Hyper temporal NDVI images for modelling and prediction the habitat distribution of Balkan green lizard (*Lacerta trilineata*)

Case study: Crete (Greece)

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By

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Abstract

In the study of species environment relationship, it would be desirable to find predictors those can better explain the habitat characteristics of the species. One of the main problems in habitat distribution modelling is missing covariates (i.e. limiting predictors), reflecting lack of knowledge which environmental factor constrain the distribution of species.

This study aims to model the temporal pattern of vegetation dynamic, to explain the geographical distribution of the reptile species. The Balkan green lizard (*Lacerta trilineata*) in Crete Island, Greece was selected as the case study.

The ISODATA clustering algorithm was used to recognize the temporal vegetation dynamic pattern. The separability divergence method was employed to identify the appropriate number of classes based on spatio-temporal patterns of vegetation.

The 81 observation points of the species occurrences were provided from Natural History Museum of Crete and field work data collection. Classified hyper-temporal NDVI in addition with other environmental variables (e.g. climate data, soil, etc.) were used as biophysical features of the ecosystem. The predictability of classified hyper-temporal NDVI images was investigated by comparing the performance of models based on different combination of variables. For each predictor variable alone, regularize training gain calculated to see the drop in gain when the variable is omitted from the full model. The results show that the classified hyper temporal NDVI can significantly improve the predictability of the model. In all developed models, hyper-temporal NDVI emerged as the most important predictor. The result indicates when NDVI is omitted from the model, the training gain significantly decrease, which suggests it contained the most useful information that are not presented in the other variables.

The result indicates strong relationship between some NDVI classes and high probability occurrence of the species. Considering these results the probability of species occurrence was highest in sites, where shrubs and rocks were dominant, or in old olive plantations and abandoned agriculture.

Acknowledgements

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Table of contents

Contents

List of figures

List of tables

1. Introduction and background

Prediction of species distribution and identifying the knowledge required to do this is important for many applications in ecology, evolution, conservation and management of environmental impacts. A key component in predictive habitat distribution modelling is characterization of species' distribution in ecological space, based on quantifying species-environment relationship, which can be useful in understanding the potential distribution in geographic space (Pearson *et al.*, 2006). It is the reason that they usually combine multivariate statistical analysis with Geographic Information Systems (GIS).
Detailed knowledge of species' ecological and geographic distributions is fundamental for conservation planning and for understanding ecological and evolutionary determinants of spatial patterns of biodiversity (Elith *et al.*, 2006). Understanding the key environmental variables that determine the suitability of an area for a species is particularly important in this way. Techniques that characterize the geographical distributions of species by relating the observed occurrence localities to environmental data have been widely applied across a range of biogeographical analysis and become an increasingly important issue in conservation biology (Guisan & Thuiller, 2005; Pearson *et al.*, 2007).

1.1. The use of NDVI images in habita distribution modeling

Recently the use of remote sensing in habitat distribution modelling is widespread. One of the most common products of satellite images is the Normalize Difference Vegetation Index (NDVI). It can be used for quantifying productivity and ground biomass of ecosystem(Tucker, 1979a). NDVI is able to separate vegetation from non vegetated areas, and most of the time it is highly correlated in faunal species occurrence and diversity (Leyequien *et al.*, 2007). Since 1990 the use of NDVI is increasing in predicting wildlife and habitat suitability (Leyequien *et al.*, 2007).
Plant productivity and biomass of ecosystem vary in space and time, and the spatial heterogeneity in productivity is hypothesized to influence species distribution and local abundance of individuals (Brown, 1988; Currie, 1991; Brown & Gibson, 1983; Gaston & Blackburn, 2000; Oindo & Skidmore, 2002; Seto *et al.*, 2004).

Verlinden and Masogo (1998) explored the possibility of using NOAA-AVHRR NDVI imagery to monitor vegetation condition in the southern Kalahari. They used ground survey for estimating the grass greenness and used it to test the validity of the satellite imagery. There was a significant correlation between grass greenness and NDVI. The result showed that density distributions of some species were related to habitat greenness. This study proved satellite imagery could be used to test habitat suitability for wildebeest, hartebeest and ostrich on a regional scale in the Kalahari.
Musiega and Kazadi (2004) investigated the influence of vegetation (NDVI), landscape and relief on herds' migration routes. Then they simulated the migration routes using GIS and Remote sensing techniques. The result indicated that the green vegetation availability is shown to be a major criterion in route choice for this case. This study also showed during the dry season the migration is most based on greener grass, but during the season of abundance relief becomes critical in making route choices for herds' migration. The writers claimed this method in this paper is viable for rapid prediction of approximate routes for the migrating wildebeest in different climate conditions.

Zinner et al. (2001) described the habitat quality of two different taxa of baboons, hamadryas baboons *(Papio hamadryas hamadryas)* and olive baboons *(Papio h.Anubis)* in Eritrea based on NDVI. They used 12 years (1982_1993, EROS 1997) to calculate the average NDVI for each pixel of the terrestrial area of Eritrea. In this study the vegetation were classified in the survey area. The vegetation was categorized at around 100 selected sites using Landsat MSS satellite data. Both baboon taxa tend to select better quality habitats, characterized by a higher NDVI value. For these two taxa Hamadryas baboons showed a greater ecological plasticity than olive baboons.

Hurlbert and Haskell (2003) used NDVI to find the variation in geographic patterns between seasons of avian richness in North America. The result showed positive relationship between available energy and species richness. Seasonal NDVI explained 61% of the variation in richness. Seasonal NDVI and habitat heterogeneity together explain up to 69% of the variation in richness.

Oindo and Skidmore (2002) assessed the relationship between species richness of vascular plants and mammals with interannually integrated maximum NDVI (e.g. average, standard deviation) at landscape scale. The result of the statistical analysis indicated that the maximum average of NDVI has a negative correlation with species richness of mammals and plants. They result confirmed the decrease of species richness of plants with an increase of average NDVI, but there was a positive correlation between species richness and habitat heterogeneity.

Osborne, Alonso and Bryan (2001) presented predictive models for great bustards in central Spain based on high resolution radiometer (AVHRR) satellite imagery combined with other environmental variables. The result showed NDVI based on AVHRR satellite imagery and other GIS layers have potential to map distribution at the large spatial scale and could be apply to other species. They proved in high NDVI values the probability of occurrence of bustards is significantly higher than areas with lower NDVI values.

In reptiles and amphibians distribution modelling only few studies, used remote sensing but both was innovative and successful. Raxworthy et al. (2003) assessed and predicted the distribution of known and unknown chameleon species in Madagascar, using a combination of satellite data (MODIS), historical and delineate ecological niches, based on environmental geographical information system, to predict geographical distribution of species. This study leads to the discovery of seven new species of chameleon.

Scribner et al. (2001) used in situ and remotely sense of the data of the aquatic and terrestrial environment, to examine the correlation of the habitat characteristics with population demographic and genetic characteristics of the common toad. This study was one of the few that focussed on the sub species level.

While remotely sensed data for animal diversity assessment using habitat characteristics is increasingly used, its application to reptile and amphibian distribution modelling remains poorly explored. Despite the success of the above presented studies, there is still a gap between ecological theory and the application of remotely sensed data(Leyequien *et al.*, 2007). One of the problems is that there is no clear understanding over which spatial scales the species habitat relationship apply for species of interest, specifically those of limited vagility(Leyequien *et al.*, 2007).

1.2. Species distribution modeling

The question of how plants and animals are distributed on earth in space and time has a long history which has fascinated many biogeographers and ecologists and inspired them to seek explanations (Guisan & Thuiller, 2005). In order to get a better insight into potential habitat distribution in geographic space, identification and quantification of the relationship between species and environment, it is necessary to produce the suitability map and predict its' distribution. Modelling and predicting habitat distribution is therefore considered to be a useful approach to monitor and protect the endemic and endangered species.

There are several terminologies and frameworks including habitat suitability/selection models, habitat/species distribution models, resource selection functions, ecological niche models or gradient analysis, which Hirzel and Le Lay (2008) argued, they all address similar issues with different tools. Indeed, a striking characteristic of these models is their reliance on the ecological niche theory (Guisan et al., 2000; Guisan et al., 2005).

Many modelling techniques are now available for predictive habitat distribution modelling. Guisan and Zimmerman (2000) provided an interesting synthesis review of the state-of-the-art in pre-2000 period of habitat distribution modelling which was updated by Guisan and Thuiller (2005). They defined species distribution models as "empirical models relating field observations to environmental predictor variables, based on statistically or theoretically derived response surfaces (Guisan & Zimmermann, 2000). Species data can be presence-only, presence-absence or abundance observation based on random or stratified field sampling, or observation obtained opportunistically, such as those in natural history collections (Guisan and Thuiller, 2005). Environmental predictors can exert direct and indirect effects on species (Austin, 2002; Guisan and Thuiller, 2005), and reflect the three main types of influences on the species (Guisan and Thuiller, 2005): (i) limiting factors, defined as factors controlling species eco-physiologically (e.g. temperature, water, soil); (ii) disturbances, defined as all types of perturbations affecting environmental systems; (iii) resources, defined as all compounds that can be assimilated by organisms (e.g. energy). Six steps of the spatial distribution modelling procedure are discussed by Guisan and Thuiller (2005): (i) conceptualization; (ii) data preparation; (iii) model fitting; (iv) model evaluation, (v) spatial prediction, and (vi) assessment of model applicability.

Many statistical methods and tools have been applied and introduced by studies for habitat distribution modelling. These studies show considerable focuses on the performance of models regarding optimising goodness-of-fit between predictors and response variables (i.e. it is handling as a purely statistical problem). These methods are vary in how they model the distribution of the response (species), select relevant predictor variables, define fitted functions for each variable, weight variable contributions, allow for interactions, and predict geographic patterns of occurrence (Guisan and Zimmermann, 2000; Elith et al., 2006).

There are three major components in any framework for statistical modelling in plant ecology. They need all an ecological model, a data model and a statistical model. Ecological model consist of the ecological knowledge to be used or tested in the study. The data model consists of the decisions made based on the way that the data should be collected, measured or estimated. The statistical model is the choice of statistical method, error function and significance test (Austin, 2002). Many statistical methods and tools have been applied and introduced by studies for habitat distribution modelling. These studies show considerable focuses on the performance of models regarding optimising goodness-of-fit between predictors and response variables (i.e. it is handling as a purely statistical problem). These methods are vary in how they model the distribution of the response (species), select relevant predictor variables, define fitted functions for each variable, weight variable contributions, allow for interactions, and predict geographic patterns of occurrence(Guisan & Zimmermann, 2000)

1.3. Problem statment and justification

One of the major issues in species habitat distribution modelling is getting data that are from the correct 'scope' in both space and time (Rushton *et al.*, 2004; Vaughan & Ormerod, 2003). In the real world it is not easy to know the ecological requirements for species, as some of them are unknown or immeasurable (Rushton *et al.*, 2004). Some studies show that models with fewer variables contain fewer nuisances and have greater generality. (Guthery *et al.*, 2005) and Seasholtz (1993) mentioned if two models in some way adequately model a given set of data, the one that is described by a fewer numbers of parameters will have better predictive ability. This concept is considered as a general principal of parsimonious data modelling. Therefore, it should be preferable to develop a model with fewer variables which can be a representative of the habitat for target species in space and time.

Some studies about reptile species and amphibians in European countries show decreasing in population due to climate change, natural disaster, human activities and habitat fragmentation. More than half of all European amphibians (59 percent) and 42 percent of reptile species are in decline, which means that amphibians and reptiles are even more at risk than European mammals and birds (IUCN). For 23 percent of amphibians and 21 percent of reptiles the situation is severe and that they are classified as threatened in the European Red List. "*Southern Europe is particular rich in amphibians but climate change and other threats are placing its freshwater habitats under severe stress.*"

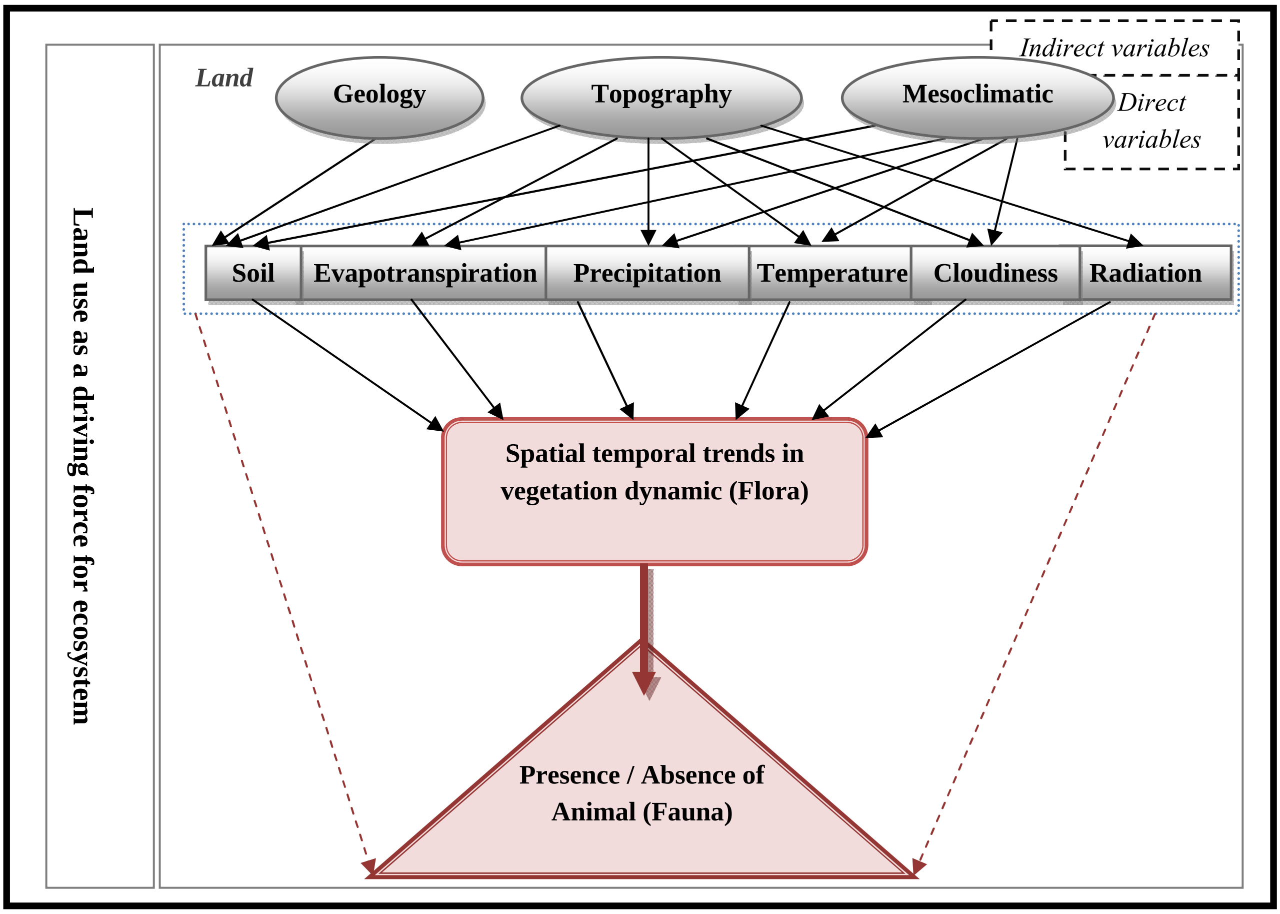

Figure 1: Ecosystem in space and time

Figure 1 shows how direct and indirect resources effect on vegetation dynamic and presence/absence of fauna, and this research aims to find the relationship between spatio-temporal changes in vegetation and animal distribution.

1.4. Target species *Lacerta trilineata* (Balkan green lizard)

1.4.1. Range

The Balkan green lizard (*Lacerta trilineata*) is a species of lizard in the *Lacertidae* family. It is found in a greater part of the southern Balkans (coastal Croatia, Bosnia-Herzegovina, Montenegro, the FYR of Macedonia as well as Albania, Bulgaria and Romania) and Turkey. *Lacertidae* in Greece occurs the main land as well as many islands is the most widespread, especially the larger islands like: Crete, Lesbos and Rhodes.

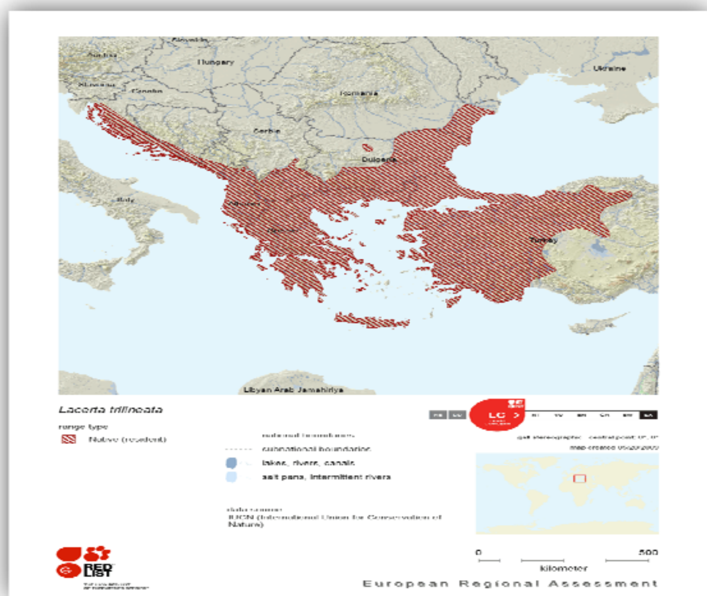

Figure 2: *Lacerta trilineata* distribution. Source: www.iucnredlist.org

1.4.2. Biology

Lacerta trilineata is the largest lizard in Greece, measuring up to 16 cm SVL with tail at least twice as a long. Adults tend to be bright green with fine black stippling on the back but overall colour may appear more tan, gray or yellowish. The sides and the throat in particular are bright yellow (in some islands populations the throat is blue. Males may have light blue spots around their necks. Young and sub adults are brown, with 3-5 light streaks on the back, and possible some light marks on the sides. One of these lines is in the centre of the back. Males have a broad head with wide cheeks but a characteristically narrow snout. Females lay 6-18 large eggs in sheltered places at the beginning of June. Juveniles are up to 3.5 cm in SVL long upon hatching and mature after 2years. Three-line lizards feed mainly on arthropods, with *coleopteran* being the mail prey group.

Lacerta trilineata consume also plant materials (fruit, flowers). Adults have been observed swimming across streams. The species is good climber. *Lacerta trilineata* is protected by national legislation (Presidential decree 67/1981). It is also considered a species of community interest, listed in Annex IV of the EU Habitats Directive, and Annex II of the Bern Convention.

Figure 3: *Lacerta trilineata* (Balkan green lizard)

1.4.3. Habitat

This species is found in natural and semi natural areas. It is associated with dense vegetation. Depending on the site it is found on bushes, brambles, meadows and abandoned cultivated lands, dry stone walls and roadsides. It can be also appeared close to stream and ditches. It generally occurs in a relatively moist habitat. In Greece the distribution of *Lacerta trilineata* is from sea level up to at least 1,600 m a.s.l. Young individuals are often seen in slightly different habitats, with denser and lower vegetation such as high grass and small shrubs.

Figure 4: *Lacerta trilineata* habitat

1.5. Research Objective

The objective of this research is to assess the potential of hyper-temporal NDVI images to model the habitat distribution of the Balkan green lizard (*Lacerta Trilineata*).

1.6. Research questions

I. Does the predictability of *Lacerta trilineata* improve in the model which uses the classified hyper temporal NDVI as an explanatory variable?

II. Which explanatory variable has a better contribution to predict the *Lacerta trilineata* distribution, classified hyper-temporal NDVI or statistical parameters derived from the original NDVI time series (e.g. Annual average of NDVI)?

III. Are there any significant difference in performance between the models considering (SPOT) hyper-temporal NDVI images (1km) and the models consider MODIS hyper-temporal NDVI (250m) in habitat distribution of *Lacerta trilineata*?

1.7. Research hypothesis

I. *H0*: There is no significant difference between a model which considers hyper-temporal NDVI images and a model which does not consider hyper-temporal NDVI images as an explanatory variable.

II. *H0:* There is no significant difference between hyper-temporal NDVI images and statistically derived NDVI in predictive distribution of *Lacerta trilineata*.

III. H0: There are no significant differences between the models consider SPOT hyper-temporal NDVI images (1km) and the models consider MODIS hyper-temporal NDVI (250m) in distribution of *Lacerta trilineata*.

2. Materials and Methods

This chapter describes materials and methods of this study. The general methodology for modelling the predictive habitat distribution of *Lacerta trilineata* is showed in Figure 5. The flowchart shows the general pattern of the research; further all steps will be described in more detail.

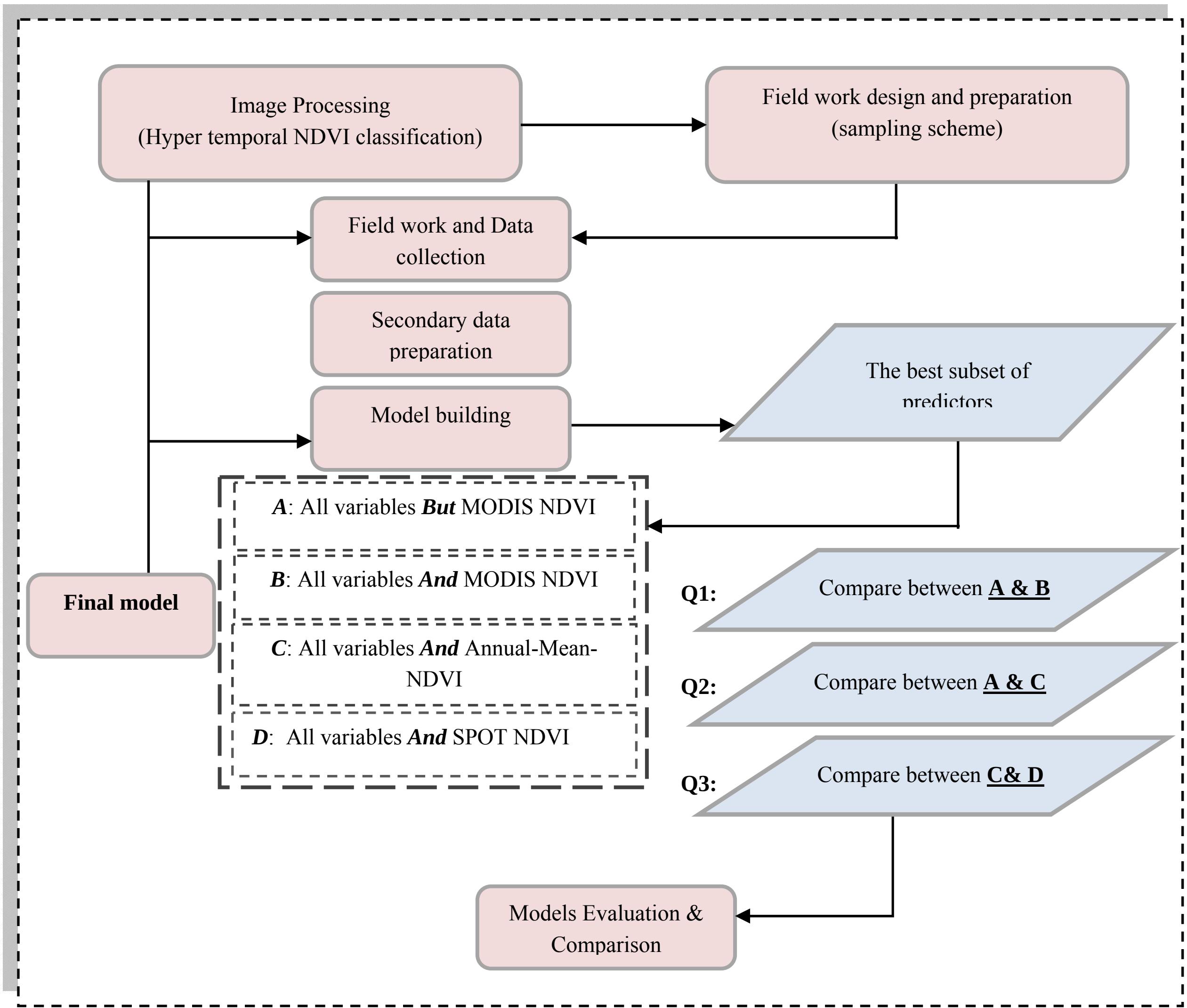

Figure 5: General methodology

2.1. Study area

The island of Crete (Greek: Κρήτη, transliteration: *Krētē*, modern transliteration *Kriti*) with 8,336 km^2 extent, is the largest island of Greece and the fifth largest island in the Mediterranean Sea (Figure6). Its population reaches approximately to 600,000 inhabitants. The main landscape of Crete consist of high mountains, with a few plains in the coastal area, where the majority of agricultural activities are existed(Chartzoulakis & Psarras, 2005).

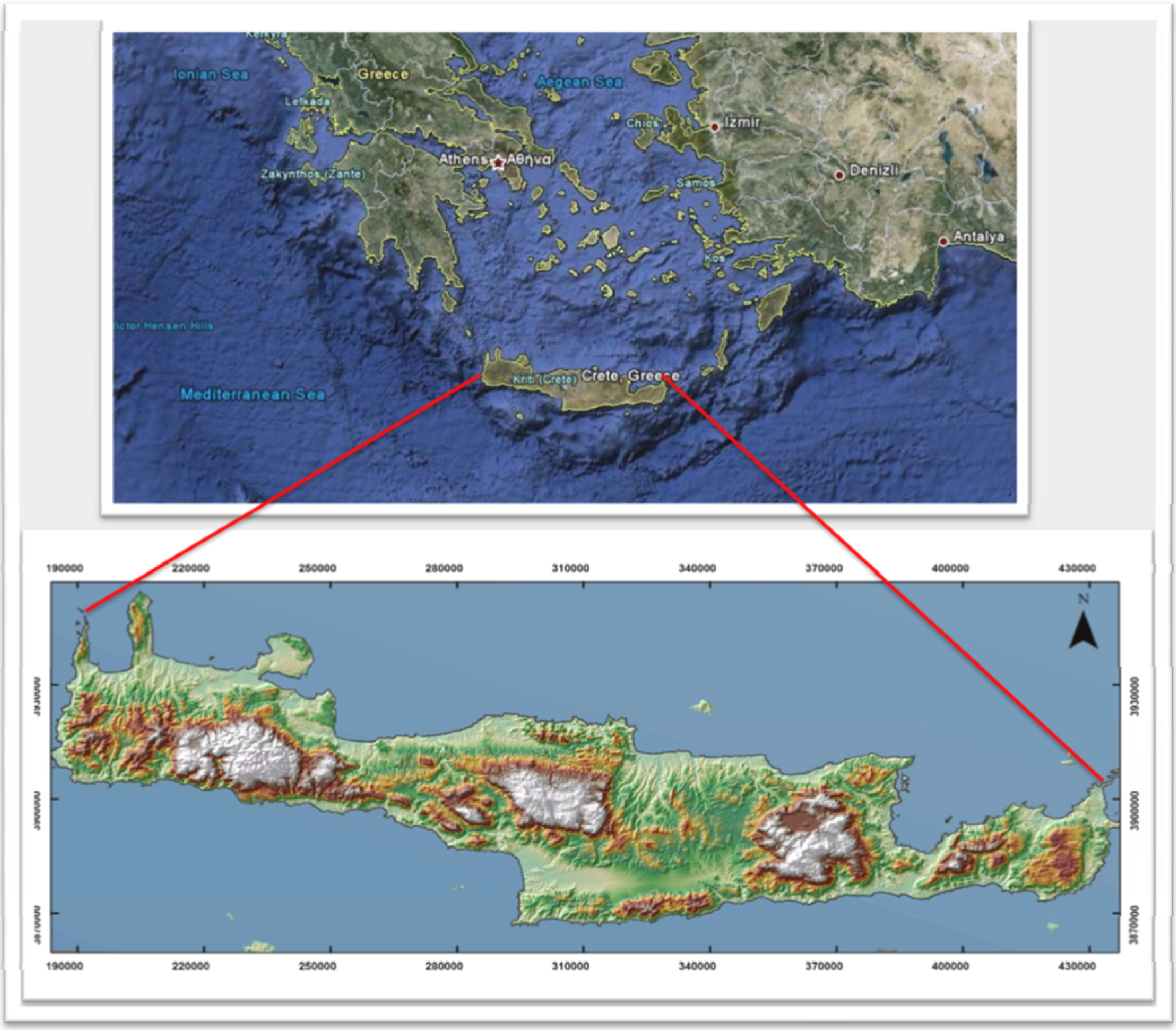

Figure 6: The location of the study area

The climate of Crete is humid Mediterranean with long hot and dry summers and comparatively humid and cold winters. During the winter the temperature decreases by altitude, while during summer it increases from the coast to up the mainland. About 70-80% of annual rainfall occurs in 3-4 months, while summers are usually long and dry (Chartzoulakis & Psarras, 2005). The annual precipitation is about 927 mm. The range of precipitation in coastal areas or low land is approximately 300 to 700 mm, while in mountains this range reaches to 2000mm. Although the rate of precipitation is high in the area, it is estimated that 63% is lost due to evapotranspiration. Consequently only 27% of rainfall goes to reaching the groundwater.

Agriculture is an important source of income for the region of Crete. Olive plantations are the most important crops and it is cultivated almost all over the island(Chartzoulakis & Psarras, 2005).

Despite the history of human habitation in the island which was about 8,000 years ago, during the Neolithic, but yet the species richness is high and the environment remains very diversify. The main reason for that is the geographic position of the island and because it is situated between three continents: Europe, Asia and Africa (Yaleuniversity, 2005).But these years the agricultural intensification causes habitat fragmentation and has its effect on the vegetation composition.

Figure 7: General landscape of the study area

2.2. Data sets

2.2.1. Environmental predictors

The selection of environmental predictors was based on data availability and ecological processes which influence to presence/absence of *Lacerta trilineata.*

In this study we focused on the hyper temporal NDVI images as a main variable, to find out its importance in distribution modelling of *Lacerta trilineata.* Some prepossessing analysis (e.g. Multicollinearity) has been done to check if variables are correlated with each other or not. As is showed in Table1, different data with different spatial resolution and sources were used in this study. Appendix B shows the legend related to all categorical data used in this study.

Table 1: Environmental predictors available for this study

No	Variable	Data type	Spatial Resolution	Temporal resolution	Source Of Data
1	Altitude	Continuous	3 arc seconds(~90m)	2000	USGS / SRTM
2	Slope	Continuous	3 arc seconds(~90m)	2000	USGS / SRTM
3	Aspect	Categorical	3 arc seconds(~90m)	2000	USGS / SRTM
4	Geology	Categorical	3 arc seconds(~90m)	2000	NHMC
5	Soil type WU	Categorical	1:1,000,000(1km)	1966	Wageningen university
6	Soil type WRB full	Categorical	1:1,000,000(1km)	2004	ESBN **(vector)
7	Dominant parent material	Categorical	1:1,000,000(1km)	2004	ESBN **(vector)
8	Depth of rock	Categorical	1:1,000,000(1km)	2004	ESBN**(vector & raster)
9	Volume of stones	Categorical	1:1,000,000(1km)	2004	ESBN**(vector & raster)
10	MODIS NDVI	Categorical	250m	2000-2009(16 days)	http://modis.gsfc.nasa.gov/
11	Land cover CORIN	1:100,000	1:100,000 (300m)	2000	EEA
12	Bioclim Data 19 (layers)	Continuous	0.5Degrees(~50km)	2005	Worldly/Hijmans et al
13	Average Annual NDVI	Continuous	250m	2000-2009(16 days)	http://modis.gsfc.nasa.gov/
14	SPOT NDVI	Categorical	I km	1999-2009(10 days)	CNES/SPOT image

2.2.2. Species data: *Lacerta trilineata*

The set of presence only data was provided by the Natural History Museum of Crete (NHMC, 2009). NHMC is the only source for obtaining occurrence data in Crete. It operates under the framework of the University of Crete since 1980, being a pioneer institute at national and European level in the different activities related to the natural environment of Crete.
The dataset used in this research consist of 78 observation points (X, Y coordinates) of *Lacerta trilineata* of which the occurrence of the location has been given by NHMC (Appendix A). Observation points with less than 1km accuracy were omitted from the dataset; only 68 occurrence points are used for further analysis. Figure8 shows the occurrence records for *Lacerta trilineata* across the study area.

Recently the use of museum datasets is becoming increasingly common as a tool for addressing biodiversity conservation and management problems (Guralnick & Van Cleve, 2005).
Although natural history museum datasets are often the best source of information available in biodiversity and species occurrences (Krishtalka & Humphrey, 2000), but several crucial problems need to be addressed. These datasets are often large in size and complex in structure. In many cases biases, gaps and potential pitfalls are common to them(Soberon *et al.*, 2000). Natural history collections are *ad hoc* datasets that have been developed from efforts of multiple collectors over long periods of time. Even with potentially billions of specimen records available worldwide, questions remain: are the data resolved unbiased enough (Soberon *et al.*, 2000)to be an appropriate sample at the spatial and temporal scales of interest? Even if it appears that museum data provide good estimates of species richness, do they match species richness estimates from more systematically collected data sets? If museum data provide useful estimates of species richness, another problem is how to use this information to examine biodiversity and its relationship to environmental change (Colwell *et al.*, 2004).
Another challenges in using data from natural history collection is the spatial error, accompanies the documentation of every collecting event, but its significance is only apparent in the context of a particular analysis. Specifically, the scale of a given analysis determines the needed precision of localities within a sampling domain. Historically, most collecting events or localities were recorded as textual descriptors and were not accompanied by collector-assigned coordinates. Even when the coordinates were recorded, the source from which the localities were derived and associated levels of precision (map scale, datum, GPS) are often preserved in the collection data base(Rowe, 2005).

Recently some studies are assessing and analysing this datasets. For example, Soberon (2000) analyzed one medium-sized database from the perspective of its weakness in its use for two important conservation objectives: obtaining lists of species and for the estimation of species' geographic range. In this paper they focused more on the gaps and biases of the databases when they are used to obtain listing of species or provide the basis for area of distribution extrapolation.

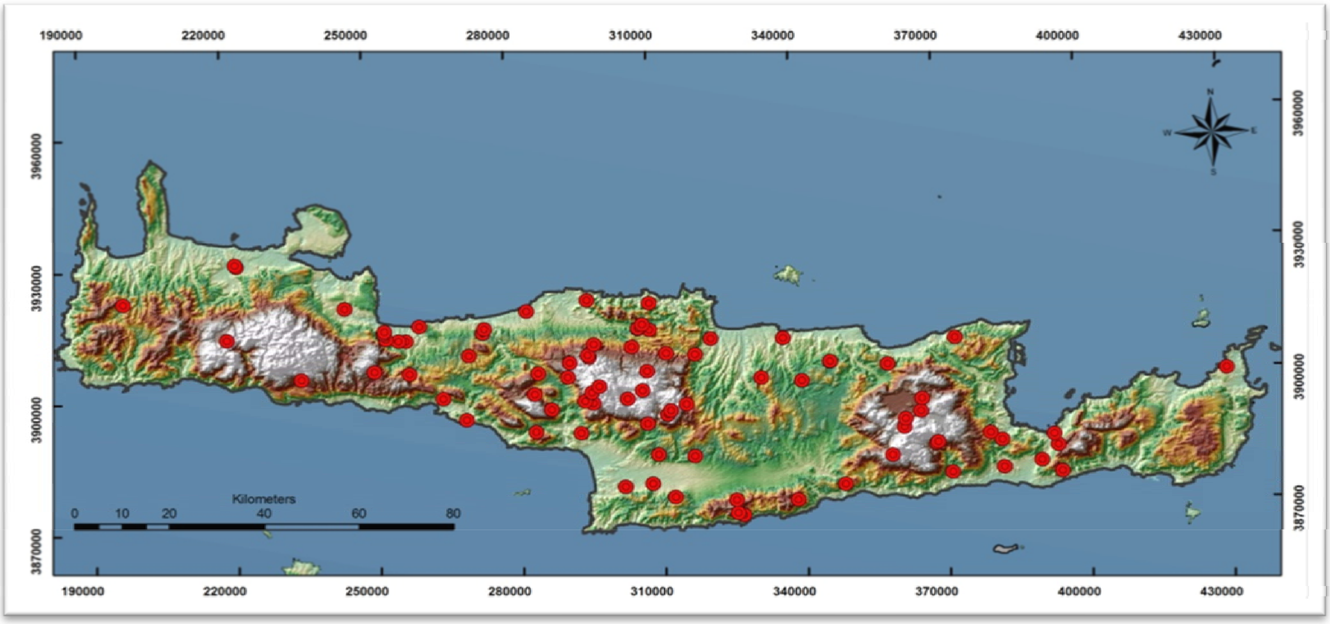

Figure 8: Occurrence records for *Lacerta trilineata* (81records) used in this study. Data derived from Natural History Museum of Crete and fieldwork

However, we are awarded of all probable errors of biases in natural museum datasets, but, because they are the only sources for species occurrences data, can be considered as the only solution at this time.

2.2.3. Hyper temporal NDVI images

As each plant grows, sickens, heals and dies; the concentration of chlorophyll in its tissues and its biomass fluctuates over time, and this change can be detected by NDVI(Tucker, 1979b). Plant productivity and biomass of ecosystem vary in space and time (Leyequien *et al.*, 2007), and this study aims to find out the relationship between spatio temporal changes in vegetation (vegetation dynamic) and presence/absence of a certain species.
For this objective time series of MODIS NDVI from 18 February 2000 to 28 July 2009, with the interval of 15 days (218 images) used to model the vegetation dynamic. The NDVI classification processed using the approach methodology developed by De Bie *et al*., 2008.
In the first step all 218 NDVI images were stacked, and then ISODATA clustering algorithm in ERDAS Imagin9.3.2 used to generate the classification. ISODATA is an unsupervised clustering method that uses minimum spectral distance formula to form clusters(Campbell, 2008).
To find the appropriate number of classes the classification was started from 10 to 100 classes. The maximum number of iteration was set to 50 (the general rule is half number of classes) and the convergence threshold was set to 1 (so the classification will not stop earlier than 50 iterations).
To compare the separability between classes, the divergence statistical measures of distance (class separability) between generated cluster signatures were used (Swain & Davis, 1978).
Excel software was used to make a graph of minimum and average separability. The peak in average and minimum divergence indicate the appropriate number of classes for the specific area.
In this study, based on the adequate number of minimum and average divergence, 65 classes for NDVI were selected for further analysis. Figure9 shows all steps in image processing.

The following flow chart schematically shows the procedure of hyper temporal NDVI classification.

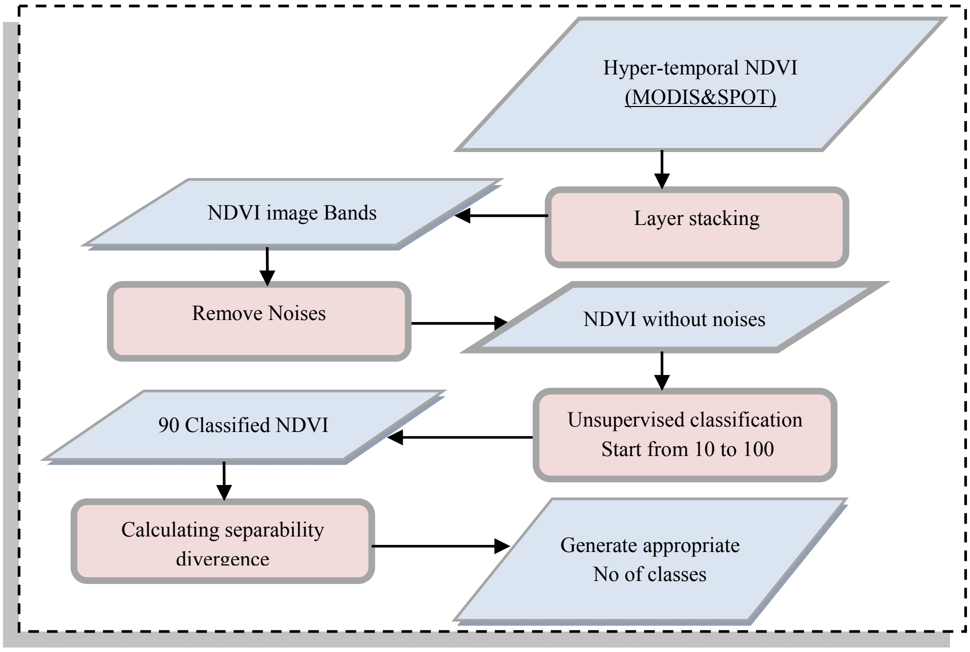

Figure 9: Full image processing of SPOT & MODIS NDVI classification

2.3. Data collection

2.3.1. Fieldwork design and procedure

The main objective of this fieldwork was to record habitat and microhabitat characteristics of *Lacerta trilineata* based on the classified NDVI. The classified NDVI map helped us to develop a better understanding of the ecological surface cover variables influencing habitat suitability for the species. In fact we wanted to know which classes of NDVI have more or less potential of possible occurrence for *Lacerta trilineata*. For that reason in each sample location the land cover percentage of plants, rocks, stones and soil were visually estimated. Field collection took place between 21st September 2009 and the 11th October.

The coordinates of each location were measured with a global positioning system (GPS). Basically 28 random sampling were generated based on hyper temporal SPOT NDVI (1km). The land cover (CORIN2000) was used to remove those classes with less probability of species occurrence (e.g. urban areas, industrial areas, olive plantations, etc).

During the fieldwork, we realized that the SPOT NDVI with 1km resolution could not explain adequately the habitat characteristics of *Lacerta trilineata*. Due to the reason that the Crete Island is very fragmented, 100 random sampling were generated based on 65 classes of MODIS NDVI (250m). These points were created, taking into consideration the time to spend for travelling, between the sample points and accessibility of each point. Not all classes in the MODIS NDVI map were sampled, as some of the classes were located in inaccessible areas. For instance, class 6, 10 were located in top of the mountain. 11 species occurrences recorded during the field work and added to the NHMC dataset. The lizards were identified visually using the field guide of (Valakos *et al.*, 2007).

2.4. Multicollinearity diagnostic between predictors

Multicollinearity is a statistical term for the existence correlation amongst two or more explanatory variables in statistical modelling. It occurs when variables are highly correlated. In this situation, reliable estimation of the parameters is vulnerable. When two variables are highly correlated, they are basically the same phenomenon or construct. In the other words, they both convey essentially the same information.
Multicollinearity is one of the crucial problems in habitat distribution modelling (Brauner & Shacham, 1998). The principle danger of such data redundancy is over fitting in statistical models. The Variance Inflation Factor (VIF) (Montgomery *et al.*, 1982), one of the common indicators to detect multicollinearity, was used in this study to find and remove the variables, those increase the risk of multicollinearity in the modelling.

$$VIF = \frac{1}{1 - R^2{}_i}$$

2.5. Predictive species distribution modeling

Many modelling techniques are now available for predictive species distribution modelling. Guisan and Zimmerman (2000) provided an interesting synthesis review of the state-of-the-art in pre-2000 period of habitat distribution modelling which was updated by Guisan and Thuiller (2005). They defined species distribution models as “empirical models relating field observations to environmental predictor variables, based on statistically or theoretically derived response surfaces” (Guisan & Zimmermann, 2000).
Species data can be presence-only, presence/absence or abundance observation based on random or stratified field sampling, or observation obtained opportunistically, such as those in natural history collections (Guisan & Thuiller, 2005).
Many statistical methods and tools have been applied and introduced by studies for habitat distribution modelling. These methods are vary in how they model the distribution of the response (species), select relevant predictor variables, define fitted functions for each variable, weight variable contributions, allow for interactions, and predict geographic patterns of occurrence (Elith *et al.*, 2006; Guisan & Thuiller, 2005). Statistical methods such as GLM (Generalize linear methods) are suitable to use for predictive modelling, when we deal with presence/absence datasets. Availability of presence/absence occurrence data allows us to use a variety of standard statistical techniques. However, for most of species, absent data are not available (Phillips *et al.*, 2006). There are limited numbers of methods that can be used to model the distribution of species using presence-only data (Yost *et al.*, 2008).
Recently, Phillips et al. (2006) introduced the use of the Maximum Entropy (Maxent) method for modelling species geographic distributions with presence-only datasets. Maxent is a general purpose machine learning method with a simple and precise mathematical formulation (Phillips *et al.*, 2006). Maxent is able to make predictions or inferences from incomplete information. The method estimates

a target probability distribution that is closest to uniform, or spread-out, subject to a set of constraints that represent our incomplete information about the target distribution (Yost *et al.*, 2008).
The unknown probability distribution, denotes as π, is over a finite set X (the set of pixels in the study area). The distribution π assigns a non-negative probability π(x) to each point x, and these probabilities sum to 1.
The approximation of π is a probability distribution (ˆπ). The entropy of ˆπ is defined as (Phillips *et al.*, 2006):

$$H(\hat{\pi}) = -\sum_{x \in X} \hat{\pi}(x) \ln \hat{\pi}(x)$$

In this equation 1n is the natural logarithm (Phillips *et al.*, 2006). The entropy is non-negative and is at most the natural log of the number of elements in X. Entropy is a fundamental concept in information theory (Phillips *et al.*, 2006).
When Maxent generates a probability distribution, it starts at uniform distribution (gain = 0) and performs a number of iterations to adjust feature weights and maximize the likelihood of presence at the sample locations, called the training gain (Phillips *et al.*, 2004; Riordan & Rundel, 2009). The test gain is the average log probability of the presence samples used to test the model. For example, if the model test gain is 2, the average likelihood of a test presence locality is exp (2) (about 7.4) times greater than that of a random background pixel (Phillips *et al.*, 2004). This value is analogous to deviance, a measure of goodness of fit, used to assess performance of generalized linear and additive models (Phillips *et al.*, 2004) and has been used as another measure of overall model performance (Phillips *et al.*, 2004; Buermann *et al.*, 2008).

Philips et al. (2006) stated that Maxent offers many advantages include the following: (1) it requires only presence data, together with environmental information for the whole study area; (2) it can be used for both categorical and continuous environmental parameters; (3) efficient deterministic algorithms have been developed that are quarantined to converge to the optimal (maximum entropy) probability distribution. Baldwin (2009) argued about the potential weakness of Maxent. According to his review, one of the major problem deals with ability to transfer finding from within a sampled area to un-sampled area (transferability of model). This transferability could be an issue, because the composition of environmental variables always varies in space. He also argued that the second problem with Maxent could be related to model evaluation. According to him, just because a model can be built does not mean that it is informative (Baldwin, 2009).
In order to evaluate the performance of model, Maxent uses AUC, developed from ROC plots (Area Undere the Receiver Operating Characteristics Curve). It provides a ranked approach for assessing differences in significant (Phillips *et al.*, 2006). It also provides useful information about the model, but the testing for significance just show how much the model performance is better than random, not if it performs worse than random (Baldwin, 2009).
Like asall modelling approaches, Maxent also is influenced by high heavily biased sampling distribution. Philips et al. (2009) argued that the bias can be reduced by introducing the same bias to background locations (Phillips *et al.*, 2009; Baldwin, 2009). However, the use of Maxent is widespread because it shows a great potential to assess the relationship between habitat characteristics and species occurrences (Baldwin, 2009).

2.6. Model building in maxent

The maximum entropy (Maxent) technique is selected for modelling species distribution in this study, because it has seen a widespread recent use to habitat distribution modelling (see section 2,5), and is working with presence-only data. The main objective of this step was to build a model with adequate performance and best subset of environmental variables. The full model may be oversized (i.e. one or more predictors may have little predictive power) or redundant (some predictors may be correlated in a significant manner, hence resulting in multicollinearity).The stepwise selection of predictors is useful to make an optimized selection of predictors as input to predictive models. In this study, the stepwise selection was applied by systematically dropping predictors one at a time (Jacknife test) as assessing the performance variation in model accuracy on the test data. The Jacknife test also was used for identifying which predictor has more contribution in the model. For each predictor variable alone, regularize training gain calculated to see the drop in gain when the variable is omitted from the full model. Therefore, to accomplish the first goal in the modelling, processes started with a full model that contains all environmental variables. Then the predictors with lowest decline in the training gain were removed one by one from the model, and finally, the remaining variables were used for the next step.

Subset with 75% of the total 81 presence records were randomly selected as training or calibration data, and 25 % (n=20) as test or validation data. As usually the species occurrence data are subjected to bias (see discussion), the performance of models can be varied when the random subset selection of data is repeated. To deal with sample selection bias, bootstrapping method with100 random partitions (replications) of the presence records was used (section 2.7). The average behaviour of Maxent, then, was assessed to see how the models were changed with different random seeds used for each run. In this case, different random test/training partition was made and a different random subset of the background was used to build each model to obtain the best estimate of the species distribution and creating a probability map for *Lacerta trilineata*.

Setting of the other parameters of Maxent are presented in this study, are the recommended defaults by software. Because these setting have been tested on large datasets and tend to perform well (Phillips *et al.*, 2006).

However, the logic of the best model choice in this study was to find the one, which had the fewest predictors with an average training gain not significantly different from the full model or the model with the highest training gain. The following flow chart below Figure 10, schematically, shows the procedure to build the final model.

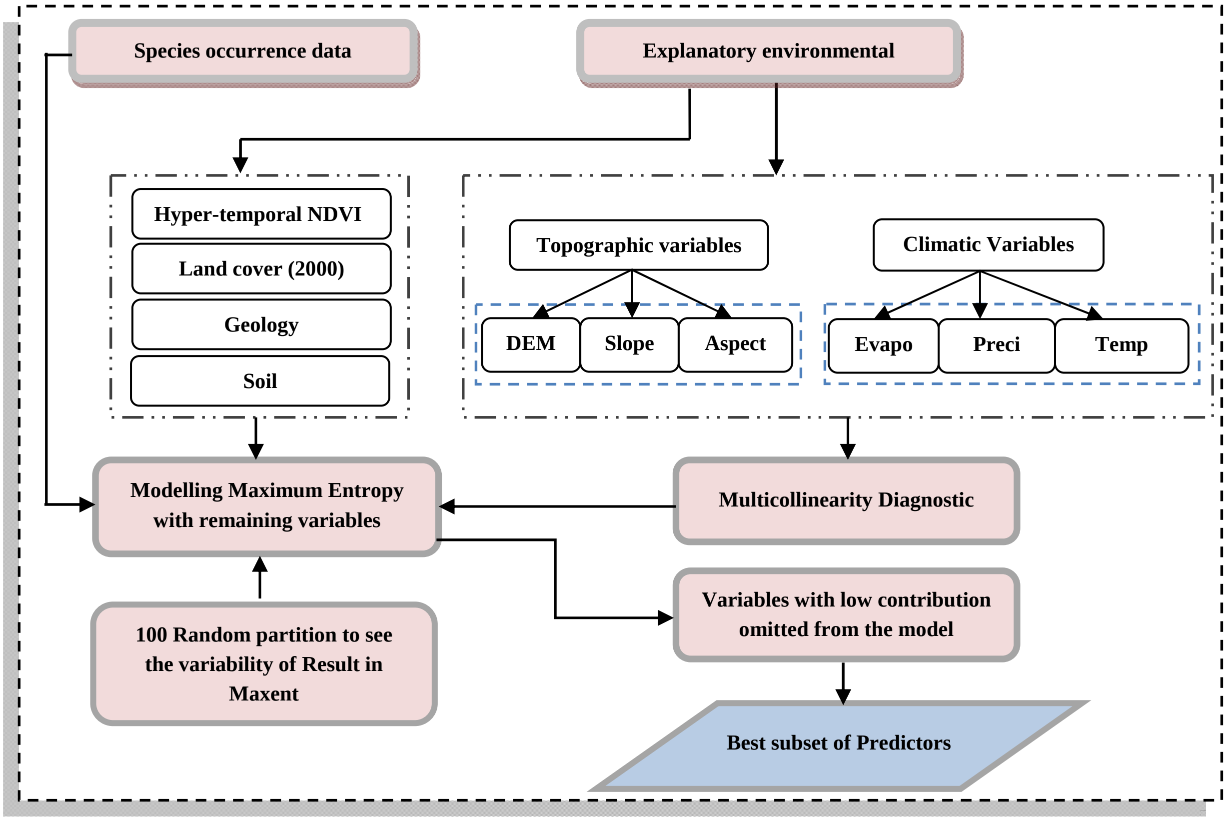

Figure 10: Stepwise selection of predictors

2.7. Model validation and hypothesis testing

As mentioned previously (section 2.6), the selection of environmental variables was carried out based on the importance of the variables and their effect on the performance of the model. After all, just building a model does not mean that it is informative (Baldwin, 2009). There are several approaches that can be used to assess the performance of the models. The AUC index which is developed from ROC plot was used in this study. One of the main advantages of ROC analysis is that area under the ROC curve (AUC) provides a single measure of model performance, independent of any particular choice of threshold (Phillips *et al.*, 2006). Recently AUC is wildly used to estimate the predictive accuracy of distribution models (Lobo *et al.*, 2008).

Because the species sample data are often subjected to bias, some methods (e.g. bootstrapping) are suggested for dealing with sample bias. Bootstrapping provides a realistic estimate of the predictive performance of a model, without incurring the expenses of collecting an independent data set to validate the model. This method involves resampling the data with replacement, and conducting a series of models. This simulation provides an estimation of the optimism arising from in-sample validation. The estimate of optimism is used to provide an adjusted estimate of the model evaluation statistics (AUC). The bootstrapping implemented here is believed to provide the least biased estimation of predictive performance.

In order to test the hypotheses, Wilcoxon signed rank test was used for matched pairs. Wilcoxon signed rank test is a non parametric method and can be used as an alternative to the paired student t-test when the assumption of normality in the population is violated. We used this test to determine whether there is a significant difference, at the confidence level of 95% (α=0.05), in the measure of AUC, and also training gain. The 100 samples generated via the bootstrapping simulation in each scenario were used to test the hypotheses.

3. Results

3.1. Multicolinearity diagnostic

Multicollinearity diagnostic was performed in SPSS software considering continuous environmental variables. Following Nether et al. (1996) and Chatterjee et al. (2000) who suggested that multicollinearity is only sever at VIFs > 10 (Chatterjee & Hadi, 2006), all predictors with VIFs more than 10 excluded from the final list. Table 2, shows the remained predictors with the corresponding VIF values after multicollinearity diagnosis. Average-Annual-NDVI, Annual-precipitation, Digital Elevation Model (DEM), Slope, Potential-Evapotranspiration and Actual-Precipitation, as continuous predictors, were selected for model building.

Table 2: Explanatory variables used for model building after multicollinearity test

Environmental Variables	***VIF***
Slop	1.213
Annual precipitation-Precipitation	1.089
Annual-Mean-NDVI	7.622
DEM	2.763
Potential_Evapotranspiration	4.143
Annual-Mean-Temperature	9.243
Actual_Evapotranspiration	3.862

3.2. Model building

The average behaviour of Maxent in 100 bootstrap simulations using all variables (the remained predictors after multicollinearity test) revealed that some variables (e.g. DEM, Slope, Aspect) had the least predictive power. According to the result of Jacknife test (Figure 11), excluding these variables does not change the measures of AUC and gain. Regarding this result, the most important variable is the classified hyper-temporal MODIS NDVI. This gain will be decreased if this layer omitted from the model, which suggests hyper temporal NDVI contains useful information that are not existed in other variables. After NDVI, the CORIN2000 (land cover) and Annual-precipitation are the second and third important variables, respectively.

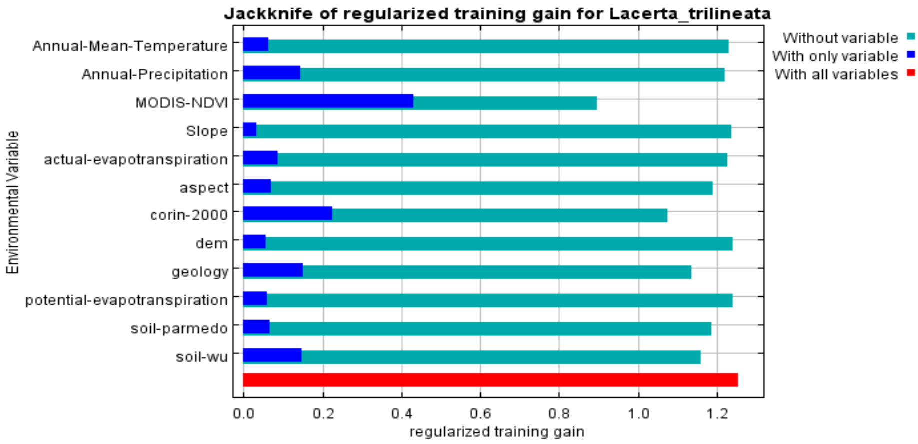

Figure 11: Results of the jackknife test the stepwise selection of predictors applied to the model.

Stepwise procedure was started by omitting the Slope, and AUC slightly increased after that. In the next steps, the gain and AUC were not changed when DEM (model 3) and Actual-Evapotranspiration (model 4) were omitted from the model. Therefore, regarding the parsimonious rule (less is better), the model excluding these variables is preferable. In the next step (model 5), the AUC and gain was decreased when the Annual-temperature was omitted. Consequently, based on these results the final set of the predictors are those were used in model 4, and presented in the Table 3. The comparison of performance measures in stepwise procedure is provided as a graph in Figure 12.

Table 3: Final subset of environmental variables used to model *Lacerta trilineata* in Crete Island

No	***Environmental Variables***
1	MODIS-NDVI
2	corin-2000
3	soil-wu
4	geology
5	Annual-Precipitation
6	aspect
7	soil-parmedo
8	potential-evapotranspiration
9	Annual-Mean-Temperature

The output from exploratory tools, such as stepwise selection of predictors, is useful to make an optimized selection of predictors as input to predictive models. The stepwise selection was applied by systematically dropping predictors one at a time as assessing the performance variation in model accuracy on the test data.

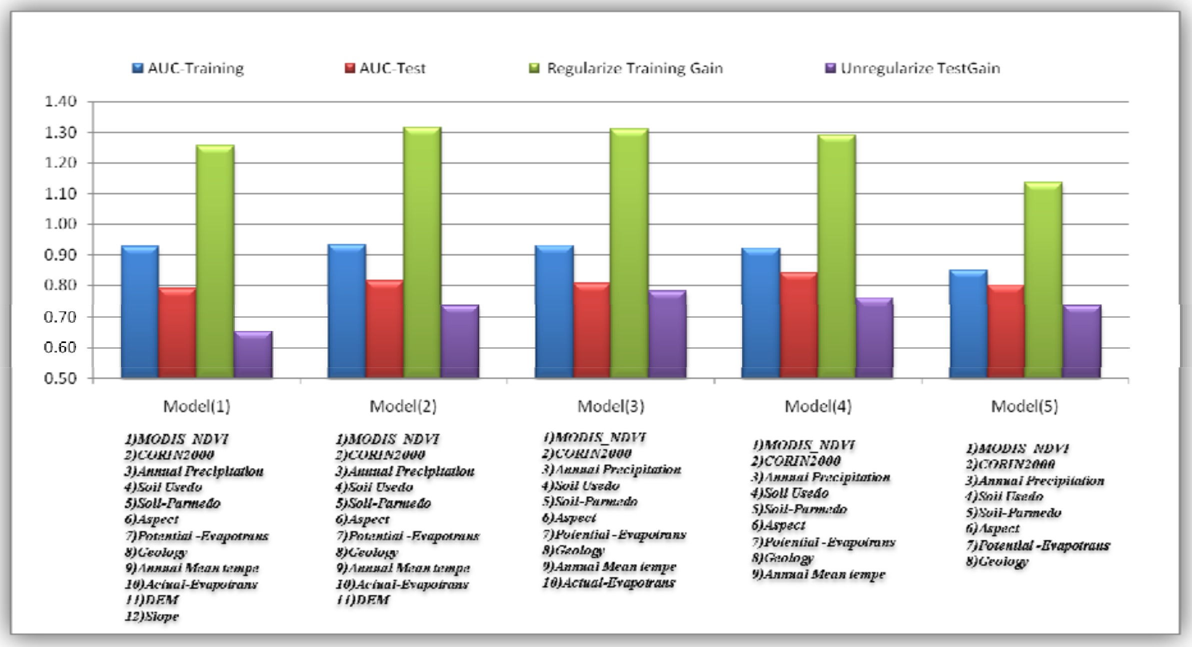

Figure 12: Comparing Values for Training AUC, Test AUC, Regularize training gain, Unregularized Test gain, in different combination of variables

3.3. Model performance and validation

3.3.1. To compare model with and/or without MODIS NDVI

The behaviour of Maxent in 100 bootstrap simulations, in which the classified MODIS NDVI was used, indicates that the most important predictor, based on AUC and gain measures, is classified MODIS NDVI (Figure 13b). The gain was decreased incredibly when MODIS NDVI was omitted from the model Figure 13a. The average of AUC and regularize training gain values for the models included MODIS NDVI were as following: AUC test=0.78, AUC training= 0.92, Regularize training gain=1.2. These measures for the models excluded the MODIS NDVI were: AUC test=0.72, AUC training=0.86 and Regularized training gain=0.81. The Land cover (CORIN), Soil-wu, Geology, Aspect, Annual-Precipitation, Soil-Parmedo, Annual mean temperature, and potential evapotranspiration can be ranked as second, third and etc. important variables, respectively. As was expected the average AUC test /training and Gain is less than when the model included hyper temporal NDVI.

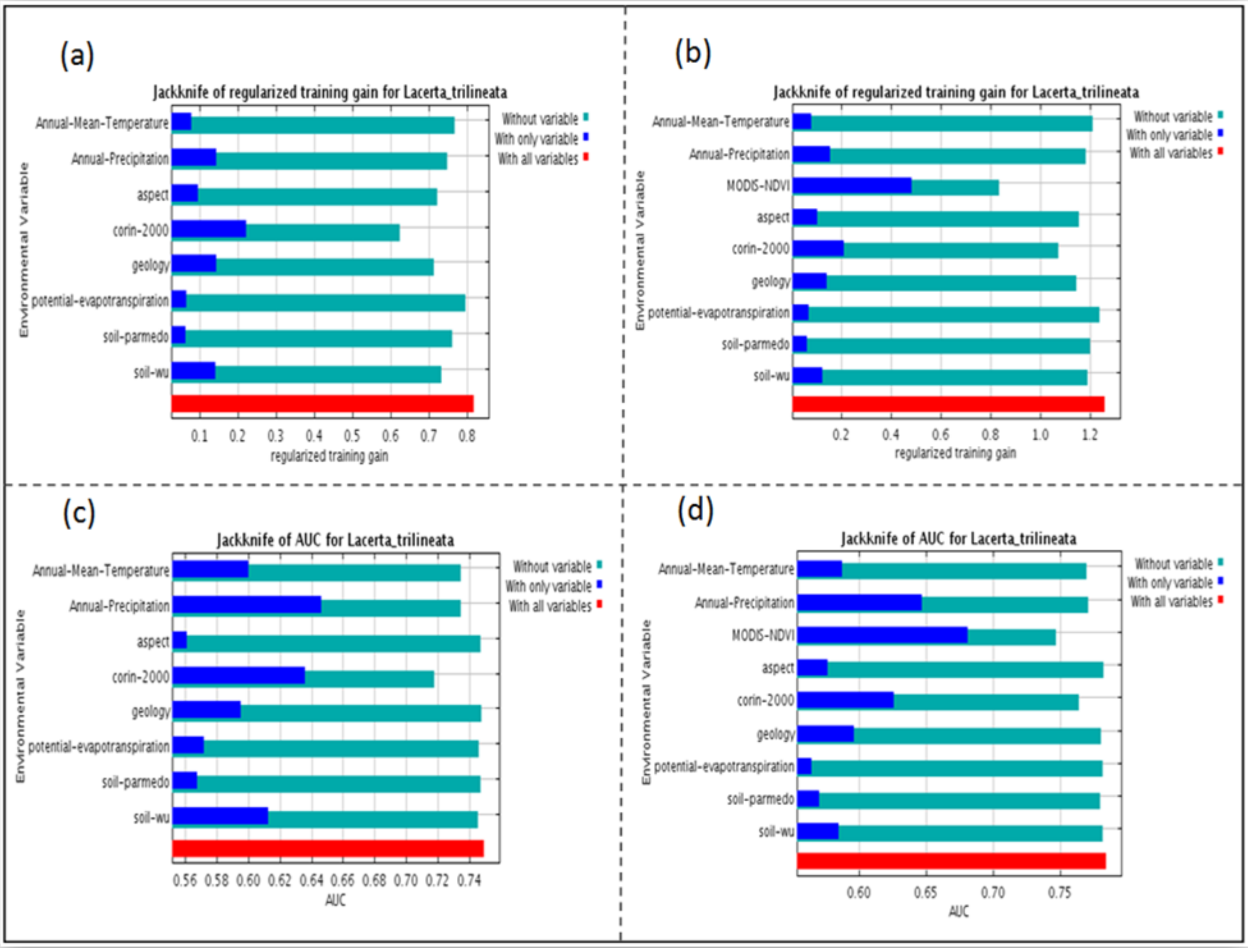

Figure 13: Jacknife results show the importance of predictors based on AUC and training gain; **(a)** Jackknife test for variable importance (*All variables* *BUT* *NDVI)* AUC Test=*0.72*, AUC Training=*0.8*& Regularized training gain=*0.81***(b)** Jackknife test for variable importance (*All variables* *AND* *NDVI)*AUC Test=0.78, AUC Training= 0.92, Regularize training gain=1.2 **(c)** AUC for models considered all variables excluded classified MODIS NDVI; **(d)** AUC for models considered all variables included classified MODIS NDVI.

Testing the hypothesis that whether classified hyper temporal MODIS NDVI significantly improved the performance of the model, suggest that the improvement was significant. From the Wilcoxon test of AUC, the *P*-value=*1.345e-15*, shows evidence against null hypothesis.

3.3.2. To compare model with annual mean NDVI and classified MODIS NDVI

The behaviour of Maxent in 100 bootstrap simulations, in which the annual average of NDVI (a continuous variable) was used, indicates that the most important variable is land cover (CORIN) and after that Annual-precipitation, Soil-wu, Aspect, Geology, Annual-mean-temperature, soil-parmedo and Annual-Average-NDVI are respectively in the next positions of importance (Figure 14).

The inclusion of the annual mean of NDVI, as a predictor, in the model just slightly improved its performance compare to the model without NDVI, (AUC training increased from 0.86 to 0.87, AUC test changed from 0.72 to 0.74 and training gain from 0.81 to 0.92).
Testing the hypothesis that whether there is a significant difference between predictability of annually averaged MODIS NDVI and classified hyper temporal MODIS NDVI, suggest that the classified MODIS NDVI performs better. From the Wilcoxon test of AUC, the *P*-value=*0.02*, shows evidence against null hypothesis.

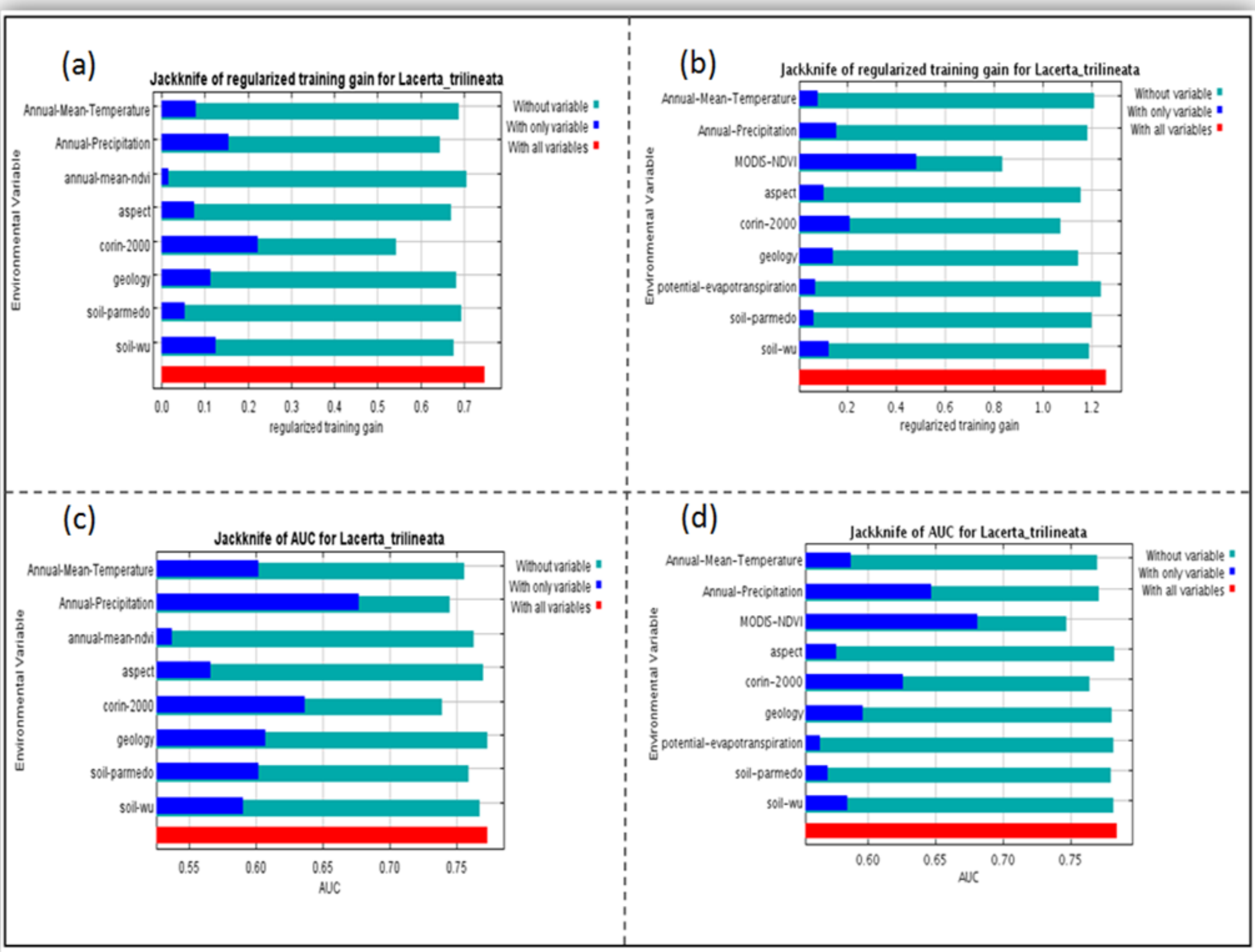

Figure 14: Jacknife results show the importance of predictors based on AUC and training gain; **(a)** Jackknife test for variable importance (*All variables AND annual average of NDVI)*AUC Test=*0.74*, AUC Training=*0.87* & Regularized training gain=*0.92;* **(b)** Jackknife test for variable importance (*All variables AND* classified MODIS NDVI*)* AUC Test=0.78, AUC Training= 0.92, Regularize training gain=1.2; **(c)** AUC for models included Annual-Mean-NDVI; **(d)** AUC for models considered all variables included classified MODIS NDVI.

3.3.3. To compare hyper temporal SPOT NDVI with hyper temporal MODIS NDVI

The average behaviour of Maxent in 100 bootstrap simulations, in which the classified SPOT NDVI was used, indicates that the most important variable is SPOT-NDVI. The average contribution of SPOT-NDVI in the models is 24.4%and after that, land cover (CORIN), soil-wu, geology, aspect, Annual-precipitation, soil-parmedo, Annual-Mean-Temperature, Potential-evapotranspiration respectively are in the next positions of importance Figure 15. The averages of AUC and gain in these models were: AUC test=*0.72*, AUC training=*0.86* and Regularized training gain=*0.8*. Comparing the contribution (as an index of variable importance) of SPOT NDVI (24.4%) with MODIS NDVI (34.4%) indicates that the MODIS NDVI can explain the distribution of the species, more efficiently. However, the hypothesis test also supports this statement.

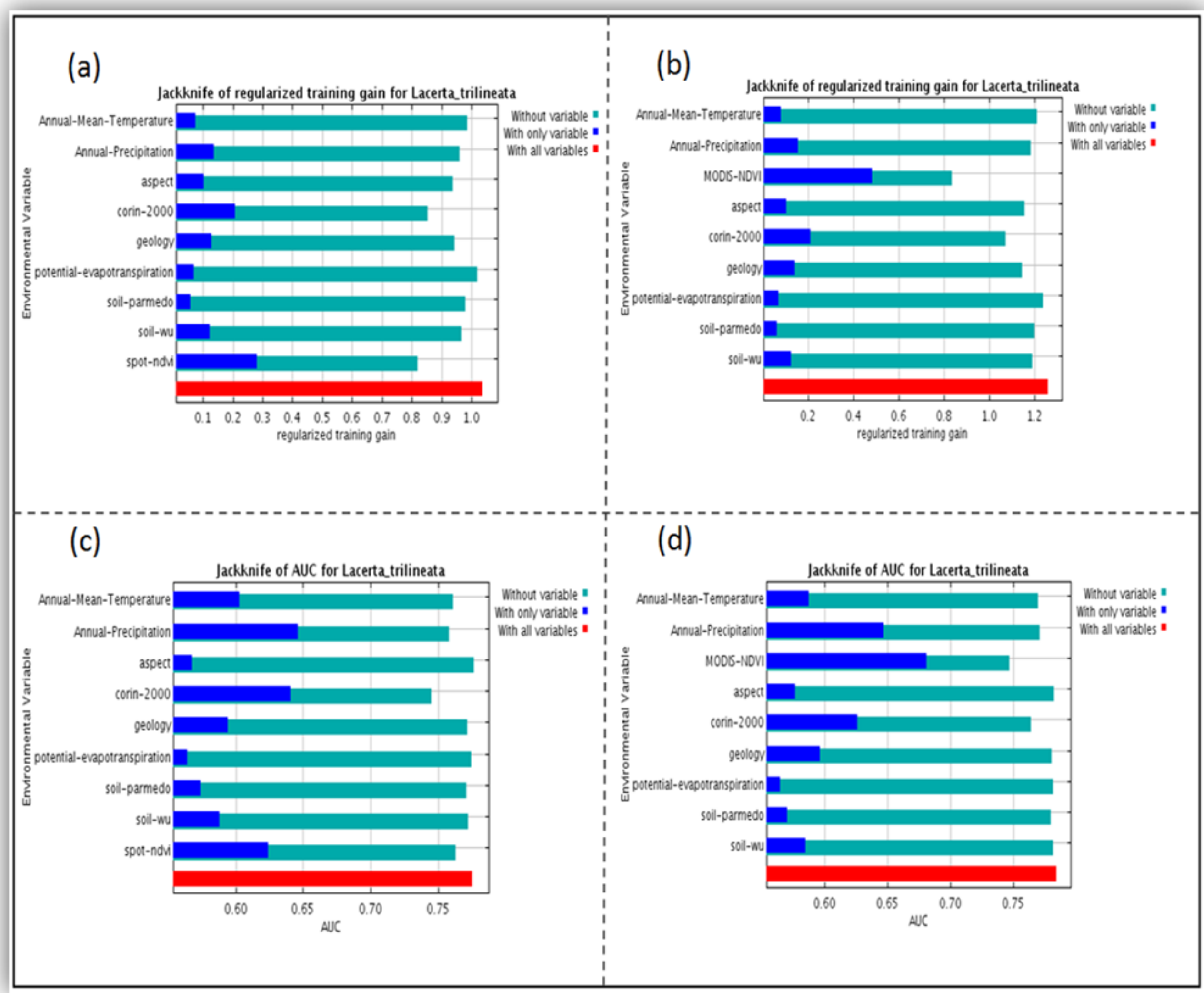

Figure 15: Jacknife results show the importance of predictors based on AUC and training gain; **(a)** (*All variables <u>AND</u> SPOT NDVI)* AUC test=*0.72*, AUC training=*0.86* and Regularized training gain=*0.8* **(b)** Jackknife test for variable importance (*All variables <u>AND</u> MODIS NDVI)* AUC test=*0.78*, AUC training=*0.92*, Regularize training gain=*1.2* **(c)** Jackknife test for AUC in the model included SPOT NDVI **(d)** AUC for models considered all variables included e model included MODIS NDVI

Testing the hypothesis that whether there is a significant difference between predictability of classified hyper temporal SPOT NDVI and classified hyper temporal MODIS NDVI, suggest that the classified MODIS NDVI performs better. The results imply that both models consistently perform better than the model without considering classified NDVI. From the Wilcoxon test of AUC, *P*-value=0.07 shows the null hypothesis cannot be rejected at the level of 95% confidence, but it is rejected at the level of 90%. This hypothesis also was test by comparing the regularized training gain, that the *P-value=9.8e-14* shows that based on the gain measure, the null hypothesis is rejected.

3.4. Habitat preferences

3.4.1. *Lacerta trilineata* prediction across the study area

Figure 16, shows the map, probability distribution of *Lacerta trilineata*. It was produced based on the average Maxent in 100 bootstrap simulations.
The red and yellow colours represent the suitable habitats for the species, while the green and blue represent the areas with lower suitability to unsuitable area. Visual interpretation suggests that the chance of occurrence in the central parts of the island is very high.
Figure 17 presents the probability of the species occurrence based on the model excluded hyper temporal NDVI. Comparing this map with previous one Figure 16 implies that many details are missed in the second map.

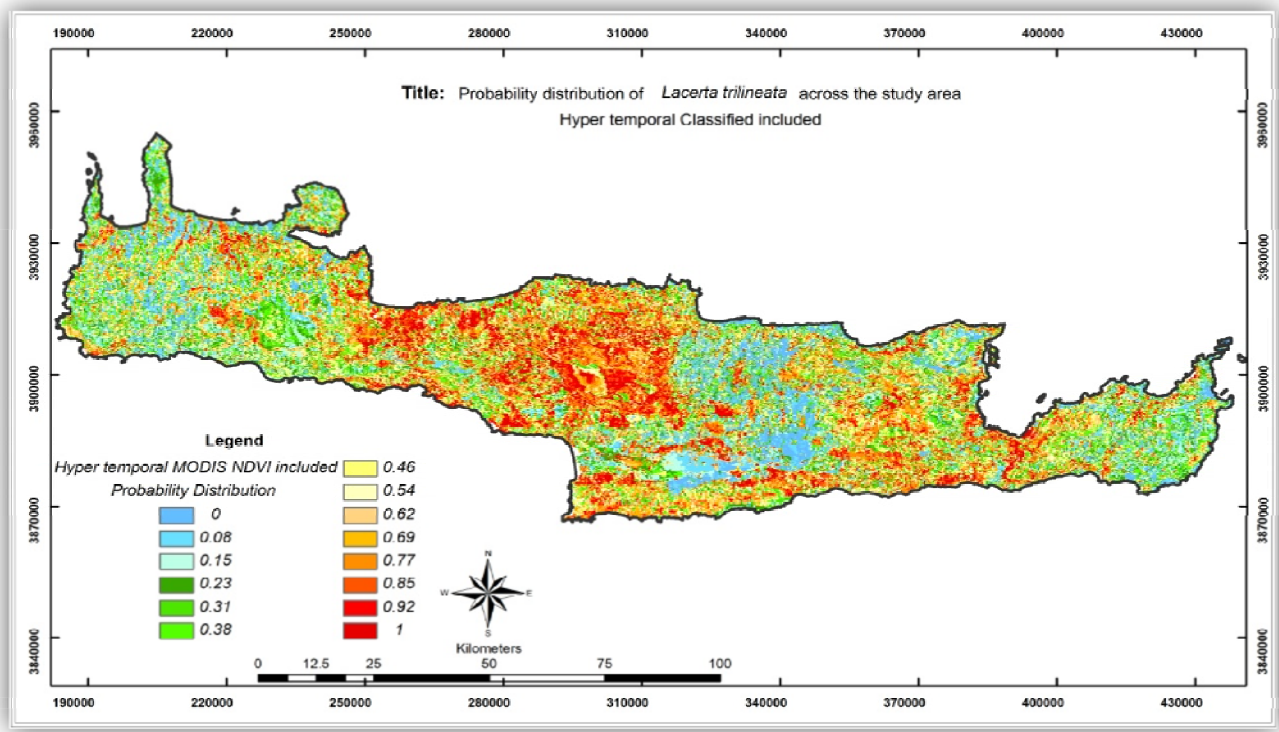

Figure 16: The probability distribution of Lacerta trilineata across the study area (hyper temporal classified NDVI is included)

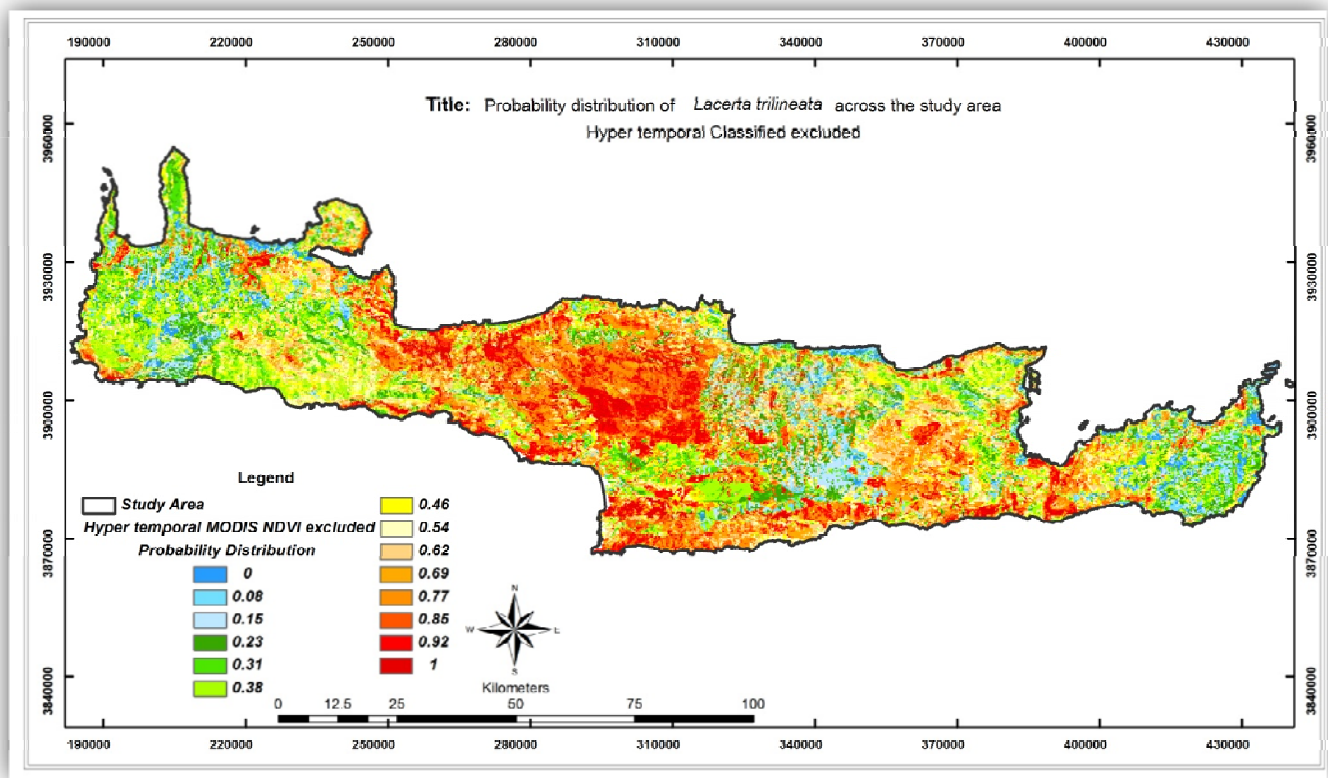

Figure 17: The probability distribution of *Lacerta trilineata* across the study area (hyper temporal classified NDVI is excluded)

3.4.2. Predictor variables

The species response shape to each predictor was produced by Maxent through 100 bootstrap simulations. In Figure18 the red colour indicates the average probability of species response to the values of predictor, and the blue colour represents its variability. These curves imply how each environmental variable affects the Maxent prediction, and therefore, it indicates how the logistic prediction changes as each environmental variable is varied, keeping all other environmental variables at their average sample value.

Response curve related to hyper temporal classified NDVI implies some classes have more potential for the species occurrences. The probability is equal or more than 0.4 in all classes of land cover (CORIN) map. But it suddenly reached to 1 in complex agricultural area and old agricultural areas (Appendix B). It implies that distribution of the species is widespread. The response shape related to precipitation shows there is a positive relationship between occurrence probability and precipitation.

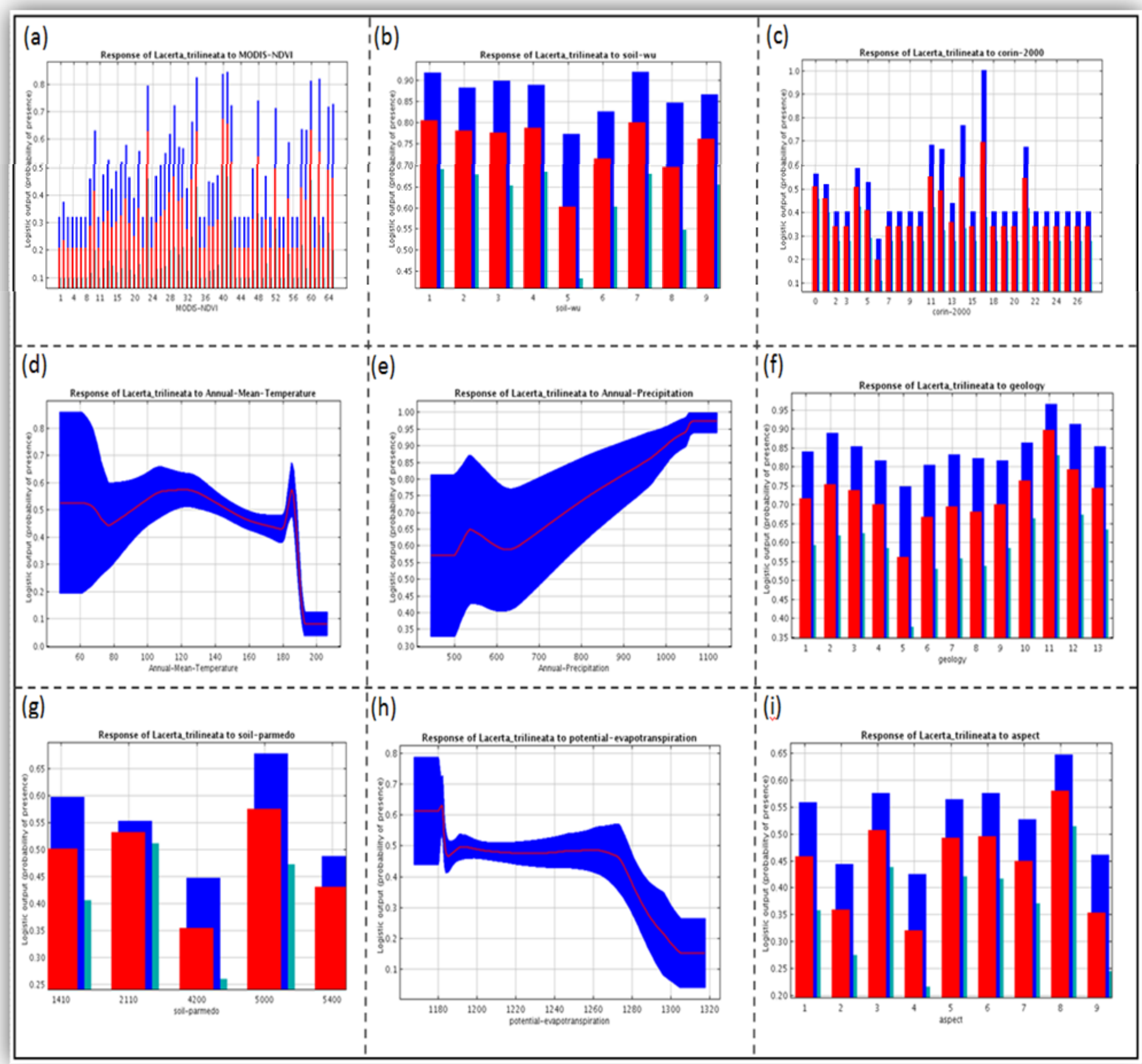

Figure 18: The species response shapes to each predictor ; **(a)** classified hyper temporal MODIS NDVI; **(b)** soil type classes; **(c)** land cover classes; **(d)** annual mean temperature; **(e)** annual precipitation; **(f)** geology classes; **(g)** dominant parent material classes; **(h)** potential evapotranspiration; **(i)** aspect classes.

3.4.3. Interaction of classified hyper temporal NDVI and probability of occurrence

In order to investigate the habitat characteristics of the species based on the results, the NDVI classes were attributed with land cover and probability values. This combination makes it possible to interpret the complex patterns of classified NDVI with land cover map and field work data. The mean probability in each class of NDVI was calculated by statistical summarizing the probability values within classified map. The standard deviation (STD) of the probability values within each NDVI classes Table 4 was used to investigate the variability of probability in each class. A lower standard deviation indicates the lower variability close to the mean, whereas higher standard deviation indicates that the probability is spread out over a large range of values. For example, class *41* has the most contribution in comparison with other classes. Species response shows the probability of 0.84 for this class, while the mean of probability in this class is *0.54* and the standard deviation is *0.25*. However, the final classification of NDVI was provided based on response curves values, and not based on the mean value in each class, because the high number of standard deviation shows, the variability and dispersion of probability in classes.

Cover percentage based on land cover and field work was assigned to each NDVI class to get a general overview of NDVI classes. However it should be emphasized that NDVI classes are not necessarily related to a specific kind of land cover, besides each class consists of complex patterns with different land covers and ecosystem boundaries.

Finally based on probability of occurrence, all 65 classes of NDVI were sorted in to 7 classes as follows: *Very high*, *High*, *relative high*, *medium*, *relative low*, *low*, *very low* Table 4. Appendix C shows all detail about land cover and field data for all NDVI classes.

Table 4: The probability occurrence of the species in each NDVI class, based on response curve and probability map.MIN=minimum probability in each class, MAX=maximum probability in each class of NDVI.MEAN= the average of probability in each class.STD=standard deviation.

Probability	MIN	MAX	MEAN	STD	NDVI	Probability
Very high	0.0253	0.9993	0.587	0.2549	41	0.84
	0.0622	0.9894	0.6706	0.2295	34	0.83
	0.0094	0.995	0.6544	0.2285	40	0.83
	0.0174	0.9952	0.5499	0.2366	62	0.82
	0.0163	0.9972	0.569	0.248	60	0.81
	0.0446	0.988	0.717	0.1947	23	0.8
High	0.0109	0.9924	0.6181	0.2278	48	0.74
	0.106	0.9817	0.7064	0.1772	29	0.72
	0.0115	0.9978	0.5665	0.2437	42	0.72
	0.032	0.9745	0.5664	0.2189	65	0.72
	0.0169	0.9968	0.5534	0.253	52	0.71
	0.0144	0.9941	0.5049	0.2484	64	0.71
Relative high	0.0431	0.9968	0.7171	0.2085	33	0.68
	0.0177	0.9972	0.5344	0.2427	58	0.63
	0.0089	0.9977	0.4703	0.2336	59	0.63
	0.0706	0.9772	0.7148	0.1818	10	0.62
	0.0119	0.9926	0.5443	0.2399	28	0.61
	0.0327	0.9838	0.5609	0.2115	19	0.6
Medium	0.5171	0.62	0.5569	0.0451	17	0.59
	0.0091	0.9982	0.4993	0.2417	55	0.59
	0.0974	0.9859	0.6568	0.1879	30	0.58
	0.0164	0.9797	0.5426	0.2277	21	0.58
	0.0572	0.9845	0.6262	0.2059	31	0.58
	0.0213	0.9798	0.5272	0.2164	27	0.55
	0	0.9942	0.6019	0.2094	13	0.52
	0.0325	0.9608	0.4916	0.214	16	0.52
	0.0364	0.9733	0.5555	0.2178	26	0.51
	0.009	0.969	0.3486	0.2395	47	0.5
Relative low	0.1153	0.9616	0.641	0.189	15	0.49
	0	0.9894	0.6275	0.1763	12	0.49
	0.0363	0.9912	0.6422	0.1699	18	0.48
	0.0283	0.9947	0.5888	0.2174	25	0.48
	0.0261	0.9963	0.4842	0.2294	50	0.48

Probability	MIN	MAX	MEAN	STD	NDVI	Probability
Relative low	0.0309	0.9736	0.4801	0.2139	9	0.48
	0.0145	0.9876	0.4594	0.225	39	0.48
	0.0266	0.9899	0.5687	0.2274	37	0.45
	0.0189	0.9821	0.5498	0.2127	38	0.44
	0.0435	0.9911	0.4754	0.2117	14	0.42
	0.0154	0.9921	0.4316	0.2299	32	0.42
Low	0.0557	0.9819	0.4495	0.2151	20	0.39
	0.0901	0.993	0.377	0.2034	2	0.38
	0.0501	0.996	0.4801	0.1966	22	0.33
	0.0096	0.9851	0.3979	0.2464	35	0.33
	0.0162	0.9817	0.3625	0.235	36	0.33
	0.0151	0.9837	0.3462	0.2261	53	0.33
	0.0093	0.974	0.3104	0.2368	57	0.33
	0.0089	0.9426	0.2516	0.2127	56	0.33
	0.0093	0.957	0.1895	0.1769	54	0.33
Very low	0.0167	0.9944	0.408	0.247	44	0.32
	0.0167	0.9894	0.382	0.231	49	0.32
	0.0101	0.9619	0.3278	0.2093	24	0.32
	0.0162	0.988	0.3261	0.2276	43	0.32
	0	0.9575	0.3201	0.2336	3	0.32
	0.0145	0.9664	0.3101	0.2291	46	0.32
	0.0231	0.9682	0.2844	0.1953	61	0.32
	0	0.8669	0.2788	0.1907	8	0.32
	0.0108	0.9927	0.262	0.2228	45	0.32
	0.0146	0.9875	0.2368	0.2363	63	0.32
	0.0238	0.8162	0.2334	0.2455	4	0.32
	0.0225	0.9951	0.1927	0.1583	51	0.32
	0.0672	0.196	0.1557	0.0522	7	0.32
	0.0208	0.2934	0.1191	0.089	5	0.32
	0.0702	0.9409	0.3989	0.1932	6	0.31
	0	0.953	0.3163	0.2027	11	0.31
	0	0.7746	0.3091	0.1131	1	0.31

4. Discussion

4.1. Habitat characteristics of *Lacerta trilineata*

The results from this study revealed that the classified hyper temporal NDVI layer was the most important predictor variable for predicting the distribution in distribution of *Lacerta trilineata*. This concurs with Herkt (2000), who found similar results for SPOT NDVI when modelling the geographic distribution of *P.erhardii* in Crete Island.

The results indicate that temporal changes in vegetation as an environmental explanatory variable can significantly improve the performance of the model. Obviously it contains some unique information not present in other variables. In fact the vegetation dynamics or plant species growth and establishment patterns, are a result of seasonal variations in climate and ecoclimatic dynamics(Leyequien et al., 2007), and it is leading to changes in species composition and distributions(Hobbs *et al.*, 1990). Consequently, annual variations in vegetation can induce changes in the spatial distribution of plant phenology and growth (Tucker & Sellers, 1986; Leyequien *et al.*, 2007). Therefore, analysis of temporal changes in vegetation can potentially provide a key to understand the influence of climate variability on shaping ecosystem and habitat characteristics of the species(Leyequien et al., 2007).

The probability distribution map shows the “preferable” habitat of *Lacerta trilineata* across the study area (Figure16). The resulted response curve indicates a strong relationship between some NDVI classes and high probability occurrence of the species. Considering these results the probability of species occurrence was highest in sites, where shrubs and rocks were dominant, or in old olive plantations and abandoned agriculture. According to the field work and on the results *Lacerta trilineata* were most common in areas of intermediate disturbance such as old cultivated areas and near roads. The map indicates the probability of occurrence is mostly higher in the margins between agricultural lands and semi-natural areas. Previous studies on lizard populations experiencing the usefulness of these intermediate levels of disturbance for lizards, and have provided some supports for this hypothesis. For example, Germaine and Wakeling (2001) argued that lizard abundance and species richness peaked at intermediate levels of urbanisation in Tucson, Arizona. Common chameleons (*C.chamaeleon*) in southern Spain were most common in areas with intermediate disturbance, such as cultivated areas and near roads(Hodar et al., 2000). Another justification for this strong relationship could be addressed to the spatial-temporal resolution of classified MODIS NDVI, which is higher comparing with other predictors. Therefore it can better explain the ecosystem/habitat characteristics of the species.

While *Lacerta trilineata* is reported as a common species in Crete Island (IUCN), but the probability map, surprisingly shows that, there are some patches where the probability of occurrence of the species is very low. The visual comparison between model with and without NDVI (as one of the predictors), indicates, the probability occurrence becomes lower in specific areas in the model with NDVI. It could be an evidence, to show finer resolution for such a fragmented area (Crete Island) is more useful than variables with poor spatial resolution. One of the most probable reasons might be because the area is fragmented; therefore the resources are not homogenously distributed in the whole island. Due to that reason, there are small patches in different parts of the study area while they are isolated by less or unsuitable areas. The concept of fragmentation is popular among ecologists to describe and explain ecological patterns and processes in human-modified landscapes(Haila, 2002).

There are several studies concerning lizard distribution in fragmented areas. For instance Fischerand Lindemayer (2005), examined lizard distribution patterns in a fragmented plantation landscape in south-eastern Australia. The result proved not all lizard species responded in the same way to fragmentation. However this generalist species is able to thrive in a wide variety of ecological conditions and can make use of a variety of different resources. Besides, there are some other factors influencing presence/absence of the species, and might be not considered in this research (missing predictors). It could affect strongly on the performance of the model and increase the risk of uncertainly in ecological interpretation of the result. It has been showed in recent analysis that the inclusion of additional predictor variables those representing the presence/absence of known competitors, food availability, shelter-related variables, presence of hiding places (specifically for lizards) and other biotic factors, can significantly increase the predictive power of models(Guisan & Thuiller, 2005). However *Lacerta trilineata* highly responded to temporal patterns of vegetation. It might be because it is related to dense vegetation(Valakos et al., 2007) and NDVI can nicely explain the microhabitat of the species.

The jackknife test indicated that after classified NDVI, land cover is second most important for predicting the *Lacerta trilineata* distribution. The average probability in land cover classes indicates the beaches, dunes and sandy have the highest probability and after that, principally agriculture with natural vegetation and Natural grassland has the most probability of occurrences. The probability in city areas and bare rock is low. Regarding to response curves (Figure 18) the probability occurrence of the species is more equal or more than 0.4 in all classes. The behaviour of the species towards land cover can be another evidence for the idea that the species is more comfortable in intermediate level of disturbances.

This concurs with Hernandez et al. (2006), who confirmed the results of other researchers that the ecological characteristics of species affect modelling accuracy. Species, which are widespread in both geographic and environmental space, as is the case with *Lacerta trilineata*, are generally more difficult to model than species with a more specific spatial distribution.

Annual precipitation was also a significant predictor in the distribution of *Lacerta trilineata* Figure 18. The response shapes show a positive relationship between precipitation and species occurrences. Precipitation is the only climatic variable that contributes in the model. Evapotranspiration and temperature did not have a strong contribution in the model. Some studies have argued that evapotranspiration should be considered as an important predictor. For example, Rodriguez et al. (2005) examined the geographical patterns of species richness for reptiles and amphibians, considering the productivity, ambient energy, water energy balance habitat heterogeneity and climatic variability as predictors. They pointed out that the annual potential evapotranspiration (an index of atmospheric energy) explained 71% of the variety of reptiles. Our results, however, indicate that the importance of this variable is the lowest in comparison with other predictors.

A possible explanation as to why evapotranspiration did not contribute in the model could be that the, climate variables such as temperature, precipitation, evapotranspiration, are appropriate at global and meso-scales(Phillips et al., 2006), this could be attributed to the fact that climate depicts less variation over short distances compared to global and continental scale(Skidmore et al., 2006). Moreover they often tend to be less precise(Guisan & Zimmermann, 2000). For instance more bioclimatic parameters such as those used in this study are developed by elevation-sensitive spatial interpolation of climate station data (Hijmans et al., 2004)which introduce spatial uncertainties. The problem of accuracy and spatial uncertainties becomes even more important when models are developed for mountainous terrain with heterogeneous topography, where vegetation is distributed in mosaic-like patterns with sharp transitions from one vegetation type to another(Brown, 1994).

However predictive models are suffering from different sources of errors and uncertainty. They can be related to bias in sampling data, positional and attribute accuracy of data and etc. The results of this study also are subjected to such uncertainties.

4.2. Uncertainty in habitat distribution modeling

4.2.1. Bias in data

One of the major problems in habitat distribution modelling is related to species data available which are often not specifically collected for the purpose, and instead may consist of *ad hoc* collection of existing data, bias in geographical and/or environmental space (Barry & Elith, 2006)As mentioned in (section 2.2.2) sampling is often more frequent close to roads(Kadmon et al., 2004). Bias in data mean that the modelled relationships are dominated by the patterns at sample site rather than the patterns across the entire study area and this in turn is likely to lead to marked spatial variation in prediction uncertainty, i.e. to spatial error (Barry & Elith, 2006). For a realistic predictive distribution model, species presence records must cover the full geographic and ecological extent of its known distribution. As showed in Figure8 most of the observation points for *Lacerta trilineata* are provided in the central parts of the study area. West and east of the island contain less observation points, because of the accessibility especially in the mountainous area such Crete Island; it is not easy to generate random sample points without considering accessibility, thereof it can be considered as a source of bias.

4.2.2. Scale issue

A central and recurrent problem in SDM building is identifying the appropriate scale for modelling(Wiens, 2002). Scale is usually best expressed independently as resolution and extent of the study area. The first possible mismatch can occur between different data with different spatial resolution and sources. The problem then is to combine these different types of data in a single model(Guisan & Thuiller, 2005). Aggregating of these data to a coarser resolution can sometimes causes errors in final model. However, the resolutions (grid size) among selected predictors influence model results. The model could be improved if data at a finer resolution were available. In comparison with MODIS NDVI (with 250m resolution), other variables were contained poor spatial accuracy (deviations of up to 1 km). It could possibly explain why Bioclim data and especially classified hyper temporal SPOT NDVI (with 1km grid size) had less contribution in the model. It should be considered that finer resolution usually provides better predictions for fixed or locally mobile organisms (Guisan & Thuiller, 2005) (e.g. lizards). Another reason regarding why SPOT NDVI had lower contribution in the models might be the fragmentation in the study area. Therefore, SPOT NDVI with 1 km resolution is not able to explain the habitat characteristics of the species in this scale of research and in such a fragmented area.

5. Conclussion

Knowledge on species distribution patterns at regional scale and using high quality of explanatory variables, can explain the habitat and micro-habitat characteristics of the species, and makes it easier to explain its general ecological requirements. Predicting their potential distributions in unsampled locations may lead to their discovery or reveal factors that might explain their absence. More importantly, from a conservation perspective, it provides the opportunity to assess the possible disturbances that may keep species away from the area and thus design appropriate conservation measures. However this study revealed that time series analysis of vegetation indices have the potential to properly explain the geographical distribution of species, and might be considered as a better predictor when compared to other biophysical factors such as topography and climate.

Nevertheless, we offer some key perspectives from this study and these are highlighted as follows:

- The encouraging results in this study suggest that hyper temporal classified NDVI will become an extremely useful tool for ecologists aiming to achieve a better understanding of how vegetation dynamics effect on distribution and presence/absence of fauna species.

- Remotely sensed images with a high temporal variation, and moderate spatial resolution, appear have a high potential to explain the habitat and microhabitat characteristics of the species, compared to other predictors such as climate data and land cover. They have more details in both spatial and temporal dimension to explain the habitat characteristics of the species.

- The distribution map derived from the model in which hyper temporal NDVI was included, shows more details comparing with the one excluded NDVI. Visual interpretation suggests that the chance of occurrence in the central parts of the island is higher than other parts of the island.

- The results suggest that some classes of NDVI have more potential for species occurrences. Based on land cover map and field work data, these classes were found to associate mostly with the old and abandon agricultural areas, sclerophyllous vegetation and rocks.

- The results addressed the low contribution for Bioclim data (Potential-evapotranspiration, Temperature etc.). It could be attributed to the fact that climate depicts less variation over short distances compared to global and continental scale, and quality and source of data is also important.

- The methodological framework adopted in this study is simple, robust and replicable. Spatio-temporal changes in vegetation can be considered as a powerful predictor for modelling and predicting the species distribution.

6. Recomendations

- Re-test the hypothesis for a specialist species is suggested for the future studies.

- In order to make Hyper temporal NDVI images more interpretable in habitat distribution modeling, it would be desirable to find a relationship between NDVI classes (i.e. temporal patterns of vegetation dynamic) and other biophysical characteristics of the ecosystem (e.g. Altitude, Precipitation, Evapotranspiration, and Temperature etc.) for future studies.

- Recently, many studies proved that there is a relationship between the NDVI and available energy and primary productivity. It would be promising to properly explain this relationship by considering temporal pattern of vegetation dynamic.

- The bias in data collection and the quality of predictors are the big challenges to improve the result. Therefore, there is a necessity to apply statistical techniques to deal with bias in species data and uncertainty in ecological interpretation.

- The concept of hyper temporal NDVI that was considered in this study more focused on the temporal pattern of vegetation dynamic (i.e. changes in time), while spatial pattern (i.e. change in space) might be important and informative. Therefore, this topic is worthy for further study to make a plausible link between spatial pattern and temporal dynamic. It might be useful to study the habitat/ecosystem functions.

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8. Appendix

Appendix A: List of observations specimens of *Lacerta trilineata*. Source (NHMC, 2006)

No	X	Y	No	X	Y	No	X	Y
1	326717.1	3869620.1	28	297334.96	3900003.4	55	255411.4	3911884.9
2	325529.82	3870105.1	29	331565.17	3900778.4	56	308280.95	3912564.4
3	338303.03	3872631.5	30	290757.04	3902326.2	57	252726.43	3912340.8
4	325322.77	3873074.4	31	358244.32	3902954.4	58	305908	3912807
5	312525.8	3874226.4	32	307503.57	3903110	59	305913	3912959
6	348424	3875831.4	33	284572.72	3903440	60	273236.11	3913045.5
7	302032.52	3876936.7	34	234692.92	3903794	61	219311	3913303
8	394246.96	3877193	35	346118	3903918	62	252350.2	3913674.8
9	307868.72	3877445.8	36	346120	3903956	63	306862	3913774
10	371171.89	3877767.8	37	257456.37	3904249.7	64	273524.07	3913962.8
11	382041.54	3878590.3	38	250058.46	3905053.5	65	252500.11	3914136.6
12	390049.87	3879851.8	39	291286.37	3905597.3	66	259915.13	3915033.9
13	358561.38	3882157	40	317743.55	3906611.3	67	282616.31	3917667.7
14	393606.06	3883284.7	41	295378.21	3906723.6	68	308459.61	3918644.9
15	316940.31	3883380.8	42	311672.8	3907041.2	69	244303.41	3919662.7
16	309295.5	3884019.3	43	295142.04	3907188.2	70	295418.01	3919795.4
17	367989.14	3884500.3	44	270155.28	3907998.5	71	340077.06	3899766.5
18	368318.5	3884773.5	45	372662.23	3908459	72	312198.21	3894025.9
19	381807.34	3884867.4	46	304492.63	3908753.5	73	365210.73	3894830.7
20	392852.01	3885780.1	47	296490.44	3909640.6	74	287159.62	3895069.8
21	379390.87	3886505.7	48	336402.43	3909646	75	315528.18	3895297.5
22	361322.51	3888428.8	49	321194.34	3910021.4	76	296006.35	3896212.1
23	293205.38	3889496.4	50	256949.26	3911811.7	77	294287.6	3896736.4
24	283709.06	3890119	51	303198.34	3896962.8	78	364871.99	3891989.8
25	361640.62	3890319.1	52	264416	3898363	79	311591.83	3893067.4
26	307202.72	3891125.1	53	283717.35	3898653.1	80	269190.82	3893398.8
27	295810.31	3898702.3	54	429699.54	3899559.1	81	306407.82	3898769.4

Appendix B: The legend of categorical predictors used in this study. Codes are the same as codes in response curves.

Geology	***Code***
Plattenkalk', bedded limestones	1
Carbonate rocks of Pindos zone nappe	2
Carbonate rocks of Tripolis zone nappe	3
Carbonate rocks of allochthonous tectonic units	4
Neogene rocks	5
Neogene rocks	6
Phyllites - Quartzites	7
Quaternary rocks	8
Carbonate rocks of Trypali zone nappe	9
Flysch - schists of allochthonous tectonic units	10
Flysch of the Pindos zone nappe	11
Flysch of the Tripolis zone nappe	12
Ophiolite complex of allochthonous tectonic units	13

Soild-Parmedo	***Code***
acid regional metamorphic rocks	4200
fluvial clays, silts and loams	5400
flysch	1410
limestone	2110
unconsolidated deposits (alluvium, weathering resi	5000

Soild-WU	***Code***
Calcaric Fluvisols	1
Calcaric Recosols	2
Calcaric Recosols Stony	3
Eutric Lithosols	4
Calcaric Lithosols 1	5
Calcaric Lithosols 2	6
Chromic Luvisols 1	7
Chromic Luvisols 2	8
Lake	9

Corind(Land-cover)	***Code***
Continuos urban fabric	0
Discontinous urban fabric	1
Industrial or commercial units	2
Road and rail networks and associated land	3
Port area	4
Airports	5
Mineral Extraction sites	6
Dump sites	7
Sport and leisure facilities	8
Non-irrigated arable land	9
Permanently irrigated land	10
vineyards	11
Fruit trees and berry plantation	12
Olive Plantation	13
Pastures	14
Complex cultivation patterns	15
Land principally occupied by agriculture	16
Broad-leaved forest	17
Coniferous forest	18
Mixed forest	19
Natural grassland	20
Moors and heathland	21
Sclerophyllous vegetation	22
Transitional woodland shrub	23
Beaches,dunes and sand plains	24
Bare rock	25
Sparsely vegetated area	26
Water bodies	27

Appendix C: The probability occurrence of the species in each NDVI classes, land cover percentage and field work data for each class. The firs table shows the legend of land cover.

	Legend of the landcover table	
	P-L	Probability occurences level
	MIN	minimum Probability in each class
	MAX	Maximum probability in each class
	STD	Standarid deviation in each class
	NDVI	NDVI classes
	P1	probability occurences based on response curve with all variables
	P2	probability occurences based on response curve with only the correspondig variable
Land cover	B	Buildup area
	A	Agriculture
	F	Coniferous forest
	R	Rocks
	N	Natural grassland & Schlorophylous vegetation
	S	Sparsely vegetated-area

- Describing the NDVI classes based on land cover

							Land Cover					
P-L	**MIN**	**MAX**	**MEAN**	**STD**	***NDVI***	**P1**	**B**	**A**	**F**	**R**	**N**	**S**
Very High	0.0253	0.9993	0.5870	0.2549	*41*	0.84	*3.51*	*78.60*	*0.00*	*0.00*	*16.63*	*1.27*
	0.0622	0.9894	0.6706	0.2295	*34*	0.83	*0.25*	*15.56*	*1.71*	*0.00*	*82.03*	*0.45*
	0.0094	0.9950	0.6544	0.2285	*40*	0.83	*2.73*	*20.66*	*5.02*	*0.00*	*71.39*	*0.20*
	0.0174	0.9952	0.5499	0.2366	*62*	0.82	*0.30*	*35.56*	*23.17*	*0.00*	*40.96*	*0.00*
	0.0163	0.9972	0.5690	0.2480	*60*	0.81	*0.54*	*89.61*	*1.36*	*0.00*	*8.48*	*0.01*
	0.0446	0.9880	0.7170	0.1947	*23*	0.80	*0.17*	*4.39*	*0.55*	*0.00*	*94.00*	*0.89*

- Describing NDVI classes based on field work data

NDVI	Tree%	High-Shrub%	Low-Shrub%	Herbs%	Grass%	Rock%	Stones%	Bair-Soil	Bush%	Litter%	X	Y
41	35planted(Pine&Cypress)	0	0	15	20	10	2	3	0	15	332009.200	3875647.042
	90(Olive&Grape)	0	0	0	3	0	2	5	0	0	332383.700	3886566.431
	45(Olive plantation)	0	0	15	5-Dry grasses	3	2	20	2	3	340077.064	3899766.465
34	5	3	0	20	0	3	0	2	50	7	217337.502	3913320.659
	5	3	3	40	15	0	0		10	4	216929.132	3913464.979
40	0	35	55	0	2	10	2	2	0	1	376406.730	3879747.227
	55 (Olive plantation)	0	0	0	0	35	5	5	0	0	318985.790	3890280.227
	0	5	40	10	0	25	0	10	0	0	319295.038	3890313.783
62	0	0	80(hegza-spinny)	2	0	15	2	0	0	0	257456.373	3904249.683
	0	0	80	0	0	20	0	0	0	0	197859.368	3918151.482
60	60(Wild Olive)	30	0	0	2	1	0	2	0	5	306896.293	3913759.310
23	5	5	35	5	20	25	1	2	0	2	365210.732	3894830.736
	0	0	60	0	0	35	5	10	0	0	191888.283	3912220.365

- Describing the NDVI classes based on land cover

P-L	MIN	MAX	MEAN	STD	NDVI	P1	B	A	F	R	N	S
High	0.0109	0.9924	0.6181	0.2278	48	0.74	1.70	45.99	2.00	0.00	50.27	0.03
	0.1060	0.9817	0.7064	0.1772	29	0.72	0.00	0.05	10.23	0.50	88.40	0.82
	0.0115	0.9978	0.5665	0.2437	42	0.72	1.66	61.28	0.09	0.00	36.82	0.16
	0.0320	0.9745	0.5664	0.2189	65	0.72	0.20	61.42	19.70	0.00	18.68	0.00
	0.0169	0.9968	0.5534	0.2530	52	0.71	0.87	81.61	0.18	0.00	17.34	0.00
	0.0144	0.9941	0.5049	0.2484	64	0.71	0.46	72.47	9.05	0.00	18.03	0.00

- Describing NDVI classes based on field work data

NDVI	Tree%	High-Shrub%	Low-Shrub%	Herbs%	Grass%	Rock%	Stones%	Bair-Soil	Bush%	Litter%	X	Y
48	0	65(2m)	15		5		0				318906.373	3890289.710
	80(Olive plantation-5m)	0	0	2	3	0	2	5	0	3	318182.886	3912812.519
	0	45	25	5	3	15	1	1	0	0	318174.456	3912834.033
42	80(Olive plantation)	0	0	10	1	0	3	5	0	1	335727.672	3876193.880
	15	5	30	2	1	0	45	1	0	1	409489.003	3878160.087
65	60(Old olive plantation)	0	0	5	25	0	1	7	0	2	354633.643	3900969.611
52	55(Olive Plantation-5m)	0	0	0	15(70cm)	1	0	30	0	0	318828.406	3890417.325
	0	1	60	5	1	30	2	0	1	0	243306.348	3923801.391
64	35	0	15	20	1	5	2		20	2	305939.226	3912759.873
	70(Olive Plantation)	0	0	5	10	0	5	7	1	2	305906.973	3912764.786
	70(Grape plantation)	0	20	2	2	0	1	5	0	1	305909.691	3912805.753
	35	50	2	3	1	1	3	1	0	2	305555.541	3912861.287

- Describing the NDVI classes based on land cover

P-L	MIN	MAX	MEAN	STD	NDVI	P1	B	A	F	R	N	S
Relative high	0.0431	0.9968	0.7171	0.2085	33	0.68	0.00	57.66	0.00	0.00	42.24	0.10
	0.0177	0.9972	0.5344	0.2427	58	0.63	0.37	57.88	8.50	0.00	33.20	0.03
	0.0089	0.9977	0.4703	0.2336	59	0.63	0.06	97.97	0.14	0.00	1.83	0.00
	0.0706	0.9772	0.7148	0.1818	10	0.62	0.00	0.01	0.60	2.99	74.90	21.50
	0.0119	0.9926	0.5443	0.2399	28	0.61	7.75	41.51	0.41	0.01	49.85	0.46
	0.0327	0.9838	0.5609	0.2115	19	0.60	1.24	2.16	2.91	0.04	91.33	2.32

- Describing NDVI classes based on field work data

NDVI	Tree%	High-Shrub%	Low-Shrub%	Herbs%	Grass%	Rock%	Stones%	Bair-Soil	Bush%	Litter%	X	Y
58	0	0	0	0	50(Regenerating)	35	15	5	0	1	195308.066	3920729.558
59	80(Old olive plantation)	0	0	2	10	0	1	5	0	2	348116.867	3888660.849
28	75(Grape plantation)	0	0	0	5	0	5	10	1	2	316577.937	3887500.830
	0	40	40	15	0	0	2	2	0	1	190257.915	3932845.742
	0	15	40	10	0	30	2	3	0	0	232036.044	3933115.578
	2	20	50	3	0	15	2	10	0	0	206066.812	3951203.368
19	1	0	30	0	0	65	1	2	1	0	252627.041	3903602.135

- Describing the NDVI classes based on land cover

P-L	MIN	MAX	MEAN	STD	***NDVI***	P1	B	A	F	R	N	S
Medium	0.5171	0.6200	0.5569	0.0451	*17*	0.59	*0.28*	*9.30*	*0.00*	*78.55*	*11.87*	*0.00*
	0.0091	0.9982	0.4993	0.2417	*55*	0.59	*0.44*	*79.32*	*0.73*	*0.00*	*19.48*	*0.02*
	0.0974	0.9859	0.6568	0.1879	*30*	0.58	*0.08*	*16.38*	*0.00*	*0.00*	*82.47*	*1.08*
	0.0164	0.9797	0.5426	0.2277	*21*	0.58	*18.48*	*36.83*	*0.13*	*0.00*	*42.17*	*2.38*
	0.0572	0.9845	0.6262	0.2059	*31*	0.58	*0.61*	*11.15*	*0.17*	*0.00*	*87.60*	*0.47*
	0.0213	0.9798	0.5272	0.2164	*27*	0.55	*0.82*	*2.48*	*9.97*	*0.06*	*85.81*	*0.86*
	0.0000	0.9942	0.6019	0.2094	*13*	0.52	*13.84*	*17.39*	*0.22*	*0.00*	*68.02*	*0.54*
	0.0325	0.9608	0.4916	0.2140	*16*	0.52	*9.95*	*9.90*	*0.86*	*0.15*	*75.83*	*3.31*
	0.0364	0.9733	0.5555	0.2178	*26*	0.51	*0.99*	*4.90*	*0.02*	*0.00*	*92.66*	*1.43*
	0.0090	0.9690	0.3486	0.2395	*47*	0.50	*0.95*	*95.64*	*0.00*	*0.00*	*3.40*	*0.00*

- Describing NDVI classes based on field work data

NDVI	Tree%	High-Shrub%	Low-Shrub%	Herbs%	Grass%	Rock%	Stones%	Bair-Soil	Bush%	Litter%	X	Y
31	0	2	60	3	15	20	0	0	0	0	263445.598	3899546.503
	0	0	60	10	0	20	3	2	0	5	190457.712	3911789.110
	1	30	45	2	1	15	5	3	0	0	312396.300	3912737.804
27	50(Pine&Cypress)	0	3	2	0	40	0	1	0	5	362369.682	3881346.997
	1	0	40	15	0	40	0	2	1	1	252474.852	3903632.342
	0	0	25	45	3	20	0	0	0	10	252307.475	3903830.434
13	0	2	45	2	0	35	1	10	0	0	307061.854	3867949.198
	0	25	15	2	1	35	20	10	0	2	305728.765	3868440.257
	1	3	35	10	0	30	5	15	0	1	388971.547	3874136.728
	0	1	40	3	0	10	35	10	0	0	410170.041	3876660.581
16	0	1	50	2	0	25	5	5	0	3	396886.255	3888038.010
	3	2	55	2	0	15	30	5	0	0	396508.456	3888070.286
	0	0	80	5	0	5	5	5	0	0	189467.997	3927599.063
26	30(Old Olive &Oak)	10	40	5	5	10	0	0	0	0	351046.422	3879500.250
	0	0	55	1	0	15	5	20	0	0	287060.480	3894017.005
	5	35	25	2	0	20	5	10	0	0	309352.708	3910590.027
47	50(Old olive plantation)	7	0	3	19	1	0	20	0	1	346697.440	3907333.827
	25	45	0	20	3	1	0	1	0	5	346700.294	3907355.506

- Describing the NDVI classes based on land cover

P-L	MIN	MAX	MEAN	STD	NDVI	P1	B	A	F	R	N	S
Relative low	0.1153	0.9616	0.6410	0.1890	*15*	0.49	*0.00*	*0.05*	*3.24*	*1.06*	*91.32*	*4.32*
	0.0000	0.9894	0.6275	0.1763	*12*	0.49	*7.06*	*1.27*	*0.37*	*0.26*	*74.43*	*16.61*
	0.0363	0.9912	0.6422	0.1699	*18*	0.48	*2.04*	*2.17*	*1.03*	*0.10*	*88.81*	*5.85*
	0.0283	0.9947	0.5888	0.2174	*25*	0.48	*3.31*	*36.08*	*0.00*	*0.00*	*58.35*	*2.26*
	0.0261	0.9963	0.4842	0.2294	*50*	0.48	*1.00*	*40.54*	*8.29*	*0.00*	*50.10*	*0.05*
	0.0309	0.9736	0.4801	0.2139	*9*	0.48	*10.69*	*6.07*	*0.29*	*0.27*	*76.19*	*6.49*
	0.0145	0.9876	0.4594	0.2250	*39*	0.48	*0.66*	*12.68*	*21.55*	*0.00*	*64.90*	*0.20*
	0.0266	0.9899	0.5687	0.2274	*37*	0.45	*0.22*	*32.80*	*0.12*	*0.00*	*66.57*	*0.29*
	0.0189	0.9821	0.5498	0.2127	*38*	0.44	*0.36*	*31.65*	*0.00*	*0.00*	*67.24*	*0.74*
	0.0435	0.9911	0.4754	0.2117	*14*	*0.42*	*2.30*	*3.76*	*0.13*	*0.01*	*87.43*	*6.51*
	0.0154	0.9921	0.4316	0.2299	*32*	0.42	*3.22*	*11.81*	*4.62*	*0.00*	*79.79*	*0.57*

- Describing NDVI classes based on field work data

NDVI	Tree%	High-Shrub%	Low-Shrub%	Herbs%	Grass%	Rock%	Stones%	Bair-Soil	Bush%	Litter%	X	Y
12	12(Oak&Pin)	0	20	20	0	45	0	3	0	0	356895.130	3879248.040
	0	0	35	3	0	35	15	5	0	0	283538.882	3893767.415
	3	20	10	0	0	50	15	5	0	0	201119.186	3904452.905
9	1	25	45	2	0	10	5	10	0	0	370028.514	3874271.899
	0	5	65	5	0	15	10	3	0	0	425715.547	3875856.537
	0	0	30	5	0	30	20	15	0	0	429236.895	3877650.881
	0	0	45	5	0	5	35	5	0	0	431303.307	3880549.883
18	2	0	30	2	0	35	25	2	0	0	401287.470	3880284.637
	0	0	25	2	0	40	25	5	0	0	269258.475	3897876.952
	20	3	10	2	0	10	30	30	0	0	187073.553	3915074.799
39	2	0	70	0	0	5	20	0	3	0	206415.210	3918698.593
50	60(Olive plantation)	0	0	0	15	1	0	30	0	5	318864.988	3890563.309
	0	0	3	15	0	0	2	75	0	0	425048.363	3894929.480
	1	1	60	0	5	5	20	0	5	0	257210.741	3906841.875
37	5	25	65	5	0	3	0	0	0	2	272310.745	3895159.996
	5	25	65	5	0	0	1	0	0	0	272402.847	3895241.842
	0	2	60	20	0	15	0	2	0	3	376326.383	3905336.764
38	1	0	70	1	15	10	0	0	0	0	264425.542	3898201.090
	5(New olive plantation)	0	0	0	40	20	0	5	0	0	264444.311	3898238.900
	0	10	70(Spinny)	0	0	10	0	0	0	0	345405.883	3905699.026
14	0	1	70	2	0	0	10	15	0	0	239989.367	3899248.963
	0	0	45	2	0	0	10	15	0	0	254940.746	3899905.007
32	0	30	30	3	0	0	15	5	0	0	421432.566	3878242.262
	0	3	65	5	0	0	2	2	0	0	421117.189	3882125.693

- Describing the NDVI classes based on land cover

P-L	MIN	MAX	MEAN	STD	NDVI	P1	B	A	F	R	N	S
low	0.0557	0.9819	0.4495	0.2151	*20*	*0.39*	*0.95*	*2.82*	*0.09*	*0.00*	*93.58*	*2.57*
	0.0901	0.9930	0.3770	0.2034	*2*	0.38	*0.08*	*0.00*	*0.00*	*21.40*	*24.95*	*53.57*
	0.0501	0.9960	0.4801	0.1966	*22*	0.33	*1.09*	*11.59*	*0.00*	*0.00*	*84.21*	*3.11*
	0.0096	0.9851	0.3979	0.2464	*35*	0.33	*4.32*	*47.33*	*0.77*	*0.00*	*47.44*	*0.14*
	0.0162	0.9817	0.3625	0.2350	*36*	0.33	*0.28*	*3.47*	*23.40*	*0.01*	*72.47*	*0.38*
	0.0151	0.9837	0.3462	0.2261	*53*	0.33	*0.04*	*65.22*	*2.23*	*0.00*	*32.47*	*0.04*
	0.0093	0.9740	0.3104	0.2368	*57*	0.33	*0.10*	*92.11*	*0.12*	*0.00*	*7.60*	*0.07*
	0.0089	0.9426	0.2516	0.2127	*56*	0.33	*0.17*	*98.58*	*0.00*	*0.00*	*1.25*	*0.00*
	0.0093	0.9570	0.1895	0.1769	*54*	0.33	*0.00*	*99.53*	*0.00*	*0.00*	*0.47*	*0.00*

- Describing NDVI classes based on field work data

NDVI	Tree%	High-Shrub%	Low-Shrub%	Herbs%	Grass%	Rock%	Stones%	Bair-Soil	Bush%	Litter%	X	Y
20	0	0	35	1	0	0	5	15	0	0	314073.583	3890597.033
	0	0	70	10	0	0	2	3	0	0	278891.323	3892718.821
	0	0	60	1	1	10	0	25	0	1	287047.928	3893434.930
	0	0	60	1	0	0	2	30	0	0	287115.697	3893513.166
	0	0	50	1	2	20	0	15	0	5	287027.776	3893931.293
22	0	0	50	1	0	0	20	30	0	0	315135.573	3890975.132
	0	5	25	0	0	75	0		0	0	322227.420	3912318.399
35	0	0	35	1	1	65	0		0	0	355566.367	3879389.271
	0	2	45	3	0	0	10	5	0	0	432366.255	3884076.860
36	40(Oak&Cypress)	5	10	0	0	65	0	1	0	0	217148.252	3913114.320
	65(pine)	0	0	0	0	35	0		3	20	219292.088	3918246.974
53	0	0	3	0	60	0	0		0	0	195287.708	3920640.836
	70(Olive Plantation)	0	0	0	0	20	0	2	0	0	195288.518	3920677.211
54	70-20(Olive&Grape)	0	0	0	30	0	0		0	0	347624.869	3889317.896

- Describing the NDVI classes based on land cover

							Land Cover					
P-L	MIN	MAX	MEAN	STD	*NDVI*	P1	B	A	F	R	N	S
very low	0.0167	0.9944	0.4080	0.2470	*44*	0.32	*0.22*	*31.37*	*1.49*	*0.00*	*66.70*	*0.21*
	0.0167	0.9894	0.3820	0.2310	*49*	0.32	*0.20*	*56.19*	*0.21*	*0.00*	*43.39*	*0.02*
	0.0101	0.9619	0.3278	0.2093	*24*	0.32	*4.91*	*8.65*	*2.09*	*0.01*	*82.93*	*1.40*
	0.0162	0.9880	0.3261	0.2276	*43*	0.32	*0.13*	*61.12*	*0.00*	*0.00*	*38.33*	*0.41*
	0.0000	0.9575	0.3201	0.2336	*3*	0.32	*4.64*	*25.48*	*0.96*	*0.00*	*61.27*	*7.64*
	0.0145	0.9664	0.3101	0.2291	*46*	0.32	*0.45*	*23.18*	*22.35*	*0.00*	*53.95*	*0.05*
	0.0231	0.9682	0.2844	0.1953	*61*	0.32	*0.00*	*98.86*	*0.04*	*0.00*	*1.10*	*0.00*
	0.0000	0.8669	0.2788	0.1907	*8*	0.32	*52.19*	*2.00*	*0.03*	*3.49*	*23.03*	*19.25*
	0.0108	0.9927	0.2620	0.2228	*45*	0.32	*0.88*	*95.61*	*0.00*	*0.00*	*3.29*	*0.21*
	0.0146	0.9875	0.2368	0.2363	*63*	0.32	*0.19*	*97.43*	*0.42*	*0.00*	*1.96*	*0.00*
	0.0238	0.8162	0.2334	0.2455	*4*	0.32	*32.87*	*8.19*	*0.00*	*11.42*	*40.09*	*7.43*
	0.0225	0.9951	0.1927	0.1583	*51*	0.32	*0.00*	*99.92*	*0.00*	*0.00*	*0.08*	*0.00*
	0.0672	0.1960	0.1557	0.0522	*7*	0.32	*71.82*	*9.55*	*0.00*	*12.58*	*6.05*	*0.00*
	0.0208	0.2934	0.1191	0.0890	*5*	0.32	*84.49*	*0.36*	*0.00*	*4.89*	*1.72*	*8.54*
	0.0702	0.9409	0.3989	0.1932	*6*	0.31	*0.00*	*0.00*	*0.04*	*5.40*	*51.51*	*43.04*
	0.0000	0.9530	0.3163	0.2027	*11*	0.31	*21.34*	*4.30*	*0.01*	*1.28*	*72.19*	*0.89*
	0.0000	0.7746	0.3091	0.1131	*1*	0.31	*0.36*	*0.00*	*0.00*	*61.00*	*0.39*	*38.24*

- Describing NDVI classes based on field work data

NDVI	Tree%	High-Shrub%	Low-Shrub%	Herbs%	Grass%	Rock%	Stones%	Bair-Soil	Bush%	Litter%	X	Y
20	0	0	35	1	0	0	5	15	0	0	314073.583	3890597.033
	0	0	70	10	0	0	2	3	0	0	278891.323	3892718.821
	0	0	60	1	1	10	0	25	0	1	287047.928	3893434.930
	0	0	60	1	0	0	2	30	0	0	287115.697	3893513.166
	0	0	50	1	2	20	0	15	0	5	287027.776	3893931.293
22	0	0	50	1	0	0	20	30	0	0	315135.573	3890975.132
	0	5	25	0	0	75	0		0	0	322227.420	3912318.399
35	0	0	35	1	1	65	0		0	0	355566.367	3879389.271
	0	2	45	3	0	0	10	5	0	0	432366.255	3884076.860
36	40(Oak&Cypress)	5	10	0	0	65	0	1	0	0	217148.252	3913114.320
	65(pine)	0	0	0	0	35	0		3	20	219292.088	3918246.974
53	0	5	3	5	60	0	2	1	15	5	195287.708	3920640.836
	70(Olive Plantation)	0	0	0	1	20	2	5	0	2	195288.518	3920677.211
54	70-20(Olive&Grape)	0	0	0	20	0	0	10	0	0	347624.869	3889317.896
56	90(grape plantation)	0	3	1	0	0	0	5	0	1	335819.517	3906612.662
57	80(Olive plantation)	0	0	1	2	0	2	10	1	3	350534.399	3882995.329
3	0	0	80	3	1	10	0	0	2	0	425967.682	3897779.884
8	0	0	70	2	0	13	0	15	0	0	418915.374	3898183.416
24	0	2	55	2	1	10	0	20	0	0	407017.140	3882977.404
	0	0	50	5	2	15	5	5	10	3	186437.238	3916953.952
43	70(Olive Plantation)	1	15	0	5	5	0	1	0	3	376616.026	3902547.508
44	5	0	20	1	1	70	5	0	3	0	364905.523	3894911.746
45	90(Grape plantation)	0	0	2	1	0	0	5	0	2	340437.041	3907998.951
46	0	3	70	0	2	20	0	5	0	0	207066.697	3919114.350
	70(Old olive plantation)	2	0	15	0	0	0	0	13	0	193961.035	3919676.970
49		0	0	0	0	0	0	0	0	0	345936.222	3904650.582
	35(Fruits)	0	0	0	65	0	0	0	0	0	258402.472	3905410.809
51	85(Olive plantation)	0	0	0	3	0	0	10	0	2	340798.551	3907105.809
61	grap plantation85%	0	0	1	2	0	0	10	0	1	335795.309	3906798.678
63	70(olive)	0	0	5	5	5	2	5	2	3	205468.443	3935438.242
11	0	15	10	2	0	40	20	10	0	0	305955.272	3868442.075
	0	1	40	1	0	15	40	4	0	0	367377.727	3872985.330
	2	2	35	0	0	35	0	25	0	1	370108.061	3874167.236