedentary but during harsh weather birds from central European population migrate south to Mediterranean islands and northern Africa (Atlas Mountains), south Turkey, Levant region, and as far south as northern Egypt along the Nile River. It can be observed across wide elevation range. It breeds from the lowland oak areas to the upper forest belt in good food years[1] ("BirdLife International," 2012). The owl has relatively small body and wide wing length (♂ 298.9 mm ± 7.1, ♀ 303.4 mm ± 5.7) resulting in a relatively low wing loading[2]. This adaptation reflects the main hunting strategy of the bird – mainly by flight in relatively open areas. It will also hunt from perches when available but is not dependent on them. Preferred hunting grounds in Europe are forest edges, agricultural edges, grass fields, meadows, and bog, but if owl competition is high, also sparse forests are visited for hunting (Galeotti et al., 1997).

Long-eared Owls utilize stick nest build by crows (*Corvus* sp.) mostly on conifer trees located at the forest edges, in small tree groups across fairly open landscapes, but also on seldom trees. Territorial behaviour is observed only if the resources are not sufficient. Thus, social behaviour is common in food rich areas where conspecifics share hunting resources and defend only nearby nest territory (Glutz von Blotzheim & Bauer, 1980). This social behaviour extends to the wintering season when large groups of birds gather at communal roosts. Roosts are common in gardens, parks, or cemeteries and are often associated with food rich areas around settlements. Communally roosting birds disperse nightly into nearby home ranges to hunt; these on average 20.3 km^2, though only c. 20% of range used each night; these smaller areas were possibly used by individuals exclusively (Wijnandts, 1984).

Long eared Owls feed on small mammals (prey weight 31.2 ± 0.13 g), main prey group is voles (Arvicolinae) and mice (Murinae). Shrews are taken to a much lesser extent[3] and some authors suggest active dislike shown towards this group (Birrer, 2009 and citations within). Not surprisingly there is a big variability in the diet across Europe and during the seasons (Birrer, 2009). With increase of forested hunting grounds the proportion of wood mouse (*Apodemus sylvaticus*) and bank vole increase (*Myodes glareolus*) while field vole (*Microtus agrestis*) and field mouse (*Apodemus spp*) become less abundant in the diet. Prey species composition in the diet also changes from higher to lower latitudes. Populations in northern

[1] There is a distinct cyclic fluctuations in abundance of small mammal, very prominent in northern Europe and less so in more mild southern climates

[2] Ratio between wing area and body mass

[3] Unlike sympatric *Tyto alba* (e.g. Milchev et al., 2006)

part of the areal feed on few main pray species (main prey group is voles) (Marti, 1976), while diet composition becomes more diverse to the south of Europe (especially in the Mediterranean basin). This is mainly due to greater variability of habitats and diversity micromammalian fauna in the Mediterranean. Winter diet is in general more diverse with sometimes significant increase of proportion of birds (mainly wintering passerines) (Cecere et al., 2013).

Overall wide geographical range suggests that this species tolerates wide array of environmental and climatic conditions. It is therefore regarded as one of the most common and widespread owl species in Europe. However, estimating the exact numbers and population size is difficult because of strictly nocturnal activity (at least in the temperate region), low vocalization, and secretive behaviour around roost sites. Long-eared owl is listed as Least Concern in the IUCN Red List due to its extensive geographical range, but population trend is believed to be decreasing and further studies are needed to validate population estimates ("BirdLife International", 2012). Nevertheless, classical census estimations studies tend to be less accurate for cryptic and nocturnal animals with low detectability rate. In such cases distribution models and expert knowledge are useful for refining population estimates, and guide conservation practice in areas with significant number of individuals. Improving on the knowledge of home range size and habitat selection is then important first step in understanding the species requirements for specific areas.

Several studies have analysed the habitat preference of Long-eared owls in Mediterranean agricultural landscapes, however olive groves are not the dominant land cover type in these studies. Martínez & Zuberogoitia (2004) analysed the habitat preference of the Long-eared owl in Mediterranean semi-arid landscape in southeast Spain, where the dominating land cover type was dry arable lands. The study identified environmental features that are preferred by the owls at three spatial scales – nest site, home range, and landscape. At the home range scale significant predictors of site occupancy were open areas, forest edges, and low human disturbance. A similar study from central Italy (Bartolommei et al., 2012) analysed the presence of nocturnal birds in relation to variables describing extent and configuration of seven main land use type. Similarly to the previous study, the authors find that long-eared owl presence depends on the proportion of arable land, small scale cultivations, and household areas.

Landscape heterogeneity is the primary factor for higher biological diversity in Crete (Benton, Vickery, & Wilson, 2003) and important factor for Long-eared owls (Lucio & Atauri, 2001). Mediterranean mixed agricultural areas provide high prey diversity Cecere et al.(2013). Indeed, Long-eared owl diet in Mediterranean show higher species diversity compared to other regions (Birrer, 2009; Escala et al., 2009) confirming its opportunistic strategy towards food selection and suggesting birds hunt along diverse habitats conditions. However, more diverse food diet might also suggest low prey densities forcing birds to utilize more diverse food sources in order to survive. In any case, it is likely that diversity of habitat conditions will have significant effect on where the bird selects to breed and hunt.

2.2. Measuring landscape structure

Mediterranean intensive agricultural areas are dominated by olive plantations and exhibit significant spatial and temporal diversity (Lucio, 2001). Normally, deriving landscape characteristics is done through visual interpretation of aerial photographs (e.g. Martínez & Zuberogoitia, 2004). Alternatively, GIS methods can be used to derive predictors. On the other hand, landscape heterogeneity metrics relating to extent of habitat, composition of patches, and spatial configuration of landscape patches can be derived from discrete land cover maps. These have been used to describe relationship between species and landscape structure (Bennett, Radford, & Haslem, 2006). However, definition of land cover classes is not always in line with what is relevant for the species. More often habitat maps are produced general purposes accommodating range of applications.

Meso-scale habitat map of Crete was produced by (Sarris et al., 2005) based on 14 habitat categories from Habitats Directive plus water, residential and agriculture classes. The authors classified Crete from LANDSAT-7 ETM images using object oriented classification method aided by visual image interpretation. They suggest that high resolution remote sensing (RS) products would be needed to derive better separability of agricultural classes inside mixed human dominated landscapes. Indeed, remote sensing products with very high resolution have already been used to study olive plantations in regards to estimating productivity of olive plantations (Torres et al., 2008) or for quantification of soil erosion (Karydas et al., 2009) showing good accuracy in separating olive canopy from soil. A standardized method for monitoring agricultural productivity and landscape structure inside olive groves can be beneficiary for ecological research as well.

Medium spatial resolutions data are widely available with new Landsat (USGS, 2015) and Sentinel (ESA, 2015) missions. Their relatively low cost and consistency provide good trade-off between cost and applicability and make them ideal for long term land monitoring applications. In addition, new land surface cover estimations are being developed and are expected to be available in near future (Copernicus, 2015). These will improve spatially explicit population models and other types of predictive or habitat suitability analysis. Still, discrete fine scale land cover maps will be needed to model landscape structure. Therefore, classification of highly heterogeneous olive plantation using combination of medium resolution RS image and mixed classification approach can produce useful habitat map for studying animal resource use.

For this study, predictors were extracted from ASTER VNIR satellite images with nominal resolution of 15 m. Predictors are derived either directly from the ASTER images or from the land cover map produced for this study. Hence they convey information at two spatial scales – nominal scale of 15 meters for ASTER derived predictors, and landscape scale with minimum resolution equating the minimum patch size. In addition, several features of landscape were measured on the ground and locations of coniferous trees were recorded. In general, predictors fall in the following three categories: land cover, information on surrounding context, and distance to spatial objects with importance for the survival of the animals (e.g. roads, conifers). Two separate habitat selection models were built to reflect on the scale difference in the predictors and study which spatial scale predicts better habitat selection.

2.3. Perceptual range

Resource selection studies aim at quantifying the process of selection by animals. Therefore, they are built with intention to provide explanation and are regarded mostly as explanatory model. In such cases variable selection should be done on the basis of ecological interpretability. Garton et al. (2001) recommends a priori selection of set of candidate variables with a biological basis for inclusion. At small scales the immediate context of the surroundings becomes important, especially in highly mobile species such as birds. Thus, when the landscape context is used as a predictor, a question arises on the proper scale at which to calculate the landscape structural properties[4]. One way to decide on the scale for which to calculated landscape metrics is to use the species range of perception. It is a concept widely used in

[4] Landscape structure indices are derived by summarizing the landscape surrounding the focal pixel. A moving window of predefined size calculates the needed statistics for all pixels. Applied for the entire area the operation produces a map with same resolution, where each pixel value is the outcome of the focal calculation.

landscape connectivity analysis. Perceptual range is defined as the maximum distance from which an animal can perceive the presence of remote landscape elements such as patches of habitat (Zollner, 2000). It is important parameter in individual-based spatially explicit population models as it will determine the dispersal capabilities of animals in fragmented landscapes. Active research is done to derive a measurement on the extent of animal's horizon. Generally, crude measure of perceptual range is derived through experimental translocation of individuals to novel areas and studying their behaviour.

2.4. Analysing animal home range and resource selection

Analysing animal space use in relation to environmental covariates falls under the broad category of resource selection studies. Although descriptions of animal use of resources is available from as back as 1920's, numerical methods for estimation of selection were developed recently (Manly et al., 1993). They were aided by developments in the fields of statistics and computer science. Special section of Journal of wildlife management reviewed the subject with the goal to guide wildlife researchers in their choice of appropriate methods for analysing animal-habitat use (Dale & Mcdonald, 2006). The validity of certain methods have been discussed (Johnson et al., 2006) and call for unification of fields widely separated before proposed (Moorcroft, 2008). Nevertheless, the field is still relatively new and active research is underway.

Resource selection studies make use of standard sampling design for wildlife studies e.g. transect or random plots, but also more advanced data provided by radio-telemetry (Hirzel & Guisan, 2002). In former case response variable is often in binomial form of used vs. unused resource units which allow for the use of general linear or additive models (Hastie & Tibshirani, 1990). Other methods include Compositional analysis (Aebischer, Robertson, & Kenward, 1993), discrete-choice modelling (M Dale Strickland & Mcdonald, 2006). However, more often there is no estimation of unused resources, e.g. when using radio-telemetry. This has led to development of statistical procedures comparing used vs. available resources summarized in four study designs depending on the kind of species data available and how is resource availability defined (Manly et al., 1993) (Box 1.)

Resource use / availability studies are built on the ground that if resources are used disproportionate to their availability they improve animal fitness (Thomas & Taylor, 2006). The main concept in resource selection studies is the resource selection probability function (RSPF). It describes how likely is that certain environmental resources are chosen by the animal (Figure 2.1 a) (Manly et al., 1993; Strickland & Mcdonald, 2006). However, direct estimation of RSPF is impossible since it is an unknown probability density function from which we have representative sample in form of collected observations. In such cases, a function proportional to RSPF can be derived by weighing the distribution of available resource units to the distribution of used resource units (Figure 2.1). Statistical models based on use-availability

Box 1. Study design for resource selection function based on resource use / availability data.

In Design I studies individual animals are not separable and inference can be made on the entire population. Data often comes from standard point or transect counts and unused resources are either also known or estimation of available resources is calculated based random sample plots. On the contrary, Design II studies define individual animals, often using radio-telemetry data. However, resource availability is defined for the entire population e.g. using GIS or remote sensing methods. For Design III and Design IV resource use is again identified for each individual while availability is uniquely identified for each individual and each observation respectively. For further explanations and appropriate methods for analysing resource selection refer to Manly et al. (1993) and Millspaugh (2001).

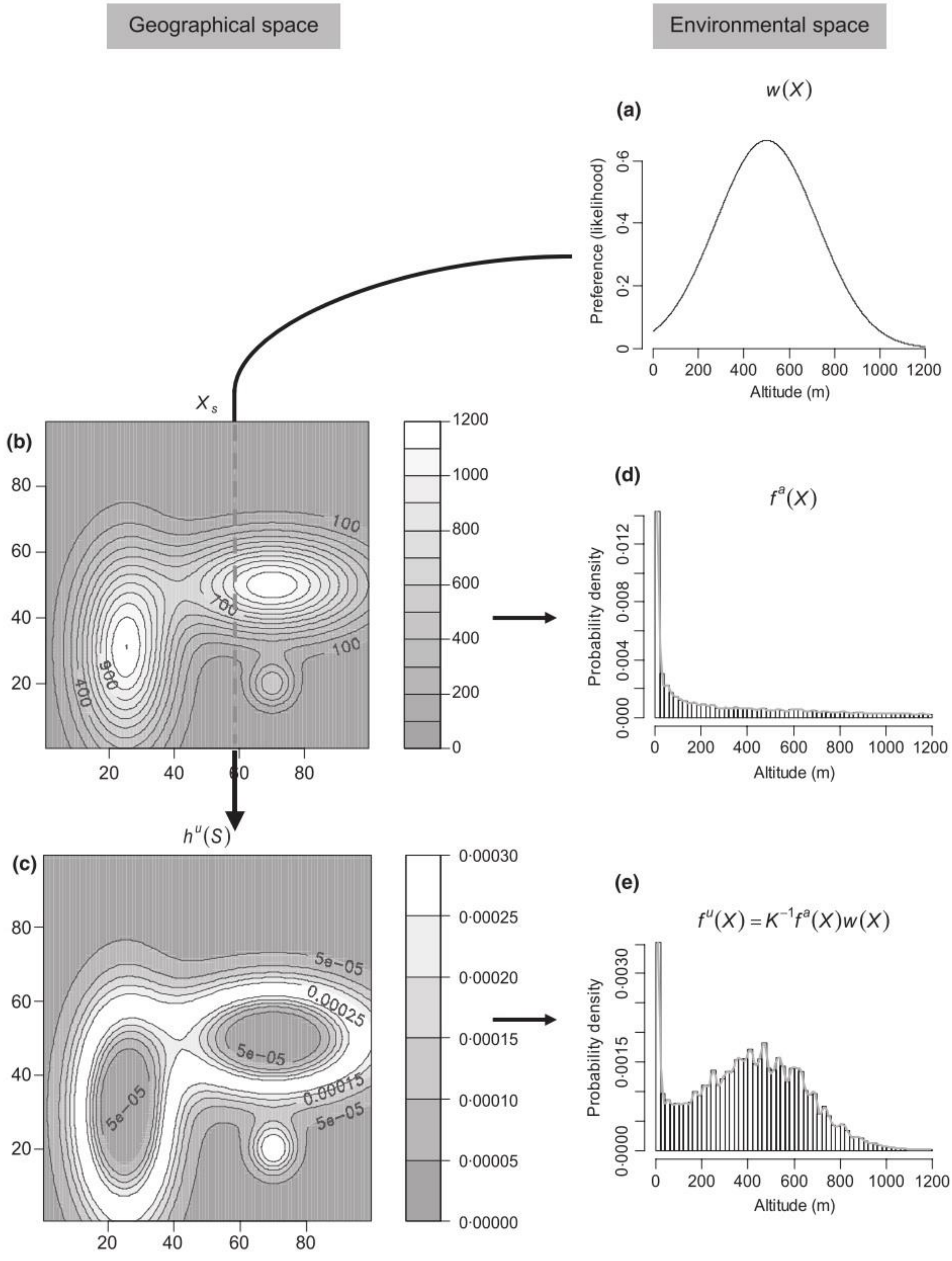


Figure 2.1. Clarifying the interpretation of usage, availability and preference in gegraphical and environmnetal space. The preference function (a) describes the likelihood that particular value of an environmental condition is selected if offered. Individuals move within a landscape in which environmental resources are heterogeneously distributed (b). Furthermore, resources are not equally available (d). Animal will choose the environmental conditions proportional to its preference, resulting in expected geographical distribution (c). Sites belonging to preferred habitats will be used most often (e). If the use of habitats (e) is divided by their availability (d) resulting RSF is proportional to (a). Adapted from: Aarts, Fieberg, & Matthiopoulos (2012)

study design allow for estimated the resource selection function (RSF) which is proportional to the theoretical resource selection by the animal. The rationale is that disproportionate use corresponds to higher preference towards resources. Such models have strong applications in wildlife and natural resource management (Strickland & Mcdonald, 2006), land use planning, and spatial explicit population modelling (Perry & Bond, 2013).

Defining resource availability correctly is critical for subsequent inference about resource selection (Thomas & Taylor, 2006). According to Manly et al. (1993) availability is the amount of accessible resources during certain period of time. There is an implicit assumption of equal accessibility of all habitat patches within the study area (for other assumptions regarding resource selection studies see Box 2). Available habitats are therefore defined from study area boundaries in specific temporal and spatial scale. Therefore choice of appropriate scale – study area boundaries and temporal frame, affects RSF as it will determine the amount and proportion of available resources for the animal. If scale is poorly defined the estimated amount of available resource will differ from the true available resources and render the resource selection analysis invalid.

Box 2. Assumptions associated with radio tracking data

Resource selection studies rely on strong assumptions(Aebischer et al., 1993). These can be broadly associated with the form of the statistical function and the biological theory. Species data normally is not collected without error. Uncertainty in **positional accuracy** can bias the estimated resource selection and have the general effect of lowering the accuracy of resource selection function by adding additional variability to the model. Telemetry studies should include estimation of positional error. GPS collars provide more accurate estimate and most importantly, explicitly inform the users on locational accuracy.
Independence among individuals means that sampled individuals are representative sample from the whole population and inference applies to the whole population. Obtaining independent sample of individuals from the population is, however, difficult task because of the effort needed to capture, locate and track animals. Often this assumption is violated and inference on the population should be done with this in mind. There are several ways of determining independence among individuals. For example, three dimensional Moran’s I statistic can be used to evaluate correlation between two individual radio tracking time series provided that they have been sample at the same temporal scale.
Another important assumption when dealing with radio-tracking data is **independence between relocations**. Observations from the same individual are inherently correlated especially in cases when relocations are taken at short intervals. Time to independence is a statistic trying to quantify how much time should last until two consecutive observations can be regarded independent from each other. There is obviously a trade-off between ensuring statistical robustness of collected data and information gained. Alternatively, when using logistic regression and relocations as the experimental unit (design I) adjustments can be made using auto logistic regression models.
Other common assumptions in resource selection studies, more related to species behaviour and environmental conditions are:

- **optimal use of space,**
- **equal access to all available resources,**
- **and constant resources**.

The former assumption is based on optimal foraging theory that animals act in such way as to maximize overall fitness of the population. Assumption of equal access to resource is often violated when animals are territorial and the way of dealing with it is to analyse resource selection inside each individual home range (second order selection). Dynamic nature of natural systems is in direct contrast to the last assumption of constancy in resource units. Nevertheless, most of the studies are performed for a short period of time to meet this assumption.

Animals selection towards the environment conditions can be at different scales (D. H. Johnson & Prairie, 1980). Resource selection occurs at species range scale, population, home range, habitat patch, and sites (Table 2.1)(Meyer & Thuiller, 2006). Following this framework, extent and grain size of study area should be dictated by one of selection order. Furthermore, grain size should equate the one step lower than extent in the selection order in the framework. For example, study at home range scale (second order selection) should define the study boundaries as the boundaries of individual home range of animal, while grain size should coincide with minimum patch (third order selection). In practice however, grain size is often set by data availability and sampling design.

Table 2.1. Hierarchical selection orders in studying species habitat interaction. Adapted from Meyer & Thuiller (2006)

Order	Biological level	Scale of used area within available habitat	Comment and examples
0	Species	Geographical range within world or parts of world	Biodiversity assessment, Climate change
1	Population	Regions containing populations within geographical ranges	Reserve design, land-use planning.
2	Individual	Home ranges within regions	Reintroduction, habitat management, conservation of used sites
3	Individual life requirement at patch scale	Patches within home ranges	
4	Individual life requirement at local scale	Microhabitats within used patches	Protection or creation of key life-history attributes

Equivalence of used/available and presence only methods in species distribution modelling (SDM) have been known for some time (Warton & Aarts, 2013). Hence, presence only methods in SDM can be transferred to resource selection analysis. MaxEnt approach (Box 3) for example weighs used locations to background locations – a representative sample of the available resources. Produced response curves by the model also known as the "raw" output give insight about relative resource use in form of response curves. If species does not express preference towards the environmental condition, the result will be flat response curve because the probability density function (PDF) of environmental covariates at presence locations (used resources) is similar to the PDF of resources across the landscape. This corresponds to the null hypothesis of no active preference, e.g. use is proportional to availability. Higher relative resource use is observed when the utilized resources (presence locations) are disproportionate relative to their availability. In other words, active preference toward these environmental conditions is observed. Hence response curve can be used to interpret relative resource preference.

For second order selection (Table 2.1) available resources are defined by animal's home range. Therefore, good estimate of to where an animal constrains its movements is important for accurately describing resource use. However there is a considerable debate to what exactly is home range. Definition of home range has been developing over the years portraying the advancement in biological and ecological science. Home range was first described as the area traversed by an animal during its normal activity (Burt, 1943). Later, to accommodate the use of more advanced statistical procedures, home range was defined from probabilistic perspective as the "extent of an area with defined probability of occurrence of an animal during specific time period" (Horne & Garton, 2006) Recently home range was defined in terms of cognitive science as the areas which an animal decides to keep updated in its cognitive map (Powell & Mitchell, 2012).

Estimating home range shape and size has since been an uneasy task and various statistical methods have been developed to approximate animal home range. Two of most reported home range estimation are based on minimum convex polygon and kernel methods. Convex hull methods estimates home range as the minimum area which includes certain percentage of points. The proportion of excluded points is arbitrary and often 5% of the furthest away points is used as threshold. However, sample size affects home range estimate(Burgman & Fox, 2003). Furthermore, there is no ecologicaly meaningful reason to select any threshold and studies should report both sample siza and MCP estimate based on all observations to facilitate comparability (Millspaugh et al., 2006). Kernel methods (Worton, 1989) gained popularity and have been widely used in habitat selection studies, home range, and behavioral studies(Millspaugh et al., 2006). By applying a bivariate kernel over the point a probability density surface is created showing the probability of finding the animal at any given time. This surface is termed utilization distribution (UD). Bandwidth controls the smoothness of the probability density surface. High bandwidth values tend to over smooth the surface and smaller values tend to converge to the actual point pattern. We analysed individual home ranges as well as joint UD of all animals to infer on the population level extent of habitat use. However, we set the study boundary to include locations more far away from the estimated home ranges to include potential dispersal habitats as well as to set a broader resource availability.

Box 3. Statistical explanation MaxEnt

MaxEnt is software widely used for modelling species distribution. The methodology was developed from the field of machine learning and since its introduction to the ecological community it is most common method used to predict species distribution. According to recent inquiry in Google Scholar, the conference proceeding by S. Phillips, Dudík, & Schapire (2004) 2004 has been cited 851 time, while the follow-up article with in depth explanation of MaxEnt approach from machine learning perspective by S. J. Phillips, Anderson, & Schapire (2006) has been cited by 4251 research articles. Good predictive accuracy and relative ease of implementation are some of the reasons for its popularity among ecological community. Nevertheless, the statistical algorithm behind the scene remains difficult to comprehend by non-statisticians and it is widely regarded as black box model.
Uninformed use can indeed lead to inaccurate and biased results. A more comprehensible statistical explanation for MaxEnt for ecologist was published by Elith et al. (2011), providing break from the machine learning terminology. In addition, any future research should consult very useful paper by Merow, Smith, & Silander (2013) which provides comprehensive explanation on how to set the appropriate parameter values to be used in MaxEnt algorithm. In fact, MaxEnt provide the users with wide range of choices for optimization of model parameters and the choice is not always straightforward but nevertheless very important for the outcome of the analysis.

Box 3. (Continued)

The popularity of MaxEnt is widely because it gives an alternative for analysing so called presence-only (PO) animal observations, moving away from traditional binomial presence-absence observations. The former type of animal records is much more prevalent, as they are easier to collect. However, PO does not come with an estimate of unsuitable environmental conditions which in turn does not allow treatment of the response as a binary variable. Therefore using classical statistical approaches such as GLM or GAM is not possible. MaxEnt goes around this problem by using presence-only data to approximate the unknown probability density function of environmental covariates from which the presence location derive. The idea of maximum entropy approach is to find the distribution which maximizes the relative entropy in geographical space (note that MaxEnt actually minimizes relative entropy in environmental space) while approximations also should satisfy constrains that the estimated moments of the distribution match the empirical average of PO. (S. Phillips et al., 2004)

Entropy is a concept drawn from information theory. It is a measure of information uncertainty. The principle of maximizing entropy was first used in natural language processing. The principle states that given prior testable information about a probability distribution, the real probability distribution from which the prior was derived is the one with maximum information entropy.

There several notations used in MaxEnt literature. Here notations proposed by Trevor Hastie were used, where: L is the landscape (or a random sample thereof); y=1 and y=0 denote presence and absence response respectively; z is vector of environmental covariates; $f_1(z)$ denotes the probability density function (PDF) of environmental covariates at presence locations, $f_0(z)$ denotes PDF of environmental covariates at absence locations; f(z) is PDF of environmental covariates across L subject to constrains.

To find the best PDF MaxEnt algorithm estimates the gain function – a penalized maximum likelihood estimation which in effect minimizes the Kullback-Leibner (KL) distance between the environmental conditions at presence locations $f_1(z)$ and the environmental conditions across the landscape $L = f(z)$ (background in MaxEnt terminology). Then the Bayes rule gives:

$$\Pr(y=1|\boldsymbol{z}) = \frac{f_1(\boldsymbol{z})\,\Pr(y=1)}{f(\boldsymbol{z})}$$

Where Pr(y=1) is the prior probability of finding the animal at certain location, e.g. its prevalence in the area. With PO data it is impossible to know the prevalence of the species and without any prior expert knowledge it is set to 0.5 in MaxEnt. Following maximum entropy principle, best solution of the problem is obtained by minimizing the relative entropy (Kullback-Leibner divergence) between the two probability density functions – distance between $f_1(z)$ and $f(z)$. This is sensible because with no observations one would have no prior knowledge about the preference of the species and will estimate the environmental covariates for the species $f_1(z)$ simply proportional to their availability in the landscape $f(z)$.

MaxEnt can model complex relationships between $f_1(z)/f(z)$ using transformations of the original environmental covariates z in the background. The expanded set of transformed covariates is called features h(z). Using transformation of the original variables is useful when interactions or nonlinear responses are expected. However, such transformations often results in highly complex and difficult to interpret response curves. Currently there are five transformations of the original data which can be used depending on desired complexity and the amount of observation points – linear, quadratic, product, threshold, and hinge features.

3. METHODS

The methodology is divided into three parts: (1) deriving predictors from medium resolution ASTER VNIR images, (2) exploratory data analysis on Long-eared owl relocations, and (3) analysis of habitat preference at home range and landscape scales. First, remote sensing data were used to classify the agricultural landscape and produce a detailed land cover map of the study area (Section 3.2.4). This was needed to reflect on the fine scale at which Long-eared data was collected. Field work was conducted to collect ground control points for validating the land cover map. Then landscape structure characteristics related to openness and diversity of the habitat were extracted both from the land cover map and from the original images. In the second step, exploratory data analysis on relocations were performed to ensure data meets assumptions and in order to define the extent of available habitats (Section 3.3). Finally, environmental predictors and Long-eared owl relocations were used to study habitat preference using MaxEnt (Section 3.4).

3.1. Study area

Messara plain is an agricultural area located in southern Crete (35° 2' 45" N, 24° 56' 17" E). With an area of 112 km^2 it is the biggest alluvial plain on the island (Figure 3.1). The plain has elongated shape with a slope gradient from east to west direction reaching Mediterranean coastline to the west. In easterly direction Messara plain slowly rises and the landscape gradually changes to a hilly terrain very typical for the island. To the north and south the plain faces steep mountain slopes shielding it from air masses coming from these directions. From east to the west a riverbed forms indentation in the soft alluvial soil.

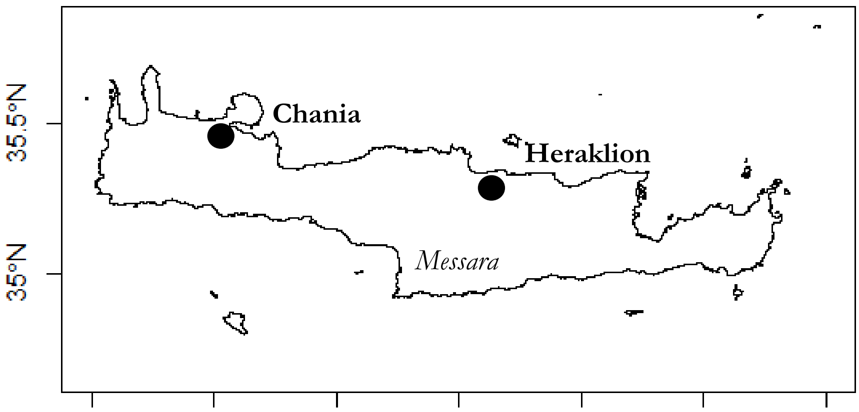


Figure 3.1. Crete island. Messara plain is located in the southern part of the island. Ref.system: UTM35, datum:WGS84

The climate is typical Mediterranean with a long and dry summer and relatively warm and rainy winter season. Messara plain is located south of the central mountain ridge of Crete which stopping northern wet air masses and minimizing the amount of rain from wet air coming from the north. Summer dry season is very prominent with no rainfall for as long as six months. Nevertheless, water table is high due to the permeable rocks in Crete. Mean summer temperatures reach 30 °C and average winter temperatures is around 2 °C. Snow is not present.

3.2. Analysis of land cover and deriving landscape characteristics

3.2.1. Field work

Field work was carried out from 19th September until 15th October 2014. The main goal was collecting descriptive data regarding the land cover in the plain and gathering ground control points to be used for accuracy assessment in remote sensing image classification.

3.2.1.1. Sampling scheme

Field plots were sampled following stratified random sampling scheme. Additional sampling effort was focused on classes with small proportional representation to ensure the number of plots per information class is sufficient for statistical inference. In cases when direct visit to plots was not possible they were relocated to the nearest accessible area from the same class.

Geographical coordinates were recorded in WGS84 Geographical Coordinate System using mobile application for Android – OfflineMaps[5], and handheld smartphone device – Moto XT1032 (Motorola Inc.). Visual assessment of positional accuracy of device in the field was possible by consulting the aerial photos stored in the handheld device. In addition, plot position was adjusted to coincide with the centre of the target class in order to minimize the number of mixed pixels in the subsequent image analysis. Fields or olive plantations smaller than 60x60 meters in size were avoided as such plots would have occupied a mixed pixel in the image.

3.2.1.2. Recording on the ground

Main vegetation class and addition characteristics were recorded for every sample plot. Seven main land cover types were identified in the study area: olive tree plantation, vineyards, irrigated vegetable fields, annual crop fields, riparian vegetation, phrygana, settlements or other build up areas (e.g. greenhouses). Additional measurements of heterogeneity in plot included: height of trees and crown diameter, distance between trees, proportion of grass vegetation/soil and rock cover, existence of irrigation system (Table 3.1).

Table 3.1. Measurements taken during fieldwork

Measurement	Describtion
Land cover	One of following classes: olive tree plantation, vineyards, irrigated vegetable fields, annual crop fields, riparian vegetation, phrygana, settlements
Understory vegetation	Proportion of vegetation on the ground (%)
Soil proportion	Proportion of soil on the ground (%)
Rock proportion	Proportion of rocks on the ground (%)
Distance between trees	Planting distance (m) inside the olive plantations
Irrigation	Presence of irrigaiton pipes - binomial (yes/no)
Mean Height	Tree height averaged over ten trees inside the plot (m)
Mean Crown	Crown diameter averaged over ten trees inside the plot (m)
Suitability	Subjective assesment of suitability for small mammals

[5] This application stores freely available geo-products such as open street maps high resolution aerial photographs and other available geo-referenced maps for offline view. Reported accuracy of the device was monitored and measurements taken after ensuring horizontal positioning accuracy of +- 3 meters.

Tree height measurements were taken using TruPulse 360 optical range finder (Laser Technology Inc.). The accuracy of the product is 0.1 m. Tree height and tree crown were measured for 10 individual trees and later summarized into one mean value for height and crown diameter, thus *assuming all trees are same size*. Understory vegetation cover was estimated visually as percentage coverage on the ground between four trees and recorded as percentage in steps by 10%. The presence of irrigation pipes was also recorded and a reference image was taken for further inquiries if needed. In addition, Coniferous trees scattered as small groups across the region were recorded. In total 300 localities were visited from which 149 were olive stands. In the subsequent analysis only 131 of the olive plots were used after excluding unusually behaving plots in the preliminary data exploration.

3.2.2. Estimating canopy structure

Olive trees are planted with regular spacing to enable the use of agricultural machines between the trees. Distance between trees and average crown size were used to estimate canopy cover (Figure 3.2). Distance between trees (a and b on Figure 3.2) was measured as an index of openness. Then, canopy cover was calculated as the area of the average crown divided by the index of openness. This estimation lies on the assumption that olive tree crown has relatively circular shape:

$$CC = \frac{\pi r^2}{ab},$$

where *a* and *b* are the distances of olive spacing in the plantation and *r* is the radius of the model tree in the plot.

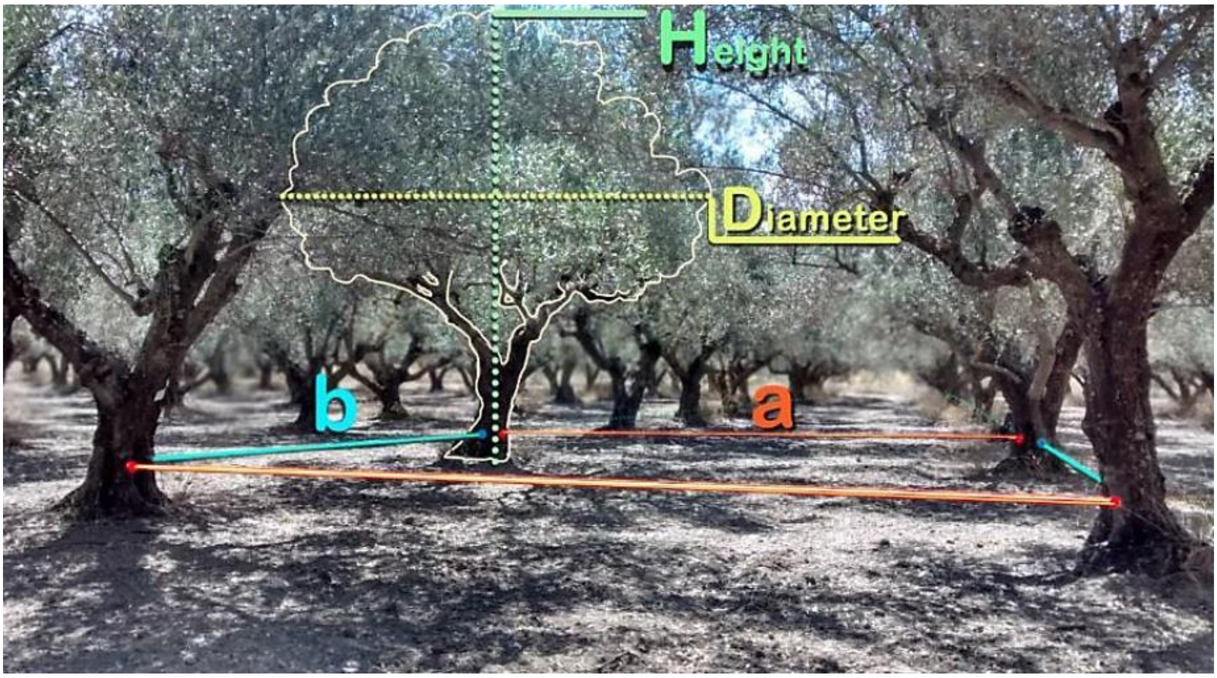


Figure 3.2 Olive grove sample plot and the measurements taken inside the plot

3.2.3. Image acquisition and pre-processing

Since 2012 ASTER SWIR sensor experiences anomalies which led to permanent shut down of thermal infrared sensor thus bands 4 through 9 are no more available. For this study we were able to make use of four bands of the VNIR sensor (Table 3.2) as well as ASTER Global DEM with a spatial resolution of 30 meters provided as advanced level product of METI and NASA. ASTER DEM product accuracy depends on ruggedness of terrain and comparative study of several DEM showed significant deviation in estimation of elevation from ASTER (Hirt, Filmer, & Featherstone, 2010). Cloud free, radiometricaly and geometrically corrected ASTER L1B scene was obtained from site ttps://lpdaac.usgs.gov/data_access maintained by the NASA Land Processes Distributed Active Archive Center (LP DAAC), USGS/Earth Resources Observation and Science (EROS) Center, Sioux Falls, South Dakota, (2015).

Table 3.2. ASTER VNIR band characteristics

Band	Label	Wavelength	Resolution
B1	VNIR_Band1	0.52 - 0.6	15m
B2	VNIR_Band2	0.63 - 0.69	15m
B3	VNIR_Band3N	0.76 - 0.86	15m - Nadir

3.2.4. Classification

Pixel based classification was performed using algorithm based on a variant of Bayes theorem named Dempster-Shaffer theory(Cayuela, Golicher, Rey, & Benayas, 2006). A key advantage in using Dempster-Shaffer logic is the explicit expression of degree of uncertainty both in regards to separability between classes and completeness of classes e.g. whether there is an undefined class (Box 4).

Seven information classes were extracted from the ASTER images (Figure 4.2). The proportion of riparian and coniferous vegetation inside the study area is negligible and therefore these classes were excluded from the analysis. Two build-up classes were needed because of the different spectral signal from the GREENHOUSE and other RESIDENTIAL areas. Furthermore, these two classes have different meaning. Most populated areas have low density infrastructure mixed with gardens or even olive tree plantations, while artificial structures are mostly lone standing big buildings inside agricultural landscape. Field data was used to evaluate the accuracy of the produced land cover map using error matrix and kappa statistics for accuracy assessment.

Land cover classification was an iterative process in which information classes were defined and training sites selected based on expert knowledge and classification uncertainty reported by Dempster-Shaffer model. Training plots were digitized using false colour composite and NDVI image as reference. In process accuracy assessment (IPAA) also included computing and examination of believe interval to identifying areas of high uncertainty. In addition, separability among classes was computed using transformed divergence method. Training plots were taken until sufficient separability is reached (around 2000 for transformed divergence). Digital elevation model was used to identify and correct low elevation phrygana. Dempster-Shafer beliefs were converted into hard classification to produce the final land cover map (Figure 3.3).

We also wanted to know how good ASTER images describe the vegetation on the ground and see if a continuous index of heterogeneity can provide useful information for the processes and situation on the ground. Therefore we derived a set of indices from the ASTER image and regressed them against the canopy cover estimation to see how these are related and whether any index can be used as a proxy for canopy cover in the region.

Table 3.3. Land cover classification used for Messara study area

Land cover type	Description
ANNUAL CROPS	Wheat is the most common annual crop in Messara plain. It is harvested by the end of spring season or in early summer. During the field visit crop plots were identified by the remains of dry wheat on the ground
OLIVE PLANTATIONS	The most common land use class in Messara plain is olive grove. Olive trees are planted in regular intervals to facilitate agricultural activities such as intercropping, removal of grasses and harvesting of production
VINEYARD	Relatively common in the western part of the study area, vineyards are planted in rows
IRRIGATED VEGETABLE FIELDS	Intensively managed fields, which are planted with different vegetable varieties throughout the season
PHRYGANA	Low, soft-leaved scrubland plant community located mostly in the northern hilly part of the study area
RESIDENTIAL	Low intensity residential areas are concentrated in several villages
ARTIFICIAL	Greenhouses, warehouses or other lone standing structures with high spectral response

Box 4. Dempster-Shafer theory and IPAA

Maximum likelihood method based on Bayesian theorem assumes that defined information classes are exhaustive and represent all possible classes. That is there are no unknown classes and even the smallest evidence for any given class is enough to classify the pixel to that class. Dempster Shaffer theory acknowledges the possibility of an unknown class. In the language of Dempster Shaffer theory that is known as level of ignorance – ones inability to commit to any class. The algorithm first assigns basic probabilities (m or BPA) based on the training set for all singleton classes and possible combinations of classes. These probabilities do not sum to unity and the remaining quantity is the degree of ignorance. Dempster-Shaffer algorithm then proceeds to quantify belief for each class. Belief for a given hypothesis equals the sum of all BPA, e.g.

$$BEL[A,B] = m[A] + m[B] + m[A,B]$$

For singleton classes belief and basic probability assignment are equal, e.g.

$$BEL[A] = m[A]$$

Belief in any given class represents the total support for a hypothesis or the hard evidence that hypothesis is true. For now everything is similar to maximum likelihood estimator.

(Box 4 continued)
Plausibility on the other hand is a measure of the degree to which a hypothesis cannot be disbelieved, e.g. it shows the degree that certain hypothesis appears to be right. In other words, there is no other evidence contradicting the hypothesis. Plausibility in one hypothesis is unity minus belief in all other alternative hypothesis.

$$PL[A] = 1 - \ BEL[!A]$$

Finally, belief interval is calculated as the difference between plausibility and belief and represents degree of uncertainty. For example, consider the case of strong belief for a given hypothesis (information class) while belief in the alternative hypothesis is weak. Plausibility then will be close to one, thus there is strong evidence for the hypothesis. Belief interval on the other hand will be small.
Contrary, if belief for the same hypothesis is low and non for the alternative hypothesis then classification uncertainty rises. In this case plausibility will still be high since there is no other contradicting hypothesis. However, since belief is relatively low, the belief interval (or classification uncertainty) will be wider than the previous case. Thus, using Dempster-Shaffer theory one have the ability to assess accuracy of the classification procedure on the fly and select training sites accordingly

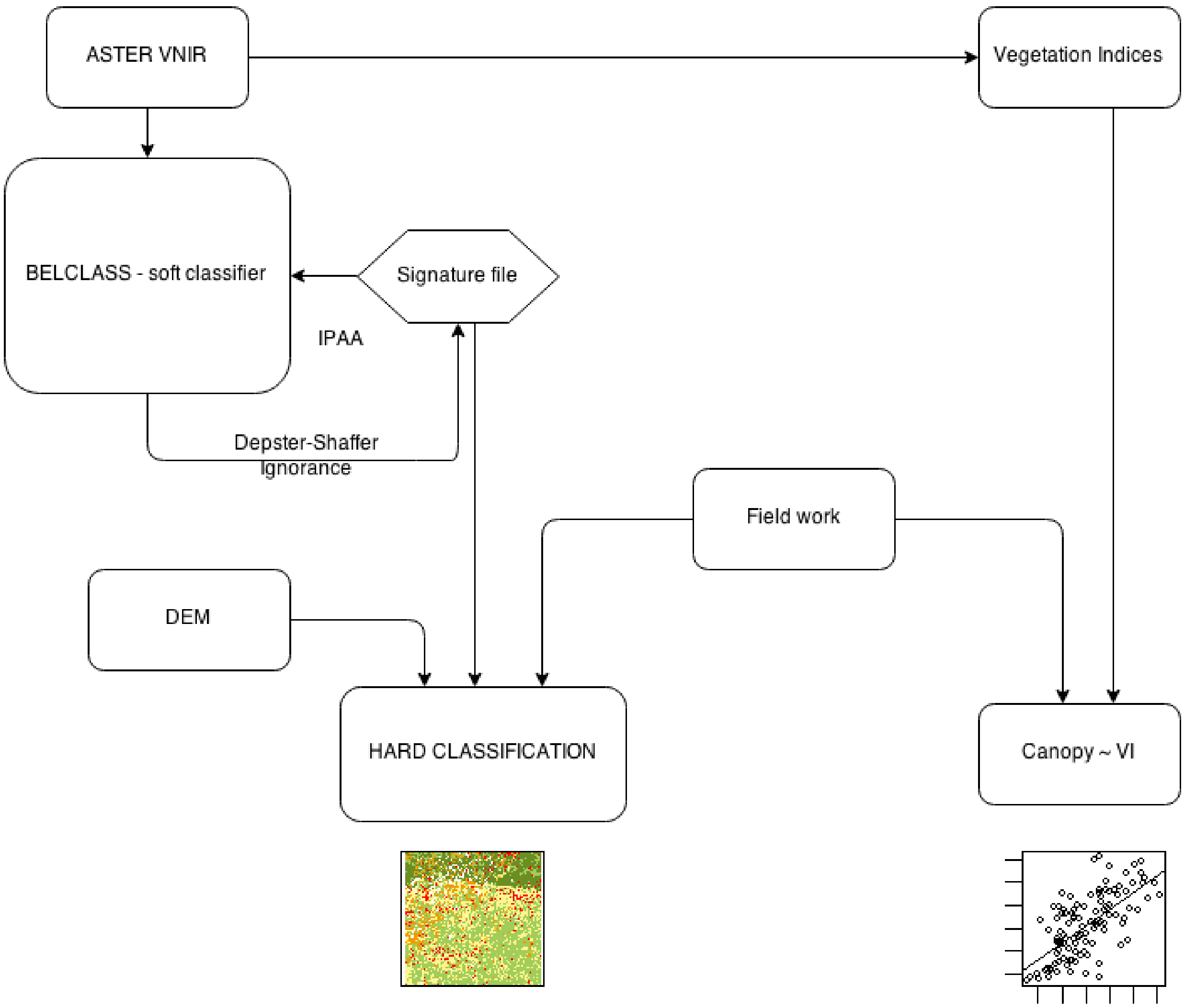


Figure 3.3 Flowchart of ASTER image analysis

3.2.5. Landscape context predictors

Landscape metrics at different spatial scales were calculated to summarize the landscape heterogeneity on the ground. Pixel size of ASTER VNIR sets the limit for the minimum possible uniform patch of landscape. In this respect, the first set of explanatory landscape variables are derived directly from the three bands of ASTER VNIR sensor (Table 3.4). Materials have specific spectral responses which are used to differentiate and infer on the state of the above ground vegetation. By comparing the values of red and near-infrared spectral response is used to describe the phonological stage of vegetation. Three vegetation indices (VI) were used to test the hypothesis that medium resolution remote sensing can predict the vegetation structure on the ground. The three VI were regressed against canopy cover and 1000 replicate bootstrap was performed to derive mean coefficient of determination. Then r^2 values were compared for significant difference using ANOVA test. The VI having best association with canopy cover on the ground was used as predictor in the habitat selection model. Contextual heterogeneity was using standard deviation filter.

Table 3.4 Vegetation indices derived at 15m spatial resolution

Spectral index	Description
NDVI	Normalized difference vegetation index is the first and most widely used index for above ground green biomass. It is based on the high contrast observed between red and NIR absorption features of healthy vegetation. Values range from -1 to 1 with higher values indicating more and healthier green vegetation.
PVI	Perpendicular vegetation index is the main distance based vegetation index. It can take values between -1 and 1 having same interpretation as NDVI.
PC1 PC2 PC3	Principal components are created by orthogonal projection of three spectral bands to derive new three uncorrelated values. The first PC accounts for the main variation in all three bands and it is a measure of overall brightness of the image. Second principal component is proxy for green vegetation.

Measurements of heterogeneity from land cover map were derived using FRAGSTATS (McGarigal et al., 2012) by applying moving window (Table 3.5). Heterogeneity measures were selected based on analysis of correlations and interpretability. Selected predictors are related to area, composition, and diversity of habitat patches.

Very useful fundamental statistic is percentage of each land cover class (PLAND) surrounding the focal cell. Radio-tracking observations come with an unknown error, therefore, considering the surrounding land cover instead of only land cover at observation location can guard from error due to radio-sampling bias.

Shannon's diversity index (SHDI) was used as a measure for local habitat diversity. Value of SHDI can be interpreted as the probability of two randomly selected pixels belonging to the same information class. Smaller values represent relatively uniform habitat. Increase in value corresponds to more diverse habitat (more information classes). The index was calculated at each spatial location (pixel) using moving window 180x180m size. SHDI is the most commonly used estimate of that sort.

Aggregation index (AI) measures how compact the land cover types are inside the study window. It counts the number of like adjacencies, which is the number of borders shared by cells from the same class. A chessboard like pattern would yield AI value of zero, while absolutely uniform landscape will have AI value of 100 %. AI does not inform on how many different classes are present rather it shows the degree to which the cells from the same class are close to each other. However, more information classes will result in less like adjacencies; hence AI has strong negative correlation to SHDI.

Table 3.5. Heterogeneity indices. Landscape contextual information related to local variability of green vegetation (NDVIsd), composition (AI), diversity, and size of patches were calculated using moving window filter.

Heterogeneity index	Comments
$NDVIsd = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \overline{x})^2}$	n = size of the window (number of pixels included) xi = NDVI inside the window xbar = mean NDVI for the window
$PLAND = P_i = \frac{\sum_{j=1}^{n} a_{ij}}{A}\ 100$	P_i = proportion of landscape occupied by class i. a_{ij} = area(m^2) of patch ij. A = total landscape area (m^2).
$SHDI = -\sum_{i=1}^{m}(P_i * lnP_i)$	P_i – proportion of landscape occupied by patch type (class) i
$AI = \left[\sum_{i=1}^{m}\left(\frac{g_{ii}}{max \to g_{ii}}\right)P_i\right](100)$	g_{ii} = number of like adjacencies (joins) between pixels of patch type (class) i based on the single-count method max ->g_{ii} = maximum number of like adjacencies (joins) between pixels of patch type (class) i based on the single-count methods P_i = proportion of landscape comprised of patch type (class) i. AI is 0 when patch types are maximally disaggregated and 100 when there is only one single patch. At landscape level this index is calculated as area-weighted average where the class is weighted proportionally to its presence in the focal radius.

3.3. Analysis of Long-eared owl relocation data

3.3.1. Data collection and exploratory data analysis

Long-eared Owls (*Asio otus* L., 1756) were equipped with VHF radio transmitters (Bio Track Inc.) during the winter months (November- February) of years 2010 to 2011 in Messara plain, south Crete. Trap locations is a regularly visited roost site located in the northern part of Messara plain in the foothills of the northern mountainous region. It is a small pine stand (*Pinus brutia* Ten.) consisting of around 30 mature pines. Tagged individuals were monitored for a period of four to seven months corresponding to the life expectancy of the transmitters. From thirteen tagged individuals, four were found dead and two transmitters had malfunctioned.

Individuals were traced using omni-directional whip car antenna until visual contact was possible. Sufficient amount of relocations (adequate for analysis of home range) were collected for five individuals due to time constrains (personal communication). The locations were noted on a 1:100 000 paper map and digitized into Hellenic Geodetic Reference system using ArcGIS v.10.0 (ESRI 2011). Individual birds were named with male Greek names for better recognition. Study duration and intensity of relocations (relocations/day) were calculated for each of five individuals.

All analysis was performed using R statistical software (R Core Team, 2015).

3.3.2. Independence of observations

Data points represent a sample from all possible location the individuals might have been for the period of study. Therefore, resource selection analysis will be valid if the assumption of independence of sample points in *time* is true. Point locations were tested for temporal randomness using Ripley's K function modified for one dimension. The logic is that if points are sampled randomly, the number of observation in any time window should follow the theoretical Poisson distribution with intensity λ equal to overall intensity of relocations. Ripley's K function is calculated as

$$K(h) = \frac{1}{\lambda}\, E(N_h),$$

where N_h is the number of events within circle with centre a random chosen event and radius *h* and λ is overall intensity of points for each individual.

Study time frame was selected to coincide on the earliest possible date with observation and end with the last observation from any individual. This way all observations can be included in the analysis. Bootstrap randomisation was used to generate 95% confidence envelope for the theoretical K expected under complete randomness assumption. Under the null hypothesis of randomness the true (observed) K(h) value should fall within the randomisation envelope. The assumption of temporal randomness is rejected if the true K is outside the 95% confidence interval

3.3.3. Home range and utilization distribution

Home range (HR) size was calculated as the area of the minimum convex polygon (MCP) containing all relocations. It was included mainly to facilitate comparability between past or future studies. MCP seldom used for drawing conclusions because it lacks statistical robustness and it is sensitive to sample size, monitoring duration, and outliers. HR estimate using this method should be interpreted with caution because unusually far away observations tend to inflate HR estimate. Therefore, it is advisable to check the gain in HR size using only certain percentage of the points closest to the centroid.

A more appropriate home range estimate is based on the Utilization distribution (UD). Bivariate normal kernel was chosen for calculating probability density function. The smoothing kernel parameter was calculated using *ad hoc* reference method (Silverman, 1986):

$$h = \sigma n^{-\frac{1}{6}}$$

where

$$\sigma^2 = 0.5(var(x) + var(y))$$

The alternative method for bandwidth selection is based on finding the minimum least-squares solution; however, in this case mean integrated square error could not be minimized. Home range calculation was performed using `adehabitat` package for R (Calenge, 2006).

3.4. Analysis of habitat preference of Long-eared owl

3.4.1. Model building and predictor selection

At the final stage of this research Long-eared owl relocation[6] data and environmental covariates were used to model the resource selection behaviour of Long-eared owl population inside Messara (second order selection in Table 2.1). Environmental predictors were divided into two categories based on their semantics and minimum scale and two separate models were built with the two groups of predictors (Table 3.6). Nominal scale model included predictors derived directly from ASTER images, hence conveying the finest spatial information possible. In contrast, second group of predictors was based from the land cover classification produced for the purpose of this study (Section 3.2.4). The land cover map is a product of aggregation of the remote sensing information into more interpretable and relevant landscape description, from which landscape contextual characteristics were extracted. However, it also adds a new layer of uncertainty to the model. Thus we wanted to see how different predictor types perform in fine scale habitat selection modelling applications. Model settings were the same for both models to ensure comparability between the two spatial scales.

Table 3.6. Predictors used in the resource selection model

Predictors	Description	Minimum information class†
Nominal level		
NDVI_s	Normalized Difference Vegetation Index – estimate of above ground green vegetation for spring and autumn	15x15 m
NDVIsd	Standard deviation of NDVI calculated for moving window of 9x9 pixel.	135x135 m
DIST_roads	Distance to roads	15x15 m
DIST_conif	Distance to coniferous trees	15x15 m
Landcover level		
LC	Land cover classification of the area produced in this study. (previous section)	Minimum patch size
ELEV	Elevation estimated from ASTER DEM product	30x30 m
PLAND1,2,3,4,5,6,7	Percentage of land cover for each land cover type within 90 m radius drown around the focal pixel	180x180 m
SHDI	Shannon's Diversity Index – commonly used estimate of landscape diversity in ecology	180x180 m
AI	Aggregation index – measure whether same class pixels are aggregated or dispersed inside the study window	180x180 m

† Pixel resolution used in MaxEnt was 15m

[6] The terms locations, observations and relocations are used interchangeably throughout the thesis to refer to Long-eared owl radio-tracking data points. While first two are most common across Species distribution studies and data analysis in general, relocations is specifically used to describe the ordered sequence of observations describing the movement pattern of a specific individual.

3.4.1.1. Elevation

Elevation (ELEV) was derived from raster DEM product at 30m spatial resolution. Elevation was resampled to 15 m using bilinear resampling method in IDRISI Selva. Accuracy of the DEM has been subject of debate Although ASTER DEM has a finer spatial resolution it has been shown that DEM produced by NASA's SRTM at 90 m nominal spatial resolution is more accurate and consistent.

3.4.1.2. Perceptual range

Animal's perceptual range is defined as extent of the habitat which is relevant when making decisions for movement. The hypothesis that there is an optimum perceptual range of habitat selection for Long-eared owl was tested using landscape context indices at different spatial scales. Standard deviation filter was applied using range of window sizes on autumn NDVI image. In total 12 window sizes were used from 5x5 until 27x27 pixels. Then, MaxEnt model was fit on each of the twelve NDVISD predictors separately using only hinge features (Box 3). Model performance statistics were evaluated to choose the appropriate window size for deriving contextual information.

3.4.2. Study area boundary selection and background data selection

Landscape boundary should include potentially available sites. It was defined as the area around the observation points adding two km from the last observation. This amounts to half the maximum distance between observations. Representative sample of 10000 background points was used to describe the available resource units across the landscape. Given the small study area it was sufficient amount for representative estimation environmental conditions. Random seed was set to a constant to guarantee same set of points is selected for each model, ensuring comparability between results.

3.4.3. Model parameterization

Both MaxEnt models were built using only hinge features in order to minimize the complexity of the model and aid easier interpretation of resulting response patterns. Hinge features enable piecewise linear model similar to GAM to be fitted to data, producing flexible and interpretable response curves. Maximizing the gain was done until either the improvement in gain was below a predefined convergence value or at the 500th iteration. Default convergence threshold of 0.0001 was used. Roughly half of the iterations for both models ended before reaching the maximum iterations limit. Regularization parameter λ was also set to the default value provided by MaxEnt as advocated by Elith et al. (2011)

3.4.4. Model Evaluation

Area under the receiver operation curve (ROC) was used as a measure of relative model performance of the two competing models. Tenfold cross-validation was used to produce one standard deviation error bands for response curves and ROC. Mean AUC values after ten-fold cross validation were compared for significant difference using one tailed Student's t test. Variability of the model is important to understand the error propagation and quantify uncertainty. Results are presented as average from the ten replications. All graphs show mean value for all replications and one standard deviation envelope.

Specificity in MaxEnt is defined using background points as pseudo-absence, since there are no true absence locations. Defined in such way, maximum achievable AUC is less than one(S. Phillips, Dudík, & Schapire, 2004). Furthermore, true maximum AUC value is unknown. Nevertheless, AUC is one of the few available methods for model evaluation and could be used for comparative analysis provided competing models have identical parameterization.

Variable importance was evaluated using both jacknife test and permutation test. The relative variable importance informs on how much specified predictor improves the gain function, which is analogous to variation explained in classical statistical models. Permutation importance is informative on how stable the predictor importance is after randomly excluding data points. Since absolute gain function is unknown the variable importance is only relative to other predictors and does not say how good the predictor is in modelling resource preference. Furthermore, to evaluate the importance of NDVI heterogeneity, nominal model was built excluding the ndvi sd predictor. The difference in model gain was evaluated using two sided t test.

4. RESULTS

4.1. Land Cover Classification of Messara

Pairwise correlations coefficients between remote sensing indices and canopy cover recorded on the ground show that NDVI have best association with canopy cover (Table 4.1). NDVI, PVI and PC2 essentially have the same interpretation – amount of above ground green biomass, while PC1 is estimate for overall brightness. Soil corrected index (PVI) and second principal component (PC2) are explaining about half of the variation in canopy cover estimate.

When linearly regressed, NDVI again was able to explain the most variation in olive canopy cover (Figure 4.1). Distribution of bootstrap r^2 values of three linear models is normal with low bias (Table 4.2.). All three VI have similar standard error bounds. Confidence levels are stretched suggesting variability in data. One-way ANOVA (Table 4.3) and *ad hoc* Tuckey's honest test showed that difference between r^2 values is significant. Nevertheless, linear model was able to explain less than half of variation in canopy cover at best.

The produced land cover map (Figure 4.2) has considerable amount of errors associated with discerning between open fields and olive groves. High errors of commission are associated with crop and vineyard classes (Table 4.4). About 1/3 of model predictions for class crop are actually olive plantations. Therefore, the map we produce has bias towards showing more crop areas than there are in reality. Overall accuracy of the produced image is just about 60%, which is below the acceptable level for ensuring comparability and inference. Kohen's kappa coefficient shows that produced map is better than simply classifying by chance ($\varkappa$=0.45).

Table 4.1. Pairwise Pearson's correlation coefficients between VI and canopy cover

	NDVI	PVI	PC3	PC2	PC1	CANOPY
NDVI	1.00	0.87	0.50	0.92	-0.68	0.64
PVI	0.87	1.00	0.49	0.98	-0.25	0.50
PC3	0.50	0.49	1.00	0.38	-0.16	0.41
PC2	0.92	0.98	0.38	1.00	-0.41	0.53
PC1	-0.68	-0.25	-0.16	-0.41	1.00	-0.51
CANOPY	0.64	0.50	0.41	0.53	-0.51	1.00

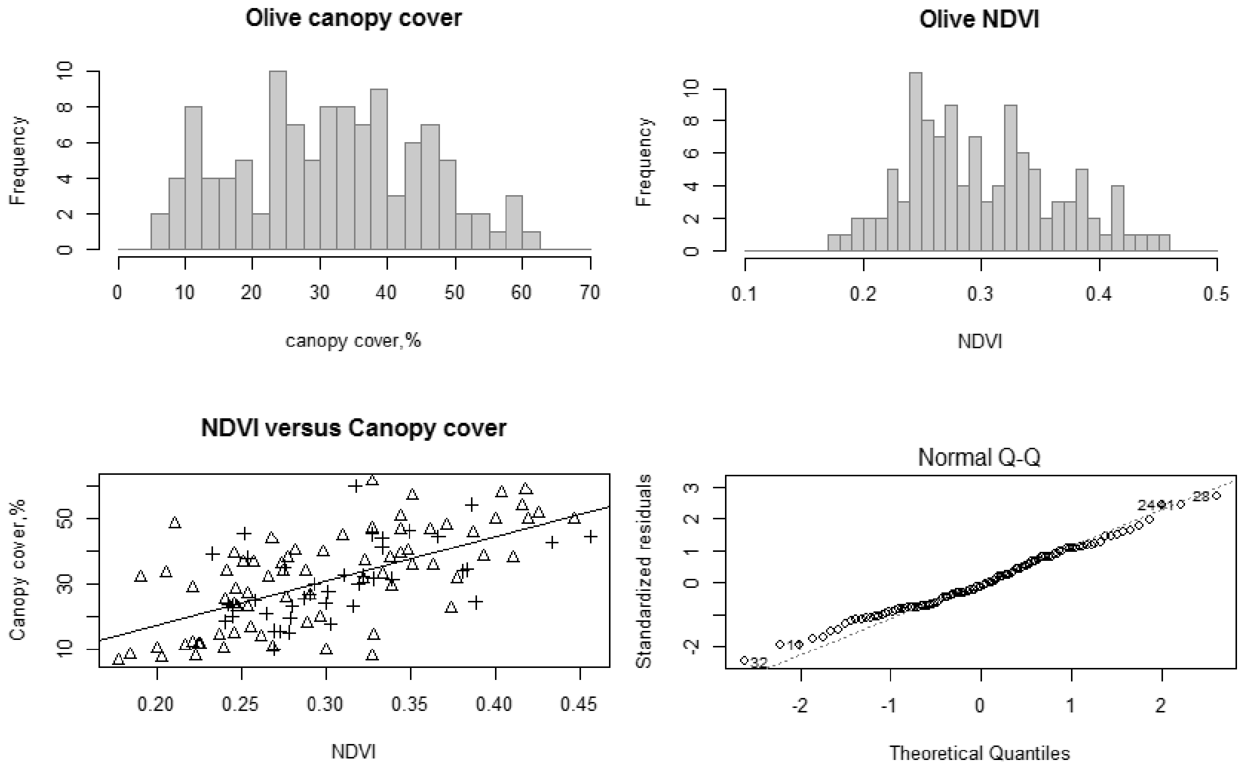
Table 4.2. Mean r^2 from linear regression model between Canopy cover and each VI

	Mean r^2	Standard error	95% confidence interval	
			lower bound	upper bound
NDVI	0.436	0.0685	0.297	0.5627
PVI	0.286	0.0646	0.152	0.409
PC2	0.32	0.0684	0.1822	0.447

Table 4.3. ANOVA on difference in group means

	df	SS	MS	F value	Pr(>F)	
Indices	2	11.9	5.95	1316	< 2.2e-16	***
Residuals	2997	13.55	0.0045			

Figure 4.1. Regression model canopy cover versus NDVI. Differentiating between irrigated (Δ) and non-irrigated fields (+) did not contribute to model performance



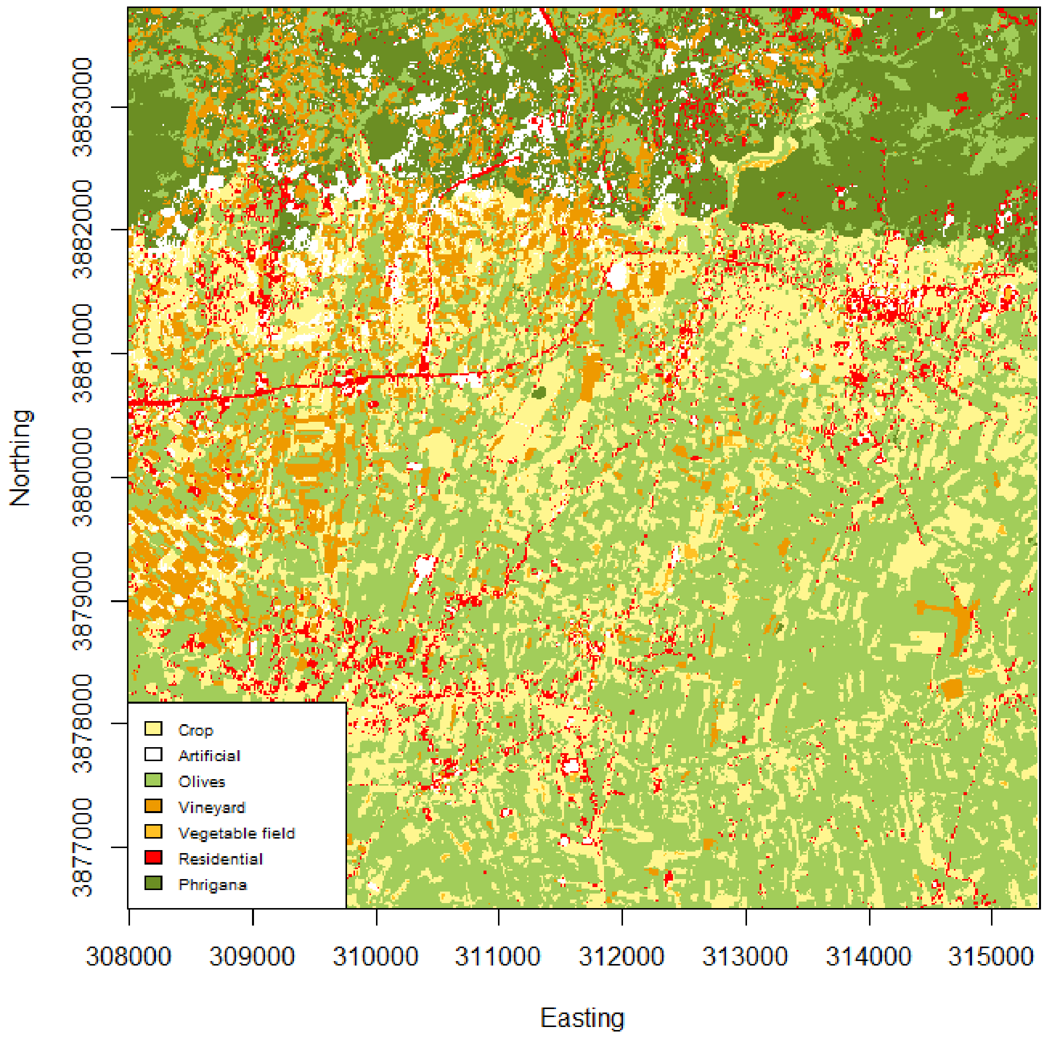


Figure 4.2. Land cover map of Messara plain. Ref.system: UTM 35-N, datum:WGS 84

Table 4.4. Error matrix for land cover map of Messara study area

	CROP	ARTI	OLIVE	VINE	VEGET	PHRYG	Total	Commission
CROP	44	2	30	4	17	0	97	0.55
ARTIFICIAL	1	7	0	0	1	0	9	0.22
OLIVE	6	1	93	10	10	0	120	0.23
VINEYARDS	5	0	4	20	5	1	35	0.43
VEGETABLE	1	0	0	0	4	0	5	0.20
RESIDENTIAL	1	5	4	0	3	0	13	1
PHRYGANA	7	0	2	0	1	11	21	0.48
Total	65	15	133	34	41	12	300	
Omission	0.32	0.53	0.30	0.41	0.90	0.08		0.40

4.2. Home Range

4.2.1. Data description

Long-eared observation data consists of 171 relocations[7] from five individuals (Table 4.5) situated in relatively flat area in the north part of Messara plain. They are spread in roughly 5x5 km square (Figure 4.3). Number of relocations differs with average of 34 observations per individual. Generally recommended minimum sample size for radio-tracking studies is between 30 and 50 observations (Downs, 2008). One unusual observation was located 15 km to the southeast near southern coastline (not shown on figures). While long distance dispersions are likely to occur this observation will bias estimations of home range and resource selection. Because HR analysis is sensitive to outliers and study area boundaries, it was removed from the analysis as outlier being unusually far away.

Comparison with HR size of Long-eared owls from Dutch population (Wijnandts, 1984) showed that Messara birds have significantly smaller home ranges ($t = 5.6078$, $df = 6.09$, $p\text{-value} = 0.0006$). However, Dutch study was much more comprehensive. Home range size based on UD is significantly bigger than MCP estimate (Table 4.5). Individuals rank in the same order in terms of home range size regardless of the method. However, the proportional difference in size of HR among individuals is higher when calculated as MCP. The biggest MCP (Vales) is nine times that of the smallest MCP (Galis). The same proportion is five for UD estimation of home range. This is expected because kernel with standard deviation bandwidth around each point will create a more relaxed estimated, while in MCP method far away observations tend to inflate the size of the polygon (Burgman & Fox, 2003).

Monitoring period spans between 6-8 months. For four individuals it includes both wintering and breeding period having also comparable sampling intensity (0.15 relocs/day). Galis was monitored only during the second half of study period coinciding with only the breeding season of this species. Relocations for Galis are distributed much closer in space - maximum distance between relocations is two times less for from other individuals. The effect of shorter monitoring period is visible also in Minimum convex polygon estimate of home range. Galis has considerably smaller home range size than other individuals. On the other hand, among other four individuals HR size is not related to monitoring time with biggest MCP for Vales but longest observation period for Christos.

Table 4.5. Summary statistics of relocation data for five Long-eared owls (*Asio otus*). Data was collected by research group at the Natural History Museum of Crete.

Name	Relocation (Summer/Winter)[1]		Study period			Duration (days)	Intensity (relocs/day)	MCP[2] 100% (ha)	UD[3] 95% (ha)
Antonis	30	(23/7)	10/8/2010	-	4/13/2011	187	0.16	292	498
Christos	41	(33/8)	10/8/2010	-	7/15/2011	280	0.15	377	850
Galis	34	(34/0)	2/2/2011	-	6/12/2011	130	0.26	96	337
Kamburakis	30	(19/11)	11/8/2010	-	6/6/2011	210	0.14	477	1067
Vales	36	(19/17)	11/3/2010	-	6/15/2011	224	0.16	900	1768

[1] February 1st was selected as breakpoint date for dividing relocation into two seasons. [2] Home range estimate based on smallest convex polygon containing 100% of relocations. [3] Home range estimate based on 95% of the volume of the Utilization distribution

[7] The terms locations, observations and relocations are used interchangeably throughout this thesis to refer to Long-eared owl radio-tracking data points. While first two terms are most common across species distribution studies and data analysis in general, relocations is specifically used to describe the ordered sequence of observations describing the movement pattern of a specific individual.

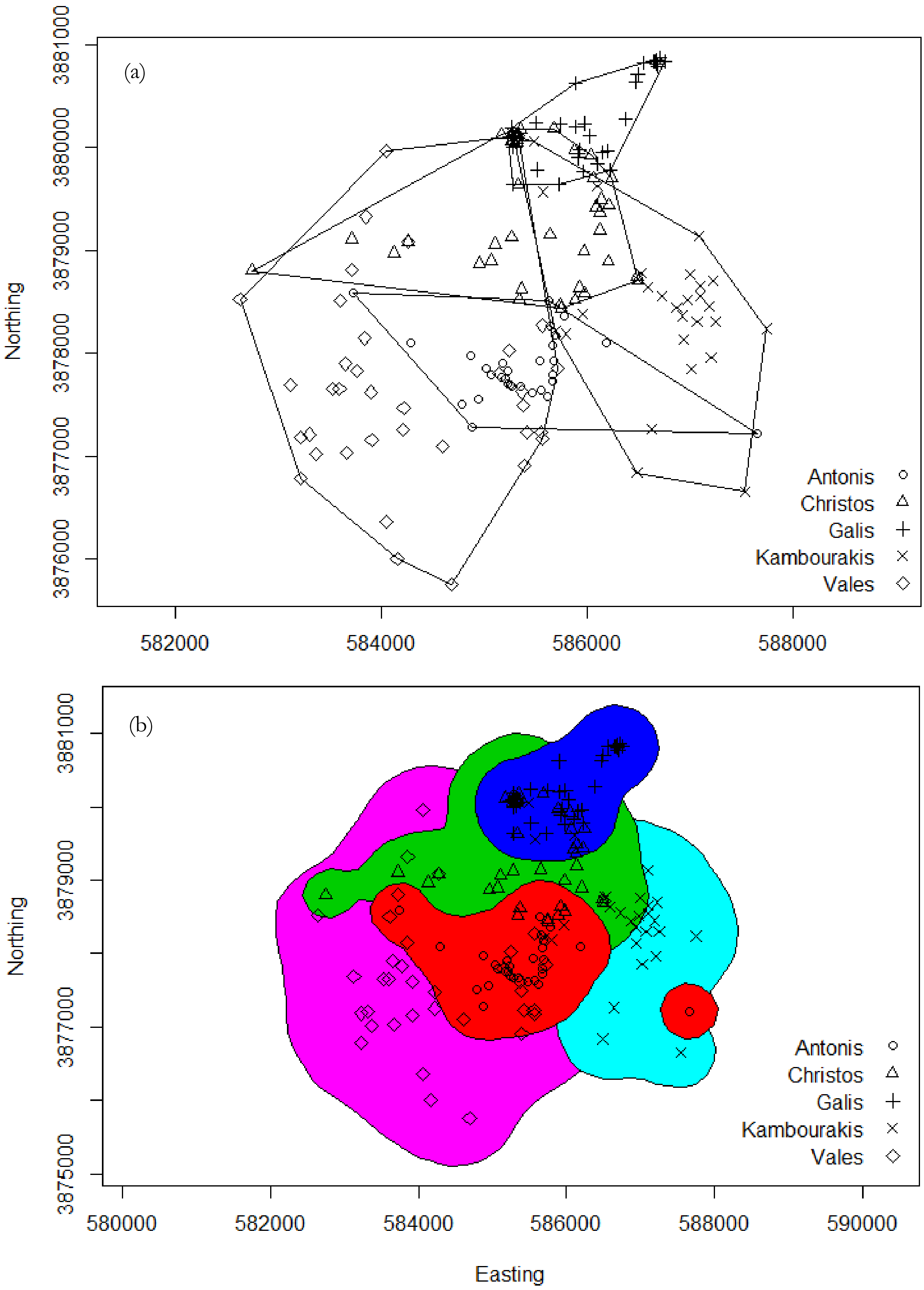


Figure 4.3. Spatial distribution of Long-eared owl relocations. Minimum convex polygon (MCP) (a), and 95% of Kernel utilization distribution (UD) (b) estimates of home range (HR). MCP is calculated using all observations. UD is calculated using the reference bandwidth. Coordinate ref. system – GGRS87 / Greek grid

4.2.2. Temporal independence

Overall, there are few winter observations than summer suggesting that inference at smaller time scales (such as seasons or months) will not be possible as there is a bias towards summer observations. Also, studying seasonal change of habitat selection is not appropriate using this data set because observations are not sufficient. Summer / winter analysis of home range runs the risk of underestimating the winter range and preferences in favour of location characteristics in summer. Only, Vales has representative sample for both seasons.

All observations suffer from small scale clustering due to unequal spread of observations across the year. For two individuals (Antonis and Galis) observed K is outside the 95% bootstrap interval. In Antonis relocations are clustered at medium distance windows. More of the observations are located in the second half of the study period and only few winter observations are available. Nevertheless, at big window sizes Ripley's K estimate stabilizes and is within confidence boundaries (Figure 4.4).

Ripley's K function for one individual (Galis) is well outside the confidence interval for all time scales. However, this is due to fact that study period for this individual is smaller than the window chosen as temporal boundaries of the study. Observations are only available for the breeding period. In fact, when same test was performed only for Galis using smaller time window, Ripley's K shows consistent pattern conforming to randomness hypothesis. Therefore, any subsequent analysis for Galis is valid only for breeding season.

Christos, Kambourakis and Vales show more stable agreement with temporal randomness hypothesis. Note the cyclical pattern observed in Kambourakis and less prominent in Vales. It corresponds to self-replication of pattern at different scales caused by the lack of observations during winter months creating two subsets of relocations. This cycle is less prominent for Vales due to smaller winter gap of observations. Vales also have the most equal proportion of winter versus summer observations and therefore narrower confidence interval.

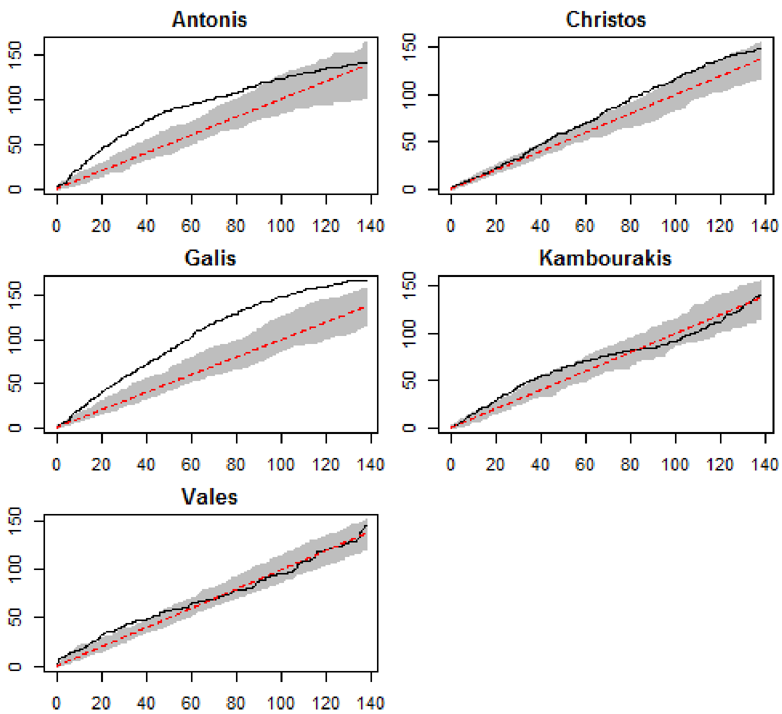
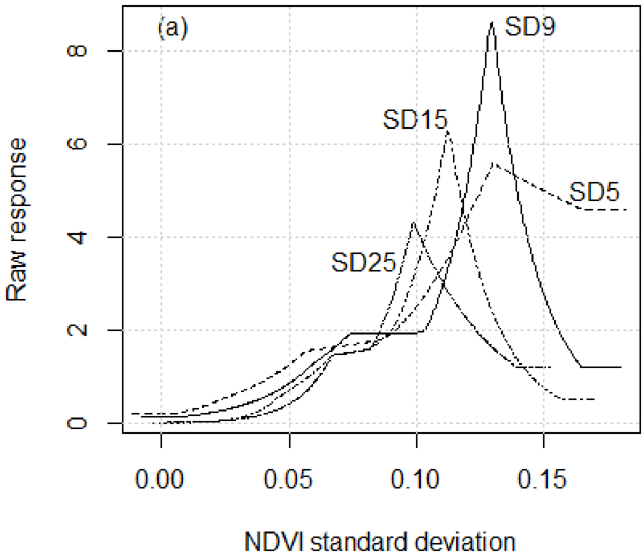


Figure 4.4. Theoretical versus observed Ripley's function for one dimensional time point pattern across continuum of temporal scales. Both axes represent time window measured in days. Grey area represents 95% confidence interval about expected K. Observed K (black) falling above the confidence interval indicates clustering of observations at corresponding time scale – observed pattern K is higher than expected, while line falling below the confidence interval indicates temporally dispersed pattern.

4.3. Long-eared owl Resource Selection

4.3.1. Perceived range selection

The preliminary MaxEnt model build with only NDVI SD as predictor showed that Long-eared owl selects more heterogeneous areas, but avoids extreme heterogeneity. Selection rate (response curves) for all twelve NDVI SD window sizes were unimodal (Figure 4.5a) peaking at above average heterogeneity levels (Figure 4.5 a). At very small window size this peak is less prominent (e.g. NDVISD5) but very good defined for bigger window sizes. The shift of the optimum towards lower NDVISD values with increased window size is due to similar change in moments[8] of the original predictors. High NDVISD values on the x axis in Figure 4.5a correspond to areas where the amount of above ground biomass changes abruptly, e.g. from olive groves to open fields or vegetable fields. Extreme values, on the other hand, represent very high difference between nearby pixels common around greenhouses or other artificial surfaces located inside the agricultural plain.



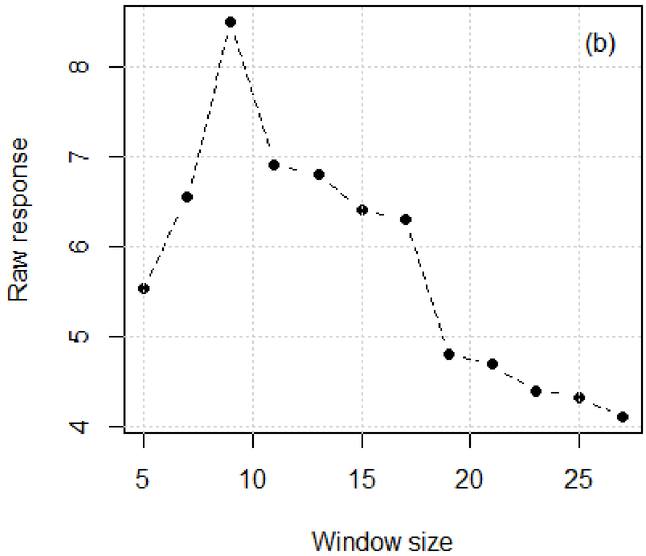


Figure 4.5. Response curves (a) and maximum (peak) response value (b) from NDVISD for different scales. Standard deviation filter was applied over the area at window size from 5 to 27 pixel side. Response is unimodal suggesting there is a clear defined preference towards certain spatial context. Raw response is maximized at 9x9 window size.

Response curves reaching higher raw score are result of better contrast between available and used habitats. More distinguishable selection is observed when using medium spatial scale – NDVISD calculated at window size 9x9 produces the highest peak in relative response (Figure 4.5b). In other words spatial heterogeneity calculated at this scale (9x9 pixels window) is better at explaining animal preference. NDVISD at this particular window size was used as a predictor in the nominal model in next step.

[8] moments are the specific measures describing the shape of a distribution – mean, variance, skewness, etc.

4.3.2. Model performance

Both nominal scale and landscape scale models show similar performance (Figure 4.6). Nominal scale model performs slightly better than Landscape model both in terms of mean AUC and cross-validation variability. However, one sided Student's t test did not prove significant difference in mean AUC (t= 0.61, p = 0.275). Uncertainty associated with landscape scale model is higher compared to the nominal scale. However, this might be due to higher number of predictors at landscape scale model which add to the uncertainty. Therefore, interpretation of the ROC values should be done cautiously. Furthermore, specificity in MaxEnt is defined using background points as pseudo-absences. Defined in such way, maximum achievable AUC is less than one and true maximum is unknown.

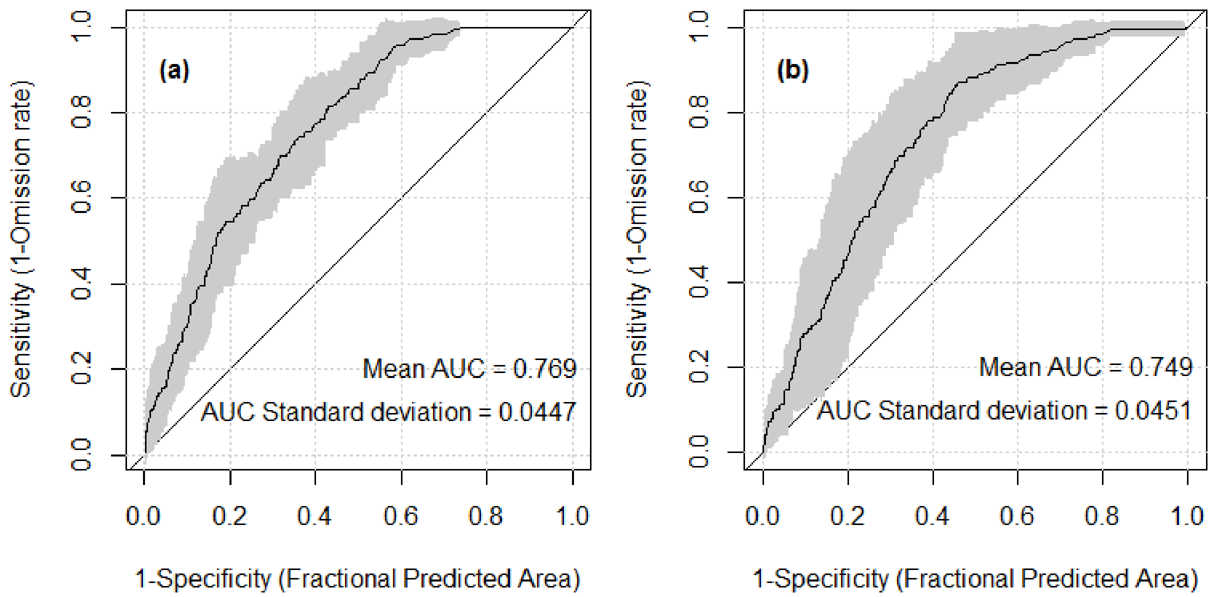


Figure 4.6. Area under the receiver operating curve (ROC) on test data for nominal scale (a) and landscape scale model (b). AUC measures the relative performance of the model. It is interpreted as the probability of a random positive instance being ranked higher than the random background value. Values above 0.5 indicate model that predicts better than random.

4.3.3. Variable importance

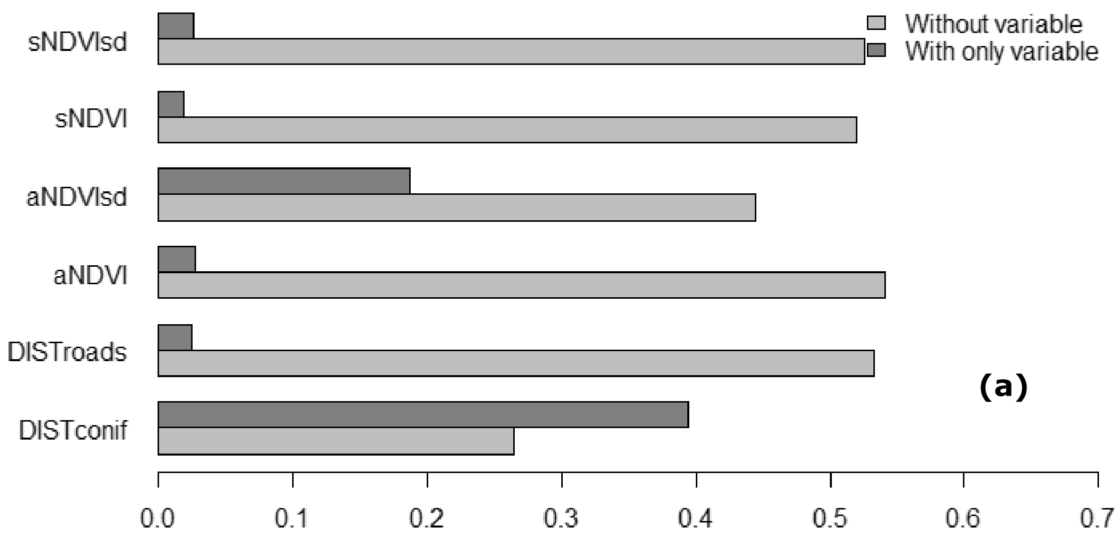
At nominal scale, distance and heterogeneity features are better predictors of Long-eared owl's behaviour than variables not conveying contextual information. Distance to conifers (DISTCONIF) and autumn NDVI heterogeneity (ANDVISD) combined contribute above 90% to model gain and first three predictor variables have 95% contribution to the model (Table 4.6). The relative contribution of the predictors changes slightly after random permutation test. However, the ranking of variables it terms of their importance is preserved indicating lower uncertainty related to correlation between variables. DISTROADS contribute less than primary productivity. Jacknife test shows similar results – gain drop is biggest when distance to coniferous is excluded it is also the single most useful variables for maximizing model gain (Figure 4.7 a).

In contrast to previous model, at landscape scale model, relative contribution is much more spread out. Proportion of open landscape (PLANDCROP) is most important predictor accounting for more than

40% of model gain. Cumulatively, first three variables account for total of 73% of contribution to gain. These are followed by long tail of small importance from other PLAND values (Table 4.6). Again, contextual estimates rank higher than variables not conveying information on spatial structure. Among the two other landscape measures – diversity and contagion, the former (SHDI) scored higher in terms of contribution to gain function. LC is a poor predictor – it has low contribution to overall model gain. The difference in the ordering of variable importance after randomly permuting data suggests more unstable model mainly due to the correlation between predictors – PLAND estimates are inherently correlated since increase in proportion of one land cover class will result in lower proportion of other classes.

Table 4.6. Relative contributions of the environmental variables to the MaxEnt model. First estimate shows the increase in regularized gain contributed by the corresponding variable. For the second estimate the values of the variables on training presence and background data are randomly permuted and model is re-evaluated on the permuted data. The resulting drop in training AUC is shown in the table, normalized to percentages. Values shown are averages over replicate runs.

Variable	Relative contribution (%)	Permutation importance (%)
Nominal scale		
DIST_conif	69.9	62.1
aNDVI_sd	20.5	21.8
sNDVI	4.5	7.4
sNDVI_sd	3	5.3
DIST_roads	1.5	1.9
aNDVI	0.5	1
Landscape		
PLAND_crop	44.2	23.8
ELEV	21.1	38.8
SHDI	7.8	13
PLAND_vine	7.1	6
PLAND_vf	6.5	2.2
PLAND_resi	4.9	4.2
LC	2.9	3.1
PLAND_olive	2.6	2
AI	2.3	2
PLAND_artificial	0.4	2.1
PLAND_phrigana	0.2	2.7



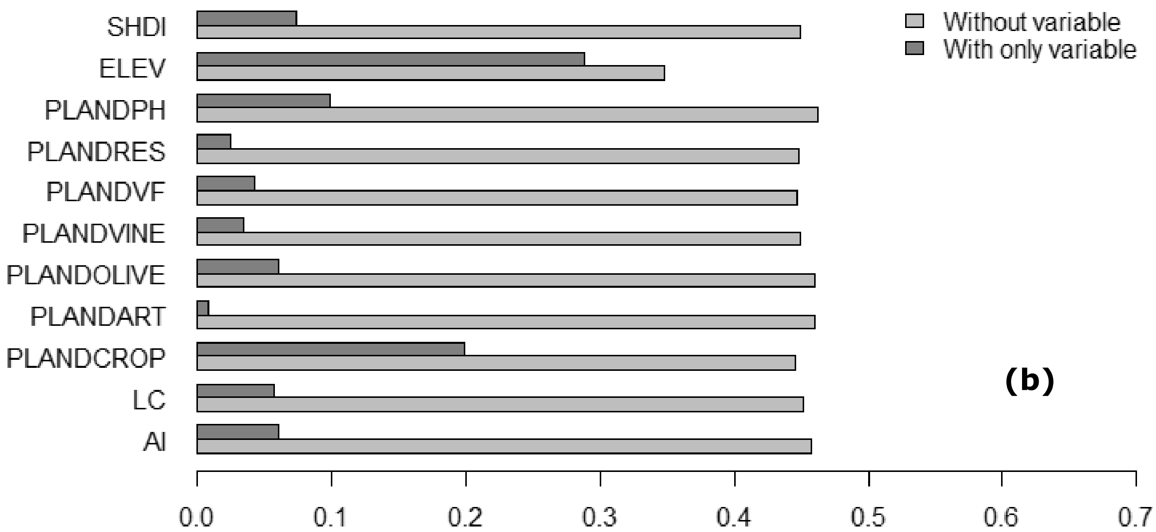


Figure 4.7. Jacknife test on regularized training gain. Nominal scale model (a) and landscape scale model (b). Model gain is shown as a function of only the variable and when the variable is omitted. The environmental variables with highest gain when used in isolation are DISTCONIF and ELEV for both models respectively. They appear to have the most useful information by itself. The environmental variables that decrease the gain the most when omitted are the same, which therefore appear to have the most information that is not present in the other variables.

4.3.4. Response curve

Response curves show the resource selection by Long-eared owls during night time hunting behaviour. Most response curves are unimodal, exhibiting wide optimum range, or reaching a flat asymptote. In addition, clear negative correlation to certain environmental conditions is also observed. In general, Long-eared owl prefers relatively open areas, while avoiding human dominated landscapes. Two set of response curves are presented. Figure 4.9 show uncorrelated response curves build using only the predictor without taking into account any interactions or correlation between explanatory variables. When the entire set of predictors is used, model response curve shapes may change due to correlations (Figure 4.10). Discussion is focused on response curves build with only one predictor to make interpretation easier.

At nominal scale Long-eared owls are more attracted to greener patches inside relatively heterogeneous areas. Long eared owls express positive response towards the level of greenness and unimodal response towards the variability of NDVI in the immediate surroundings. High autumn greenness is mostly related to vegetable fields or vineyards, while high standard deviation values are observed along the edges between different vegetation types. Heterogeneity of primary productivity is better predictor than simply greenness at presence location.

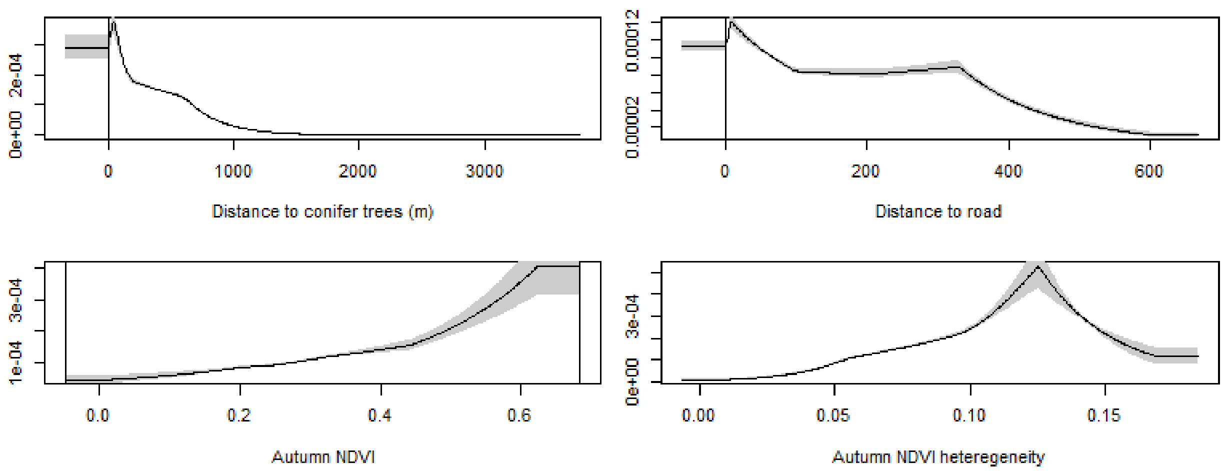


Figure 4.8. Responce curves for nominal scale. The curves are identical for both the full model and models built with only one of the variable separately

The wide plateau like response towards proportion of cropland in the immediate perceptual range indicates wide tolerance towards variability of open habitats (Figure 4.9), but also clearly points to fact that there is active avoidance of too dense or too open areas. Long eared owls are more likely to visit areas covered by at least some amount of crops, but likely to avoid vast extensive monocultures. Similarly to PLANDCROP, relative habitat selection towards proportion of olive groves (PLANDOLIVE) rises until optimum about ¾ of the local area. In fact, these two habitat types are the two most common habitats land cover types in the study area and naturally there is a negative relationship between their proportions inside a randomly chosen window – more open areas means less olive plantations.

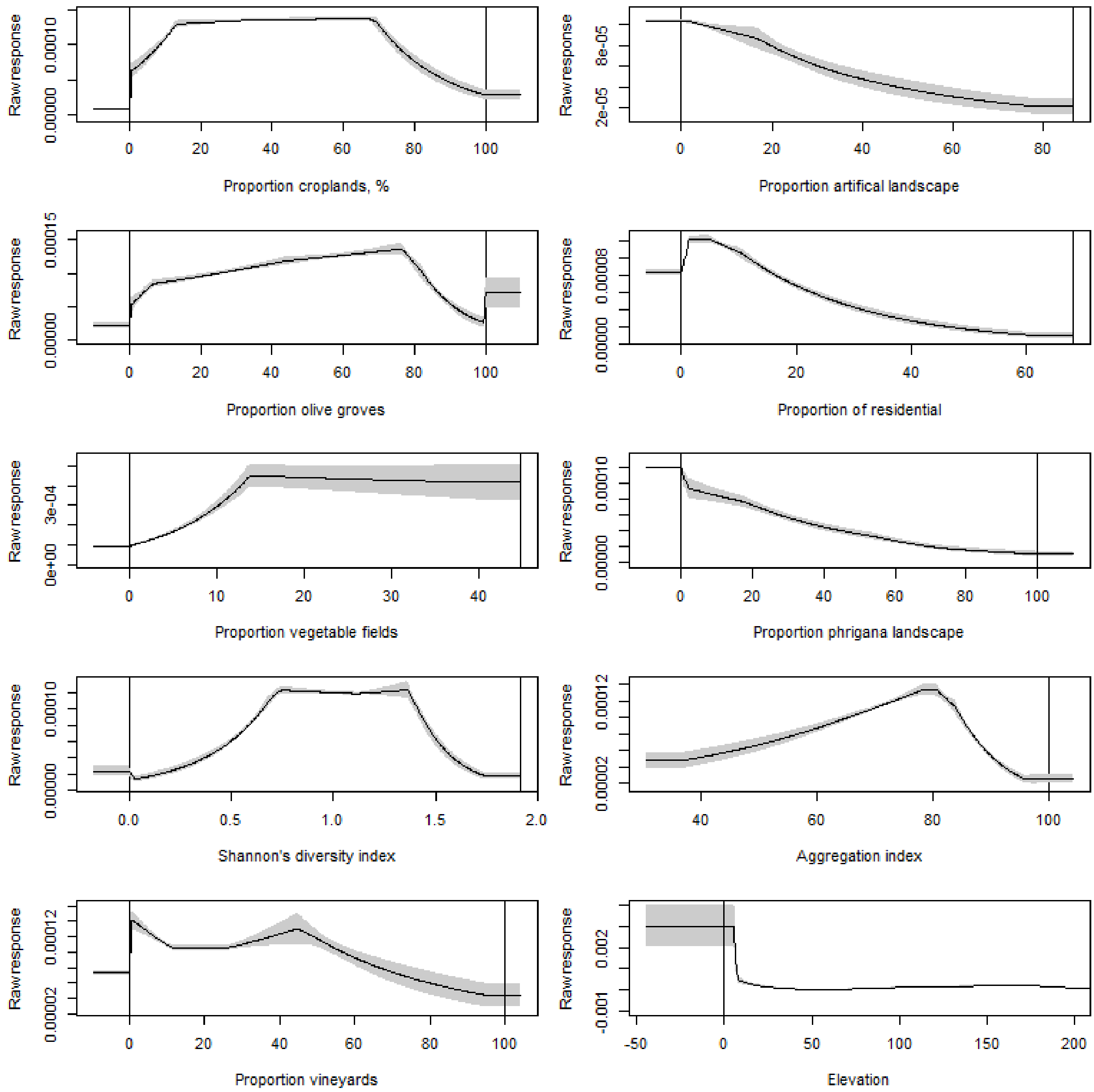


Figure 4.9. Response curves for landscape scale predictors. These responses show how each environmental variable affects the MaxEnt prediction. They are result from MaxEnt model applied with ONLY the corresponding predictor. Mean response (black line) and +/- one standard deviation from ten replicate Maxent runs (grey) is shown. Predictors were grouped based on the response pattern shown by the animal. on the right hand side are predictors which are more or less linearly related to animal response. On left hand side response has a clearly defined (and wide) optimum.

Shannon's index and Aggregation index are significantly correlated, but because they have different interpretation both indices have been kept in the model. Long-eared owls show different response pattern towards two indices. Owls seem to feel comfortable inside a wide landscape diversity range – most suitable are the intermediate values of SHDI (Figure 4.9). On the other hand, response toward the level of aggregation of same class pixels (AI) has clear unimodal shape rising steadily towards optimum around 80% (Figure 4.9). Indeed, in the aggregate model (Figure 4.10) SHDI goes to explain all the variation in data, leaving no additional variation to be explained by the AI.

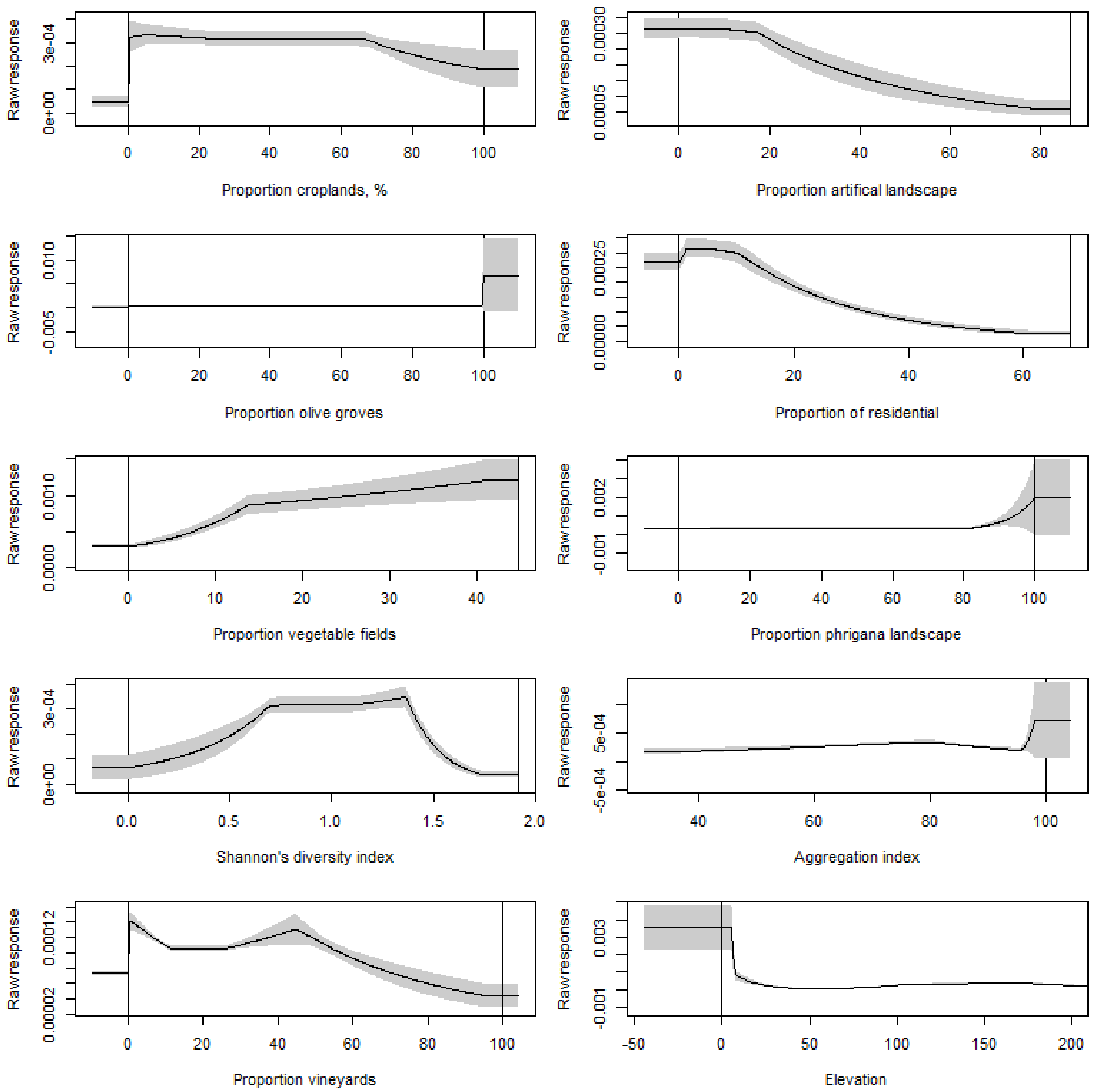


Figure 4.10. Landscape response curves. In contrast to previous figure in this set of RC show the marginal response resulting from varying each environmental while keeping all other environmental variables at their average sample value. Curves are hard to interpret if there are strong correlations present, as the model might be taking advantage of sets of variables changing together. Compared to previous RCs, some of the present curves have diminished in explanatory power because of correlation.

Linear negative response is observed toward proportion of human landscapes in the area (Artificial and Residential areas) and phrigana (Figure 4.9). Higher proportion of these types of landscape is unfavourable for the Long-eared owl which is typical farmland owl. When the entire model is taken into account, these three predictors are complementing each other and therefore redundant. In fact, when we look at the whole model (the model created with all variables included) (Figure 4.10), the correlation effect is visible. In such case Residential area explain the entire variability leaving no or little extra variation to be explained by the second predictor. In practical terms this is visible in the change of the shape of the response curves between Figure 4.9 and Figure 4.10. Variables with no explanatory power (because the variation was already explained by other variables) have flat response curves in the final MaxEnt model.

5. DISCUSSION

5.1. Land Cover

One of the advantages of using Depster Shaffer theory is the possibility to explicitly examine the uncertainty associated with the results. This gives information on the areas where prediction is not conclusive and more training areas would be needed. Classification uncertainty remains high even after multiple iterations of the in process accuracy assessment procedures. This emphasizes the difficulties surrounding land cover classification in such diverse environment. Indeed, there is low separability between land cover classes where soil reflectance constitutes major part of the signature response. In such cases, main difference between these classes is the amount of soil moisture and degree of above ground biomass. Therefore, separation based only on three spectral bands provided by the ASTER sensor does not yield acceptable results.

Several reasons for poor map prediction can be outlined .Among them most notable are low spatial resolution of ASTER images and significant temporal and spatial heterogeneity in the region. ASTER mission is in its final operational stage, and it is expected to cease to function in near future. Newer, more advanced sensors are already operational with spatial and spectral resolution comparable and superior to these of aster. In addition, availability of RS images with higher geometric resolution is increasing (e.g. New SPOT, QuickEye, Quickbird). For these images, better approach will be using semi-supervised object oriented method, as shape and geometry of spatial object becomes more important factor in image.

Land cover maps required accuracy for use in modelling applications is between 5-15%.(Englhart, Franke, Keuck, & Siegert, 2014) Similar rate of accuracy would be desired for finer resolution local land cover classifications. Landscape heterogeneity is identified as one of the major challenges for cover mapping. One way of dealing with heterogeneity is to define fuzzy classification scheme or continuous land surface characteristics, instead of discrete land cover classes. While such data products will be useful in variety of modelling applications, their use by planners and decision makers is not always straightforward. Data fusion from several sensors with different spatial and spectral resolution may provide an integrated approach and provide multi-scale data models to facilitate the development of nested hierarchical modelling applications and help planners make decisions on multiple spatial scales.

5.2. Home Range And Resource Selection

Animals select habitats in such way as to maximize their fitness and survival (Pyke, 1984). Perceptual range defines the radius window at which animal movement decisions are predictable and has strong application in landscape connectivity studies (Olden, Schooley, Monroe, & Poff, 2004). Other studies normally look at landscape structure inside an arbitrary define circle (e.g. Martínez & Zuberogoitia, 2004) or average flying distance (Bartolommei et al., 2012). Here we used simple data driven approach to infer on the best window size at which contextual information is relevant to Long-eared owl's selection behaviour (Section 4.3.1). The rationale for the inference was the fact that higher response curve values will correspond to stronger selection. Hence maximizing response corresponds at certain window size means better prediction of preference. Alternatively, best predictor selection approach based on lasso regularization can be used with Poisson point process model (PPM). Recently, equivalence between MaxEnt and PPM has been shown for species distribution modelling (Renner & Warton, 2013). The advantage of using PPM instead of MaxEnt is the relatively straightforward implementation of statistically robust methods for best predictor selection. Lasso regularization (Tibshirani, 1994) for example chooses the parsimonious model by picking a subset from all possible predictors satisfying user defined constrains. Using Lasso researchers can let the model decide on the best predictor among a set of highly correlated predictors.

Although it has been shown (Section 4.1) that there is a relationship between NDVI and canopy cover, it applies only for olive groves and not for the entire image. Therefore, NDVI remains to be interpreted as the amount of green biomass at pixel. While clearly Long-eared owls prefer high NDVI pixels, the underlying reason remains unknown and any conclusion will be speculative. In this sense, information extracted from RS images, although with good resolution, conveys difficult to interpret semantic information. Land cover classification predictors are easier to interpret because they convey comprehensible discrete information. However, using land cover map adds a new level of uncertainty to the analysis, as the map is a generalization of reality in a discrete form with error. This uncertainty associated with generalization of the RS image is traded for more easy interpretable information (e.g. land cover classes, instead of spectral response). Hence, there exist a trade-off between spatial resolution and interpretability of results. We could not prove significant difference in the predictive performance of two models. Nevertheless, landscape predictors showed greater variability in ROC results and more uncertainty on which predictors are more important. However, the apparent trade-off between model performance and increased interpretability of results is worth mentioning as a reason for developing and using land cover maps in wildlife research. The question still remains on how accurate and relevant these maps are for conservation purposes. Indeed, a unified framework with unambiguous and exclusive land cover classes defined specifically for ecological and conservation purposes will aid cross border research and improve conservation efforts (Tomaselli et al., 2013).

Results from nominal scale model confirm the importance of preserving specific landscape forming elements. It was shown that sites closer to coniferous are more likely to be visited by the animal as oppose to patches located far from potential roosts. However, results should be analysed with caution as trees are scattered relatively homogeneous inside the plain and relative contribution could stem from sampling bias. Furthermore the relatively high importance of this predictor could be due to non-exhaustive sampling of all trees in the area. Tree locations were recorded in an opportunistic way – study area was extensively traversed and trees were recorded when encountered. Furthermore, in addition to locations, other characteristics such as size and number of trees in group can be used in marked point pattern analysis to better understand the relationship between hunting behaviour and roost site availability. Lastly, field visits are time consuming and have low cost effectiveness. New airborne and space borne high resolution images can provide more accurate and relatively cheap way of identifying small individual objects through semi-supervised classification approaches.

Indeed, flight is significant part of the energy budget of the birds (Wijnandts, 1984). Therefore, it is likely that individuals select foraging patches in such way as to minimize the cost for traversing from roost to hunting grounds. Under such hypothesis relatively less prey rich but closer patches are more likely to be visited as oppose to rich but distant hunting grounds. To answer this questions further research should focus on analysing the rich micro mammalian fauna and its spatial distribution in relation to the intensive management practices in Messara. Small mammal population density in combination with information on roosting trees can be used as predictor surface for better understand Long-eared owl movement and resource selection in spatially explicit models.

The fact that NDVISD is more important than only NDVI at location is relevant both for research and for management applications. It comes to show that at fine scale the level of heterogeneity surrounding the used locations should also be considered when analysing habitat selection. Future research on animal movement inside their home range should focus on finding predictors which describe surrounding context rather than only focus on visited land cover types or vegetation structure on the spot.

Results on preferred habitat types (landscape model) confirm the widely accepted idea that Long-eared owl is generalist species tolerating diverse range of habitat conditions. Land cover type, diversity of landscape, and landscape context affect habitat selection pattern of Long-eared owl in Mediterranean intensive agricultural area of southern Crete. The animal is constraint mainly to the low elevation agro-environmental patchwork dominated by olive groves and croplands. Furthermore, it prefers relatively open areas and avoids human dominated landscapes. The wide selection optimum towards the proportion of croplands suggests that animals are comfortable with changing levels of habitat openness, which is in line with other fine scale studies (Martínez & Zuberogoitia, 2004). Bartolommei, Mortelliti, Pezzo, & Puglisi (2013) showed that probability of occurrence increases with degree of openness of habitat.

The relative predictor contribution supports the hypothesis that landscape context is more important than discrete land cover classes. At such fine spatial scale using only visited land cover type to study habitat selection can yield biased results. Birds can easily traverse long distances and, unless very fine temporal data is available to quantify time spent in each habitat type, radio-telemetry studies using compositional analysis or any other discrete choice model face errors due to timing of observation. Thus future research on habitat selection should focus on ensuring representativeness of animal space use data. This can be achieved through implementing GPS tracking with relatively high frequency of data collection, as well as using new currencies of use such as time spent inside habitat type or increased risk of predation (Buskirk & Millspaugh, 2006). With high temporal resolution data, new models based on random walk can significantly improve on the knowledge about habitat preference and actual habitat utilization (Börger, Dalziel, & Fryxell, 2008).

Strong contribution of elevation to model gain is due to the wide range of elevation included in the analysis and the fact that almost all observations are inside the lowland agricultural area. The strong preference towards lower altitudes is probably due to the main land cover type rather than elevation itself. High elevations are not favourable mainly because of dominance of phrigana and to a lesser extent of olive groves and pasturelands. Other derivatives of elevation were not used because ASTER DEM has been shown to have lower accuracy (Mukherjee et al., 2013).

Finally, there are several sources of error in statistical model building introduced at each level of model building, prompting caution when making conclusion. First input data rarely comes without any errors. Explicitly taking into account the inherent noise of data is therefore important in evaluating the full error propagation and eventually assessing the feasibility of the entire approach. Indeed, radio-tracking data can produce significant error in the cases when point locations are obtained using triangulation. Second, significant error was produced at image classification step. Highly complex landscape in Messara plain will need higher resolution remote sensing data products for estimating better the land cover. Also, landscape extent and resolution highly influence the maximum likelihood estimate of MaxEnt model by changing the availability of resources. Current implementation of background selection corresponds to the null hypothesis of equal availability of all pixels in the landscape. In reality however, under site fidelity assumption, probability of a location being visited decreases with distance from main roost site. Under low energy budget constrains animals will focus on minimizing the cost for long distance flight, selecting habitat patches closer to the roost tree. Hence, using distance to trap tree or utilization distribution as a prior probability regarding areas more likely to be visited is sensible way to control for the homing bias.

6. CONCLUSION AND FUTURE PROSPECTS

In this research we showed that Long-eared owls are attracted primarily to relatively heterogeneous areas, staying close to potential roost sites, and preferring at least some degree of habitat openness. We also showed that studying habitat preference at fine scale should consider information on landscape context instead of only visited land cover. Furthermore, the usefulness of remote sensing derived estimations of vegetation structure was shown. Complex landscape structure is common for the Mediterranean islands being a product from century long interaction between nature and human settlers. In order to preserve the unique diversity of the area management should take a holistic view considering the temporal and spatial complexity of the system, and promote practices which enhance the resilience of the agricultural systems. Management and conservation policies focused on non-interference should, thus lead to loss of land use heterogeneity which is important component for total diversity in the region. Instead, stimulating organic farming and protection and restoration of landscape forming elements such as pine trees under the new agri-environmental schemes should promote more diverse habitat in the area which will benefit Long-eared owls in the region.

The vision of the new European Common Agricultural Policy (CAP) is to use *in situ* research and monitoring schemes to receive feedback on the effectiveness of new measures. Therefore, long term monitoring of population dynamics of focal species such as Long-eared owls can yield a good estimate of the effectiveness of the EU policy and guide further improvements and conservation. Monitoring will be further aided by new RS data products from Sentinel satellite missions (ESA) expected to be available under the Copernicus Land Monitoring Program (EEA). The objective of the Copernicus Land Monitoring service is to provide land cover information for environmental and other terrestrial applications. For example, the Pan-European component will provide seamless information on specific land cover characteristics such as forest and grassland cover at 20 m resolution for the whole Europe. The High Resolution Layers (HRL) will be particularly valuable in home range and landscape scale studies. Together with improved GPS tracking technologies and new development in habitat selection studies they will facilitate development of individual based habitat suitability models. This will further increase our understanding about animal-environmental interactions and help mitigate human impact on natural systems.

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