PRESENCE OR ABSENCE?

OPTIMAL USE OF SPECIES OBSERVATION SAMPLES FOR SPECIES DISTRIBUTION MODELLING IN RELATION TO LAND COVER CHANGE

JINGYI CHEN

February 2014

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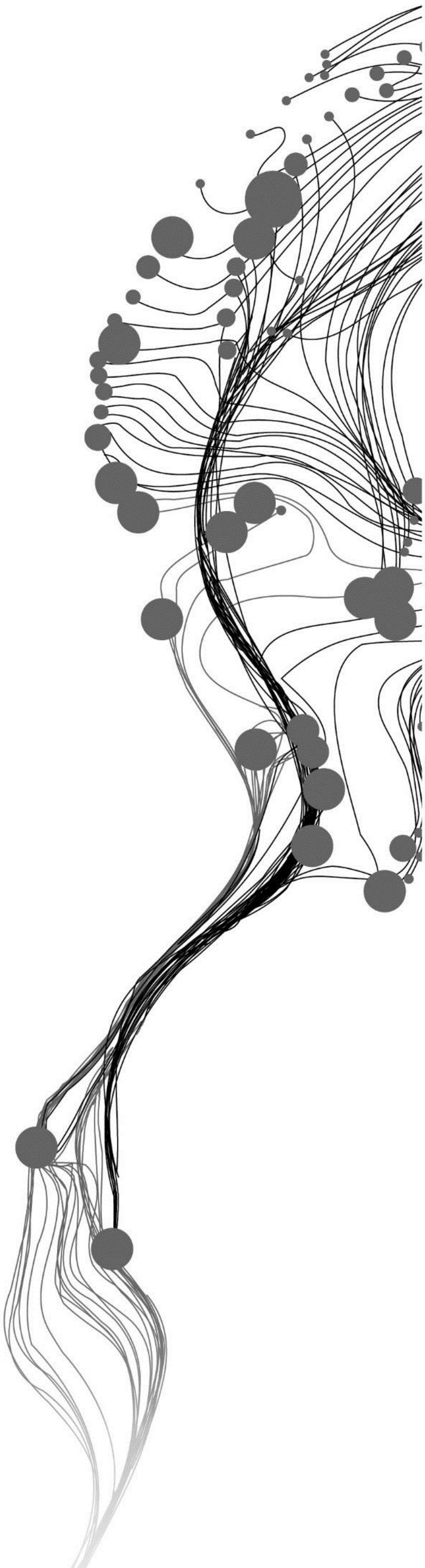

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JINGYI CHEN

Enschede, The Netherlands, February, 2014

Thesis submitted to the Faculty of Geo-Information Science and Earth Observation of the University of Twente in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation.
Specialization: Natural Resource Management

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ABSTRACT

Species distribution modelling is essential to predict the species potential distribution. It is especially useful for endangered species. However, general method of species distribution (No-change Approach) does not contain the change of the predictor within the period when species occurrence records were collected, which would lead to the wrong prediction. In this study, a new approach was generated to consider the change of the predictor (Change Approach). In the case study of the land use change detection, the change of land use considered the species distribution modelling to detect whether the land use change effects the potential distribution and increases the model accuracy.

P. viridis and *P. cretensis* were selected as target species to detect their potential distribution in relation to land cover change.

MODIS hyper temporal NDVI image was selected for land cover change detection analysis. NDVI classification image was used to describe land cover unit within the time period. According to split the time range when species occurrence records were collected into three specific time period. Two tailed independent t-test was selected to test the change of land cover. The change can be detected by comparing the mean NDVI value in the area of the specific NDVI class that is related to species habitat in different specific time periods.

MaxEnt was selected to predict species distribution because it is well performed with presence-only data, especially when the data set were in small sample size. 40 presence-only records for P. viridis, 12 presence-only records for P. cretensis and a set of 11 environmental predictors were used as reference in MaxEnt modelling. For the modelling approach, apart from land cover change, the NDVI predictor used in this study was the average value of data from 2000 to 2013. The new approach includes land cover change and the NDVI predictor that was the average of the specific time period (2010-2013). It is almost represent the current situation. The results were evaluated using the threshold-dependent True Skill Statistic (TSS) and the threshold-independent Area Under ROC Curve (AUC). The relative variable importance was assessed based on MaxEnt built-in Jackknife test.

The results expressed that the NDVI value of the NDVI class that is related to species habitat, is significantly different ($p < 0.05$ at 95% CI). The model accuracy of Change Approach is higher than No-change Approach comparing with the TSS value. Especially for P. viridis, the model performance based on Change Approach is significantly better than No-change Approach ($p=0.614$ at 90% CI).

The study indicated that the change of land cover from 2000 to 2013 is significantly different. Furthermore, the Change Approach has better modelling performance than No-change Approach. The land cover change in the time period significantly affects the potential distribution of *P. viridis*. However the change does not have significant effect on the potential distribution of *P. cretensis*.

Keywords: MODIS, NDVI, species distribution models, presence-only data, small sample size, MaxEnt, land cover change, habitat suitability, *P. viridis*, *P. cretensis*, Crete.

ACKNOWLEDGEMENTS

This thesis is an outcome of the BIOFRAG research project in collaboration with the National History Museum of Crete (NHMC) at the University of Crete, Heraklion, Greece and the Faculty of Geo-Information Science and Earth Observation of the University of Twente, Enschede, The Netherlands.

I owe special thanks to Dr. Petros Lymberakis (NHMC) for sharing his expert knowledge on *P. viridis*, *P. cretensis* and the land cover change situation in Crete Island from the past to the present and introducing me to traditional Greek cuisine, to Dr. Manolis Nikolakakis (NHMC) for his dedicated assistance in data acquisition and to Thanos Giannakakis (WWF) for introducing the wetland distribution and current situation. Without their cooperation and willingness to share data and assist in the field, this research would not have been possible.

I feel great pleasure and honour to express my sincere thanks to my first supervisor Dr. Bert Toxopeus. Fieldwork with you was very instructive and fun. I appreciate your stimulating questions and great guidance throughout this thesis research. You let me work on my own for a while but always ensured that I did not loss track. Your full trust inspired me complete confidence and independency.

I am thankful to my second supervisor Dr. Kees de Bie. I very much appreciate your critical questions and helpfulness on NDVI processing. You encouraged me to thinking scientifically. Thanks for your invaluable comments and guidance. It was my pleasure to have you as my supervisor.

My profound appreciation to my international fellow NRM and GEM students and ITC staff, for your support and precious friendship throughout these 18 months.

And to all of the friends who accompanied with me in this period of my life, you gives me encourage, supporting me to finish the thesis, share the laugh, the cry, the love, thank you!

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

1. INTRODUCTION

1.1. Background and significance

Amphibians are 'cold-blooded' creatures. This means that they regulate their body temperatures by their position in the environment and by body moisture loss. Consequently, they must live in or around water or in extremely humid environments (Gates, 1993). Over recent decades, amphibians have declined dramatically in many areas of the world because of their extreme sensitivity to their surrounding environment. Now they are even more threatened than other kinds of animal such as mammals and birds. A recent report from the IUCN's Global Amphibian Assessment indicates that as many as one third of amphibian species have undergone severe decline or extinction (Stuart et al., 2004). In Europe, nearly a quarter of amphibians are considered threatened, and a further 17% of amphibians are considered near threatened. More than half of amphibians (59%) have declining populations, a further 36% are stable and only 2% are increasing (Temple et al., 2009). "Amphibians are in an especially severe situation, suffering the double jeopardy of exceptionally high levels of threat coupled with low levels of conservation effort" (Hoffmann et al., 2010).

As most amphibians depend on water for survival, their ability to deal with climate change may be affected by fluctuation in water availability. According to Araújo et al. (2006), "studies have shown that the decline of amphibians is likely to be more severe in the south-west of Europe especially in the Iberian Peninsula, where dry conditions are expected to increase". These declines have various probable causes such as habitat loss, fragmentation and invasive alien species. At global scale, the main reason of species declines is climate change. However, in the local scale the land cover change is the most significant hypothesis proposed to explain these declines. Land cover change impacts on species distribution, both positive and negative, are already manifest in recent widespread shifts in species ranges and phenological responses. Human land use remains the main driver of present-day species extinction and habitat loss.

1.2. Land cover change detection using NDVI indices

Ecosystems are continuously changing in space and time (Christensen et al., 1996). They are exposed to intra-annual and inter-annual climate regimes and variations. Based on the research from Verbesselt et al. (2010), the ecosystem change can be defined in three categories: seasonal change, gradual change and abrupt change. Seasonal change is caused by annual temperature and rainfall interactions impacting the proportional cover of land cover types with different plant phenology. Gradual change is generally affected by inter-annual climate change, or caused by land management or land degradation. Abrupt change is caused by disturbances such as urban development, natural hazards and deforestation.

Change detection is the process of identifying the differences in the state of an object or phenomenon by the observation in different time periods (Singh, 1989). It is very important because understanding the change of land cover could increase the understanding of the relationship and interactions between human and natural phenomena, which would promote the decision making. Satellite remote sensing has long been used to detect and classify changes in the condition of the land surface over time (Coppin et al., 2004; Lu et al., 2004). Vegetation Indices (VI) as satellite derived products usually measure green vegetation growth and monitor the vegetation change. However, its estimation is affected by atmospheric particles (e.g. clouds), ground objects (e.g. soil, litter) and canopy light properties (Huete et al., 1994). VI has been successfully employed to monitor ecosystems health, land cover, crops production, deforestation and has been implemented in regional and global models (Hickler et al., 2005; Lassau et al., 2005; Lunetta et al., 2006).

The Normalized Difference Vegetation Index (NDVI) is a well-known vegetation indices which is able to "separate vegetation from non-vegetated areas, and most of the time it is highly correlated with faunal species occurrence and its diversity" (Leyequien et al., 2007). It can also been used as an input variable for species distribution model as an index linking vegetation to animal performance (Pettorelli et al., 2005). The NDVI (Myneni et al., 1995; Running, 1990) is derived from the red and near-infrared reflectance ratio (see Equation 1 below), where NIR and RED are the amounts of near-infrared and red light, respectively.

$$NDVI = \frac{\mathrm{NIR} \pm \mathrm{RED}}{\mathrm{NIR} - \mathrm{RED}} \qquad \text{Equation 1}$$

Calculation of NDVI for a given pixel always result in a ranges from -1 to 1, very low NDVI value (0.1 and below) correspond to barren areas of rock, sand or snow, moderate values (0.2 - 0.3) represent shrub and grass land, while high values (0.6 - 0.8) indicate temperate and tropical rainforests (Liang, 2005). The correlation between the NDVI and vegetation biomass, dynamics and climatic variables, has shown good results and is well established. The NDVI could then be used as a good tool to relate vegetation and species distribution in a defined time and space (Pettorelli et al., 2005).

In this study, the better quality of short term NDVI time series product was selected. The NDVI product is derived from MODIS NDVI composite data (MOD13Q1) which provides image of every 16 days at 250-meter spatial resolution. Land cover change can be monitored by NDVI time series profiles (Figure 1.1), which shows the NDVI variation and its annual change from 2000 to 2013.

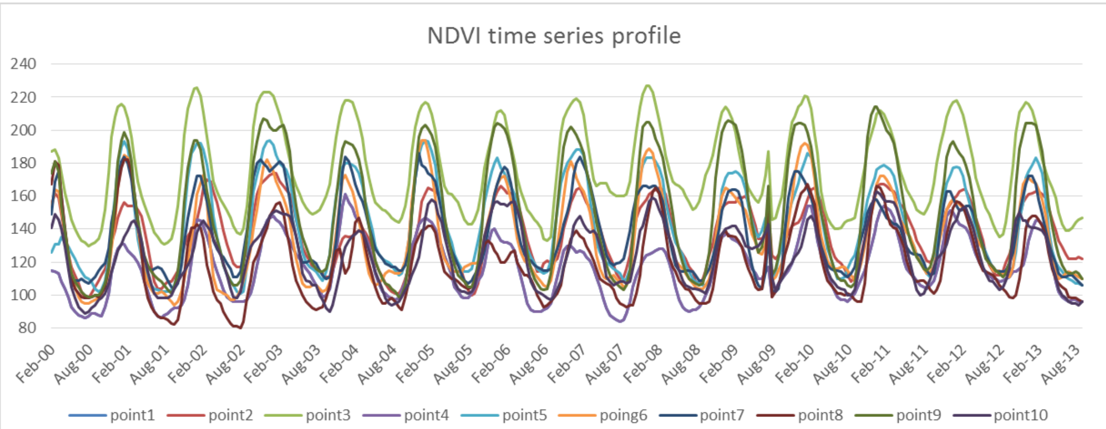

Figure 1.1 NDVI time series profile which interprets the land cover change from 2000 to 2013. The profile has seasonal variation. Each profile represents the surrounding land cover situation of species occurrence point.

1.3. Species distribution modelling

Species distribution modelling (SDM) is numerical tool that combines species distribution data with the environmental and spatial characteristics of a known location (Elith et al., 2009). It can be used to assist understanding the living circumstance of species in a specific region. Guisan et al. (2000) defines species distribution model as "an empirical model relating species observation records to environmental predictors, based on statistically or theoretically derived response surfaces". Species observation data can be presence-absence, presence-only or abundance observation based on random or stratified field sampling (Guisan et al., 2005) and environmental predictors can exert direct and indirect effects on species (Austin, 2002; Guisan et al., 2005). Several modelling methods with difference statistical bases have been developed over the years to relate the species observation data with environment predictors, for instance, generalized regression, Bayesian approach, classification rules and environmental envelope. Some of modelling methods have a batter performance on presence-absence data such as generalised linear models (GLM) and boosted regression trees (BRT), while other methods perform best with presence-only data, for instance, MaxEnt. Presence only methods rely on "the establishment of environmental envelopes around locations where species occur, which are then compared with the environmental conditions of the background area" (Brotons et al., 2004).

1.4. Problem statement

The general approach of SDM is to use statistical relationships between environmental variables and species occurrence records to predict a potential distribution associated with a particular species. It is named as "No-change Approach" in this study. The SDM is related to two sorts of variables, the species occurrence data set and the environmental variables. The species observation records were collected from the past to the present to predict current distribution. The collection of species occurrence data was taken over a long period, usually several decades. The environmental parameters were shown as the average values based on their own acquisition time range. During the time period when species data set was collected, some environmental variables changed a lot, for instance, the land cover predictor. The change of land cover is mainly caused by anthropogenic influence such as new policy and social-economic background, which means these changes are not regular even might be significant, and hard to predict. According to the no-change modelling approach, the changes caused by environmental variables were ignored. The neglect of those changes lead to incorrect predictions. For example, a certain area with suitable land cover when species was found there, and recently, it was changed to a new land cover unit which is not suitable for the species anymore. If the change cannot manifest in the model, the species would occur in an unsuitable area according to the prediction result, which does not make sense in reality.

In response to this problem, the research objective is to estimate whether the assumption which is mentioned above is true. In this study, two target species were selected to model their potential distribution in present, *Pseudepidelea viridis* and *Pelophylax cretensis* (two target species were introduced in chapter 2.2.1). The land cover variable was selected to detect if its change within the time period when all species occurrence data were recorded would affect the prediction of species distribution. According to split the collecting time range of land cover variable into several specific time periods, the change of land cover can be detected between different specific time periods. Based on the habitat characteristic of target species, detect whether the land cover in specific time period is suitable for species. Then, suitable species occurrence points was valid for SDM modelling in the specific time period. This approach is named as "Change Approach" in the study. Theoretically, the prediction by the change approach should have better accuracy than the no-change approach.

1.5. Research objectives

1.5.1. General objective

The general objective of this study is to estimate whether the change of land cover during the time period when species presence data was collected would affect the prediction of species distribution.

1.5.2. Specific objectives

To accomplish the main objective, the following specific objectives need to be addressed:

1) To determine the variations of land cover between specific time periods is significantly different.
2) To determine the valid species occurrence records for SDM modelling in different specific time periods.
3) To generate species distribution maps with the no-change approach and change approach, respectively.
4) To assess two SDM models include the land cover change and exclude the land cover change.

1.6. Research questions

To achieve the research objectives mentioned above, several research questions need to be answered:

1) Is there any significant difference between the land cover in different specific time periods?
2) Are the species occurrence points for different specific time periods the same?
3) Is the model with Change Approach better than the model with No-change Approach?

1.7. Hypothesis

Hypothesis 1

H_0: The land cover in different time periods does not have significantly different.

H_a: The land cover in different time periods have significantly different.

Hypothesis 2

H_0: The potential distribution of *P. viridis* and *P. cretensis* using Change Approach cannot be predicted significantly better than using No-change Approach.

H_a: The potential distribution of *P. viridis* and *P. cretensis* using Change approach can be predicted significantly better than using No-change Approach.

2. MATERIALS AND METHODS

The main idea of this study is to develop a new modelling approach that considered land cover change in a short time period, and evaluate the new model by comparing with the model in general approach. The flowchart below shows the general process of the research, all steps will be described with more detail in this chapter.

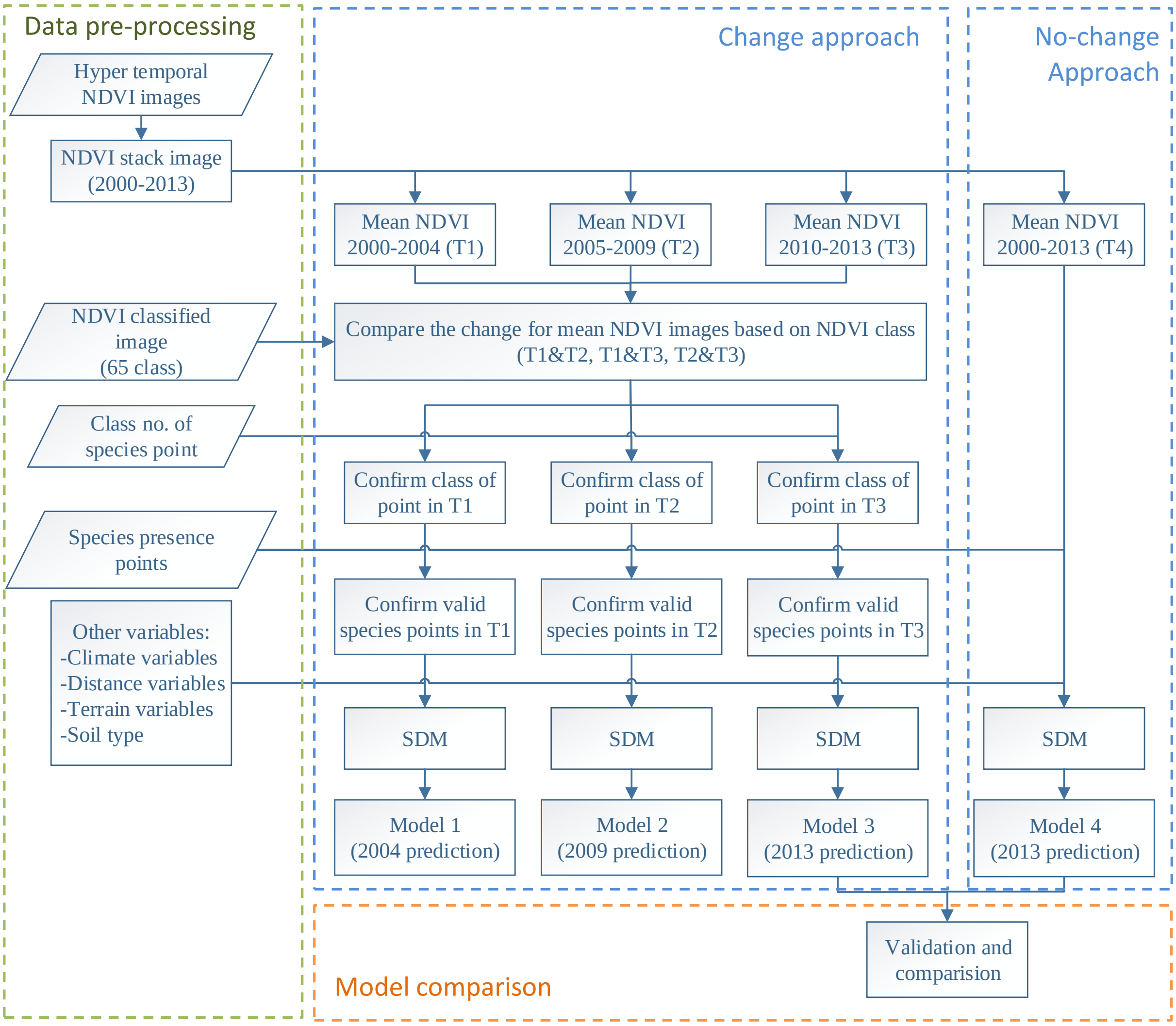

Figure 2.1 General process for modelling the species distribution in relation to land cover change. Two modelling approach was implement respectively, Change Approach and No-change Approach. Change Approach was detected the land cover change first, then use the current land cover data and valid species occurrence samples to predict the species distribution. No-change Approach was predict the species distribution using average land cover data and all species occurrence sample. Finally, compare two modelling approach.

2.1. Study area

Crete is the largest island in Greece, the island located in the eastern Mediterranean Sea and politically belongs to Greece since 1913. The island covers an area of 8,336 km^2, with a coastline of 1,046 km. About two thirds of the whole surface of the island is mountainous.

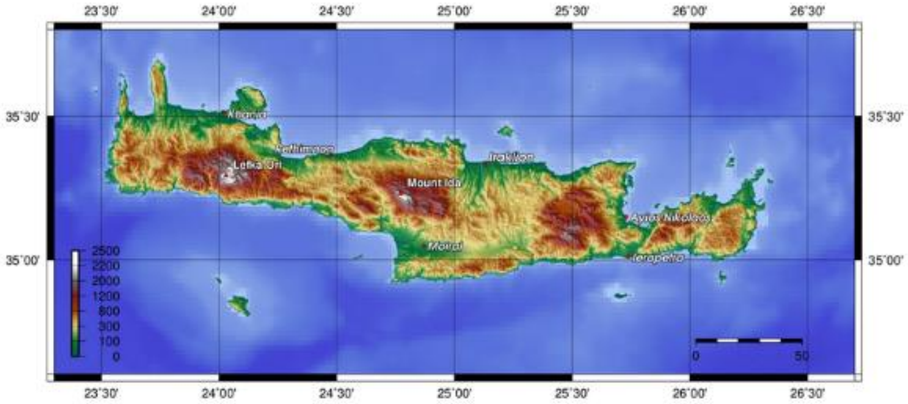

Figure 2.2 Map of study area: Crete Island (source: UNCS)

Crete has a typical Mediterranean climate, which is usually dry and hot during summer while cool and wet in winter. Evaporation is very high due to the high temperatures. In addition, climate change is one of the vital threat to the natural environment. Based on data from European weather satellites, the greenhouse effect is expected to cause a temperature increase of 2 to 3 degrees Celsius, dramatically increasing desert areas and reducing crops in most parts of the Mediterranean, especially Crete.

The island of Crete is characterized by the diversity of flora and fauna with high degree of endemism. The richness is as a result of several centuries of isolation as an island. Nowadays, 50% of land in Crete is at high risk of desertification, with the warm climate with low rainfall, and human intervention (e.g. livestock and agriculture), especially in east of Crete. Forests which are the most important element of balance in nature, are threatened not only by overgrazing but also by forest fires.

2.2. Data sets

2.2.1. Species data

a) *Pseudepidelea viridis*

Source: jean-pierre.boudot@limos.uhp-nancy.fr

b) *Pelophylax cretensis*

Source: lars.bergendorf@comhem.se

Figure 2.3 Pictures of the target species: (a) *P. viridis* and (b) *P. cretensis*

Pseudepidelea viridis (Green Toad)

Pseudepidelea viridis (Figure 2.3a), commonly known as the Green Toad and also known as *Bufo viridis*, which is listed as Least Concern species in IUCN Red List Category and Criteria. The population of *P. viridis* are widespread distributed in Europe, North Africa and West Asia. *P. viridis* lives in a wide variety of habitats, and "is more tolerant of dry conditions than many other amphibians" (Valakos, 2008). In forest zone, they tend to live in open areas and bushes, often far away from water bodies. In dry areas, they regularly enter water bodies at night to rehydrate. It may also be present in urban areas including city centres, city parks and gardens.

The main threat of *P. viridis* appears to be the loss of breeding habitats through wetland drainage, desiccation and aquatic pollution (industrial and agricultural). Populations might be locally declining due to mortality on roads (Agasyan et al., 2009).

Pelophylax cretensis (Cretan Water Frog)

Pelophylax cretensis (Figure 2.3b), commonly known as Cretan Water frog and also known as *Rana cretensis*, which is list in Endangered species of IUCN Red List Category and Criteria. This species is endemic to the island of Crete, Greece, where it is patchily distributed in the lowlands over a wide area generally below 100m elevation. It is associated with "wetlands, including slow-moving rivers and streams, lake and marshes, where breeding and larval development presumably take place" (Valakos, 2008). Because it is inseparable with water bodies, the species is especially difficult to find in dry regions.

The loss of aquatic habitats is the principal threat to this species. Extraction of stream water in the upland for agricultural irrigation leaves many lowland reaches dry during the summer month. Additional habitat loss may be occurring through infrastructure and tourism development (Beerli et al., 2009).

Species occurrence data

The Natural History Museum of Crete University (NHMC) provided the species occurrence data of the two target species (*P. viridis* and *P. cretensis*) under investigation.

The original data set of species observation was obtained from 1994 to 2013, a total of 98 observation points were obtained for *P. viridis* and 26 points for *P. cretensis*. All of the observation points were recorded with specific observation day and latitude and longitude coordinates which is then projected into Albers Equal Area Conic (WGS84 datum) projection. Since the MODIS hyper temporal NDVI images was acquired from February 2000 to present, the species presence data only observed after February 2000 were available to use in the SDM modelling. The accuracy of the data set were carefully inspected because the position of the species occurrence points in relation to the accuracy of NDVI extraction around the presence point and the accuracy of the potential distribution results. The accuracy range of presence points were defined as: 20m to 100m, 100m to 300m, 300m to 1km, 1km to 5km and more than 5km. All points with an accuracy of more than 1km were eliminated. Besides, some presence points were observed on the same day, found in the same location and with same accuracy. Since the change detection analysis of the land cover was based on the location of species presence points, the points with same location would get same change detection results. So only one presence point is useful for the same location, and others were eliminated. Therefore, after data filtering, 40 points of *P. viridis* and 12 points of *P. cretensis* were available to use for the SDM modelling as well as 18 points of *P. viridis* and 10 points of *P. cretensis* were available to use for the land cover change detection analysis.

The spatial distribution of species presence points of two target species are shown in Figure 2.4. The detail of species presence data set is shown in APPENDIX A.

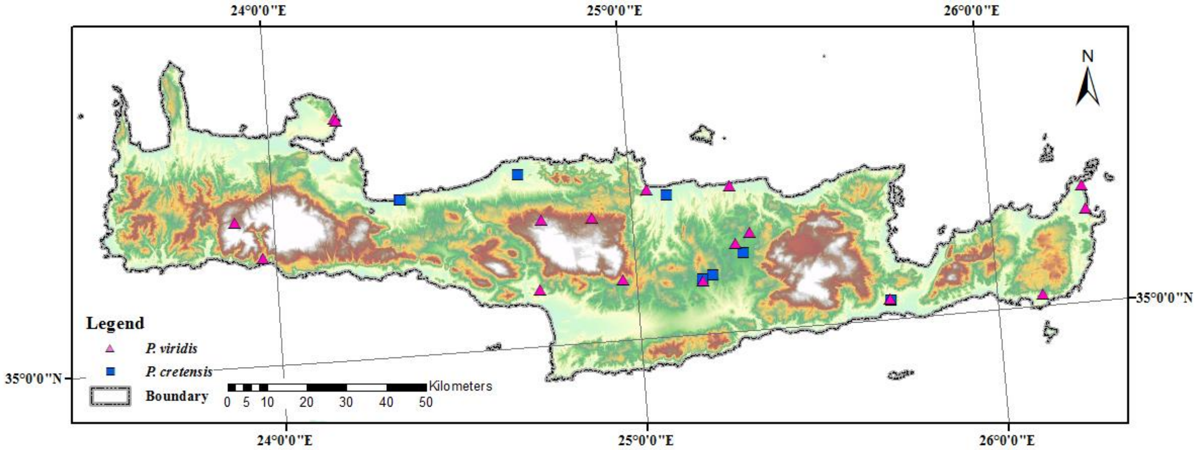

Figure 2.4 The distribution of species occurrence records of *P. viridis* and *P. cretensis* in the study area. (Data derived from NHMC)

2.2.2. Hyper-temporal NDVI images

Hyper-temporal MODIS NDVI products (MOD13Q1) provide data every 16 days at 250 meter spatial resolution in the Sinusoidal projection. Vegetation indices are used to display land cover and land cover changes.

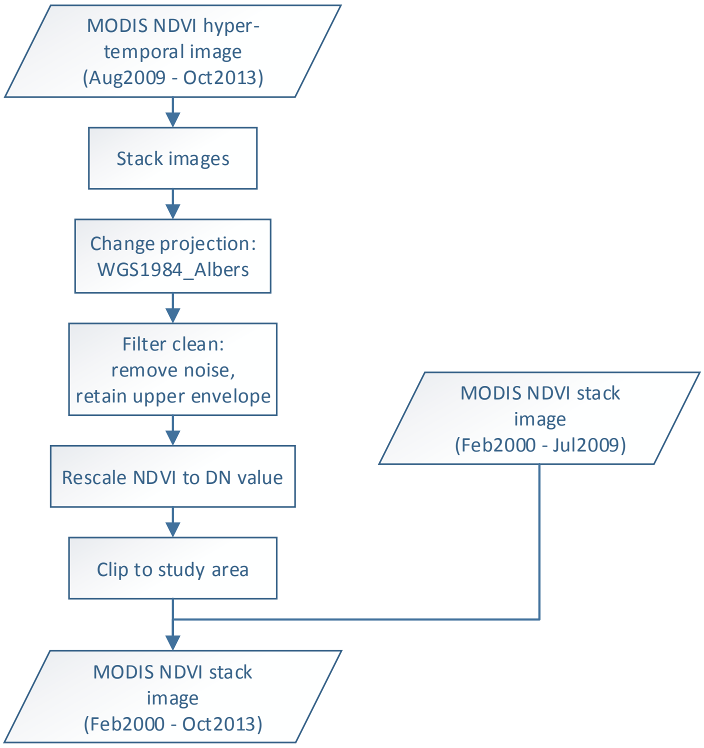

Figure 2.5 Processing of update hyper-temporal NDVI stack image to present. Download and compiled NDVI hyper-temporal images from August 2009 to October 2013, then compiled them to acquired NDVI stack image (February 2000 to July 2009).

The time series MODIS NDVI data from February 2000 to October 2013 were used to detect the change of land cover and generated as environmental layer for SDM modelling. MODIS NDVI stack image (February 2000 to July 2009) was stacked by Dr. de Bie. A time series data set of MODIS Terra NDVI data extending from August 2009 to October 2013 (95 images) was obtained from NASA Land Processes Distributed Active Archive Centre (LP DAAC) website at https://lpdaac.usgs.gov/data_access/data_pool. After download the NDVI hyper-temporal images, all 95 images were stacked and change projection to Albers Equal Area Conic (WGS84 datum) in ERDAS IMAGINE 2013. Then, the resultant 95 images were compiled into a single NDVI time series image stack of sequentially ordered NDVI images. To drive the upper envelope of NDVI stack image, the Savitzky Golay filter was applied (Beltran-Abuanza, 2009; Jönsson et al., 2004; Savitzky et al., 1964) in TIMESAT 3.1. The NDVI value was rescaled to digital numbers (DN values) of 0-255 for ease of handling and better representation. Finally, NDVI stack image was extracted to fit the study area. Finally, two time series MODIS NDVI stack images were compiled together. All the steps of image processing are shown in Figure 2.5.

2.2.3. Environmental predictors

This study focused on the effect of land cover change on the prediction of species distribution, and the land cover variable which is indicated by hyper temporal NDVI images is the major variable. The details of all predictors are shown in Table 2.1, all variables were resampled into 30m resolution and projected into Albers Equal Area Conic (WGS84 datum) projection.

Category	Variable name	Data type	Spatial resolution	Temporal resolution	Source
Land cover	NDVI in period 1	Categorical	250m	2000 – 2004	LA DACC, NASA
	NDVI in period 2	Categorical	250m	2005 – 2009	LA DACC, NASA
	NDVI in period 3	Categorical	250m	2010 – 2013	LA DACC, NASA
	NDVI in period 4	Categorical	250m	2000 – 2013	LA DACC, NASA
Climate	Annual mean temperature	Continuous	1000m	1950 – 2000	WORLDCLIM
	Mean temperature of wettest quarter	Continuous	1000m	1950 – 2000	WORLDCLIM
	Mean temperature of driest quarter	Continuous	1000m	1950 – 2000	WORLDCLIM
	Mean temperature of warmest quarter	Continuous	1000m	1950 – 2000	WORLDCLIM
	Mean temperature of coldest quarter	Continuous	1000m	1950 – 2000	WORLDCLIM
	Annual precipitation	Continuous	1000m	1950 – 2000	WORLDCLIM
	Precipitation of wettest quarter	Continuous	1000m	1950 – 2000	WORLDCLIM
	Precipitation of driest quarter	Continuous	1000m	1950 – 2000	WORLDCLIM
	Precipitation of warmest quarter	Continuous	1000m	1950 – 2000	WORLDCLIM
	Precipitation of coldest quarter	Continuous	1000m	1950 – 2000	WORLDCLIM
Distance	Distance to wetland	Continuous	30m	2013	WWF
	Distance to river	Continuous	30m	N/A	NHMC
	Distance to road	Continuous	30m	N/A	NHMC
Terrain	Altitude	Continuous	90m	2000	USGS/STRM
	Slope	Continuous	90m	2000	USGS/STRM
	Aspect (eastness)	Categorical	90m	2000	USGS/STRM
	Aspect (northness)	Categorical	90m	2000	USGS/STRM
Soil	Soil type	Categorical	1:1,000,000	1986	Wageningen University

Table 2.1 Environmental predictors which is related to species distribution and prepared to use in SDM modelling. All predictors were classified in five categories.

Land cover variables

The land cover data was indicated by hyper temporal MODIS NDVI images.

The land cover variable used in the No-change Approach (NDVI in period 4) can be modified by calculating the average of NDVI value since February 2000 to October 2013.

The land cover variables used in the Change Approach were generated by the three specific time periods which are shown in land cover category of Table 2.1, and the detailed description of specific land cover time periods was in chapter 2.4.1. The specific land cover variable was produced by calculating the average of NDVI value in related different period. The information from these land cover variables is more detailed and close to the reality.

Climate variables

According to the habitats of two target species (*P. viridis* and *P. cretensis*), two sorts of climate variables were considered: temperature and precipitation.

These two kinds of variables were downloaded from the bioclimatic variables in WORLDCLIM database (http://www.worldclim.org/tiles.php?Zone=16). Bioclimatic variables are derived from "the monthly temperature and rainfall values and generally used in ecological niche modelling" (Hijmans et al., 2005). In this study, the climate variables were selected from bioclimatic variables represent annual trends (e.g. annual precipitation), and extreme or limiting environmental factors (e.g. mean temperature of the coldest quarter). All bioclimatic variables used in SDM modelling were list in Table 2.1 (climate variable). All climatic data layers were generated on a 30 arc-seconds (~1km) spatial resolution and in the latitude/longitude coordinate reference system (not projected) and WGS84 datum.

Distance variables

In this study, the surface water includes wetlands and rivers on Crete Island. Because of their different format, wetlands and rivers were derived in two different parameters for the modelling.

The wetland data was obtained from WWF Greece as polygon shapefile. It recorded wetlands where target species (*P. viridis* and *P. cretensis*) commonly occurred. A total of 72 wetlands (mainly dam lakes and reservoirs) were collected where the wetland area is larger than 0.1ha ($1000m^2$). Since the amphibians avoid salty water, only freshwater was available to use. The 'distance to wetland' parameter was calculated using the Euclidean distance function in ArcGIS 10.2.

The river data was acquired from NHMC as polyline shapefile. It contains information on detailed drainages in Crete Island. The major drainages were included in this parameter. The 'distance to river' parameter was calculated by the Euclidean distance function in ArcGIS 10.2.

The roads data was acquired from NHMC as polyline shapefile. It contains different road level in Crete. The roads from 1st level to 3rd level were included in the calculation. The 'distance to road' parameter were calculated by the Euclidean distance function in ArcGIS 10.2.

Terrain and soil variables

The terrain variables and soil variable (including altitude, aspect, slope, soil type) were collected and pre-processed by Herkt (2007).

2.3. Data collection

2.3.1. Fieldwork design and procedure

Fieldwork was carried out between 22nd September and the 5th October, 2013. The main objective of the fieldwork was to record current land cover which is associated with habitat characteristics of *P. viridis* and *P. cretensis*. The habitat characteristics of target species was represented by the region where species occurred, and the land cover was indicated by NDVI classification data. Therefore, the idea of the fieldwork is to record the current land cover description of NDVI classes, especially for those classes where species occurrence points were located.

A sampling strategy was designed before going to the field. The sampling design was based on species occurrence records, NDVI classes derived from hyper temporal MODIS NDVI data and the Corine land cover map. A NDVI classification image with 65 classes were generated through unsupervised classification of a time series of MODIS NDVI data by Dr. de Bie. Corine land cover 2000 map (CLC2000) was obtained from the European Environment Agency website and clipped to the extent of the study area. Based on the expert knowledge of the probable habitat types of target species, the units of agriculture areas, wetlands and inland water bodies from CLC2000 were the most relevant classes with target species' habitat. Cross the NDVI classification image with CLC2000 and species occurrence points respectively. The output NDVI units were highly related with species' probable habitat and in priority to record the current land cover. Moreover, NDVI units sufficed by the following conditions: 1) easy access from the roads (on 2nd and 3rd level), 2) the area of a NDVI units should be larger than 30km^2 (referred as the area of 5 grids in 250m spatial resolution) are also interested to survey the land cover on the field. Sample points were collected from these NDVI units. Furthermore, according to the interview during the fieldwork, there are some unique factors which would impact the land cover and species habitat, for instance, the alternative planting between olive tree and grape, the use of pesticides and fertilizers. Considering time and terrain as limited factors, a total of 123 sample points (122 points are available) were collected during the field survey and covered 38 NDVI units.

The species occurrence points, sample points, NDVI classification image, Corine image and other shapefile which is related to species habitat (e.g. wetland, road) were re-projected and stored on the IPAQ and carried to the field.

2.4. Land cover change detection

2.4.1. Detect the significant change of land cover

According to the method of Change Approach, the time range of land cover variable and species occurrence record are the same. In this study, the time period of land cover change detection and SDM modelling is from 2000 to 2013 (named as T4). To discover the land cover change within this time period, the time period was split into 3 specific periods with same interval: the first period is from 2000 to 2004 (named as T1), the second period is from 2005 to 2009 (named as T2) and the third period is from 2010 to 2013 (named as T3). If the land cover change within the three specific time periods is significant, these changes might affect the potential species distribution by MaxEnt model.

NDVI was used to monitor the change of land cover in the study area. Figure 2.6 reveals the NDVI change performance from 2000 to 2013. Pictures below shows the NDVI performance in the same area, on the same date of different years (2000, 2004, 2009 and 2013). The NDVI value was indicated by different colour, which is shown as the legend on the right. The similar colour indicates similar land cover unit, so no or little change in land cover. The NDVI image of 2000 is the beginning performance of the time period, and NDVI image of 2004, 2009 and 2013 is the latest performance in T1, T2 and T3, respectively. According to these NDVI time series image, the regions in magenta colour and yellow colour have obvious change, which indicate the land cover in the regions change in the time period.

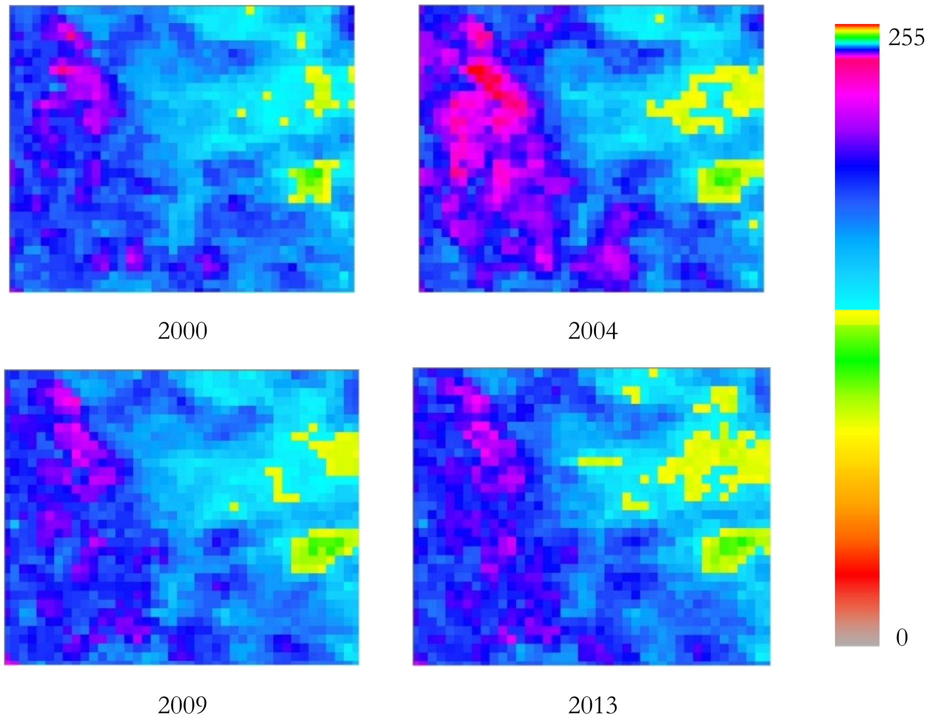

Figure 2.6 NDVI Performance in the same area, on the same date of different years (2000, 2004, 2009 and 2013). The more similar colour represents similar land cover unit, so no or little change in land cover. It is obviously that e.g. land cover in the magenta colour and yellow colour regions changes from 2000 to 2013.

The NDVI profile of species occurrence point were extracted from the hyper temporal NDVI image from 2000 to 2013 based on the location of species occurrence points. The profile interpreted the NDVI performance where the species was found, and also described the trend from during the time period. Based on the sample date, the yearly NDVI profile of species occurrence point (named as yearly profile of point) was extracted, and the profile interpret the habitat characteristic for species.

According to the variation of the NDVI profile of species occurrence point, four categories of changing tendency were generalized in Figure 2.7: no change, gradual change-1, gradual change-2 and abrupt change. Gradual change-1 means the species occurrence point was recorded before 2009 and gradual change-2 means the species occurrence point was recorded after 2009. Since the NDVI classification image was from 2000 to 2009, the profile of species presence point cannot match by profile of NDVI class visually in the whole time period. Thus, if the gradual change-2 happened, the only way to match them is compare their annual profile. The marker on the profile shows the time when species was collected. This figure indicated that the land cover around the species occurrence point has been changed in the time period.

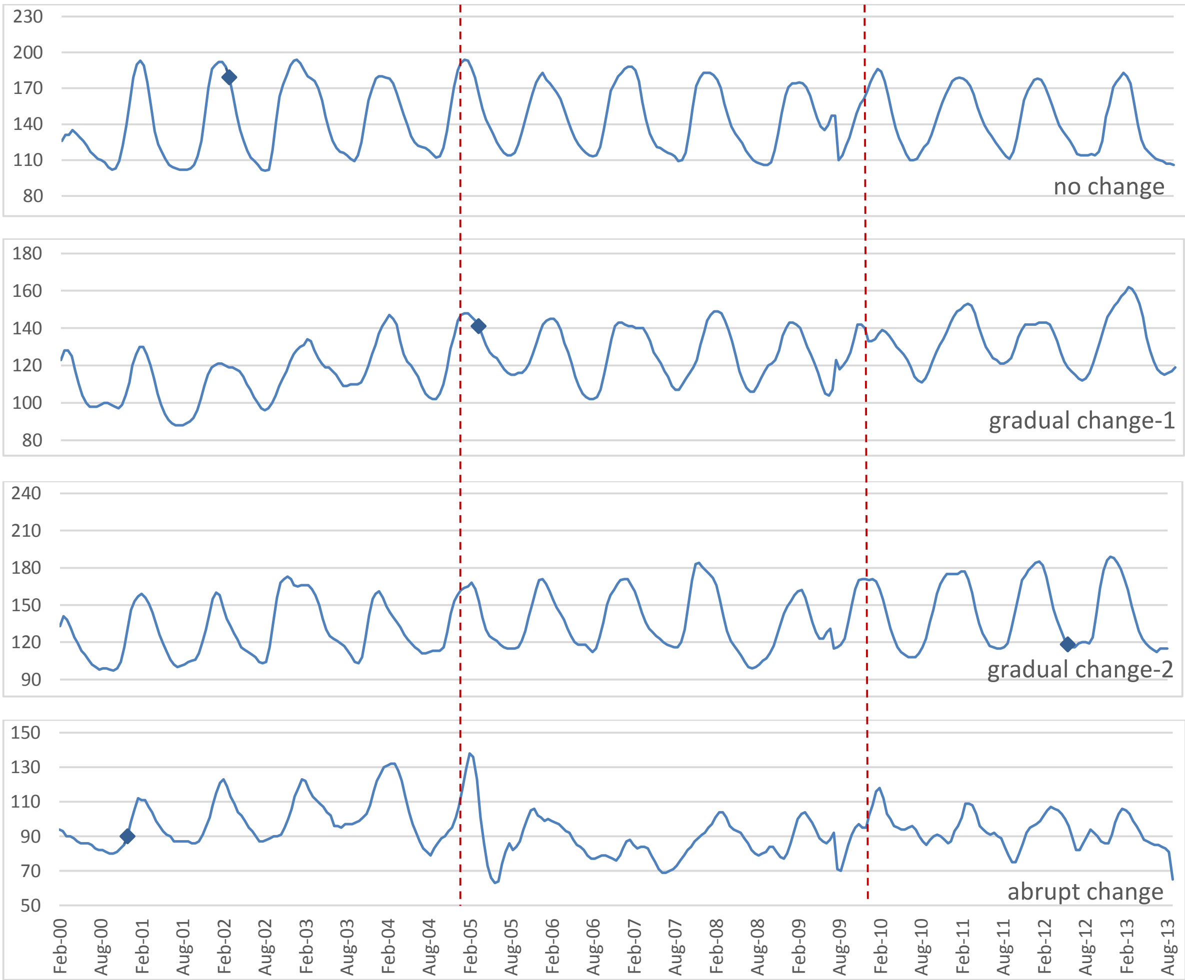

Figure 2.7 NDVI change tendency scheme which is generalized based on the trend of the average value every year, classified into four categories: (a) no change: the profile keeps stable in whole period, (b) gradual change-1: the profile changes gradually when species occurrence point was found before July 2009, (c) gradual change-2: the profile changes gradually when species point was found after July 2009, (d) abrupt change: the profile has abrupt change in whole period (the profile changes suddenly in August 2005).

The valid NDVI class which represents the target species habitat (named as class of point) should be extracted before the change detection analysis. There are two methods to extract the valid class. The first method is point visualization. Based on the spatial location of each species occurrence point, visualize the class of NDVI classification image that species occurrence point is located in. Another method is to analyse the annual NDVI profile. Extract annual NDVI profiles of 65 classes from the NDVI classification image and gather with the yearly profile of point together. Then, cluster the similar profiles by hierarchical cluster analysis (HCA). If the yearly profile of point and annual profile of class were in the same cluster, the performance of their profile are closer than others. After that, compare the result of two methods, the class which represents species presence point can be confirmed. These classes also represent the habitat of target species and are valid to use in the change detection method. Furthermore, the accuracy of species occurrence points can be evaluated and increased according to comparing two methods mentioned above, if the number of NDVI class were same with two method, the represented species were in a correct location, otherwise species points were in a wrong location.

The approach of land cover change detection is shown in Figure 2.8.

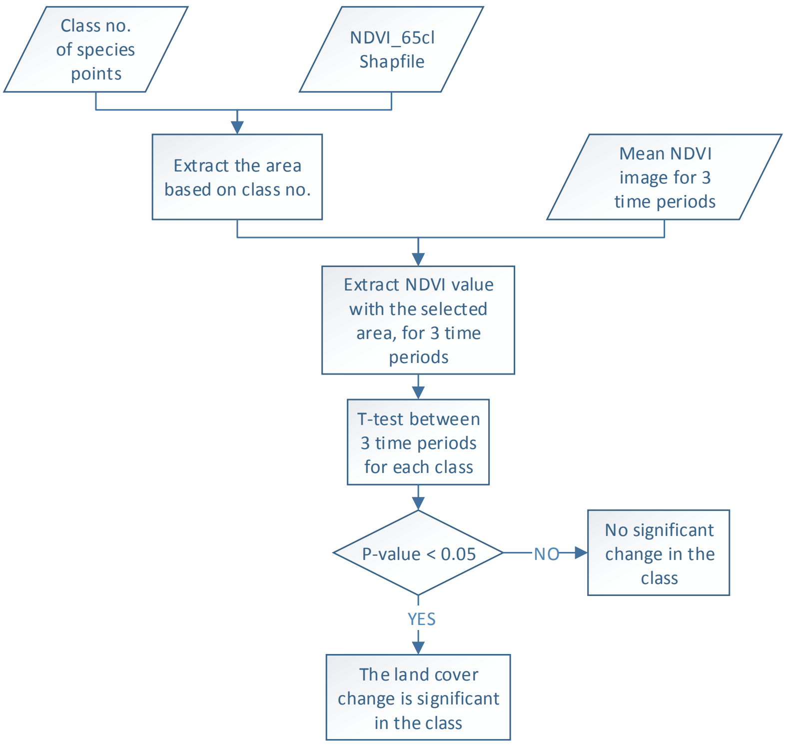

Figure 2.8 The processing of land cover change detection. Based on each class of point, the average NDVI value in different periods has been compared pairwise using t-test. If p-value < 0.05, the land cover between two periods has a significant change.

The change of land cover can be detected by analysing the difference of NDVI value per pixel in three specific time periods, based on each NDVI class of point. Two tailed t-test was used to test if the change is significant or not. First of all, calculate the mean NDVI value for each specific time period based on hyper temporal NDVI stack image. Second, for each specific time period, extract all mean NDVI values which is located in the area of the class of point. Then, t-test was used to pairwise compare the selected mean NDVI values of three specific time periods for each class of point. If the p-value is less than 0.05, there is a significant difference of mean NDVI value between two specific time periods. Which means the land cover in the covering region of the class of point has significantly changed between the two different specific time periods. Otherwise, if the p-value is more than 0.05, and the change of land cover is not significant between two specific time periods.

2.4.2. How does the land cover change?

If the change of land cover within three specific time periods is significantly different, the land cover change for each species occurrence point can be discovered.

For each specific time period, generate the annual profile of species occurrence point from NDVI stack image. Then, using HCA three times to cluster the annual profile of species occurrence points (the annual profile is different in three specific periods) and the annual profile of 65 classes for each specific time period which have similar profile performance. After that, for the cluster which has species point inside, One-Way ANOVA test was used to determine the closest profile of NDVI classes and compare with the annual profile of the species occurrence points. Therefore, this class that represents the land cover of the species point in a specific time period. For each species occurrence point, the NDVI class in one specific time period when species was found is the class that represents species habitat. Next, compare the class from other two periods with this NDVI class. If they are the same, the species occurrence point is valid in other time period, otherwise the point should be eliminated from that time period.

According to the same method, using HCA and One-Way ANOVA test for the annual profile of 65 classes and the profile of field observation point in 2013, the assumed land cover description for NDVI classes can be detected.

2.5. Multi-collinearity diagnostic between predictors

Multi-collinearity is a statistical analysis for the existence correlation amongst two or more explanatory variables in statistical modelling. It occurs when variables are highly correlated. When two variables are highly correlated, they are basically the same phenomenon or construct. In other words, they both convey essentially the same information.

The principle danger of such data redundancy is over fitting in statistical models. The Variance Inflation Factor (VIF) is one of the common indicators to detect multi-collinearity (Montgomery et al., 2012). Multi-collinearity analysis was conducted in SPSS using linear regression. Variable with the highest VIF (>10) value was considered to be removed.

$$VIF = \frac{1}{1 - Ri^2}$$

Where R_i^2 is the value obtained by regressing the i^{th} predictor on the remaining predictors. If VIF value of variable more than 10, it means the variable definitely has multi-collinearity issues, and the variable should eliminated before running the model.

Environmental variables	**VIF**
Slope	1.877
Aspect (eastness)	1.542
Aspect (northness)	1.337
Soil type	1.873
Distance to river	2.424
Distance to road	1.965
Distance to wetland	2.044
Annual mean temperature	4.815
Annual precipitation	4.577

Table 2.2 The results of the multi-collinearity test of the environmental variables. All variables were valid to use in SDM modelling, as VIF < 10 for all of them.

There are 18 environmental variables to test their multi-collinearity. As can be observed from Table 2.2, only 9 variables passed the test. However, the altitude variable has been found to be a key factor for amphibians (Dayton et al., 2006). Thus, it was considered as one of the variables though it had a VIF value far more than 10.

2.6. Predictive species distribution modelling

If land cover changed significantly between 2000 and 2013, the relationship between land cover change and species habitat can be evaluated by running the MaxEnt model including the land cover change or ignore the land cover change, and compare the prediction maps of species habitat by two models.

Species distribution modelling refers to models which use species' observation and their biological characteristics to predict its potential distribution. Presence-only methods rely on the establishment of environmental envelopes around locations where species occur, which are then compared with to the environmental conditions of background areas (Brotons et al., 2004). In this study, MaxEnt model was chosen to predict the species distribution.

2.6.1. MaxEnt Entropy modelling

"MaxEnt combines presence-only data with ecological layers to create species distribution models using a statistical method called maximum entropy" (Jaynes, 1991). Species environment is estimated by finding a probability distribution that is based on a distribution of maximum entropy and is in reference to a set of environmental variables (Phillips et al., 2006). In species distribution modelling, "the pixels of the study area make up the space on which the MaxEnt probability distribution is defined, pixels with known species occurrence records constitute the sample points, and the features are climatic variables, elevation, soil category, vegetation type or other environmental variables" (Austin, 2007).

Furthermore, MaxEnt has the strongest performance and prediction accuracy when the observation points are in low sample size. According to Hernandez et al. (2006), compared with other species distribution model (e.g. GRAP, Bioclim), MaxEnt has highest performance while the sample size from 5 to 25, and the average range in values for prediction success was smallest with sample size from 5 to 100.

2.6.2. Modelling with No-change Approach and Change Approach

To predict the distribution of two target species with MaxEnt method, all the environmental layers were required to be in the same projection, spatial resolution and need to be converted into ASCII format. The species occurrence records (with species name and their XY coordinates) were prepared in Excel 2013 and saved as CSV format.

Each species' presence points was randomly divided into two portions, a subset with 70% of species occurrence records were selected as training data, and 30% were used as validation data. Since data set for two species are very small (especially for *P. cretensis*), bootstrapping simulation used to model validation because it is sampling with replacement.

The objective of MaxEnt modelling was to discover whether the change of land cover affect the prediction significantly during the total time range from 2000 to 2013. Thus, two modelling approach were used to predict the distribution of target species. The No-change Approach excluded the land cover change. The approach was following the general MaxEnt method, the land cover variable was described by mean NDVI value between 2000 and 2013, the same time range as land cover change detection. Thus, the result of this model was predict the species distribution in 2013. The prediction by this approach was used a reference results. The Change Approach included the land cover change within the total time range. Based on the analysis of land cover change detection, the land cover, which is related to species habitat, was significantly different in three specific time periods which were defined in chapter 2.4.1. And for each specific time period, only valid species occurrence points can be used in the model. Therefore, the MaxEnt model was run three times based on different specific time periods. The result of each model was representing the species distribution based on the land cover in a certain period. And all three prediction maps shows the prediction of species distribution in different land cover. Furthermore, the model in the latest period interpreted the current prediction.

Model no.	Same variable	Different variable
Model 1	Climate, terrain, distance to surface water and road, soil type	Land cover between 2000 and 2004
Model 2		Land cover between 2005 and 2009
Model 3		Land cover between 2010 and 2013
Model 4		Land cover between 2000 and 2013

Table 2.3 The description of environmental variables used in four models. Variables which are under the 'same variable' column were used in all four models, while variables under the 'different variable' column were used for that specific model only.

Overall, four kinds of model were generated for each target species (as shown in Table 2.3). All environmental variables were used in all models except the land cover variable. The land cover variable of the first model was acquired between 2000 and 2004 (T1), the land cover variable of the second model was acquired between 2005 and 2009 (T2), and the land cover variable of the third model was acquired between 2010 and 2013 (T3). Those three models express the results of the Change Approach according to the time sequence. The land cover variable of the fourth model was acquired between 2000 and 2013 (T4) while this time period is same as the time period of change detection analysis. And the fourth model shows the result of the No-change Approach.

2.6.3. Model evaluation

One fundamental issue in the development of distribution models is the assessment of predictive accuracy (Barry et al., 2006; Guisan et al., 2005). Thus, model evaluation is considered to form a very important process during the modelling. The accuracy of distribution model can be measured by discrimination capacity (Pearce et al., 2000), which measures the model's ability to distinguish between sites where the subject species has been detected (presence sites) and those sites where the species is known to be absent (absence sites). A range of indices are used to evaluate through discrimination capacity. In this study, the threshold-dependent True Skill Statistic (TSS) was employed to evaluate if the prediction with land cover change was better than the prediction without land cover change. And the threshold-independent Area Under ROC Curve (AUC) was employed as single indicator of model performance (Hanley et al., 1983).

True Skill Statistic (TSS)

"TSS is defined as TSS = Sensitivity + Specificity -1, while Sensitivity is the probability that a model correctly predicts the observed presence site and Specificity is the probability that a known absence site is correctly predicted" (Liu et al., 2011). TSS takes into account both omission and commission errors, and ranges the value from 0 and 1, and the degree of agreement for the TSS evaluation was separated as: perfect TSS > 0.9, excellent 0.85 < TSS < 0.9, very good 0.7 < TSS < 0.85, good 0.5 < TSS < 0.7, fair 0.4 < TSS < 0.5 and poor TSS < 0.4 (Monserud et al., 1992). The TSS is better for the model using presence-only data and works well with a small sample size model.

Since the output from the models are probabilities which are continuous (between 0 and 1), they needed to be converted to binary values (presence or absence) in order to calculate TSS. This was done using '10 percentile training presence' logistic threshold. It has been applied especially in species with low dispersal ability and "has been considered as a more conservative threshold because it does not overestimate the potential distribution result" (Rödder et al., 2009). Values above the threshold are reclassified as predicted presences, while values below the threshold are reclassified as predicted absences. The evaluation was replicated 10 times and the model evaluation value were averaged.

Area Under ROC Curve (AUC)

AUC is widely used to evaluate the predictive accuracy of species distribution model using presence-absence data. As AUC is independent of both threshold setting and prevalence, it is a highly effective method for assessing the performance of ordinal score (i.e. presence-only) distribution models (Allouche et al., 2006). The AUC is derived by using all possible thresholds to plot sensitivity versus specificity. The range of AUC between 0 and 1, a value of 1 stands for perfect discrimination, if the value is more than 0.75 the model is rated 'good', while a value of 0.5 indicates a performance is worse than random model (Graham et al., 2006).

Regarding the value of AUC, the AUC value is correlated to the size of the study area and the prevalence of the occurrence points, for instance, if you use a small study region or if the occurrence points are localized in a small area and have small prevalence, you will get a high AUC value. Unlike AUC, TSS values are not affected by the prevalence of the occurrence point or the size of the study region.

3. RESULTS

3.1. Change detection

3.1.1. Species NDVI profile

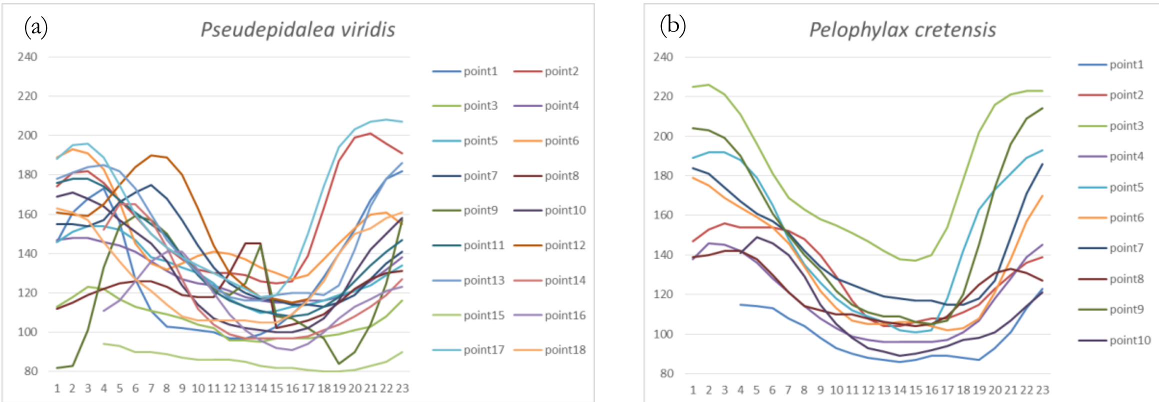

Figure 3.1 NDVI profile description of two species. The profile was collected from the pixel where the species observation point is located, and extracted in the year when the species was found. Each profile represents the surrounding land cover of the species occurrence point. (a) NDVI profiles of *P. viridis* with 18 observation points, and (b) NDVI profiles of *P. cretensis* with 10 observation points.

The Figure 3.1 shows the yearly NDVI profile of species presence point extracted from NDVI time series image in the year when species was found. The horizontal axis means 23 NDVI values were acquired in the year (according to the temporal resolution of MODIS product), and vertical axis represents NDVI value which the range is between 0 and 255. Some profile starts at 4th value because they represented species occurrence points were collected in 2000 when the hyper temporal NDVI image started on February.

Compared with the NDVI profile of two species, the NDVI range of two species are quite similar, both of them have seasonal change, the NDVI value is higher in the winter and lower in the summer. However, the maximum of *P. cretensis* ($NDVI_{MAX}$ = 226) are higher than *P. viridis* ($NDVI_{MAX}$ = 208). Besides, the profile of *P. viridis* has more variability, for instance, profiles of point 15 and point 3 were in a NDVI range from 80 to 120 with less seasonal change while the profiles of point 17 and point 2 have significant seasonal change. Compared with *P. viridis*, the profile of *P. cretensis* is relatively unitary, all profiles were in seasonal change.

3.1.2. Land cover change detection

After comparing the number of NDVI class of same species occurrence point with two methods (mentioned in chapter 2.4.1), 6 species occurrence points (4 points of *P. viridis* and 2 points of *P. cretensis*) have different represented NDVI class according to two methods. Based on the accuracy range of these points, all points were can be moved to the NDVI class which in the accuracy range and the profile is in the same cluster as species point.

Table 3.1 describes the results of land cover change from 2000 to 2013 for *P. viridis* and *P. cretensis*, and it reveals whether the land cover change is significant or not. The class number means the NDVI class of point which is related to species' habitats. T1, T2 and T3 represent different time periods of 2000 to 2004, 2005 to 2009 and 2010 to 2013, respectively. T-test was used to examine the covering region of land cover change by pairwise examine NDVI values of three specific time period. The columns under P-value are its results. If the p-value is less than 0.05, there has been a significant change of land cover between two specific periods. The results which p-value < 0.05 were coloured their table cells to make it clear.

a) Change detection results of *P. viridis*

Class number	p-value T1 & T2	p-value T2 & T3	p-value T1 & T3
11	0.644	0.423	0.745
16	0.765	0.053	0.026
20	0.646	0.002	0
21	0.092	0.367	0.373
23	0.21	0.05	0.467
25	0.002	0.499	0
26	0.891	0.038	0.028
28	0.06	0.395	0.246
31	0.612	0.255	0.099
35	0.565	0.683	0.836
40	0.631	0.444	0.774
42	0.297	0.576	0.632
47	0.544	0.287	0.088

b) Change detection results of *P. cretensis*

Class number	p-value T1 & T2	p-value T2 & T3	p-value T1 & T3
13	0.688	0.956	0.633
22	0.228	0.669	0.441
25	0.002	0.499	0
26	0.891	0.038	0.028
35	0.565	0.683	0.836
41	0.013	0.22	0.206
51	0.041	0.035	0
59	0.022	0.321	0.001

Table 3.1 The results of land cover change detection for *P. viridis* and *P. cretensis* based on two tailed t-test. P-value < 0.05 (in red shading) means the land cover between two periods was changed significantly.

According to the change detection analysis, 13 classes of *P. viridis* and 8 classes of *P. cretensis* were selected to compare the NDVI performance in different specific time period. The number of the class of point are different with the number of species occurrence points because the covering region of a NDVI class would contain more than one sample point. For *P. viridis*, the land cover within the area of class 16, class 20, class 23, class 25 and class 26 has significant change between different specific time periods. Similarly, for *P. cretensis*, the land cover within the area of class 25, class 26, class 41 and class 59 has significant change between different time periods. Thus, the land cover within the region of NDVI classes which represented two target species has significantly change.

For some of the NDVI classes, a two-tailed independent t-test shows that there are significant difference in the NDVI values between specific time periods. This means the land cover related to two target species' habitat, have significant change between specific time periods. Thus, for the hypothesis 1, the Null hypothesis H_0 is rejected and the alternative hypothesis H_a is accepted.

3.1.3. Change description in specific time periods

After the significant analysis of land cover change, Table 3.2 shows the results that which NDVI class can represent the species occurrence point in different specific time period based on ANOVA. The results were under 'NDVI class' columns, T1, T2 and T3 represent three specific time periods, the class number under each specific time period column means this NDVI class represents the species occurrence point in that specific time period. The class with bolder font style means species occurrence point was observed in this specific time period.

a) the valid species occurrence samples in different specific periods of *P. viridis*

Point no.	Date (mm-yy)	NDVI class T1	NDVI class T2	NDVI class T3	Class no.
1	May-02	**25**	25	25	25
2	Jun-02	**42**	48	42	42
3	Jul-03	**11**	8	11	11
4	Mar-05	14	**16**	22	16
5	Mar-05	19	**21**	21	28
6	Jun-05	32	**32**	32	40
7	Apr-08	23	**23**	27	31
8	Mar-09	14	**14**	14	16
9	May-09	21	**16**	21	26
10	Oct-10	28	28	**28**	25
11	Jun-11	22	20	**22**	35
12	May-13	23	23	**37**	23
13	Jun-12	25	25	**41**	26
14	Feb-00	**30**	30	30	25
15	Dec-00	**11**	8	11	11
16	Jun-00	**14**	20	14	20
17	Mar-02	**43**	47	43	47
18	May-02	**19**	21	21	21

b) the valid species occurrence samples in different specific periods of *P. cretensis*

Point no.	Date (mm-yy)	NDVI class T1	NDVI class T2	NDVI class T3	Class no.
1	Jun-00	**16**	16	16	13
2	Nov-01	**28**	31	31	26
3	Feb-02	**59**	59	59	59
4	Mar-02	**16**	16	16	13
5	Mar-02	**33**	33	41	41
6	May-03	**30**	30	30	25
7	Apr-04	**30**	30	30	35
8	Aug-05	16	**16**	16	41
9	May-10	43	47	**43**	51
10	Nov-00	**13**	21	21	22

Table 3.2 The results of valid species occurrence samples in different specific periods of *P. viridis* and *P. cretensis*. Class in purple and yellow shading means the species samples represented by those class were valid to use in SDM modelling. Class under 'Class no.' column and with bold font type under 'NDVI class' can both represent species habitat, but they are not always the same. In 'Class no.' column, class in purple means it is same as the class in the period when the sample was recorded; class in blue means it is not same with the class with bolder font type but they are in the same cluster; class in red means it is not only the same with the class with bolder found type but also in a different cluster.

In addition, Table 3.2 also shows the stability of land cover for each species presence point. If the land cover of one species occurrence point is stable within three specific time period, as well as the NDVI class in each specific time period are same (e.g. point 1 for *P. viridis* and point 3 for in *P. cretensis*, columns in all time periods were fill in purple), it means this species occurrence point can be used to MaxEnt model in all three specific time periods. Based on species collecting date (NDVI class with bold font style), if number of NDVI class in one specific time period is same as the NDVI class which is represented in the specific time period when the species was found in that period (e.g. point 2 for *P. viridis* and point 5 for *P. cretensis*, also fill in purple), the species occurrence point which that NDVI class represented can be used in both time periods.

The column of 'class no.' lists the valid NDVI class represented to species occurrence point (as described in chapter 2.4.1), these class of species points were divided into three groups. The class with purple background colour means it is same as the number of class in a specific time period when the species was found. The class with blue background colour indicates that it is difference with the class in the specific time period when species was found, but two classes were in same cluster, it means their profile were closest and they represent same land cover category. The class with red background colour means it is not only different with the class in specific period, but also in the different cluster groups. The reason of the difference is that the former class represented the NDVI profile of five years (four years in T3) average value, it includes the variety in whole time periods. And the latter class indicates the annual profile for a certain year when species was found, its characteristics is more related with the species.

Since the NDVI classes with blue background colour represented species habitat, so the same class under specific time period column are also valid in distribution model (class with yellow background colour in Table 3.2). According to this processing, the amount of species occurrence point for specific time periods are increasing, in some extent, it would offset the lack of small sample size of species occurrence data set.

Combining the represented NDVI class of specific period with field land cover observation, the land cover description of NDVI class was assumed. The similar observation of NDVI class was analysed, based on annual profile of 65 NDVI class and profile of field observation points extracted from the hyper temporal NDVI image in 2013. Table 3.3 shows the example points of the assumption of the land cover change description based on field observation, the full description is in APPENDIX B.

Point no. of *P. viridis*	**Different time period** **2000-2004 (T1)**	**2005-2009 (T2)**	**2010-2013 (T3)**
Point 11			
	Class 22	Class 20	Class 22
Point 12			
	Class 23	Class 23	Class 27
Point 17			
	Class 43	Class 47	Class 43

Table 3.3 Assumed land cover description for different time periods based on field observation. The represented class of species samples in each specific periods is indicated in table 3.2.

3.2. Model evaluation and performance

3.2.1. Model validation and comparison

Evaluation with threshold-dependent indices (TSS)

Table 3.4 explained the TSS value of the models with and without land cover change for two target species. 'Equal training sensitivity and specificity' using as threshold to measure TSS. For *P. viridis*, the model include land cover change (Model 3) had a very good agreement ($0.7 < TSS \leq 0.85$) compared with the model that excludes the land cover change (Model 4) which had a good agreement ($0.5 < TSS \leq 0.7$). However, for *P. cretensis*, whether the model include the land cover change or not, the model still had a very good agreement. Compared the TSS value for the model including the land cover change (Model 3) and the model excluding the land cover change (Model 4), the former is better than the latter ($TSS_{Model3} > TSS_{Model4}$).

number of replicate	***P. viridis***		***P. cretensis***	
	Model 3	**Model 4**	**Model 3**	**Model 4**
1	0.6707	0.532529	0.9956	0.8367
2	0.6738	0.742376	0.833333	0.6875
3	0.8566	0.498053	0.799033	0.749
4	0.8225	0.482353	0.658167	0.7895
5	0.6686	0.741976	0.966	0.675
6	0.8552	0.682876	0.807633	0.8058
7	0.7446	0.482553	0.650967	0.3749
8	0.7303	0.482953	0.833233	0.843861
9	0.748	0.683453	0.998	0.8403
10	0.6052	0.493953	0.812933	0.7499
Average	0.73755	0.582308	0.83549	0.735246

Table 3.4 Model validation results based on TSS measure for *P. viridis* and *P. cretensis*. Model 3 means the model include the land cover change while Model 4 exclude the land cover change. TSS measures 10 times according to model replication and the average is the general score for the model.

All TSS values calculated from 10 replications of one model are gathered as a group, and a two tailed t-test was used to compare two models for *P. viridis* and *P. cretensis*, respectively. Because of the low sample presence data, the Confidence Interval of the Difference was changed to 90%.

For *P. viridis*, the TSS value for the two models are significantly different from each other (p = 0.074 at 90% CI). The model with land cover change (Model 3) allowed high TSS values (TSS = 0.74, meaning that on average ~87% of the presence and absence are correctly predicted). And the TSS score for model without land cover change is less (TSS = 0.58, around 79% of the presence and absence are correctly predicted). Based on this result, consider the change of land cover, the performance of distribution model was better.

On the contrary, models of *P. cretensis* with and without land cover change do not have significant difference (p = 0.614 at 90% CI), which means the land cover change in a short time period are not affecting the distribution of *P. cretensis*.

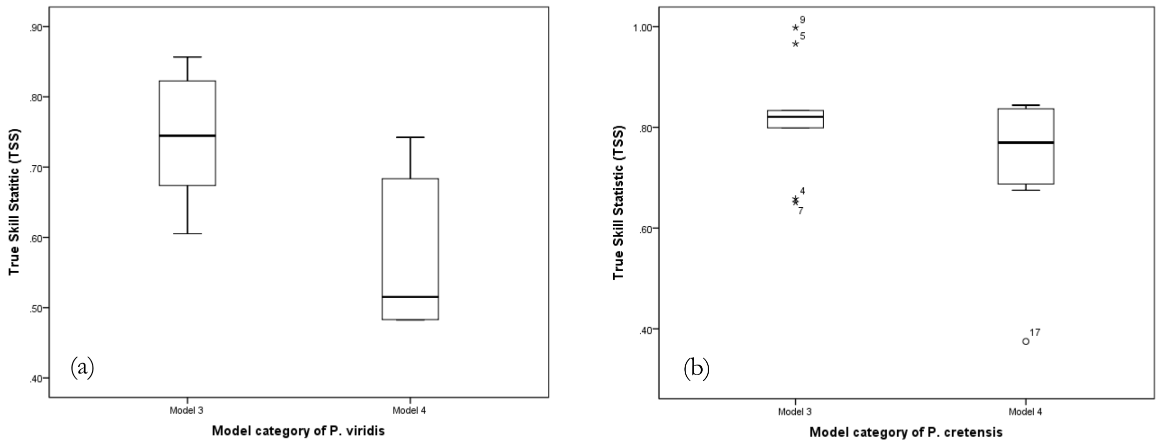

Figure 3.2 The comparison of TSS model evaluation between the models built with land cover change (Model 3) and without the land cover change (Model 4). (a) the comparison between Model 3 and Model 4 for *P. viridis*, (b) the comparison between Model 3 and Model 4 for *P. cretensis*.

The comparison results between the models includes the land cover change (Model 3) and excludes the land cover change (Model 4) and is also revealed in Figure 3.2 using boxplot.

The hypothesis 2 was answered based on t-test results. For *P. viridis*, the Null hypothesis H_0 is rejected and the alternative hypothesis H_a is accepted, whereas for *P. cretensis*, the Null hypothesis H_0 is accepted and the alternative hypothesis H_a is rejected. It means, the land cover change in a short time range affect the distribution of *P. viridis* significantly while it does not have significant effect on *P. cretensis*.

Evaluation with threshold-independent indices (AUC)

For *P. viridis*, the average AUC value for model with land cover change is 0.984, and for model without land cover change is 0.983. For *P. cretensis*, the average AUC value for model with land cover change is 0.996 and for model without land cover change is 0.994. Thus, it means the performance of all models are extremely good.

3.2.2. Jackknife test of variable importance

The Jackknife test was used for identifying which environmental predictor has more contribution in the model. For each predictor, regularize training gain calculated to see the drop in gain when the variable is omitted from the full model. The average behaviour of MaxEnt model in 10 bootstrap simulations using the variables with less multi-collinearity issues revealed that some variables had dominant predictive power while others had least predictive power.

According to the result of Jackknife test for *P. viridis* (as shown in Figure 3.3), the most important variable is the mean of MODIS NDVI in both Model 3 (ndvi_t3_10-13) and Model 4 (ndvi_t4_00-13). This gain will be decreased if this layer omitted from the model, which means the mean hyper-temporal NDVI layer contains useful information that are not present in other variables and this variable is highly related with the prediction. Except land cover variable, variables of slope and soil type also have more contribution to models whether the land cover change is considered or not. However, for the Model 3 (Figure 3.3a) which includes the land cover change as a predictor, the altitude and climate variable (annual mean temperature and annual precipitation) are important.

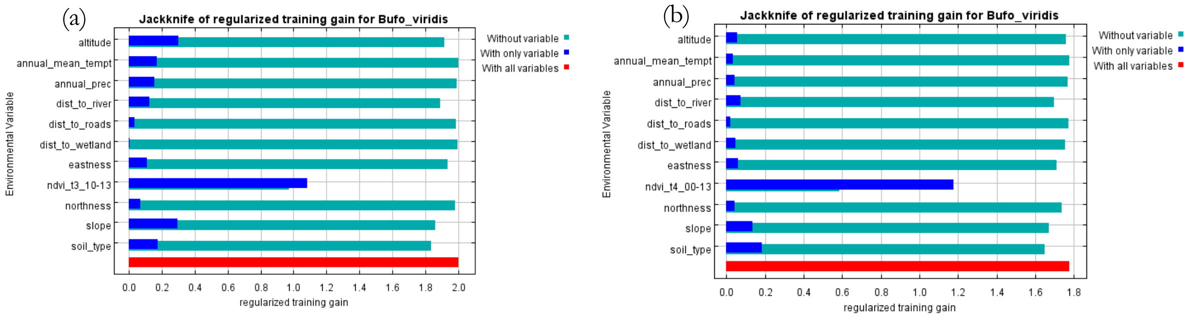

Figure 3.3 Jackknife results for variable importance of *P. viridis* predictive: (a) the importance of variables for Model 3 which include the land cover change, (b) the importance of variables for Model 4 which exclude the land cover change. Green colour shows the training gain without one variable and with remaining variables, while blue colour shows the training gain when this variable is only used in isolation. Therefore, NDVI allows a good fit to the training data in model with and without land cover change.

The result of Jackknife test for *P. cretensis* (as shown in Figure 3.4) reveals the most important variable for habitat prediction is the mean of MODIS NDVI in both model 3 (ndvi_t3_10-13) and model 4 (ndvi_t4_00-13). This gain will be decreased if this layer is omitted from the model, which means hyper-temporal NDVI layer contains useful information that does not exist in other variables and this variable is highly related with the prediction. For the both Model 3 (Figure 3.4a) and Model 4 (Figure 3.4b), after the most important variable, the slope, soil type, altitude, annual mean temperature and distance to river are respectively in the next positions of importance.

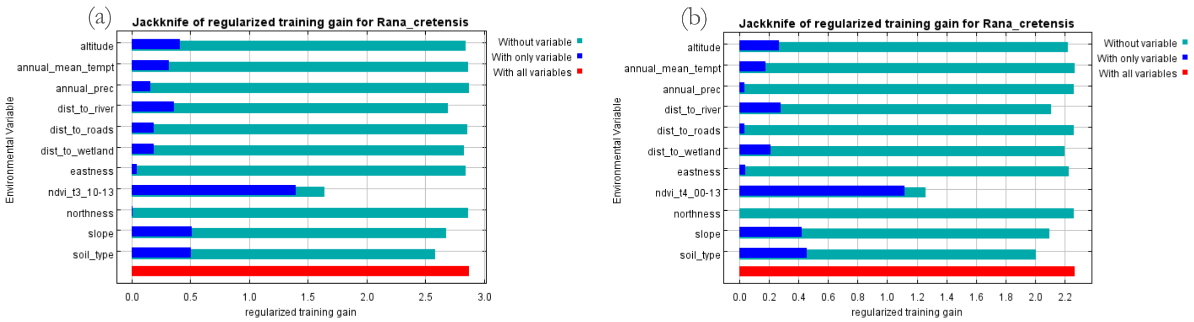

Figure 3.4 Jackknife results for variable importance of *P. cretensis* predictive: (a) the importance of variables for Model 3 which include the land cover change, (b) the importance of variables for Model 4 which exclude the land cover change. Green colour shows the training gain without one variable and with remaining variables, while blue colour shows the training gain when this variable is only used in isolation. Therefore, NDVI allows a good fit to the training data in model with and without land cover change.

3.3. Habitat prediction

Figure 3.5 and figure 3.6 reveal the potential distribution for *P. viridis* and *P. cretensis* with different land cover variables. The prediction results were generated based on the time sequence of land cover variables. Model 1, Model 2 and Model 3 represent the predicted habitat preference in 2004, 2009 and 2013, respectively. Model 4 generates the distribution map in 2013 with the land cover in whole modelling period (2000-2013) while the Model 3 applied the land cover variable in last specific time period (2010-2013). The forth model shows the modelling results by No-change Approach, which does not consider the land cover change within the whole period, whereas the first three models represent the Change Approach including the land cover change in the period. These models manifest the prediction in certain period following the time sequence. Moreover, all species occurrence points were used in No-change Approach modelling and for Change

Approach modelling, only valid species occurrence points were used for the model in specific time periods based on Table 3.2. Overall, the first three models shows the change of species distribution based on the land cover situation in the specific period. As well as the fourth model indicates the prediction without land cover change (merely average land cover indices were used), it was equivalent to the combination of the first three models, to some extent.

During the predictive distribution map, different colour shows the different probability of species occurrence. The red colour represent the highly suitable habitats for target species (the probability of species occurrence is trend to 1) while the green colour represent the unsuitable area (the probability of species occurrence is trend to 0).

To compare *P. viridis* prediction in 2013 with/without land cover change

The potential distribution maps based on model 3 (Figure 3.5c) and model 4 (Figure 3.5d) both indicate the distribution of *P. viridis* in 2013. Compared with those two prediction maps, there is some difference between them. Compared with model 4, the distribution of *P. viridis* in Model 3 was expanded, especially along coastline district, eastern island and central southern island. More area interpreted with red and yellow colour in Model 3. On the contrary, the probability of species occurrence in Model 3 were decrease in the central and northern district, the green colour were expanded and more clear on the map. Thus, the land cover change significant affect the distribution of *P. viridis*.

To compare *P. viridis* prediction from 2000 to 2013 based on land cover change

Model 1 (Figure 3.5a), Model 2 (Figure 3.5b) and Model 3 were generated in a time sequence. Since land cover variable used in these model were also generated in different specific time period, the difference between the potential maps were based on the difference of land cover in three time periods. According to three prediction results, the probability of distribution was increasing in eastern and central southern island from 2000 to 2013. And in the northern district, the probability of distribution was increasing in 2009 and then decreased in 2013.

To compare *P. cretensis* prediction in 2013 with/without land cover change

The potential distribution maps based on Model 3 (Figure 3.6c) and Model 4 (Figure 3.6d) both indicate the distribution of *P. cretensis* in 2013. Compared with those two prediction maps, the distribution were almost same except the western and central southern area, which was revealed by higher probability (interpreted as red colour). The prediction was reasonable, based on the statistical comparison with two models.

To compare *P. cretensis* prediction from 2000 to 2013 based on land cover change

Model 1 (Figure 3.6a), Model 2 (Figure 3.6b) and Model 3 were generated in a time sequence. According to three prediction results, the distribution probability in the whole island decreased gradually from 2000 to 2013, except the northwest corner and eastern area where the probability was increased in 2009 and then decreased in 2013.

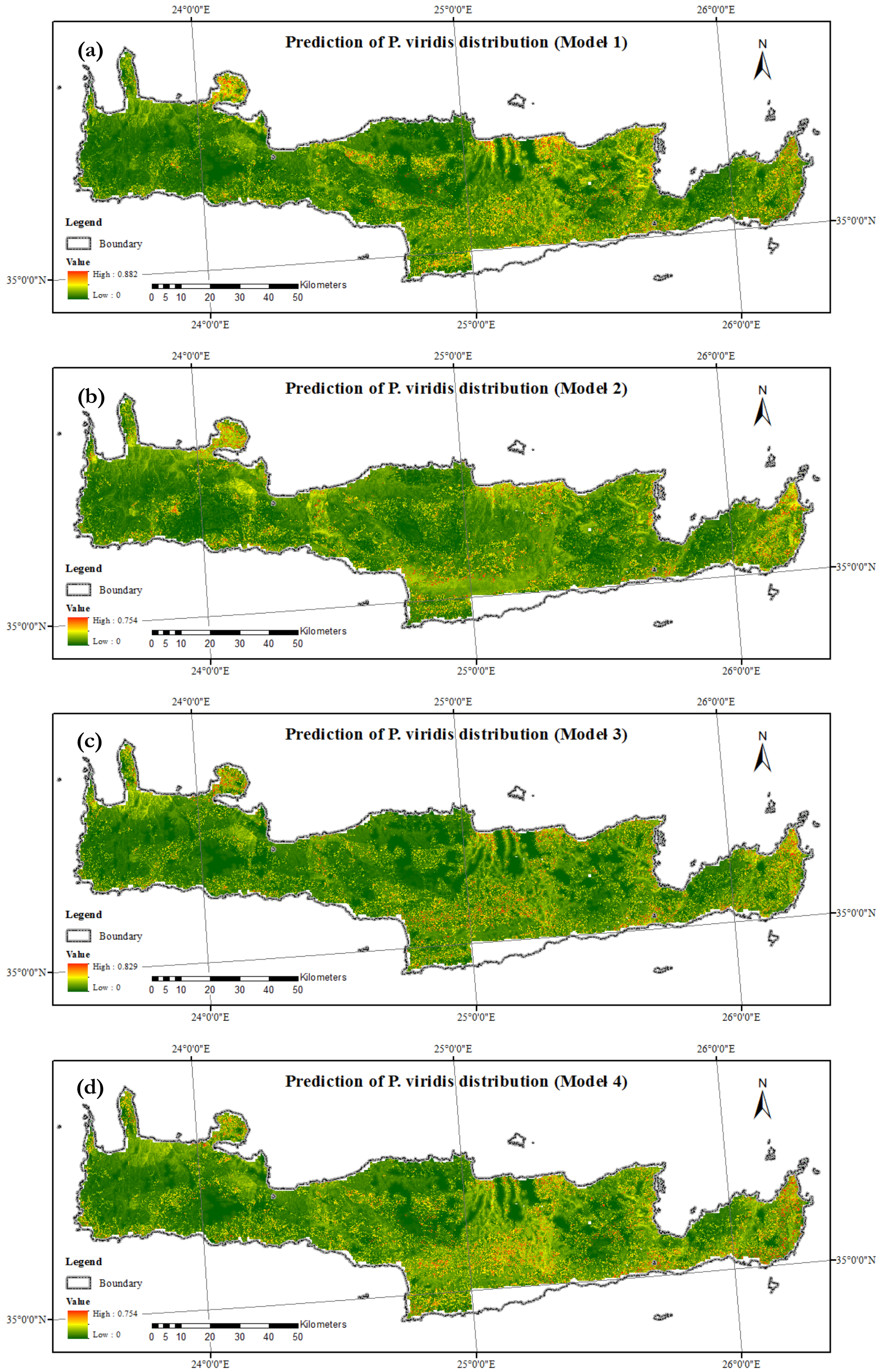

Figure 3.5 Probability of occurrence for *P. viridis* based on MaxEnt modelling. Model 1 (a) represents the prediction in 2004, Model 2 (b) represents the prediction in 2009. Both Model 3 (c) and Model 4 (d) predict the species distribution in 2013 while the former includes land cover change and the latter exclude land cover change.

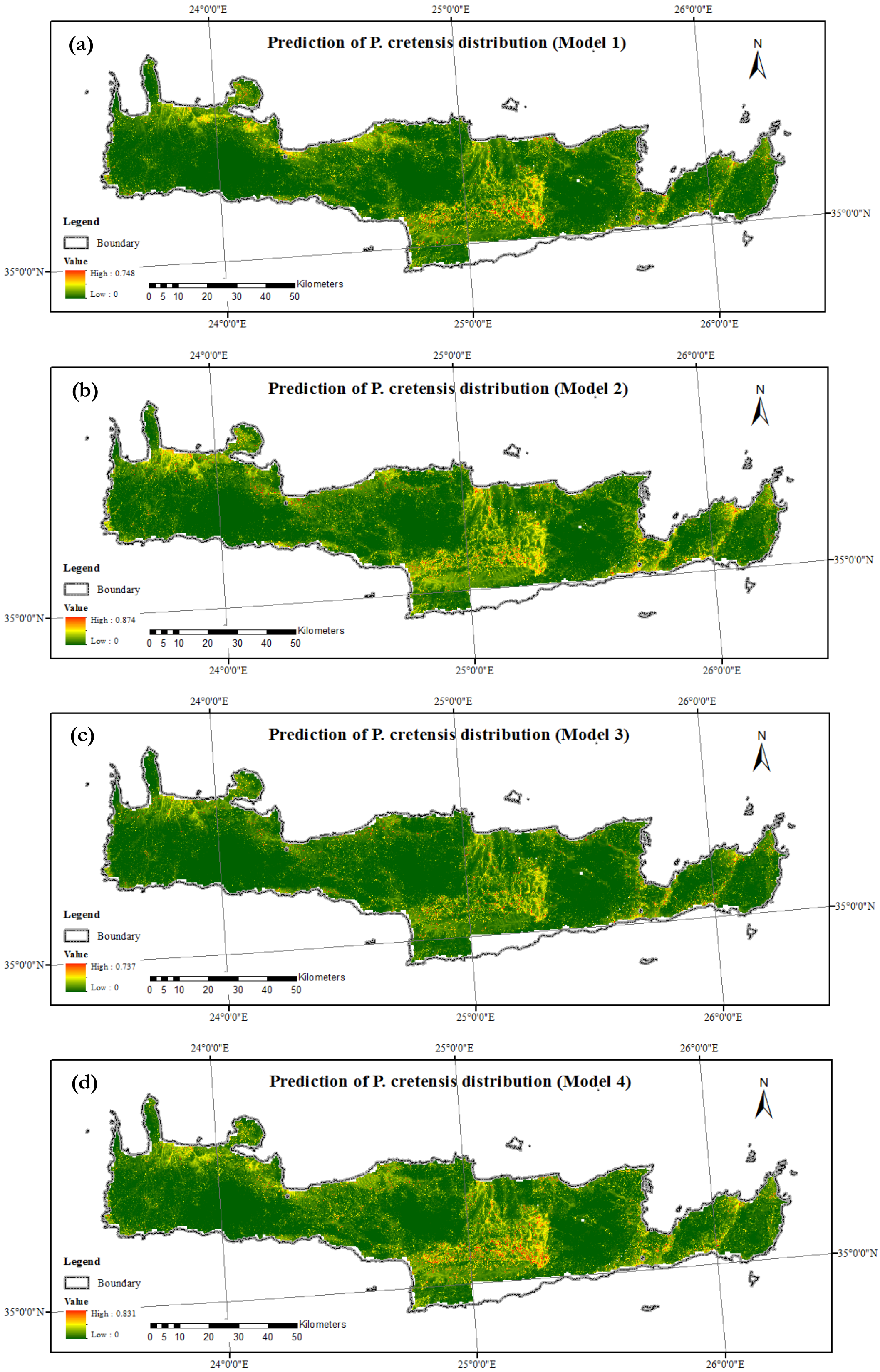

Figure 3.6 Probability of occurrence or *P. cretensis* based on MaxEnt modelling. Model 1 (a) represents the prediction in 2004, Model 2 (b) represents the prediction in 2009. Both Model 3 (c) and Model 4 (d) predict the species distribution in 2013 while the former includes land cover change and the latter exclude land cover change.

4. DISCUSSION

4.1. Land cover change detection

4.1.1. Species NDVI profile

The yearly profile of target species indicated their habitat characteristics. The profile of *P. viridis* has more variety than *P. cretensis*. The former has wide spread distribution in Crete Island and their better adaption to dry conditions suggests that they are alive in a wide variety of habitats. They can live in open area such as shrub and grassland (according to the profile of point 15), but also can live in temperate forest (profile of point 17). The latter are alive in low altitude region and highly reliable to the water body, these condition means their habitat are unitary, thus the profile extracted based on the presence points are very similar.

4.1.2. Accuracy of the species occurrence points

There are some reasons why the class of the points in two methods does not match. The first reason is the error of image, the pre-processing of remote sense image, such as correlation and re-projection, would lead to the error. The second reason is from the species occurrence data set. The species occurrence points are not only collected by student and scholars who have professional knowledge and devices (e.g. GPS) to record the species location in acceptable accuracy, but also collected by local citizens without any sampling experience or device. They recorded the location by describing the surrounding environment, which increase the error. The first reason cannot be avoided during data pre-processing. However, for the second reason, it can be solved out by moving the species occurrence point to the corrected NDVI class in its accuracy range. Thus, the accuracy of species occurrence points were increasing.

4.1.3. Land cover change detection and description

NDVI classification image plays a key role during the whole change detection progress. NDVI classification image with 65 classes indicate 65 land cover units. NDVI classes was clustered using an Iterative Self-Organizing Data Analysis Technique (ISODATA) (Ball et al., 1965) and associated temporal mean NDVI profiles (Ali et al., 2013). Thus, each NDVI class has its unique profile and interprets the land cover within a time series, and this time series profile is stabilized. In this study, habitat-related land cover was selected based on different NDVI units (name as NDVI unit selection). NDVI classification image was used to connect the land cover of species habitat and real land cover in the time series. The former was selected based on the spatial location of species occurrence points, the covering region of NDVI class in which the species was located in could represent the species habitat. The latter was the pixel-based mean NDVI values of specific time period in the region of NDVI class which represents the species habitat. Thus, these pixel-based mean NDVI values represents the land cover which in relation with species habitat in specific time periods. According to the two tailed t-test, the variation of land cover in different time periods can be measured.

Compared with other change detection method (for instance the species home range selection), habitat-related land cover was selected based on the location of species presence point and species home range (the area in which a species lives and travels (Burt, 1943)). NDVI unit selection is suitable for low sample size of species occurrence point because the variety of a NDVI class is much more than the home range of species occurrence point. In low sample size situation, home range selection might leads to under estimation of the species habitat. However, for a large sample size of species presence point, species home range selection is a good choice because the land cover of selected area is more specific to species habitat.

4.2. Model evaluation and performance

4.2.1. Model evaluation

According to Allouche et al. (2006), TSS is not affected by prevalence (the proportion of presence sample points in the whole sample size) and also not affected by the size of validation set. Thus, TSS measure is better for the model using presence-only data or low sample size data. In this study, the validity of model including land cover change is better than the model excluding land cover change for both *P. viridis* and *P. cretensis*. It means the model considered land cover change predicts the potential distribution more accurately.

According to the results of AUC evaluation for *P. viridis* and *P. cretensis*, models for two species have good discrimination whether the land cover change is considered or not. However, the AUC results should be interpreted carefully when it applied to presence-only model (Anderson et al., 2003). AUC is a discrimination indices that represents the likelihood that a presence will have a higher predicted value than an absence (Hosmer Jr et al., 2004), regardless of the goodness-of-fit of the predictions (Quiñonero-Candela et al., 2006; Vaughan et al., 2005). That means it is possible that a poor-fitted model has a good discrimination and vice versa. Another weakness of AUC is its weights omission and commission errors equally, for a looking for unknown species population point of view, low omission error are desirable (Peterson, 2006).

4.2.2. Model comparison

The validation results of models with and without land cover change of *P. viridis* were compared. The validity of model with land cover change is significantly better than model without land cover change. It means the land cover change significantly affects the potential distribution of *P. viridis*. On the contrary, for *P. cretensis*, the validity of model with and without land cover change does not have significant difference, which means the land cover change does not affect the distribution of *P. cretensis*.

Considering their habitat characteristics, the results are make sense. During the fieldwork interview and survey, as well as comparing the Google historical imagery where species presence point located in, most of the land cover change happened in agricultural area (e.g. from a vegetable plantation change to another vegetable) or arranged area (e.g. olive plantation, the ground cover changes from whitish bare soil to dense grass) where *P. viridis* is widely distributed. In contrast, *P. cretensis* as an aquatic species spends almost the entire life in water body, its habitat is extremely close to the water (less than 10m) where these region remain same during the time period. Moreover, the change of land cover occurred far away from water body and the change area does not overlay with its habitat. That is why models for *P. cretensis* have almost same validity whatever the land cover change considered or not.

4.2.3. Model performance

The potential distribution for *P. viridis* is in scatter pattern while the distribution of *P. cretensis* is clustered in certain area. The prediction is correlated with their habitat characteristic. *P. viridis* has highly suitability for environment, it can living in both moisture and dry condition, water is not necessary except for breeding, and it is adapted to the elevation up to 2500m. Therefore, its prediction scattered almost to the whole island. For *P. cretensis*, on the contrary, is sensitive to surrounding environment and it is rely on water body and living in low altitude area (less than 100m). Thus, the potential distribution avoids the high altitude area and is close to wetland or other surface water (e.g. river). Therefore two target species were modelled reasonably. *P. viridis* shows a widespread distribution within the Crete Island while *P. cretensis* is clearly presence in the low ground and near-water region and absent from the higher altitudes.

Comparing the habitat performance include the land cover change with the habitat performance without land cover change, the region with highly probability distribution are contracted. The difference between two habitat performances is generated because Change Approach is using land cover variable similar to current situation and invalid species occurrence point of were eliminated. Thus, the habitat performance without land cover change was over estimated. According to the result of validation and comparison of two modelling approach, the habitat performance including the land cover change is more close to real distribution.

4.3. Limitation and uncertainty

The number of species occurrence records are limited in the study, especially for *P. cretensis*. There are 18 points of *P. viridis* and 10 points of *P. cretensis* used in land cover change detection and 40 points of *P. viridis* and 12 points of *P. cretensis* used in species distribution modelling. For land cover change detection, limited sample points cannot acquire the large variety of land cover types, which means the NDVI profile extracted based on the location of species occurrence points cannot explain all habitat characteristics, especially for the species adapt in different land cover, such as *P. viridis*. For distribution model, even though the modelling method (MaxEnt) and model evaluation measures (TSS) are not effected by small sample size, the limited sample size still affects the potential habitat performance. The high accuracy of model performance indicates the model can predict the species distribution excellent based on certain species occurrence records and environmental variables, but it cannot indicate the potential distribution perfectly match with the real distribution. According to the binary result, the presence area is really small and located close to the species occurrence point. For the absence area, it is possible that the area is not suitable for target species and it also possible that the land cover description of the area is suitable for species but lacks species occurrence points. Moreover, modelling with No-change Approach use all species occurrence points while modelling with Change Approach only use part of them,

Another limitation in this study is NDVI classification image was generated from 2000 to 2009, because of the time limitation, it does not update to 2013. Therefore, it does not include the land cover and its change from 2010 to 2013. The classification category might not represent the current situation. It leads to more uncertainty on land cover change detection.

5. CONCLUSION AND RECOMMENDATION

5.1. Conclusion

The land cover which is related to species habitat has significant change within the specific time period when species occurrence record were collected. And according to the change of land cover, some species occurrence points are no longer appropriate for current species distribution modelling.

According to the habitat characteristics of target species, land cover change within the time period is significantly affects the potential distribution of *P. viridis*, however the change does not have a significant effects on the potential distribution of *P. cretensis*. This can be explained by the fact, that *P. viridis* distributes in a variety of land cover types around water bodies, where the land cover change might happen, while *P. cretensis* distributes extremely close to water bodies where the land cover change happened mainly outside their habitat.

To detect the effect of land cover change on target species distribution, No-change Approach and Change Approach were generalized. Based on the results of model evaluation and comparison, the Change Approach has better model validity and performance than No-change Approach. According to Change Approach, the accuracy of land cover variable and species occurrence points are increasing, it also means the performance has higher accuracy to predict the potential species distribution. Whereas No-change Approach does not consider land cover change in short period, and include species occurrence points which are not available anymore at present. Thus, the performance based on the No-change Approach would overestimate the species distribution.

5.2. Recommendation

Species occurrence points should be expanded the record to get better modelling performance.

The NDVI classification image should be updated to the present, thus the variation of land cover in current situation can be included into the classification image. And then, the NDVI classification image can be generated as an environmental variable in MaxEnt modelling.

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APPENDIX

APPENDIX A

Species occurrence data set acquired from NHMC

ID	Species name	Sample date	Longitude	Latitude	Accuracy
1	Bufo viridis	Oct-97	25.1046	35.3181	300m to 1km
2	Bufo viridis	May-02	25.1873	35.1206	300m to 1km
3	Bufo viridis	Jun-02	24.9658	35.1355	300m to 1km
4	Bufo viridis	Jun-02	24.9658	35.1355	300m to 1km
5	Bufo viridis	Jun-02	24.9658	35.1355	300m to 1km
6	Bufo viridis	Jun-02	24.9658	35.1355	300m to 1km
7	Bufo viridis	Jun-02	24.9658	35.1355	300m to 1km
8	Bufo viridis	Jun-02	24.9658	35.1355	300m to 1km
9	Bufo viridis	Jun-02	24.9658	35.1355	300m to 1km
10	Bufo viridis	Jun-02	24.9658	35.1355	300m to 1km
11	Bufo viridis	Jun-02	24.9658	35.1355	300m to 1km
12	Bufo viridis	Oct-97	25.1046	35.3181	300m to 1km
13	Bufo viridis	Oct-97	25.1046	35.3181	300m to 1km
14	Bufo viridis	Jul-03	25.7027	35.0438	300m to 1km
15	Bufo viridis	Oct-97	25.1046	35.3181	300m to 1km
16	Bufo viridis	Oct-97	25.1046	35.3181	300m to 1km
17	Bufo viridis	Jun-04	24.8303	35.0157	1km to 5km
18	Bufo viridis	Jul-04	24.8303	35.0157	1km to 5km
19	Bufo viridis	Aug-04	24.8303	35.0157	1km to 5km
20	Bufo viridis	Nov-04	25.5150	35.3090	1km to 5km
21	Bufo viridis	Mar-05	26.2639	35.2615	300m to 1km
22	Bufo viridis	Mar-05	26.2689	35.2093	300m to 1km
23	Bufo viridis	Mar-05	26.2689	35.2093	300m to 1km
24	Bufo viridis	Jun-05	23.9653	35.2416	100m to 300m
25	Bufo viridis	Jun-05	24.8941	35.0214	1km to 5km
26	Bufo viridis	May-05	24.8941	35.0214	1km to 5km
27	Bufo viridis	Jun-05	24.8941	35.0214	1km to 5km
28	Bufo viridis	Jun-05	24.8941	35.0214	1km to 5km
29	Bufo viridis	Oct-96	24.4661	35.1570	20m to 100m
30	Bufo viridis	Oct-97	25.1046	35.3181	300m to 1km
31	Bufo viridis	Jul-07	26.2688	35.2059	1km to 5km
32	Bufo viridis	Apr-08	24.8911	35.2805	100m to 300m
33	Bufo viridis	Apr-08	24.8911	35.2805	100m to 300m
34	Bufo viridis	Oct-08	25.0168	35.2975	1km to 5km
35	Bufo viridis	Mar-09	26.1032	35.2078	1km to 5km
36	Bufo viridis	Mar-09	24.1899	35.5429	100m to 300m
37	Bufo viridis	May-09	24.1947	35.5382	100m to 300m
38	Bufo viridis	May-09	24.1947	35.5382	100m to 300m
39	Bufo viridis	May-09	24.1947	35.5382	100m to 300m
40	Bufo viridis	Sep-02	25.2775	35.3242	1km to 5km
41	Bufo viridis	Oct-10	25.3284	35.2207	100m to 300m
42	Bufo viridis	Jun-11	26.1295	35.0254	100m to 300m
43	Bufo viridis	May-13	23.8918	35.3249	100m to 300m
44	Bufo viridis	Jun-12	25.0488	35.3340	20m to 100m
45	Bufo viridis	Dec-96	26.2148	35.2214	300m to 1km
46	Bufo viridis	Dec-96	26.2148	35.2214	300m to 1km
47	Bufo viridis	Dec-96	26.2148	35.2214	300m to 1km
48	Bufo viridis	Dec-96	26.2148	35.2214	300m to 1km
49	Bufo viridis	Oct-97	25.1046	35.3181	300m to 1km
50	Bufo viridis	Sep-99	24.9922	35.0766	20m to 100m
51	Bufo viridis	Jul-99	24.9922	35.0766	20m to 100m

52	Bufo viridis	Mar-99	25.8407	35.0319	20m to 100m
53	Bufo viridis	Feb-00	24.7305	35.1271	20m to 100m
54	Bufo viridis	Apr-99	24.9414	34.9369	20m to 100m
55	Bufo viridis	Nov-99	24.8286	34.9425	20m to 100m
56	Bufo viridis	Apr-99	25.2285	34.9834	20m to 100m
57	Bufo viridis	Aug-99	24.8836	35.1446	20m to 100m
58	Bufo viridis	Oct-97	25.1046	35.3181	300m to 1km
59	Bufo viridis	Aug-99	24.8836	35.1446	20m to 100m
60	Bufo viridis	Aug-99	24.8836	35.1446	20m to 100m
61	Bufo viridis	Jun-99	24.8836	35.1446	20m to 100m
62	Bufo viridis	Sep-99	25.7067	35.0431	20m to 100m
63	Bufo viridis	Sep-99	25.7067	35.0431	20m to 100m
64	Bufo viridis	Dec-00	25.7027	35.0438	300m to 1km
65	Bufo viridis	Dec-00	25.7027	35.0438	300m to 1km
66	Bufo viridis	Dec-97	25.4623	35.1829	1km to 5km
67	Bufo viridis	Feb-00	24.8418	35.3857	1km to 5km
68	Bufo viridis	Feb-00	24.8418	35.3857	1km to 5km
69	Bufo viridis	Oct-97	25.1046	35.3181	300m to 1km
70	Bufo viridis	Feb-00	24.8418	35.3857	1km to 5km
71	Bufo viridis	N/A	26.0485	35.1541	More than 5km
72	Bufo viridis	May-96	24.8714	35.2117	1km to 5km
73	Bufo viridis	Jan-96	26.2642	35.2545	100m to 300m
74	Bufo viridis	Oct-97	25.1046	35.3181	300m to 1km
75	Bufo viridis	Oct-97	25.1046	35.3181	300m to 1km
76	Bufo viridis	Jul-01	25.1033	35.3285	1km to 5km
77	Bufo viridis	Oct-97	25.1046	35.3181	300m to 1km
78	Bufo viridis	Jul-01	25.1033	35.3285	1km to 5km
79	Bufo viridis	Jul-01	25.1033	35.3285	1km to 5km
80	Bufo viridis	Jul-01	25.1033	35.3285	1km to 5km
81	Bufo viridis	Jun-00	24.7500	35.2828	300m to 1km
82	Bufo viridis	Jul-97	25.0904	34.9590	100m to 300m
83	Bufo viridis	Dec-01	26.2427	35.2441	1km to 5km
84	Bufo viridis	Dec-01	26.2427	35.2441	1km to 5km
85	Bufo viridis	Dec-01	26.2427	35.2441	1km to 5km
86	Bufo viridis	Mar-02	23.6780	35.4930	1km to 5km
87	Bufo viridis	Mar-02	25.2867	35.1976	100m to 300m
88	Bufo viridis	Oct-97	25.1046	35.3181	300m to 1km
89	Bufo viridis	May-02	25.2801	35.3285	300m to 1km
90	Bufo viridis	May-02	25.1873	35.1206	300m to 1km
91	Bufo viridis	May-02	25.1873	35.1206	300m to 1km
92	Bufo viridis	May-02	25.1873	35.1206	300m to 1km
93	Bufo viridis	May-02	25.1873	35.1206	300m to 1km
94	Bufo viridis	May-02	25.1873	35.1206	300m to 1km
95	Bufo viridis	May-02	25.1873	35.1206	300m to 1km
96	Bufo viridis	May-02	25.1873	35.1206	300m to 1km
97	Bufo viridis	May-02	25.1873	35.1206	300m to 1km
98	Bufo viridis	May-02	25.1873	35.1206	300m to 1km
143	Rana cretensis	Feb-99	24.9414	34.9369	20m to 100m
144	Rana cretensis	Jun-00	25.7067	35.0431	20m to 100m
145	Rana cretensis	Nov-01	24.3572	35.3518	300m to 1km
146	Rana cretensis	Feb-02	24.6942	35.3901	300m to 1km
147	Rana cretensis	Mar-02	25.7067	35.0431	20m to 100m
148	Rana cretensis	Mar-02	23.6780	35.4930	1km to 5km
149	Rana cretensis	Mar-02	23.6780	35.4930	1km to 5km
150	Rana cretensis	Mar-02	23.6780	35.4930	1km to 5km
151	Rana cretensis	Mar-02	25.2153	35.1328	100m to 300m
152	Rana cretensis	Mar-02	25.1167	35.2883	1km to 5km

153	Rana cretensis	May-03	25.1873	35.1206	300m to 1km
154	Rana cretensis	May-99	25.7067	35.0431	20m to 100m
155	Rana cretensis	Apr-04	25.1046	35.3181	300m to 1km
156	Rana cretensis	Apr-04	25.1046	35.3181	300m to 1km
157	Rana cretensis	Apr-05	24.8662	35.0169	1km to 5km
158	Rana cretensis	Aug-05	25.1884	35.1238	100m to 300m
159	Rana cretensis	Aug-05	25.1884	35.1238	100m to 300m
160	Rana cretensis	May-10	25.3046	35.1754	100m to 300m
161	Rana cretensis	May-99	25.7067	35.0431	20m to 100m
162	Rana cretensis	Mar-12	25.0546	35.3349	1km to 5km
163	Rana cretensis	May-99	25.7067	35.0431	20m to 100m
164	Rana cretensis	May-99	25.7067	35.0431	20m to 100m
165	Rana cretensis	May-99	25.7067	35.0431	20m to 100m
166	Rana cretensis	May-99	25.7067	35.0431	20m to 100m
167	Rana cretensis	Nov-00	24.3610	35.3526	300m to 1km
168	Rana cretensis	Feb-99	25.1046	35.3181	300m to 1km

APPENDIX B

The assumption of the land cover change description based on field observation

Point no.	Different time period		
	2000-2004 (T1)	2005-2009 (T2)	2010-2013 (T3)
P. viridis Point 2	 Class 42	 Class 48	 Class 42
P. viridis Point 11	 Class 22	 Class 20	 Class 22
P. viridis Point 12	 Class 23	 Class 23	 Class 27
P. viridis Point 13	 Class 25	 Class 25	 Class 41
P. viridis Point 17	 Class 43	 Class 47	 Class 43
P. cretensis Point 5	 Class 33	 Class 33	 Class 41