MAXENT MODELLING OF THE APENNINE BROWN BEAR USING INCIDENTAL PRESENCE RECORDS: A COMPARISON OF RAW RECORDS AND A KERNEL DENSITY IN SOUTHERN MAJELLA NP

THERESA ADJELEY ADJAYE
March, 2011

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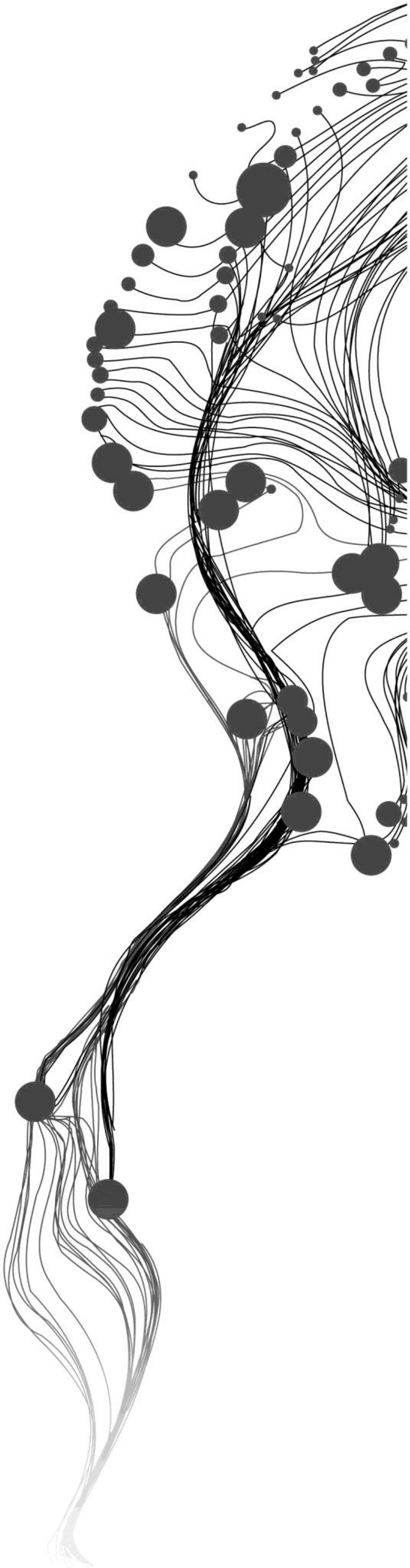

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Enschede, The Netherlands, March, 2011

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 Resources Management

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ABSTRACT

The brown bear (*Ursus arctos*) range is the most widespread of any bear species occurring in Europe, Asia and North America. In the past, the brown bear occurred throughout Europe except on islands such as Iceland and Sardinia. There are two populations of brown bears in Italy: the Alpine and the Apennine population. The Apennine brown bear is an endangered subspecies endemic to Italy and has been estimated at 40 -50 individuals and in Majella National Park (MNP), at 4-8. No studies have been conducted to identify the distribution of the brown bears in the park and the factors that influence the distribution. The objective of this study was to identify core areas of the brown bear in southern MNP, to model the core areas and to investigate the environmental predictors that affect the occurrence of the brown bear. A Kernel Density Estimate (KDE) was used to identify the core areas of the brown bear using the Hawth's Tool extension in ArcGIS 9.3. In order to avoid over-or under-smoothing the data, the likelihood cross validation (CVh) method was used to select the smoothing parameter (*h*) in Animal Space Use 1.3 Beta. A threshold of 50% of the probability volume contour was defined as the core area. Four kernels were produced representing four core areas. Thousand random points where generated on the density surface and 155 fell in the core area. Three models were produced with MaxEnt at a fine scale of 30 by 30m. The models were evaluated by the area under the ROC curve (AUC) and the jackknife test of variable importance was used to determine the important variables that affected the gain in the models. Model 1 used the raw records (incidental observations), Model 2 random points in the four core areas and Model 3 random points in the core areas with multi-year/multi season records. Ten environmental predictors were tested. Distance to dairy farms and distance to drinking water were common predictors to the three models. The predictors that only affected the brown bear distribution in Model 1 are distance to forest edge and slope. The predictors that only affected the brown bear in Model 2 and Model 3 are distance to settlements and elevation. Distance to forest edge and distance to drinking water had negative response curves; whiles distance to settlements, distance to dairy farms and elevation had positive response curves. Land cover, slope, solar radiation, distance to primary roads and distance to secondary roads are the predictors that did not contribute significantly to any of the three models. The latter is however contrary to previous studies that have found these predictors to affect the distribution of brown bears. The fine scale MaxEnt modelling predicted the core areas in the Models 2 & 3 with excellent goodness-of-fit (AUC=0.91 and 0.92).

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1. INTRODUCTION

1.1. Background and Significance

1.1.1. Background of the status of the Brown bear (*Ursus arctos* L.)

The brown bear (*Ursus arctos*) range is the most widespread of any bear species occurring in Europe, Asia and North America (Servheen, 1990). In the past, the brown bear occurred throughout Europe except on large islands such as Iceland, Gotland, Corsica and Sardinia, (Zedrosser *et al.*, 2001). The bear habitat range used to cover almost the entire coniferous, mixed and deciduous forest zones of Europe but by the late 20th century the brown bear had disappeared from most parts of its historical range due to direct persecution, economic exploitation, habitat destruction and fragmentation and human occupancy of part of its range (Zedrosser *et al.*, 2001). The development of effective guns lead to heavy hunting which caused a considerable reduction in their numbers leading to the retreat of the current population to mountainous regions, resulting in fragmented and isolated populations throughout Europe (Curry-Lindahl, 1972).

The total number of brown bears in Europe is presently about 14,000 within an area of approximately 800,000km² (Swenson *et al.*, 2000). Aside the increasing Russian, Carpathian and Scandinavian populations, brown bears still exist in the Cantabrian mountains (Spain), Pyrenees (Spain and France), Balkan mountains of Bulgaria, Dinarian mountains (Slovenia and Greece), Austrian alps and in the Apennine mountains, Italy (Breitenmoser, 1998). Two small populations of brown bears exist in Italy, the Alpine population found in the province of Trentino in the north eastern part of the Brenta mountains (Swenson *et al.*, 2000), and the Apennine population located in Abruzzo National Park (ANP) and surrounding areas including Majella National Park (MNP). This population has been separated from the Alpine population for at least 400 to 600 years (Ciucci & Boitani, 2009). The Apennine brown bear is an endangered subspecies of the brown bears endemic to Italy, where a small population estimated at 40 to 50 bears inhabits a human dominated landscape (Falcucci *et al.*, 2009). These brown bears exist as a remnant, isolated population inhabiting 3000 to 5000 km² from Molise to Marche and Umbria regions (Figure 1) (Posillico *et al.*, 2004). However, the most densely and steadily occupied area is about 1500–2500 km² in the Apennine mountains. The Apennine brown bear population is the biggest in western Europe (Swenson *et al.*, 2000).

The current extent of the brown bear range in the Abruzzo region as reported by Ciucci and Boitani (2009) is differentiated into a 'core range' (undefined) and some peripheral ranges (Figure 1). The 'core' range comprises the Abruzzo, Lazio and Molise National Parks (ALMNP) and the southern part of the (MNP). The peripheral ranges are the northwest, northeast, east part of the ALMNP and the northern part of the MNP. Most of the Apennine brown bear populations are in Abruzzo National Park (Ciucci & Boitani, 2008). Monitoring activities in MNP have revealed that the brown bear presence is stronger particularly in the southern sector of the MNP (Vancura & Kampf, 2009). Their stronger presence in the southern part of MNP is not well understood.

At present about 4 - 8 bears are permanently living inside the MNP (MNP, 2010). The existence of several and contiguous protected areas (Figure 1) enable the migration from one area to another one. The interconnection of these areas therefore plays a fundamental role especially in the southern sector of the Park where the presence of the brown bear is stronger (Figure 1). "The Apennine brown bear is protected by national law (National Laws 157/92 and 150/92) and a European directive (Habitat Directive

92/43/CEE). It is considered as a fully protected species in the Bern Convention (1979) and in the European rule (1986) on the implementation of the Convention on International Trade in Endangered Species of Wild Flora and Fauna (CITES)" (Ciucci & Boitani, 2009).

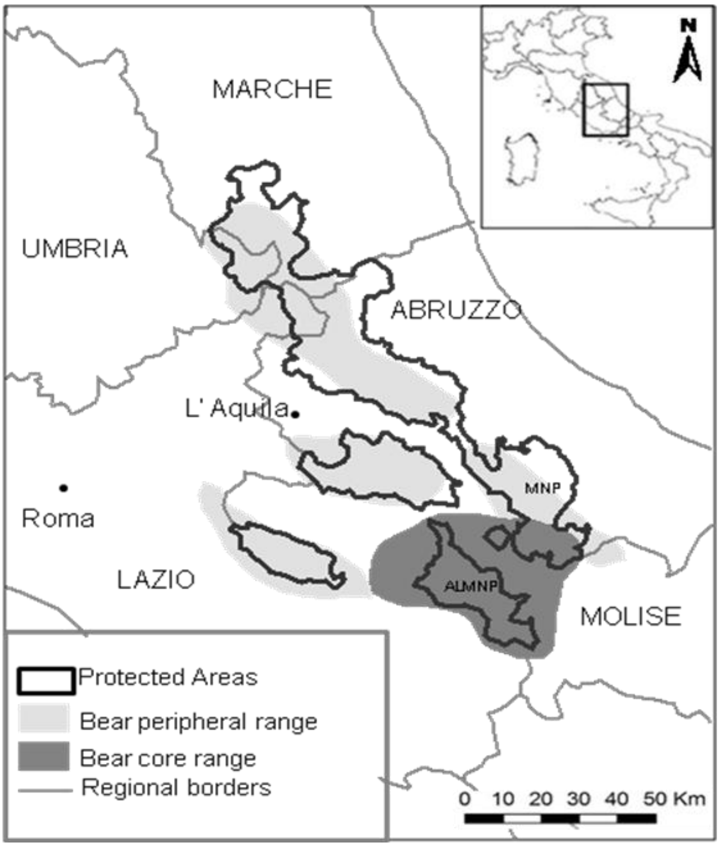

Figure 1: Approximate range of the Apennine brown bear and the distribution of Protected Areas in the Central Apennine. MNP- Majella National Park, ALMNP – Abruzzo, Lazio and Molise National Park. Modified from (Ciucci & Boitani, 2008).

1.1.2. Target species: Brown bear

The brown bear has a body length of between 2 and 3 m, a tail length between 5 to 20 cm and it weighs between 100 to 1000 kg. Males can be 50% larger than the females. Adult brown bears are solitary (Dahle & Swenson, 2003) and social groups are limited to females with cubs and male-female pairs during the breeding season (Stirling & Derocher, 1990). They are omnivorous and feed on a wide variety of foods, however the vegetal component is very high (60 - 70 %) while the animal component is about 30 - 40 % (Paralikidis *et al.*, 2010). Their diet varies with area and season depending on the availability. Vegetables such as grass, sedges roots, bulbs and mosses may be important in spring, forbs with berries and tubers in the summer and berries, fruits, beechnuts, acorns and pine seeds in the fall (Cicnjak *et al.*, 1987).

Brown bears hibernate during the winter period to conserve energy (Swenson *et al.*, 1997). Hibernation is a period of winter dormancy in animals living in cold climates, involving lowered body temperature and reduced metabolism to conserve energy stores (Nores *et al.*, 2010). They generally select den sites away from possible human disturbance and may become more nocturnal in response to human disturbance (Carter *et al.*, 2010). They feed from spring to autumn putting on enough weight to last through the dormancy period during hibernation. Studies on hibernation of Cantabrian brown bears have however shown that not all brown bears hibernate during the winter (Nores *et al.*, 2010). Brown bears have large home ranges, mean home range of female and male for the Trentino bears is 100 and 300 km^2 respectively (Preatoni *et al.*, 2005). This home range is largely affected by availability of food and by critical life stage periods such has gestation and or lactation (Preatoni *et al.*, 2005). The reproductive age of brown bear is 5 years, and breeds between May and July with 1- 4 cubs born after 8 weeks gestation period (Jerina *et al.*, 2003).

"The bear's usual domestic prey is goats and sheep, and less often cattle and horses. The bear is an opportunistic predator, so it may also attack pigs and poultry. It is also very interested in beehives, and lately Austria bears have developed a taste for rapeseed oil, thus damaging equipment that contains this type of oil, such as chainsaws and road rollers. In some areas, it invades corn and fruit tree fields. The type and proportion of damage to livestock, crops, beehives and infrastructure varies greatly between countries and regions" (Fourli & Europeas, 1999).

1.1.3. Majella National Park (MNP)

MNP is one of the newest and most diverse national parks in Italy. It was founded as late as in 1993 and is located in the province of Pescara, Chieti and L'Aquila in the Abruzzo region, Italy. It covers an area of 740.95 km2. The park is home to about 45 percent of various wildlife species found in Italy, including red deer, roe deer, chamois, wild boar, wolfs, otters and the brown bear (MNP, 2010). As much as 55% of MNP is high altitude-over 2000 m above sea level. The landscape of the MNP is dominated by NW-SE oriented limestone ridges reaching ≈2000 m: namely Morrone, Rotella, Pizzalto and Porrara in the west and the calcareous Majella massif in the northeast. In addition, the NE-SW oriented Secine (≈ 1800 m) ridge contains marls. Slivers (< 25 ha) of evergreen 'Mediterranean' holm oak (*Quercus ilex* L.) forest are found at low elevation in the north-western tip of the Morrone; smaller (< 1 ha) patches are observed at the lower eastern slopes of the Majella massif. At mid-elevation (900 -1800 m) the dominant vegetation in MNP is a contiguous, monospecific beech (*Fagus sylvatica* L.) forest (van Gils *et al.*, 2010); the beech belt also contains abandoned farmland (Gils *et al.*, 2008), pastures and hay meadows. Below the beech belt the landscape is a patchwork of villages, farmlands, shrub and forest fragments (*Quercus pubescens* Willd. and/or *Ostrya carpinifolia* Scop.). Upwards from the beech belt in the Majella massif a subalpine shrub belt occurs; the pine (*Pinus mugo* L.) shrub ('Krummholz') in the north vicariates with the dwarf juniper (*Juniperus communis* L. var. *saxatilis* Pall.) in the south. Above 1400 m, the medium monthly temperatures decline to below zero during the 3 to 4 winter months. Below 800 m (e.g. Caramanico), the medium monthly temperatures reach over 20 ℃ during the 2 to 3 summer months.

1.1.4. Species Distribution Modelling (SDM)

Species distribution modelling (SDM) has an important role in ecology and biogeography and is increasingly used in a range of applications including biodiversity assessment, conservation biology, wildlife management and conservation planning (Araújo *et al.*, 2006; Baldwin & Bender, 2008; Marmion *et al.*, 2009; Smulders *et al.*, 2010). SDM refers to models which use a species observed distribution and\or environmental characteristics to predict its actual or potential distribution (Hengl *et al.*, 2009). Models exploring the relationship between species occurrences and a set of predictor variables produces two kinds of useful outputs: estimates of the probability of occurrence of a species at a given unrecorded location and estimates of suitable areas for a species (Segurado & Araujo, 2004). Various statistical and machine learning methods have been introduced in conjunction with geographical information systems (GIS) and remote sensing (Austin, 2002). The propagation of broad scale data coupled with the increase in GIS, statistical software and computing power have improve the ability and choices available to model and map complex species environment relationships. Generalized regressions, classification techniques, environmental envelopes, Bayesian approach, and neural network are among the groups of methods developed over the years (Guisan & Zimmermann, 2000). Some of the methods are based purely on presence only data whilst others are based on presence/absence data. Methods requiring presence/absence data include generalized linear models (GLM), generalized additive models (GAM), classification and regression tree analysis and artificial neural network (ANN). Presence only methods include Ecological niche Factor analysis (ENFA), Genetic Algorithm for the Rule - Set Prediction (GARP), Bioclimatic Envelope Algorithm (BIOCLIM), DOMAIN, and MAXENT (Hengl *et al.*, 2009).

Maxent was chosen for this study because of the following advantages (Phillips *et al.*, 2006).

1. It requires presence only data rather than presence/absence data
2. It can utilize both categorical and continuous environmental predictors, and incorporate interactions between different predictors
3. It creates outputs, which allow interpretation of the contribution of predictors to the model
4. It is robust to sample size as low as 10.

1.2. Research Problem

Human activities especially in densely populated landscapes have deprived wildlife of the most suitable habitat, confining them to remote and less accessible areas(Posillico et al., 2004). Bears are found in forested areas with generally low human density where they survived persecution (Swenson et al., 2000). The dominant forest type in MNP is beech, (*Fagus sylvatica* L.) which makes up about 70% of the forest (Gelete, 2010). Beech and oak (*Quercus cerris* L. and *Quercus pubescens* Willd.) woodlands, provide most of the forest-related bear foods such as beech nuts and oak acorns in autumn (Posillico et al., 2004).

There is increasing public interest in the conservation of endangered animals like the brown bear (Simberloff, 1998). The brown bear is considered endangered by the Italian World Wildlife Fund (Ciucci & Boitani, 2009). However there is negative attitude towards the brown bear since it is known to cause damage to livestock, crops, and beehives (Ciucci & Boitani, 2008). Depredation brings economic losses to livestock owners and this may bring conflict between them and conservation managers. Compensation is also paid by government to livestock owners whose livestock has been predated on by brown bears (Cozza et al., 1996). MNP has reports on the depredation of livestock, damages to beehives and gardens.

Owen (2009) reported that a brown bear was shot in Bavaria for savaging sheep and others have been poisoned by livestock owners in Abruzzo National Park (WildlifeExtra, 2010). In the light of their persistent small population size, a renewed effort at conserving and managing the Apennine brown bear is critically needed (Ciucci & Boitani, 2009). The status and trends of the bear habitat have not been undertaken in the region (Falcucci *et al.*, 2008). Mapping of the core areas of the brown bear and identification of the factors affecting the brown bear occurrence in MNP has not been done. There is a need to study and understand the factors that contribute to the presence of the bears in the southern part of MNP, which forms part of the core, bear range in the Abruzzo region. Understanding the current distribution of the brown bear is essential to assess its habitat needs and to draw up preventive measures to curb livestock depredation. The findings may provide information that will aid Park Management in planning conservation activities aimed at conserving and managing the remaining brown bear populations in MNP.

1.3. Research Objectives

1.3.1. General Objectives

To contribute to the understanding of the distribution of the brown bear in the southern part of the MNP to provide information for conservation planning and management in MNP.

1.3.2. Specific Objectives

1. To identify the core areas of the brown bear in southern MNP

2. To determine the effect of environmental and anthropogenic variables on the distribution of the brown bear in southern MNP.

3. To model the core area of the brown bear using the raw incidental records and random points generated in the core area with MaxEnt and compare the outputs.

1.4. Research Questions

1. Can the core areas of the brown bear be estimated using Kernel Density Estimates (KDE)?
2. Does elevation, slope, solar radiation, land cover, distance to water, distance to settlements, distance to dairy farms, distance to forest edge, distance to primary roads and distance to secondary roads affect the occurrence of the brown bear in southern MNP?
3. Are there differences or similarities between the models with raw records and random point of the core area?

1.5. Hypothesis

H_0: Kernel Density Estimates cannot be used to estimate the core area of the brown bear in MNP.
H_1: Kernel Density Estimates can be used to estimate the core area of the brown bear in MNP

H_0: Elevation, slope, solar radiation, land cover, distance to water, distance to settlements, distance to dairy farms, distance to forest edge, distance to primary roads and distance to secondary roads do not affect the distribution of the brown bear in southern MNP.

H_1: Elevation, slope, solar radiation, land cover, distance to water, distance to settlements, distance to dairy farms, distance to forest edge, distance to primary roads and distance to secondary roads affects the occurrence of the brown bear in southern MNP.

H_0: There are no differences between model outputs for raw incidental records and random points of the core area.
H_1: There are differences between model outputs for raw incidental records and random points of the core area.

2. MATERIALS AND METHODS

2.1. Study area

The study was carried out in Majella NP between latitude 13059'19.919 E and 14014'24.951E and between longitude 41050'48.28N and 4200'17.822N covering an area of 221.75 km2.

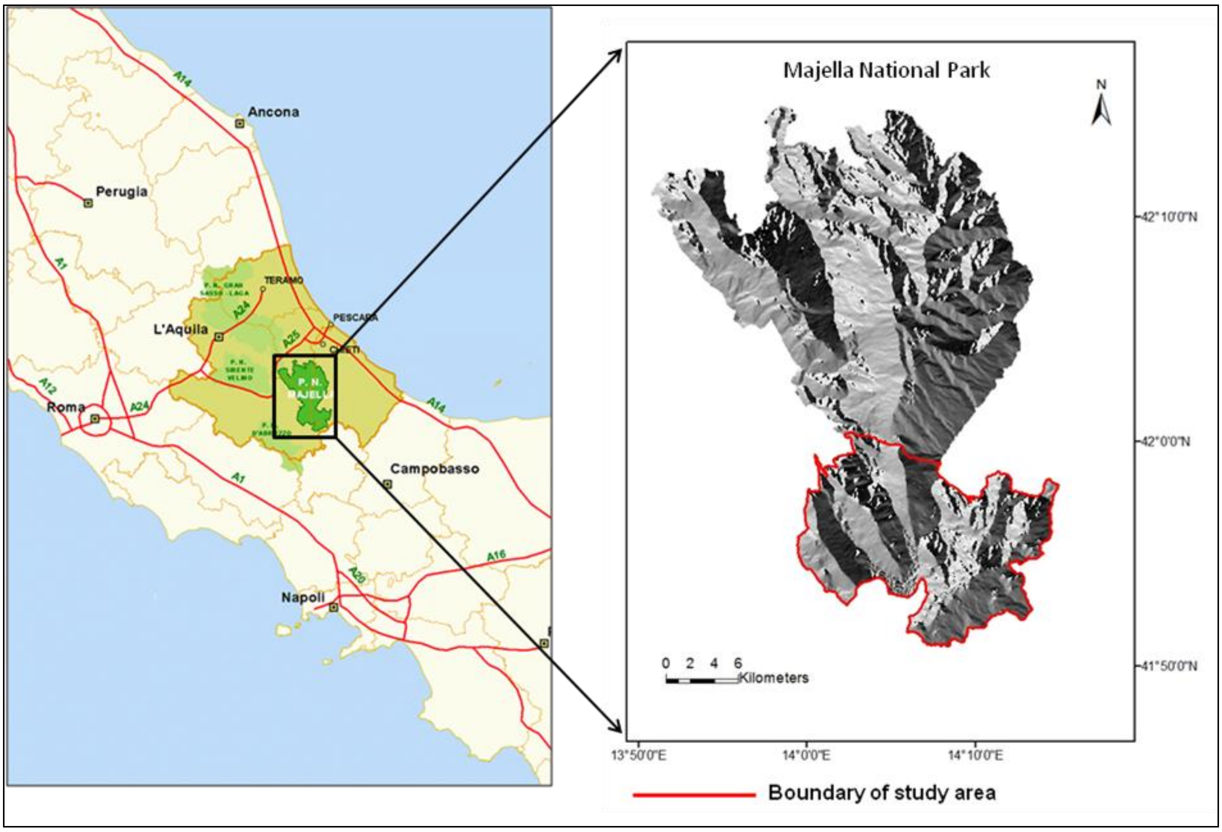

Figure 2: The location of Majella NP (left) and the study area within Majella NP (right)

2.2. Materials

The data used for this study are as described in Table 1.

Table 1: List of materials used for the study

Material	Resolution	Source	Year
Digital Elevation Model (DEM)	30 m	ASTER DEM	2008
Land cover Map MNP	1:25,000	MNP	1999
Aerial photograph (Digital Colour Photo	0.5m	MNP	2007
Carta Turistica Parco della Majella	1:50,000	MNP	1999
Bear location records MNP (135)	GPS-coordinates	MNP (Marco Carafa and Antonio Antonucci)	1996 -2010

2.3. Methods

2.3.1. Data collection

The fieldwork was carried out from the 6th of September to the 1st of October 2010. The objective of the fieldwork was to collect brown bear occurrence records from the MNP, to collect field data on the land cover/land use, to identify water sources and food sources of the brown bear, assess the type of roads, farms/farming practices and familiarization with the ecology of the study area.

Due to the mountainous nature of the study area and its difficulty and accessibility, the trails in the park (Figure 4) were used as transects. Observations were made along the trails. Data on the identified food sources (wild pears - *Pyrus communis* L, wild apples - *Malus sylvestris* L, *Rosa canina* L, *Rhamnus alpina* L , berries - *Arctostaphylos alpine* L, cherries - *Prunus avium* L, acorns and beech nuts) of the brown bear was collected. The water sources located in the park were recorded. Observation was made of the type of farms. The farms identified are dairy farms with electric fence and shepherd dogs, dairy farms with non-electric fencing.

The map and the aerial photograph (Table 1) of the study area was converted to ECW and saved on the IPAQ which together with the GPS aided in navigation through the area. The GPS coordinates and the type of vegetation cover/land use type (i.e., beech forest, oak forest, coniferous, meadow, crop fields grasslands) where recorded. GPS locations of the dairy farms, water points and food sources were also recorded with the IPAQ GPS. The vegetation types observed in the field were beech forest - *Fagus sylvatica*, oak forest – *Quercus cerri* & *Quercus pubescens*, conifer, open grassland, crop fields (cereal fields) and meadows. The cereal fields were identified by their rectangular pattern, residue of harvested cereal, rolled cereal grass (Appendix 2) and ploughed fields. The signs of the brown bear that were looked out for in the field were the scats, scratch marks on trees, hairs caught on tree barks, dens and footprints on the mud.

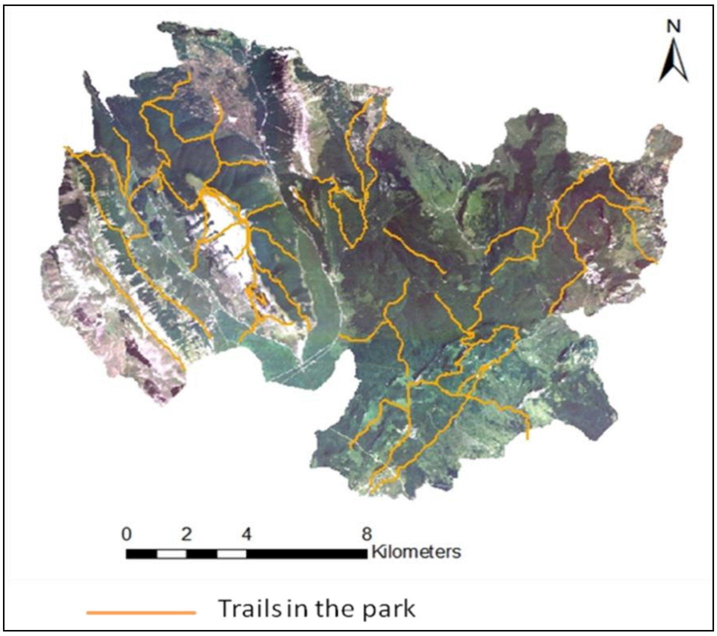

Figure 3: Trails in southern MNP

2.3.2. Brown bear Occurrence Data

One hundred and thirty-five (135) occurrence records (Appendix 6) were provided by the MNP (compiled by the Park zoologists, Marco Carafa and Antonio Antonucci) on the 3rd of November 2010. It consist of X, Y coordinates (WGS 1984, UTM zone 33N) of where the bear has been observed by either direct sightings or signs of its presence. These signs included footprints on the snow and mud, predation on wild and domestic animals (sheep and chicken), scat, fur, rolled stones, scratches and digs on predated animals. The period of the records spans between 1996 and 2010 and it includes the day and month it was recorded. Sixty-four out of the total records felled within the study area. The occurrence records were prepared in excel and saved as comma delimited (CSV).

2.3.3. Kernel Density Estimation (KDE).

Presence only data are common in animal studies (Pearce & Boyce, 2006). The vast majority of data available today consist of presence only data sets collected in an adhoc and non stratified basis (Zaniewski *et al.*, 2002). Horne *et al.*, (2007) suggested kernel smoothing techniques to correct observation bias. Kernel density estimation transforms a sample of observations, recorded as geographic referenced points data into a continuous surface, which indicates the intensity of individual observations over space. KDE was introduced to ecologist as a home range estimator by Worton, (1989). Although the term "home range" is used by many ecologists, there is disagreement over its meaning and how to measure it (Anderson, 1982). Most home range method defines the range as some fixed percentage usually 95% confidence region obtained from the animal utilization distribution function (Worton, 1987). The existence of core areas within the home range was suggested by J.H Kaufmann (Samuel *et al.*, 1985) and attention has focused on the determination of core areas because they can be estimated with greater precision (Worton, 1987). Samuel et al., (1985) defined core areas as areas receiving concentrated use by resident animals and is the 50% probability contour (Ostfeld, 1986).

The kernel can predict where an animal has occurred but was not observed (Kie *et al.*, 2010). In order to improve the accuracy of the prediction, the kernel density approach was employed here. A kernel is placed over each location, and the value of the probability density at any point in space is estimated by summing the kernel contribution from each kernel at that point (Horne & Garton, 2006). The kernel estimate has a high density where there is a concentration of points than where there are few points (Worton, 1989). This approach excluded the random animal excursions and lowered the noise in the training data set. The width of each kernel is referred to as the smoothing parameter (*h*). Selecting an appropriate smoothing parameter (*h*) is a critical step in kernel estimation. The smoothing parameter determines the amount of smoothing of the point pattern. Horne & Garton (2006) investigated two methods for choosing the smoothing parameter; least squares cross validation(LSCVh)and likelihood cross validation (CVh).they recommended the CVh method for estimating the high use area of the utilization distribution. The aim of the LSCVh method is to minimize the integrated least square error (ISE) between the true and the estimated distribution and CVh method is to minimize the Kullback-Leibler (KL) distance between the true and the distribution. ISE and KL are referred to as the standardised score function. The minima found can be either global (i.e., the true lowest point in the function) or local (i.e., the lowest point only within a certain neighbourhood of the function). The smoothing parameter was selected based on the likelihood cross validation (CVh) method (Horne & Garton, 2006). This method was chosen in order to avoid over-smoothing or under-smoothing the data. Previous studies on black bears have shown that the fixed kernel estimator using the CVh to choose the *h* yielded the most accurate estimates of home range size and had the smallest variance(Preatoni *et al.*, 2005).

The brown bear CVh was calculated using the Animal Space Use 1.3 Beta software program. This was done by loading the shape file of the presence points in the programme. Based on the CVh obtained from the Animal Space Use1.3 Beta, kernel analysis was performed using the kernel density estimator in Hawths Tool within ArcGIS 9.3 and normalised between 0 and 1. A threshold of 50% of the probability volume contour (Ostfeld, 1986) defined the core area of the brown bear. Thousand random points were then generated on the kernel density surface using the Hawths Tool in AcrGIS 9.3 and the points in the core area were selected for the modelling. In all 155 points were located in the core area (Figure 6).

2.3.4. Environmental variables

Ten environmental variables were selected for their potential importance based on knowledge and from published sources of what would likely have relevance in relation to the brown bears (Carter *et al.*, 2010; Graham *et al.*, 2010; Kobler & Adamic, 2000). The environmental variables used in this study are elevation, slope, incoming solar radiation, distance to drinking water sources, distance to primary or secondary roads, distance to settlements, distance to forest edge, land cover and distance to dairy farms. Previous studies have not considered dairy farms as an environmental variable that can affect the brown bear distribution. This was included because of the type of farm and farming practices (e.g. farms with Apennine shepherd dogs, electric and non-electric fencing), reports of predation on sheep and chicken and damages to beehives.

Predictive models developed for mountainous terrain are usually based partially on topographic factors (Fischer, 1990; Guisan *et al.*, 1999). The main requirement of distribution modelling is the DEM (Guisan & Zimmermann, 2000). The topographic variables, elevation, slope and solar radiation were derived from ASTER DEM (Table 1). It has a spatial resolution of 30 m. Slope in degrees was calculated using the spatial analyst tool in ArcGIS 9.3. It was assumed by Carter *et al.* (2010) that bears energy expenditure increases as the variability in terrain slopes increases; therefore bears might avoid greater slope variability to minimize energy expenditure.

Water bodies are usually for drinking and roads are sometimes use as travel routes or as food sources (soft mast and green vegetation along roadside) (Carter *et al.*, 2010). The water sources were of two sources, from field observation and from the topographic map. The roads, water sources and settlements were digitized from the (Carta Turistica Parco Nationale della Majella, Table 1, in ArcGIS 9.3. The main roads in the map were classified as primary roads and the state roads as secondary roads based on field observations. The distances from the roads, water sources, settlements, dairy farms and forest edge were calculated using the Euclidean distance function in ArcGIS 9.3. All the data layers used for the modelling were in the same projection, extent and resampled into 30m resolution to match the spatial resolution of the topographic variables. The environmental layers were then converted to ASCII format and saved in one directory in Arc GIS 9.3. All the environmental layers were continuous except land cover which was categorical. Land cover and land use is a potential determinant of bear presence because of its association with food abundance and den selection (Carter *et al.*, 2010). Therefore, the 1999 land cover map of MNP was improved using ground truth data collected during fieldwork and reclassified into ten land cover/land use classes (Table 2). This was then converted into raster and subsequently to ASCII format for input into the Maxent model.

Table 2: Land cover/land use classes and its reclassification

Vegetation cover	Reclassified Class
Oak forest	1
Open grassland and shrubs	2
Abandoned farmland	3
Beech forest	4
Coniferous	5
Crop fields	6
Bare ground sparse vegetation	7
Subalpine grassland	8
Alpine grassland	9
Meadow	10

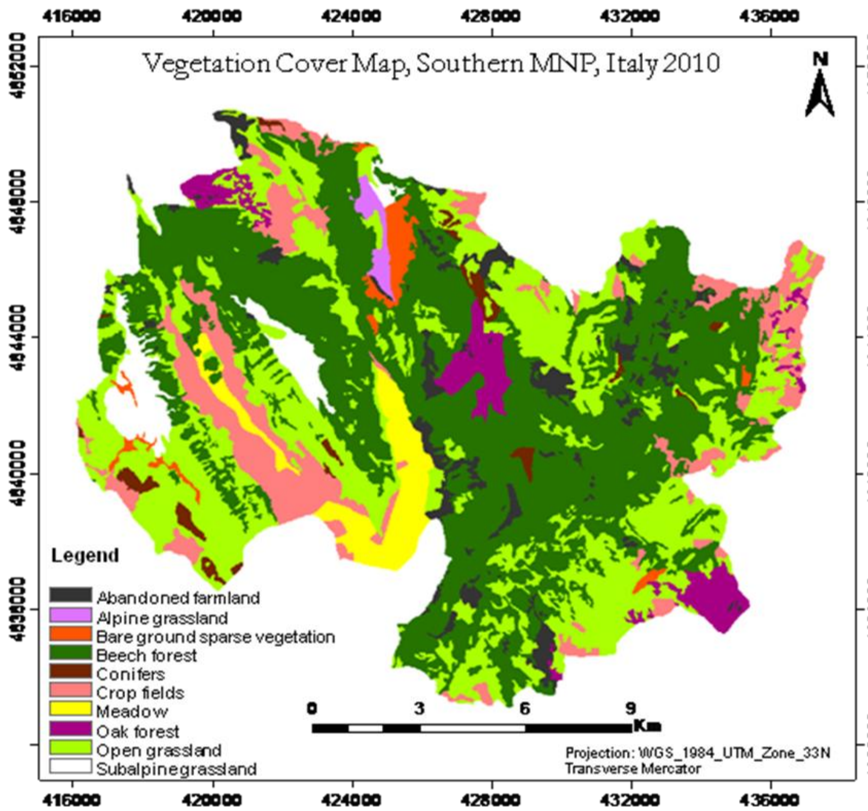

Figure 4: Vegetation Cover Map of Southern MNP

2.3.3. Multicolinearity Diagnostics

Multicolinearity is used to denote the presence of linear relationship or near linear relationship among explanatory variables (Silvey, 1969). Multicolinearity in data is a statistical issue because it inflates the value of least squares estimator and a numerical issue because small errors in input may cause large errors in the output (Mansfield & Helms, 1982). The preferred method for checking multicolinearity problems is the calculation of variance inflation factor (VIF) (Lin, 2008) shown in Equation (1).

$$VIF_j = 1/(1 - R_j^2) \qquad \text{Equation (1)}$$

Where R^2 is the coefficient of determination obtained after regressing the j^{th} predictor on the remaining predictors.

From the above formula, if R^2 is 0, then the VIF will be 1, if R^2 approaches 1 then the VIF will approach infinity. A VIF greater than 10 indicates the presence of strong multicolinearity.

Multicolinearity analysis was conducted for the continuous environmental variables using linear regression in SPSS 17.0 statistical software. The categorical variable, land cover cannot be tested in this way. All the variables had VIF less than 10 after the first run of the colinearity diagnostics therefore all the variables were used to run the model.

2.3.4. Modelling and Analysis – MaxEnt Modelling

The model is based on maximum entropy principle which states that the best available predicted distribution is one which maximizes the input information entropy and the output is the niche the species occupies (Phillips *et al.*, 2006). Usually the input variable is a range of environmental variables and the niche is defined in terms of these environmental variables. The potential distribution is then defined in terms of these environmental variables which correspond to the species occurrence data (Anderson *et al.*, 2003). 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 (Austin, 2007). Maxent produces a distribution map that illustrate the likelihood of finding the species of interest in a particular area (Phillips & Dudík, 2008). These maps can be constructed to represent the probability of finding a particular species in a given area or indicate whether a species is likely to be present or absent in a given area (Baldwin, 2009).

Two types of models were built. One using the occurrence records (Model 1) from the MNP and the other using random points generated from kernel density map (Model 2). This is to compare the two models to establish whether there are similarities or differences in the resulting model out puts. Sightings were associated with human activities. Therefore, the sightings do not reflect habitat conditions in their immediate location, but they may be related to the landscape characteristics in a relatively large area surrounding the point of observation. The presence data was split into two, 70 % for training the model and 30 % for testing the model. The train data set was used to make predictive models and the test dataset was used to cross validate the accuracy of the model.

2.3.5. Model Evaluation

Model evaluation forms an important part in model building (Vaughan & Ormerod, 2005). As with any modelling approach the goodness of fit of the model should be tested to determine the relevance of the model (Baldwin, 2009). The area under the curve (AUC) of the receiver operating characteristic (ROC) has become a dominant tool in evaluating the accuracy of models predicting distributions of species (Peterson *et al.*, 2008). ROC curves are constructed by using all possible thresholds to arrange the scores into confusion matrices, obtaining sensitivity and specificity for each matrix and then plotting sensitivity against the corresponding proportion of false positive (equal to 1- specificity)(Allouche *et al.*, 2006). Sensitivity represent how well the data correctly predicts presence, whereas specificity provide a measure of correctly predicted absences (Baldwin, 2009). In this case presence only data is used so the model is tested against a random model (Phillips *et al.*, 2006). A good model is defined by a curve that maximizes sensitivity for low values of the false – positive fraction (Hernandez *et al.*, 2006). The significance of the curve is quantified by the area under the curve (AUC) and has values that range from 0.5 -1.0. Values close to 0.5 indicate a fit no better than expected by random, while a value of 1 indicates a perfect it. An AUC >0.9 denotes very good, AUC 0.7-0.9, good and AUC<0.7 is uninformative (Baldwin, 2009).

2.3.6. Jackknife test of variable importance

Jackknife test was used to evaluate the importance of each environmental variable to explain the distribution of the brown bear. The contributions of each environmental variable are tracked at each step of the training process as the model is being trained. Maxent assigns the increase in the gain of the model to the environmental variable that the feature depends on. Three different gains are calculated; one with all the predictors, one with only the predictor in isolation and one excluding one predictor. This is to establish the effect of the predictors on the performance of the model in terms of gain. The variable that reduces the gain most when excluded from the model becomes the most important.

2.3.7. Softwares and equipment used

The following softwares and equipment were used to achieve the set objectives:

a) ESRI ArcGIS 9.3
b) Arcpad 7.1
c) Animal Space Use 1.3 Beta
d) MaxEnt 3.3.3
e) SPSS 17.0
f) Microsoft excel
g) Endnote X3
h) Hp IPAQ& GPS

3. RESULTS

This section presents results from the kernel density estimates, Multicolinearity diagnostics and the MaxEnt modelling.

3.1. Kernel Density Estimates (KDE)

The Animal Space Use 1.3 Beta produced two results (Figure 5); the CVh and LSCVh smoothing parameter (h) represented graphically in Figure 5. The plot of the LSCVh and CVh functions versus the h value revealed global minima at a 1204m for CVh and 742m for the LSCVh. The low *h* value at which different low ranges was explored to determine if there are multiple minima is 602m and for high *h* value was 1334m The CVh is the preferred choice (Horne & Garton, 2006).

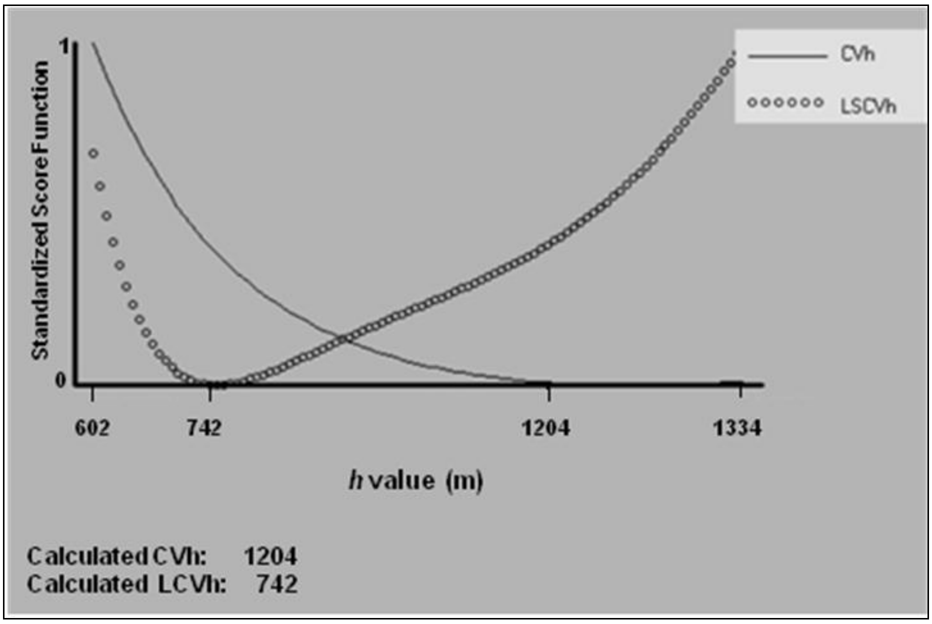

Figure 5: Plot of standardized (i.e., 0 to 1)LSCVh and CVh functions over a range of smoothing parameter (*h*) values

Four kernels or core areas where produced, kernel A, B, C and D (Figure 6). The kernel density output was normalised between 0 and 1(1 representing high probability area (red) and 0 representing low probability areas (green). Kernels A, B and C have multi-year/season observations (Appendix 7) whiles kernel D has two years records and recorded in one season (autumn). From the occurrence records (Appendix 6), Kernel B also has a female with two cubs. Kernel A encompasses north of Mt. Rotella, and north of Mt. Pizzalto, Kernel B - Mt Porrara, Kernel C - Mt Secine and Mt. Pizzi and Kernel D - Mt. Lucino, Mt de Mezzo, and Mt. Larroca.

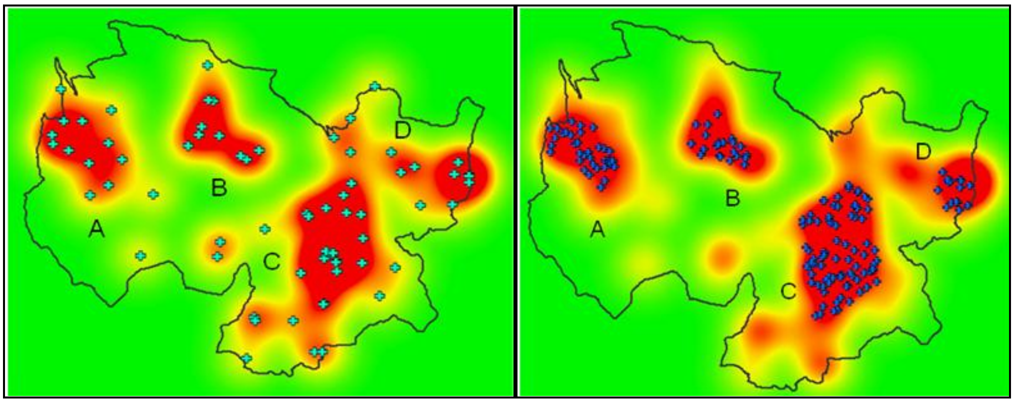

Figure 6: KDE with 64 observations (left) 155 random points (right) in the core area (red)

3.2. Multicolinearity Diagnotics

The result of the Multicollinearity diagnostics is as shown in Table 3. A variance inflation factor (VIF) greater than 10 shows high correlation between the environmental variables. The continuous environmental variables in this case had VIF less than 10 and therefore all were used in the model.

Table 3: Result of the Multicollinearity Diagnostics of Environmental variables

Environmental variable	**VIF**
Elevation	2.373
Distance to water	1.092
Distance to primary roads	1.493
Distance to secondary roads	1.509
Distance to settlements	1.356
Distance to forest edge	2.039
Distance to dairy farms	1.509
Slope	1.418
Solar radiation	1.671

3.3. MaxEnt Model Outputs

This section presents the outputs of the Maxent modelling for three categories of presence points: 64 raw incidental observations, 155 random points in the core area and 140 random points in the core area with multi-year /multi-season records – denoted as Model 1, Model 2 and Model 3 respectively. The following MaxEnt outputs are described: Jackknife test of variable importance, the relative contribution of environmental variables to the model, the response curves and a predictive map.

3.4. Jackknife test of important variables

Model 1: incidental observation

Figure 7 shows the results of the jackknife test of variable importance for Model 1. The environmental variable with highest training gain (top) when used in isolation is Distance to forest edge, which therefore appears to have the most useful information by itself. This is followed by slope, distance to dairy farms and distance to drinking water. Distance to primary or secondary roads, elevation, land cover, distance to settlements, incoming solar radiation have low gains when used in isolation. The environmental variable that decreases the gain the most when excluded from the model is distance to forest edge, which therefore appears to have the most useful information that is not present in the other variables. Solar radiation and distance to settlements have no significant effect on the overall training gain when excluded from the model. The model also produced jackknife test for the test gain (center), and the AUC (bottom) which shows the variables with highest test /AUC gain when used in isolation, the variables that decrease the overall gain when excluded from the model and the variables that do not significantly reduce the overall test / AUC gains.

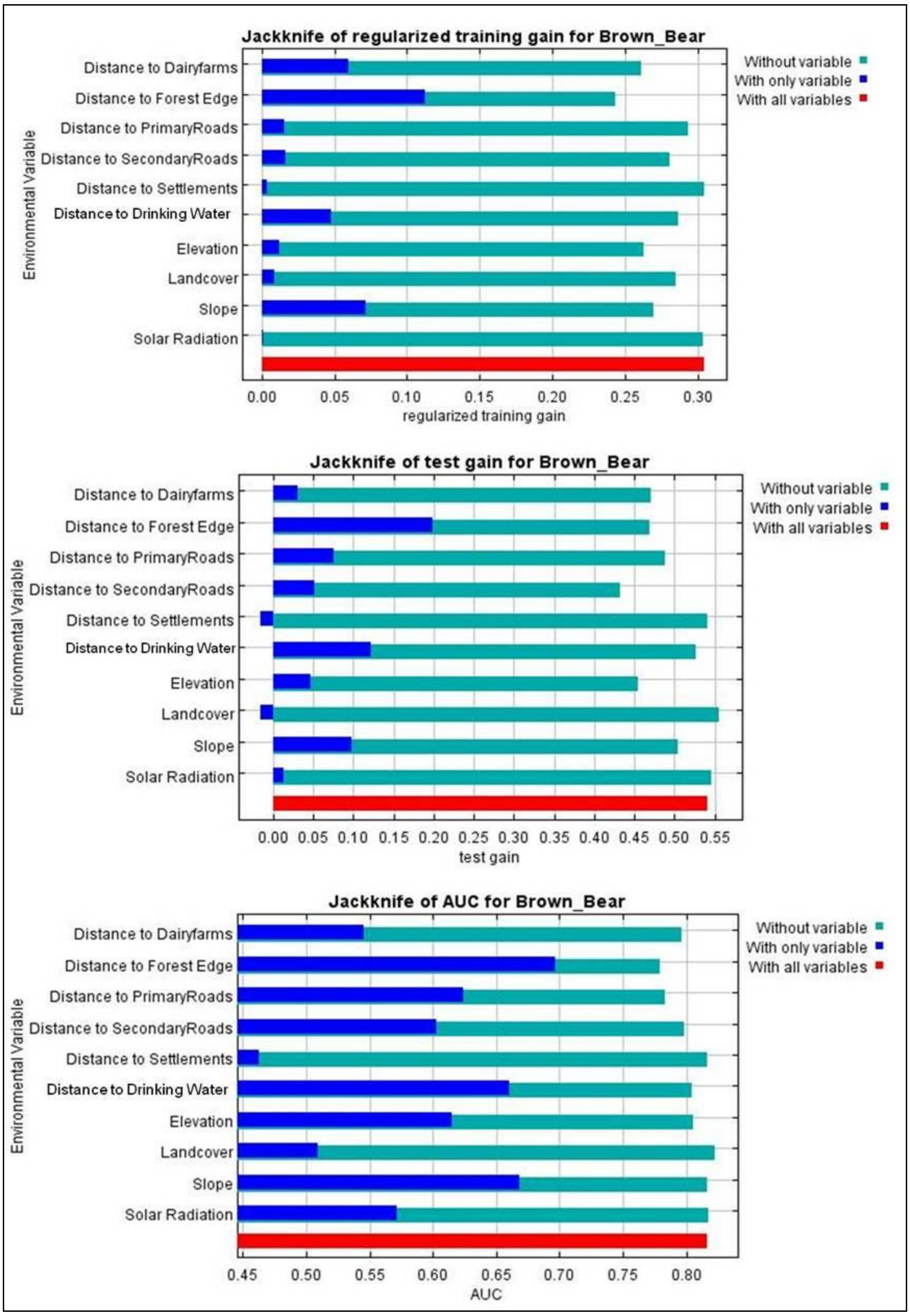

Figure 7: Jackknife results of variable importance in the regularised training gain (top), test gain (centre) and AUC (bottom) for Model 1 (incidental observations)

Model 2: All kernels

From the jackknife test results of Model 2, (Figure 8), the environmental variable with the highest training gain (top) when used in isolation is elevation, which therefore implies that it has the most useful information by itself. This was followed by distance to drinking water, distance to primary roads and distance to forest edge. The environmental variable that decreases the training gain the most when excluded is distance to drinking water, which therefore appears to have the most useful information that is not present in the other variables. This is followed by distance to drinking water, distance to dairy farms, elevation and distance settlements. Land cover, slope, solar radiation, distance to forest edge, distance to secondary roads and distance to primary roads when excluded from the model one by one has no significant decrease in the overall training gain. The model also produced jackknife test for the test gain (center), and the AUC (bottom) which shows the variables with highest test /AUC gain when used in isolation, the variables that decrease the overall gain when excluded from the model and the variables that do not significantly reduce the overall test / AUC gains.

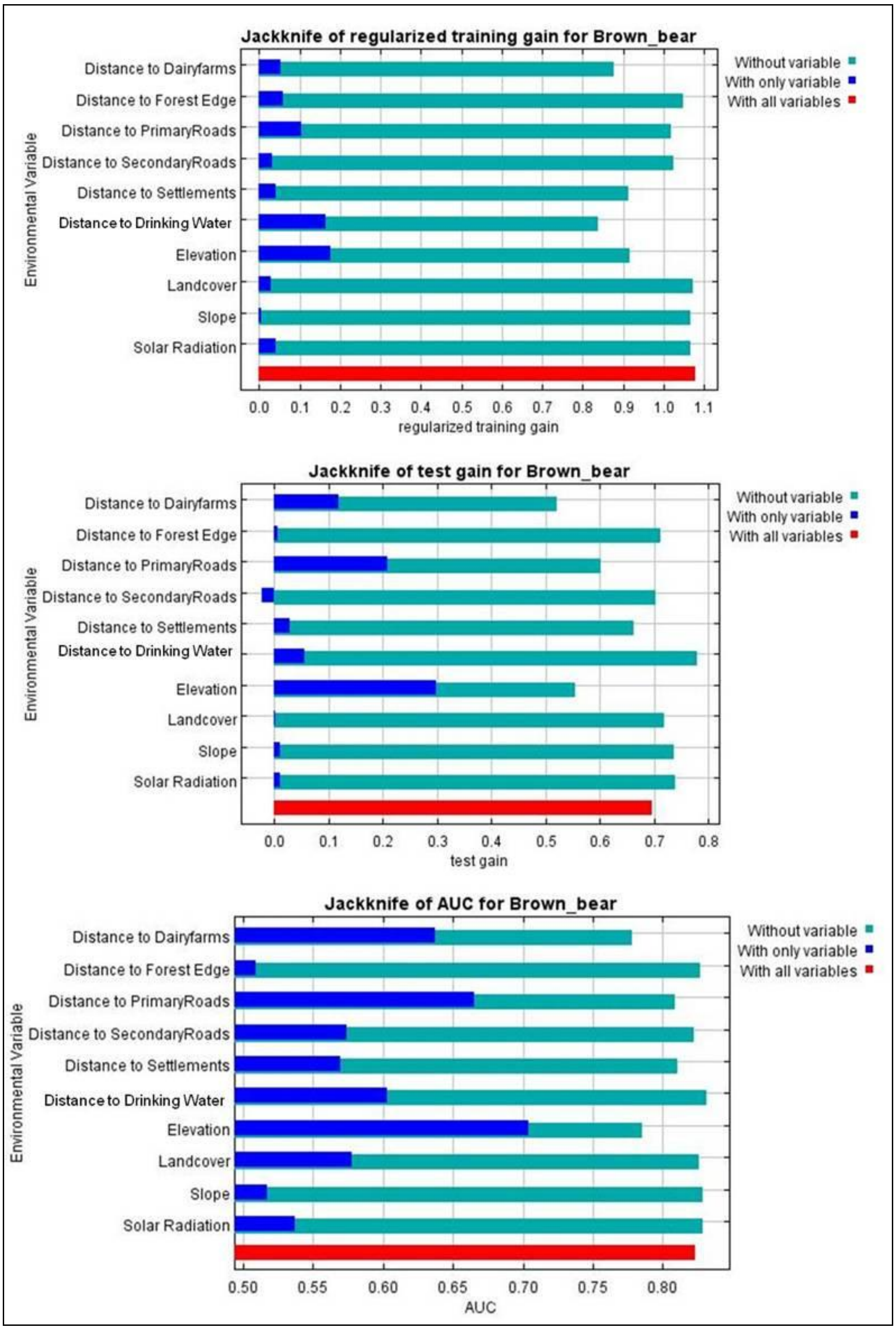

Figure 8: Model 2 (all kernels) jackknife results of variable importance in the regularised training gain (top), test gain (centre) and AUC (bottom).

Model 3: kernels with multi-year/multi-season observations

From the jackknife analysis results of Model 3 (Figure 9), the environmental variable with the highest training gain when used in isolation is elevation, which therefore implies that it has the most useful information by itself. This was followed by distance to water, then distance to primary roads, distance to dairy farms and distance to settlements. The environmental variable that decreases the training gain the most when excluded is distance to settlements, which therefore appears to have the most information that is not present in the other variables. This is followed by distance to dairy farms, elevation and distance to drinking water. Land cover, slope, solar radiation, distance to secondary roads, distance to primary roads and distance to forest edge when excluded from the model one by one has no significant decrease in the overall training gain. The model also produced jackknife test for the test gain (center), and the AUC (bottom) which shows the variables with highest test /AUC gain when used in isolation, the variables that decrease the overall gain when excluded from the model and the variables that do not significantly reduce the overall test / AUC gains.

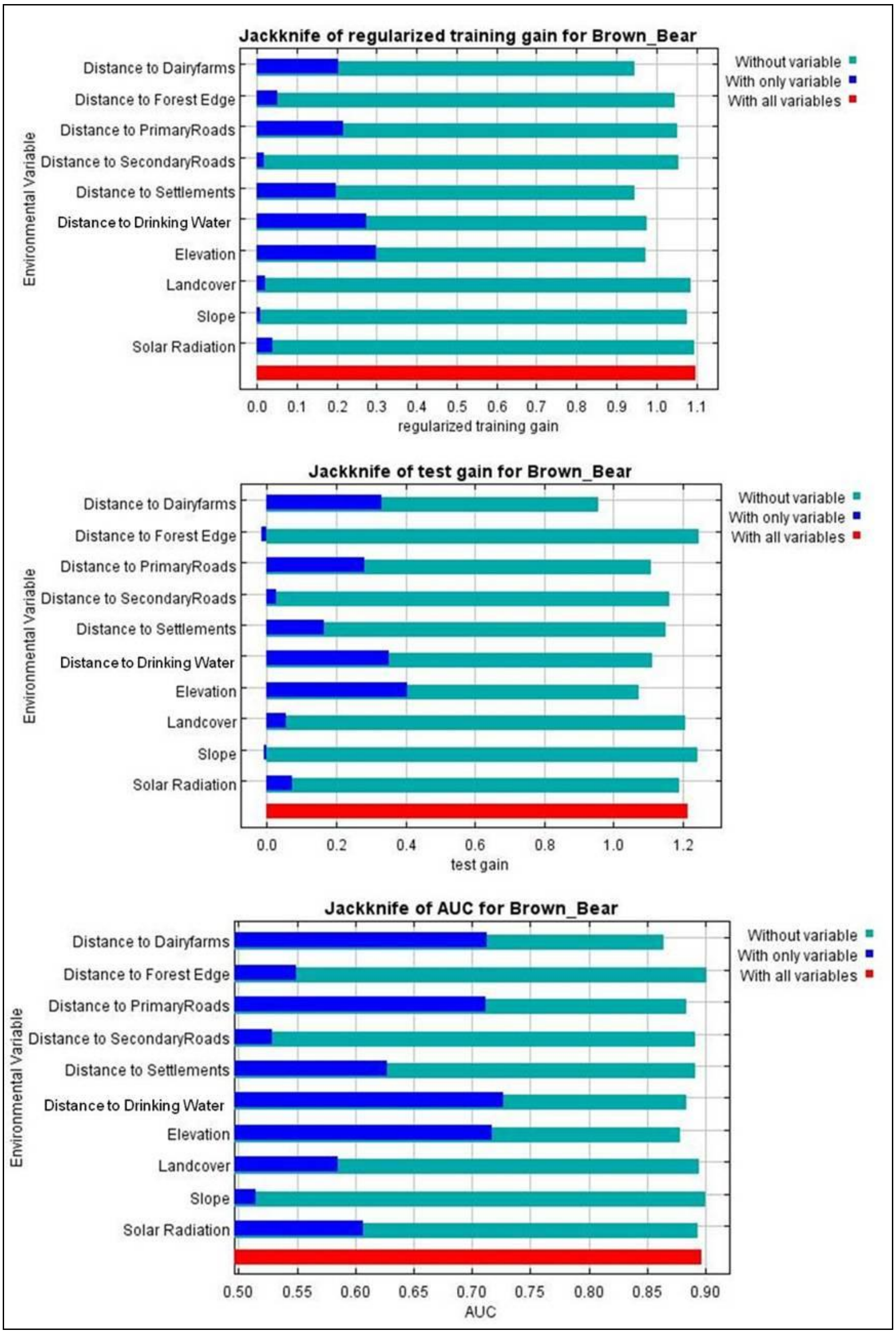

Figure 9: Model 3 Jackknife results of variable importance in the regularised training gain (top), test gain (centre) and AUC (bottom)

3.4.1. Relative contribution of the predictor variables to the MaxEnt Models 1, 2 and 3.

Table 4 shows the comparative table for the predictor variables in the three models. In Model 1, distance to forest edge was the variable with the highest contributor with 33.3% and the least contributor was distance to settlements with 0% contribution. In Model 2, elevation contributes the greatest with 23.3% and land cover the least with 1.1%. In Model 3, Elevation was found to be the most important and contributes more to the model with 29% and Solar radiation the least, contributing only 0.6%. The four important variables for the three models, (highlighted in yellow, orange and green for Model 1, 2 and 3 respectively). Distance to drinking water and distance to dairy farms appears in all the three models, while elevation and distance to settlements are common to Models 2 and 3. Elevation, distance to dairy farms and distance to settlements show a positive response while distance to water and distance to the forest edge show a negative response in Model 1. The Train AUC for Models 1, 2, and 3 are 0.81, 0.91 and 0.92 respectively. The table also shows the percentage contribution of the variables in the three models. In Model 1, the highest contributor is distance to forest edge, in Model 2 and Model 3 the highest contributor is elevation.

Table 4: Comparative table of the relative contribution of the predictor variables, response curves and AUC for the three Models.

Variable	Model 1 AUC Train 0.81 observations			Model 2 AUC Train 0.91 Kernels			Model 3 AUC Train 0.92 Multi Year/Season		
		Curve	%		Curve	%		Curve	%
Elevation	False	NA	7.7	True	+	23.3	True	+	29
D Settlements	False	NA	0	True	+	16.8	True	+	23.6
D Water	True	-	12.5	True	-	18	True	-	16.6
D Dairy farms	True	+	18.8	True	+	13.8	True	+/-	10
D Forest edge	True	-	33.3	False	NA	5	False	NA	8.4
Slope	True	+/-	10.6	False	NA	1.3	False	NA	0.9
D Primary roads,	False	NA	6.1	False	NA	12.8	False	NA	4.5
D secondary roads	False	NA	5.2	False	NA	6.3	False	NA	4.9
solar radiation	False	NA	0.1	False	NA	1.6	False	NA	0.6
land cover	False	NA	5.7	False	NA	1.1	False	NA	1.5

3.4.2. Predictive Maps

Figures 10, 11 and 12 show the probabilistic predictive map produced by MaxEnt Models 1, 2, and 3 respectively. The MaxEnt predictive map uses colours that indicate predicted probability that conditions are suitable. Warmer colours (red) indicate high probability of suitable conditions for the species and green indicates low probability.

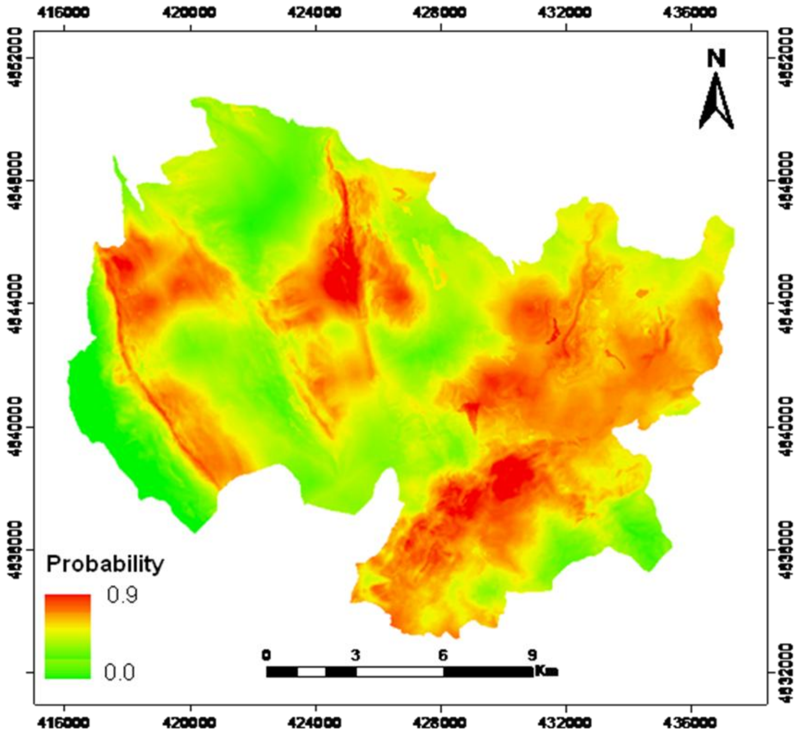

Figure 10: Probabilistic predictive map of brown bear for Model 1 (incidental observations)

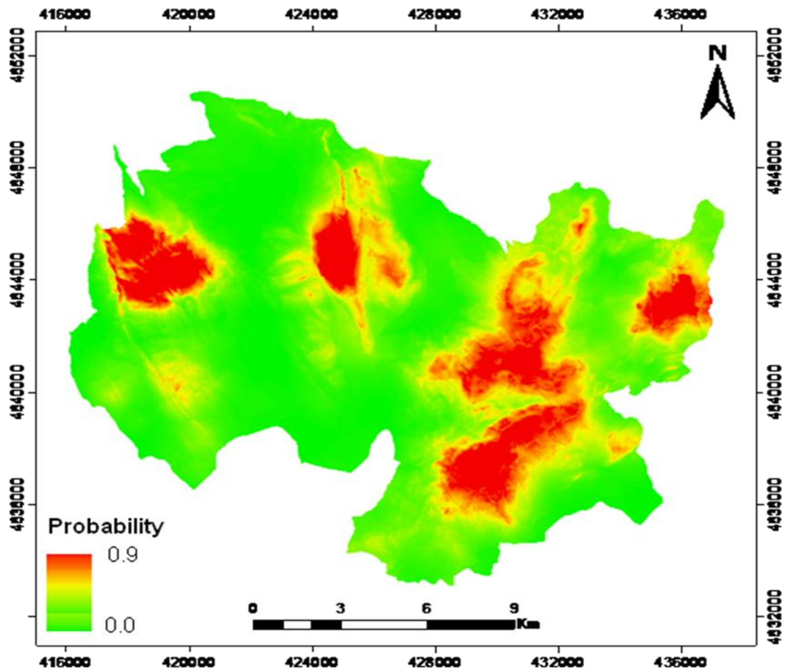

Figure 11: Probabilistic predictive map of brown bear for the Model 2 (all kernels)

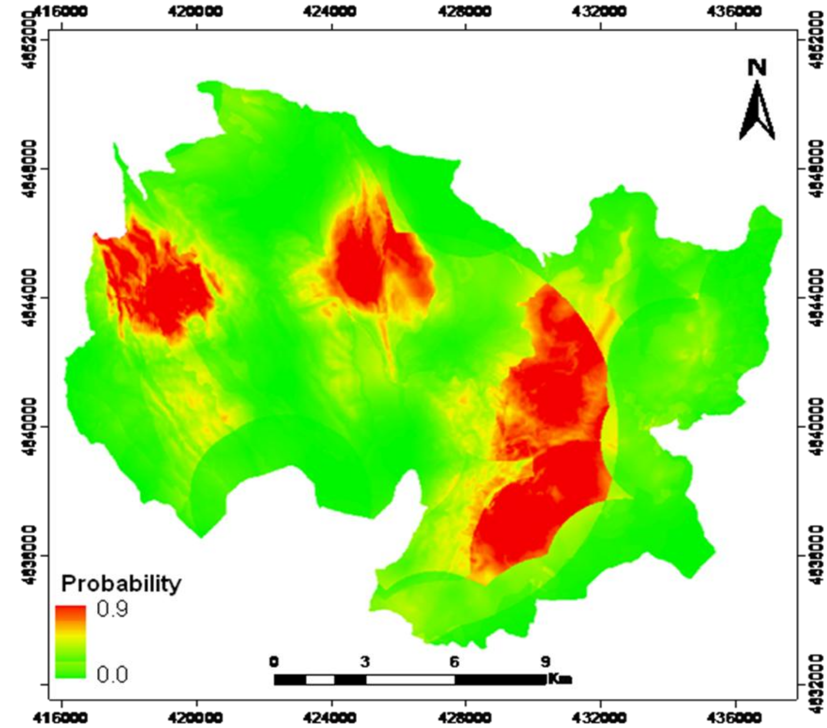

Figure 12: Probabilistic predictive map of brown bear for the Model 3(multi-year/multi-season kernels)

3.4.3. Model Performance and Evaluation

Figures 13, 14 and 15 show the ROC curves for Models 1, 2 and 3 respectively. In Model 1, the AUC of the training data set of 45 records was 0.81 and that of the test data set of 19 records was 0.82. Model 2 ROC curves show high accuracy of the generated model with AUC 0.91 for training data and 0.82 for test data. The AUC for Model 3 shows much higher accuracy of 0.92 for training data and 0.89 for test data. The red (training) line shows the “fit” of the model to the training data. Comparing the training AUCs of the three models, it is observed that Model 3 has the highest AUC followed by Model 2 and then Model 1.

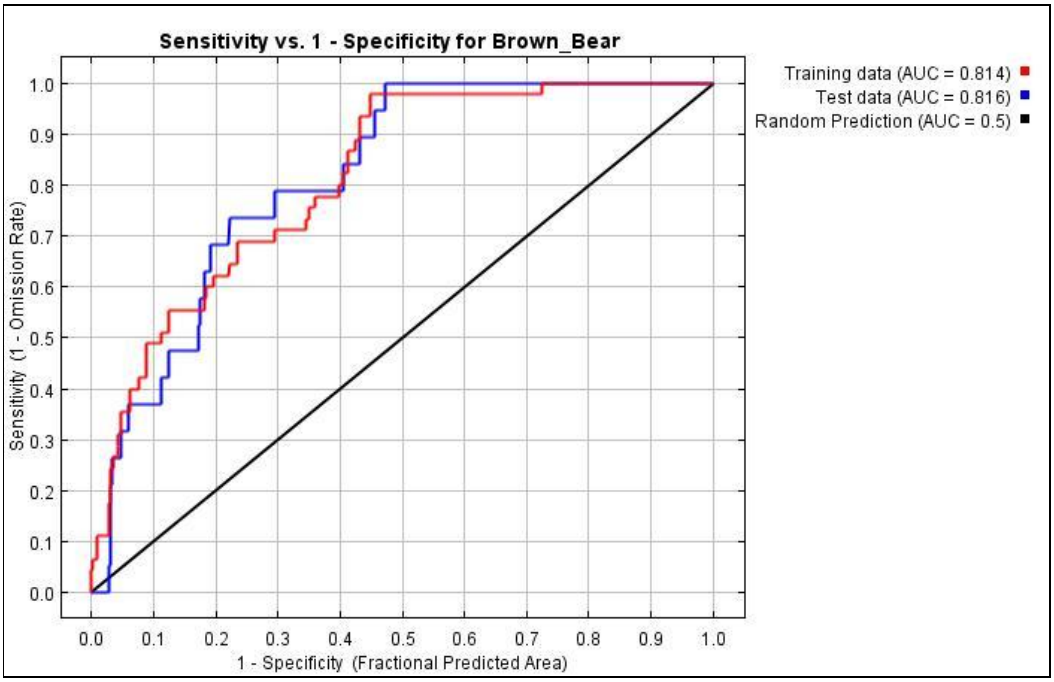

Figure 13: ROC curve of Sensitivity versus Specificity for the Model 1

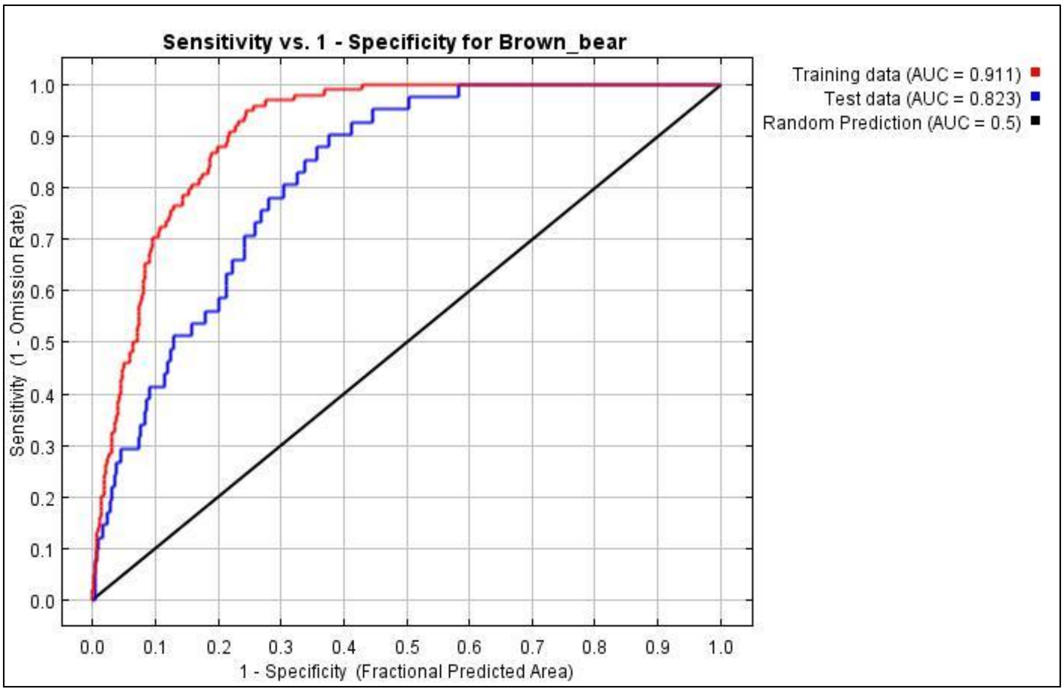

Figure 14: ROC curve of Sensitivity versus Specificity for the Model 2

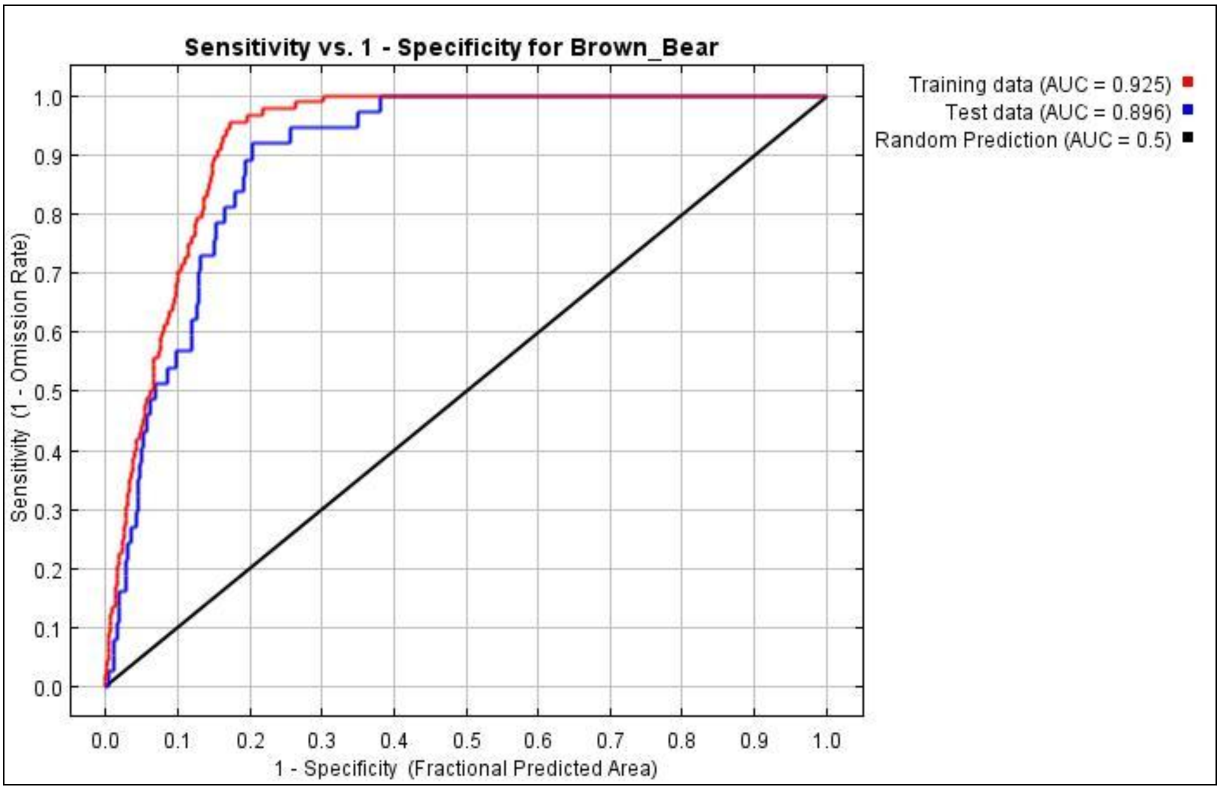

Figure 15: ROC curve of Sensitivity versus Specificity for the Model 3

3.4.4. Response curves of the predictor variables.

Model 1: Incidental Observation

Figure 16 shows the response curve for Model 1.

The probability increases linearly from 0.20 to 0.60 as distance to dairy farms increases to 13 000m.

The probability of occurrence of the bear decreases from 0.64 to 0.05 as distance to the forest edge increases from zero to 3300m. Thus, the closer to the forest edge, the higher the probability. The closer to the water sources the higher the probability of finding the bear. Probability decreased from 0.60 to 0.41 at a distance of 1000m away from the water source and then became stable between1100 and 5000m. The probability increased from 0.20 to 0.45 at a slope of 9 degrees and then decreased to 0.09. As the slope become steeper, the probability of occurrence decreases.

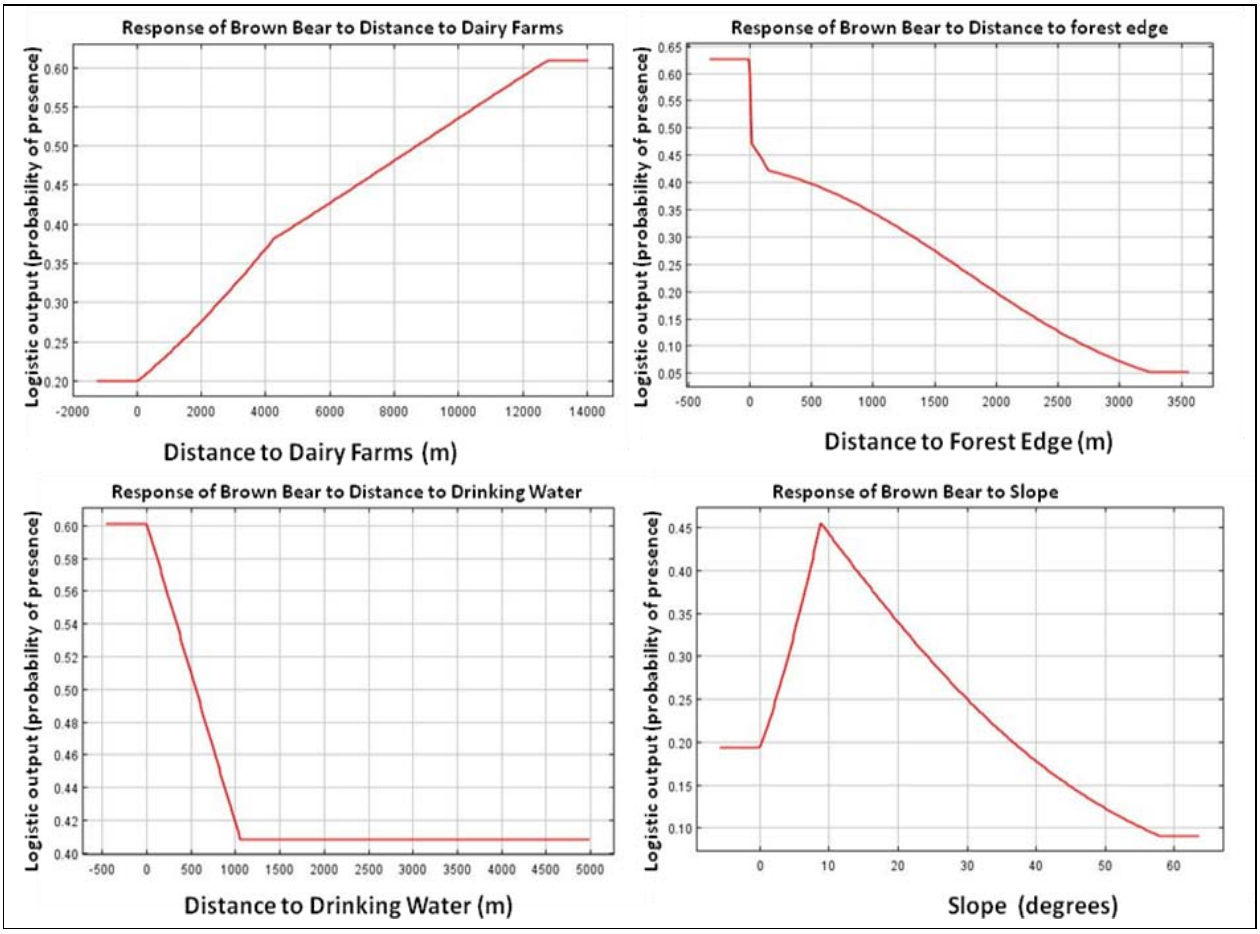

Figure 16: Response curves of the four predictor variables that most affected MaxEnt Model 1

Model 2: All Kernels

Figure 17 also shows the response curves of the four most important predictors in Model 2. The probability of finding the bear increased from 0 to 0.9 at a distance of 10 000m away from dairy farms and then gradually decreased to 0.85 from 10 000m to 14 000m. The probability also increases to 0.8 at an elevation of 1850m and drops to 0.75. It then increased again to 0.9 then becomes stable at 2100m. The probability also decreased from 0.60 to 0 as distance to water increased. The probability increased to 0.75 as the distance to settlements increased to 8000m

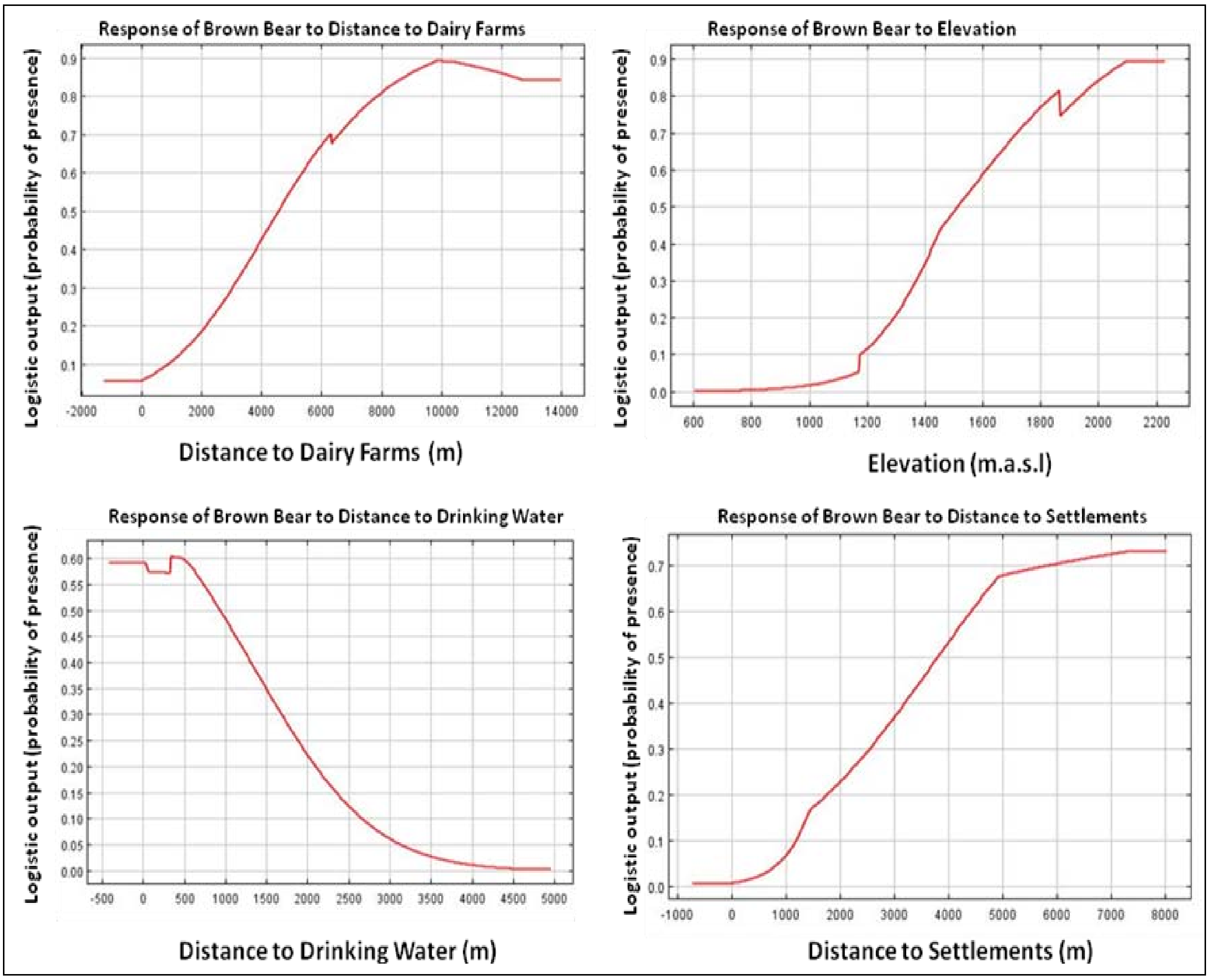

Figure 17: Response curves of the four most important predictor variables of the MaxEnt Model 2

Model 3: Multi-year/Multi-season

The response curves in Figure 18 shows how each of the four most important predictor variables (distance to dairy farms, elevation, distance to water and distance to settlements) affect the MaxEnt prediction in Model 3. The probability of occurrence of the bear increases linearly as the distance to the dairy farms increases until it reaches 0.79 where it drops sharply to 0.50 at a distance of 6000m.the probability then starts decreasing from 8000m and becomes stable between 13 000m and 14 000m. As elevation increases, the probability of occurrence increases to 0.70 at elevation of 1800m.The probability then drops sharply to 0.62 from 1850m, starts increasing again and becomes stable from 2100m. As distance to water increases, the probability of occurrence of the brown bear also decreases up to approximately 2500m. As distance to settlements increases, the probability of finding the bear also increases attaining a sharp rise of 0.50 at a distance of 2000m. It continues to increase gradually to 0.80 where it becomes stable from distance of 7200 to 8000m.

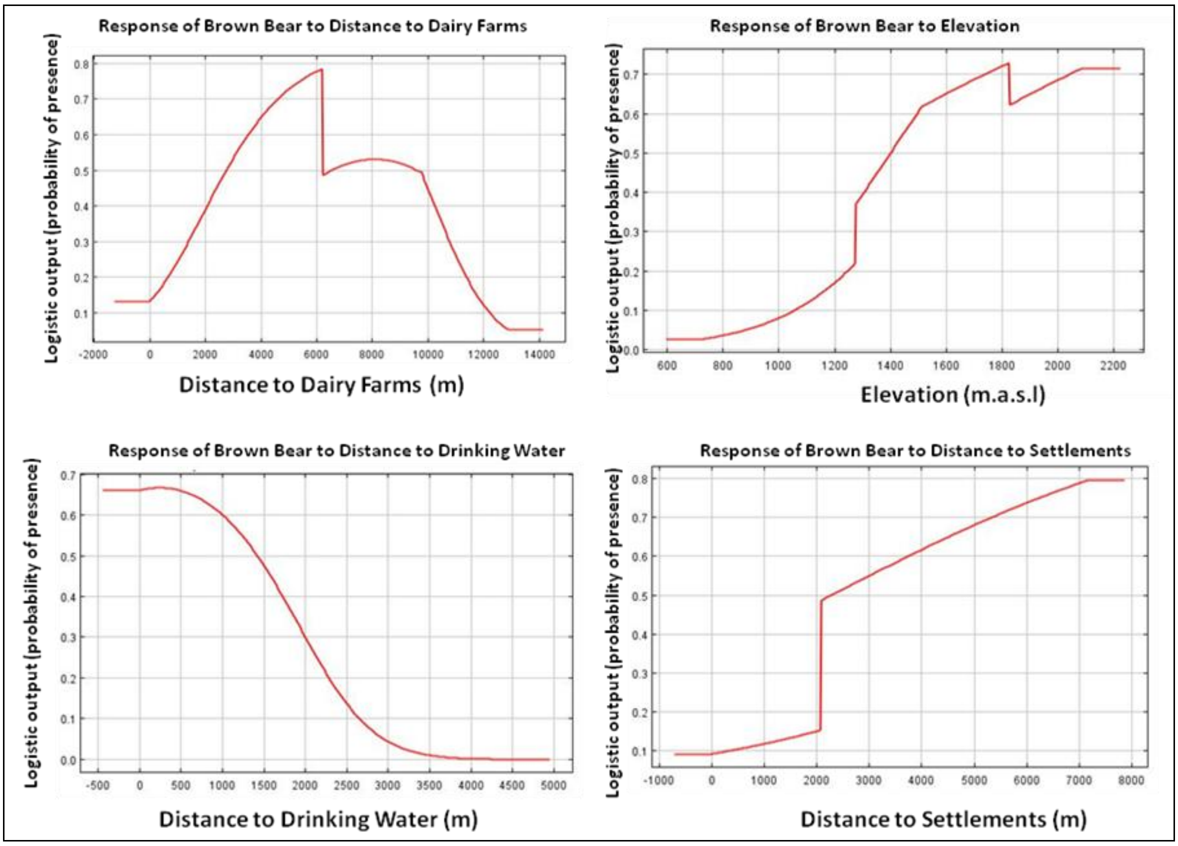

Figure 18: Response curves of the four important predictor variables of the MaxEnt Model 3

4. DISCUSSION

The extents of the kernels or core areas, A, B, C&D (Figure 6) are 10, 12, 5, and 26km² respectively. This is similar to the extent of the core area of ten brown bears (three males, and seven females) in the Brenta mountains, North-Italy a year after their release into the park (Preatoni *et al.*, 2005) and five female back bears in North California's Pisgah National Forest (5.9 -21.5km²) (Seaman & Powell, 1996). Five female brown bears in Slovenia however had a much higher extent between 39-63km² (Kaczensky *et al.*, 2003). Therefore, the four kernels found by this research in southern Majella could imply four adult bears because there are four to eight bears permanently resident in the park and their presence is stronger in the southern part of the park. The records (Appendix 6) show that bear observations cover all four seasons indicating that the bears in these kernels may be resident. A female with two cubs was sighted in Porrara (kernel B) in the summer of 2010. This indicates permanent residence in kernel B. Kernel D may represent a migrating bear that had wandered into that area predating on chickens and sheep.

Model 1 with observations points (incidental records without planned inventory scheme) had the lowest AUC (0.81), but still informative (Baldwin, 2009). The model predicted large areas around Mt Secine and Mt. Pizzi as having a higher probability of occurrence. This is because the occurrence records were denser in this area. Forest edge and slope contributed greatly only in model 1. The probability of finding the bear decreases as the distance from the forest edge increases. The reason is that, the observations made were biased towards places close to the forest edge. Observation from the field showed that people hardly enter the forest. Fruit trees were also found near the forest edge. This could also explain why forest edge affects the occurrence. Similarly, human - bear observations occurred on gentle slopes accessible to humans. Therefore steeper slopes showed low probabilities.

The results (Table 7) show that the two predictors common to all the three models are distance to dairy farms (positive response) and distance to drinking water (negative response). Due to the nature of the terrain, which consists mainly of Limestone Mountains (Appendix 2), surface water is scarce in MNP. The water sources (Appendix 1) are pools of water, small rivers, springs or concrete water basins. Footprints of different animals were found around the water sources encountered in the field. This means that other animals also depend on the water. The concrete water basins provide water for mules but that can be used by wildlife. Kaczenky (2006) found however that Croatia shares the same landscape features with southern MNP where surface water is also rare and water runoff is underground. However, Kusak & Huber (1998) stated that, the distribution of the brown bear has not been associated with availability of water in Croatia. They did not assign any reason for this. It could be that the surface water is adequate or are being supplemented with the provision of other sources.

Distance to dairy farms appears in all three models as important in the prediction. The probability of finding the bear increases as the distance from the dairy farm increases. However the curve showed this trend up to ≈ 6km distance, suggesting that bears avoid areas of high human activity. Human activities may cause bears to make temporal and spatial adjustment in activity patterns (Mueller *et al.*, 2004). The dairy farms houses seem quite recent compared to the farmhouses in the villages (Appendix 2). The parcels are larger than those of the abandoned peasant farms (Appendix 2) making these suitable for mechanised farming. Tractors and other machinery are employed on the farm for mowing meadows.

Dairy farms in the study area are fenced, either electric or not (Appendix 2). Apennine shepherd dogs freely roam in these farms and may number between two and eight. A bear surrounded by dogs was spotted at Grotta delle Femmine (Sant' Eufemia a Majella), north of the study area in autumn 2010. Presumably, bears avoid areas with resident dogs such as the dairy farm block.

Elevation and distance to settlements are common successful positive predictors in Models 2 and 3. A long history of human persecution, has affected the behaviour of the European brown bear (Swenson *et al.*, 2000). The avoidance by brown bears of the areas of greatest human activity is well known from North America. Mueller *et al.* (2004) reported that in areas where brown bears co exists with humans, bears avoided areas close to people. This agrees with the finding in this study where bears are found farther away from settlements. In Model 3, however the sharp rise in the probability at distance of 2 km may be due to the high incident of predation on sheep and chicken and ten beehives by brown bears close to kernel D. Contrarily to this, in North America some bears have rather been found closer to settlements attracted by food, garbage and sheep/chicken.

Generally, the probability of brown bear occurrence increased with increase in elevation. Studies (Apps *et al.*, 2004) have shown brown bears prefer higher elevations where human access is inhibited. In the central Apennine, Posillico *et al* (2004) reported that there is a high probability of finding the brown bear at higher elevations. They attributed it to the remoteness from human disturbance and by the active search for locally abundant *Rhamnus alpinus* (berries) patches and late season grass. Bears are often found in lower elevations after emerging from their dens (Boyce *et al.*, 2002). Higher elevations (> 1500m) are covered with snow in the winter and so they may be restricted from effectively foraging in those areas. Bears may move in the summer to alpine elevations for food. This may explain the drop in the probability at an elevation of 1850 m a.s.l. Seasonal use of elevation as been reported by (Collins *et al.*, 2005). Although the records are in the four seasons, the records are too few to do further analysis of seasonal distribution. More observations are needed to analyse the seasonal distribution of the brown bear.

Land cover, solar radiation, distance to primary and distance to secondary roads were variables that did not influence brown bear occurrence. Land cover is potentially a determinant of the presence of bears (Clevenger *et al.*, 1997), because beech and oak forest provide staple food (e.g. beechnut and acorns) and cover (Clevenger *et al.*, 1997) for the brown bear to evade detection by humans. In Slovenia, Kobler & Adamic (2000) found that brown bears prefer densely forested areas further away from settlements. Land cover did not contribute significantly to the model output as expected in southern MNP. This can be attributed to the fact that few observations were made inside the forest.

In this study, the roads did not contribute much to the brown bear occurrence. Clevenger *et al.* (1992) found distance to nearest paved road as important predictors in the Cantabria Mountains of Northern Spain and Mueller *et al.* (2004) also reported that bears avoided roads in North America. However the effect of roads on brown bears may depend on road traffic volume, which is low in the study area (own observation). Therefore, the roads did not make substantial contribution to the models.

5. CONCLUSION

The study was conducted to identify the core areas of the brown bear in MNP using the Kernel Density Estimate of the incidental records. It was also to identify environmental variables associated with the brown bear occurrence in the core areas using MaxEnt.

The findings can be summarised as follows:

1. The CVh method selected a smoothing parameter of 1204m
2. The Kernel Density Estimator identified four core areas in southern Majella NP around Mt. Rotella, Pizzalto, Porrara, Secine and Pizzi.
3. The predictors that affected the brown bear occurrence in Model 1 (incidental observations) are distance to dairy farms, distance to drinking water, distance to forest edge and slope.
4. The predictors that affected the brown occurrence in Model 2 (all kernels) & Model 3 (multi-year/multi-season kernels) are distance to dairy farms, distance to settlements, distance to drinking water and elevation.
5. The predictors common to all three models are distance to dairy farms and distance to drinking water.
6. The probability of occurrence of the brown bear in Model 1 decreases with increase in distance to forest edge and distance to drinking water.
7. The probability of occurrence of the brown bear in Model 2 & 3 increases with increase in distance to dairy farms, settlements and elevation.
8. Distance to primary roads or secondary roads, incoming solar radiation and land cover hardly influenced the prediction.
9. The fine scale MaxEnt modelling predicted the core areas in the Model 2 & 3 with excellent goodness-of-fit. (AUC=0.91 and 0.92)

Distance to dairy farms and distance to forest edge are unique predictors that have been introduced which influenced the model prediction with the latter only in model 1. Contrary to previous studies in North America where brown bears (grizzly bears) were found close to roads this study showed that roads do not affect the brown bear distribution. The comparison of the incidental presence records with the kernel density estimates was successful and unique since no such study has been done. The predictive maps produced by the MaxEnt model of the core areas closely relate to the kernels produced by the KDE.

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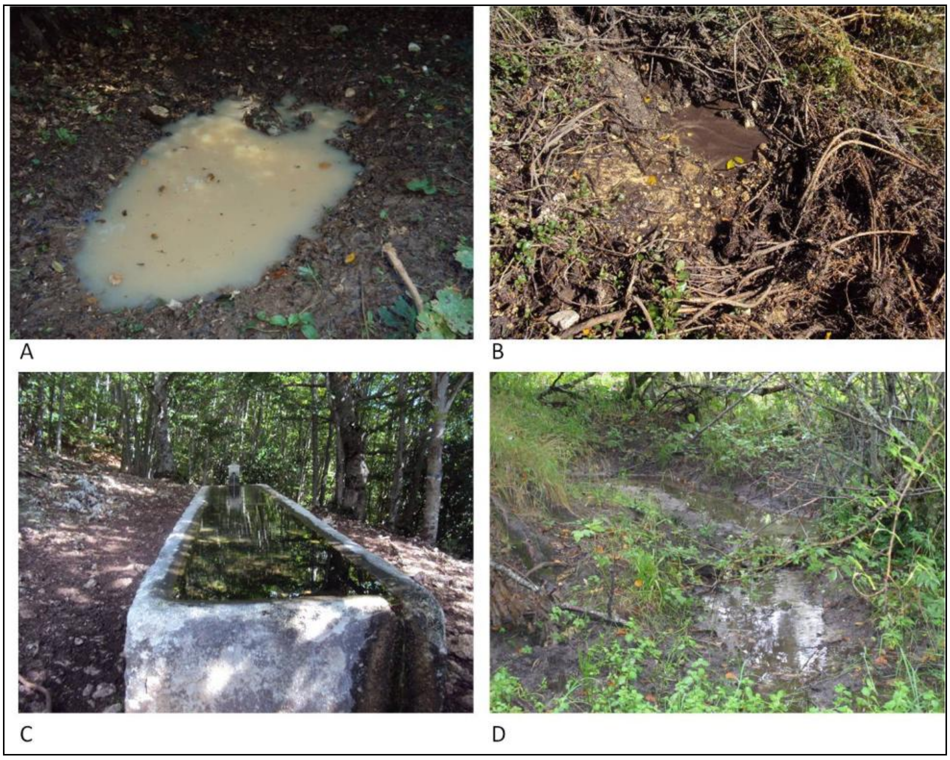
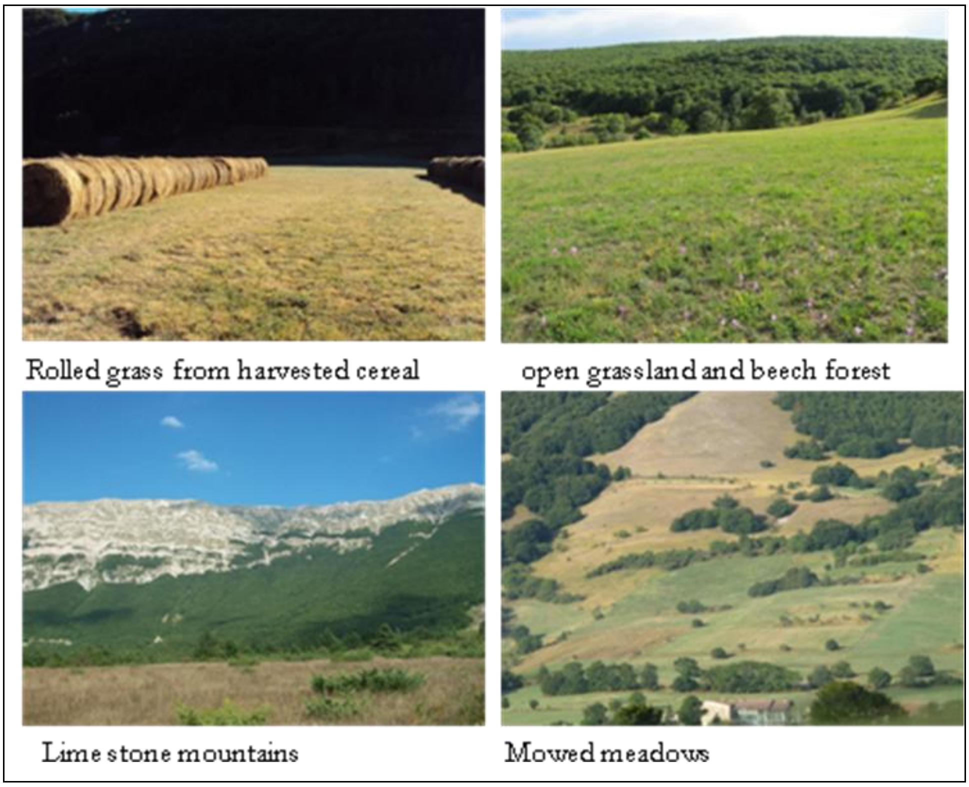
APPENDIX

Appendix 1: Field observations of water sources



A - Pool of water, B &D - spring, B – concrete water basin

Appendix 2: Field observation of cover types and dairy farm



Two fenced dairy farm

Chickens on a dairy farm

Appendix 3: Field observation fruit trees in southern MNP (WGS 1984 UTM Zone 33N)

No.	Type of fruit tree	X Coordinates	Y Coordinates
1	*Fagus sylvatica*	419706	4644620
2	*Prunus avium*	419746	4644620
3	*Prunus avium*	419764	4644620
4	*Malus sylvestris*	419880	4644580
5	*Malus sylvestris*	420028	4644600
6	*Prunus avium*	419944	4644620
7	*Malus sylvestris*	419950	4644620
8	*Pyrus communis*	419524	4644700
9	*Pyrus communis*	419524	4644700
10	*Pyrus communis*	421293	4641880
11	*Pyrus communis*	421283	4641920
12	*Pyrus communis*	421265	4642020
13	*Fagus sylvatica*	421466	4642260
14	*Rosa canina*	419453	4644520
15	*Rosa canina*	419449	4644450
16	*Rosa canina*	419372	4644290
17	*Rosa canina*	419346	4644230
18	*Rosa canina*	419348	4644220
19	*Rhamnus alpina*	419642	4644140
20	*Rosa canina*	419696	4644190
21	*Rosa canina*	419699	4644220
22	*Malus sylvestris*	419444	4644750
23	*Rosa canina*	424753	4641810
24	*Rosa canina*	424272	4642600
25	*Malus sylvestris*	421841	4646620
26	*Malus sylvestris*	421879	4646370
27	*Malus sylvestris*	421879	4646360

No.	Type of fruit tree	X Coordinates	Y Coordinates
28	*Prunus avium*	421879	4646260
29	*Arctostaphylos alpine*	421912	4646140
30	*Rosa canina*	421456	4646330
31	*Rosa canina*	421882	4646260
32	*Rosa canina*	421892	4646310
33	*Rosa canina*	421886	4646320
34	*Rosa canina*	421873	4646360
35	*Rosa canina*	421884	4646460
36	*Rosa canina*	422429	4646820
37	*Malus sylvestris*	424141	4644040
38	*Rhamnus alpina*	423721	4643930
39	*Rosa canina*	418270	4647940
40	*Rosa canina*	419516	4647850
41	*Rosa canina*	418272	4647920
42	*Rosa canina*	420703	4646560
43	*Rhamnus alpina*	419514	4647860
44	*Rosa canina*	419369	4647850
45	*Rosa canina*	426866	4644200
46	*Malus sylvestris*	431045	4643680
47	*Rosa canina*	430749	4643150
48	*Rosa canina*	430713	4642460
49	*Rosa canina*	430989	4642320
50	*Rosa canina*	425112	4640730
51	*Rosa canina*	424902	4641570
52	*Arctostaphylos alpine*	429474	4641560
53	*Rosa canina*	429468	4641570
54	*Rosa canina*	429453	4641590
55	*Pyrus communis*	429421	4641640
56	*Quercus cerris*	429420	4641640

Appendix 4: Field observation of Dairy Farms in southern MNP (WGS 1984 UTM Zone 33N)

No.	Farm	X Coordinates	Y Coordinates
1	Dairy farm	426176	4639830
2	Dairy farm	424097	4638850
3	Dairy farm	423966	4638940
4	Dairy farm	423648	4639080
5	Dairy farm	423492	4639130
6	Dairy farm	422678	4639720
7	Dairy farm	421983	4640510
8	Dairy farm	421858	4640780
9	Dairy farm	421457	4641170
10	Dairy farm	421201	4641410
11	Dairy farm	420946	4641780

No.	Farm	X Coordinates	Y Coordinates
12	Dairy farm	420710	4642290
13	Dairy farm	420155	4643420
14	Dairy farm	421820	4640410
15	Dairy farm	421771	4639890
16	Dairy farm	421646	4639420

Appendix 5: Water sources in located southern MNP (WGS 1984, UTM Zone 33N)

No.	Type	X Coordinates	Y Coordinates
1	Water	420140	4640291
2	Water	420507	4637784
3	Water	423240	4637879
4	Water	423087	4638718
5	Water	423145	4638292
6	Water	426221	4635674
7	Water	427554	4634768
8	Water	429102	4632385
9	Water	428703	4635401
10	Water	428576	4636203
11	Water	434648	4634091
12	Water	435918	4635179
13	Water	434997	4636274
14	Water	434989	4635901
15	Water	432568	4636417
16	Water	429941	4637465
17	Water	430576	4637925
18	Water	428822	4637330
19	Water	430290	4641602
20	Water	432473	4642308
21	Water	433330	4644864
22	Water	433465	4640427
23	Water	435354	4640411
24	Water	436902	4646967
25	Water	432679	4647150
26	Water	424337	4644697
27	Water	418757	4645777
28	Water	418098	4645364
29	Water	418820	4644086
30	Water	420297	4649309
31	Water	417852	4652341
32	Water	418463	4653029
33	Water	417178	4639570
34	Water	418748	4634374

No.	Type	X Coordinates	Y Coordinates
35	Water	420913	4652547
36	Water	414752	4650421
37	Water	416276	4651102
39	Water	419069	4632279
40	Water	425306	4641660
41	Water	426965	4644180
42	Water	426888	4644250
43	Water	426930	4644270
44	Water	428287	4640830
45	Water	429268	4640720
46	Water	429639	4641480
47	Water	430835	4643760
48	Water	419614	4644500
49	Water	419743	4644550
50	Water	419617	4644600
51	Water	419639	4644660
52	Water	437009	4633527
53	Water	437078	4636339
54	Water	437349	4649119

Appendix 6: Brown bear presence records provided by MNP in WGS 1984 UTM Zone 33N.

ND - No Data.

ID	MNP_ID	X Coordinates	Y Coordinates	Month	Day	Year	Type of data
1	78	431385	4645893	4	1	1996	ND
2	79	430600	4644937	5	1	1996	Sighting
3	80	432722	4637073	5	1	1996	Sighting
4	81	431363	4644223	5	30	1996	ND
5	82	432239	4660959	8	8	1996	ND
6	83	433469	4638514	6	14	1997	ND
7	84	433264	4657500	6	16	1997	ND
8	85	420484	4657187	2	15	1998	ND
9	86	ND	ND	6	8	1998	ND
10	87	412596	4663404	6	19	1998	ND
11	88	414370	4665769	7	1	1998	ND
12	89	415853	4664681	11	18	1998	ND
13	90	408028	4666910	11	26	1998	ND
14	91	424356	4650730	11	26	1998	ND
15	92	408058	4666827	11	27	1998	ND
16	93	411245	4663627	12	15	1998	Denning
17	94	414821	4657684	3	10	1999	Sighting
18	95	429469	465806	8	27	1999	ND

ID	MNP_ID	X Coordinates	Y Coordinates	Month	Day	Year	Type of data
19	96	427121	4644307	11	20	1999	ND
20	97	434391	4643485	11	26	1999	ND
21	98	433262	4644212	11	26	1999	ND
22	99	411272	4663521	11	26	1999	ND
23	100	408006	4666825	11	28	1999	ND
24	101	433755	4643241	11	30	1999	ND
25	102	411462	4659970	12	5	1999	ND
26	103	415927	4664781	12	8	1999	ND
27	104	427389	4640412	12	19	1999	ND
28	105	432532	4647470	12	21	1999	ND
29	106	420104	4660828	3	29	2000	ND
30	107	429320	4641194	4	27	2000	ND
31	108	413956	4666121	9	7	2000	ND
32	109	416718	4662617	9	8	2000	ND
33	110	ND	ND	9	15	2000	ND
34	111	ND	ND	9	17	2000	ND
35	112	422028	4660172	9	25	2000	ND
36	113	420021	4660509	9	25	2000	ND
37	114	420159	4660511	9	26	2000	ND
38	115	420238	4660350	9	27	2000	ND
39	116	419921	4660677	9	28	2000	ND
40	117	419776	4660528	9	29	2000	ND
41	119	420168	4660556	9	30	2000	ND
42	128	419952	4660692	10	1	2000	ND
43	129	419457	4659496	10	3	2000	ND
44	130	420017	4660787	10	6	2000	ND
45	131	ND	ND	10	6	2000	ND
46	132	419497	4659316	10	6	2000	ND
47	133	419187	4660770	10	7	2000	ND
48	134	419094	4662326	10	10	2000	ND
49	135	ND	ND	10	13	2000	Sighting
50	136	416698	4665435	11	13	2000	ND
51	123	411345	4667831	11	5	2001	Sighting
52	137	429061	4638205	4	29	2001	ND
53	70	420687	4643856	10	2	2002	Footprint
54	74	419800	4648950	9	6	2002	ND
55	71	421544	4639091	10	25	2003	Sighting
56	72	434922	4663300	6	24	2003	Sighting
57	73	427950	4659550	6	15	2003	Sighting
58	75	418817	4645766	8	22	2003	Scat
59	76	428710	4635843	8	20	2003	Scat
60	77	417817	4647357	8	25	2003	Scat
61	118	420177	4646331	8	22	2003	Scat
62	120	419220	4642073	11	16	2003	Damage

ID	MNP_ID	X Coordinates	Y Coordinates	Month	Day	Year	Type of data
63	121	ND	ND	8	15	2003	Scat
64	122	419149	4643664	11	21	2003	Damage
65	28	430753	4638813	10	26	2004	Hair
66	124	425128	4639042	5	21	2004	Damage
67	125	425274	4639766	5	12	2004	ND
68	126	420074	4644653	5	5	2004	Damage
69	127	422156	4642117	4	17	2004	Damage
70	15	423776	4644552	12	23	2006	Footprint on snow
71	16	424272	4645095	12	23	2006	Scat
72	17	426500	4643852	12	27	2006	Scat
73	18	424402	4645506	12	27	2006	Excavation
74	19	424980	4646782	12	29	2006	Footprint on snow
75	20	424734	4646792	12	29	2006	Footprint on snow
76	21	429400	4641018	12	29	2006	Footprint on snow
77	22	431943	4639927	12	30	2006	Footprint on snow
78	23	431177	4641199	12	30	2006	Scat
79	24	431869	4641109	12	30	2006	Scat
80	25	430195	4639026	12	30	2006	Hair
81	45	424262	4633300	9	8	2006	Predation
82	46	438104	4638385	9	11	2006	Predation
83	47	438306	4638104	9	11	2006	Hair and traces
84	48	438501	4639358	9	12	2006	Predation
85	49	438936	4639695	9	13	2006	Predation
86	50	439602	4639830	9	14	2006	Predation
87	51	437223	4641961	9	16	2006	Predation, droppings and fur
88	52	436934	4643088	9	19	2006	Predation
89	53	436252	4643118	9	20	2006	Scat , hair and footprint
90	54	436422	4643708	9	21	2006	Scratches and digs on attempted predation
91	55	436936	4643046	9	21	2006	Attempted Predation
92	56	441374	4649353	9	23	2006	Predation
93	57	438214	4645532	9	24	2006	Predation
94	58	440765	4641643	9	25	2006	Sighting
95	59	436387	4641533	9	28	2006	Attempted Predation
96	60	432660	4634074	10	3	2006	Predation
97	61	429780	4629872	10	3	2006	Sighting
98	62	436929	4642718	10	12	2006	Predation
99	63	437064	4642279	10	14	2006	Sighting
100	64	439408	4639854	10	15	2006	Predation and hair
101	65	439548	4640016	10	16	2006	Predation
102	66	438232	4638343	10	17	2006	Predation
103	67	436150	4641642	10	20	2006	Sighting

ID	MNP_ID	X Coordinates	Y Coordinates	Month	Day	Year	Type of data
104	68	434626	4641572	10	20	2006	damage to garden
105	69	437183	4640989	10	22	2006	Predation
106	9	431064	4642102	12	21	2007	ND
107	10	431915	4638745	12	6	2007	Footprint on snow
108	11	430139	4638953	9	26	2007	Scat
109	12	426506	4633992	12	10	2007	Footprint on snow
110	14	421208	4660890	2	5	2007	Footprint on snow
111	27	430238	4641457	1	1	2007	Footprint on snow
112	1	430761	4638297	11	11	2008	Scat
113	2	430257	4639303	11	11	2008	Hair
114	3	430711	4638755	11	11	2008	Hair
115	4	426875	4636048	1	30	2008	Scat
116	5	431401	4642657	9	22	2008	Scat
117	6	430544	4633979	11	24	2008	Footprint on snow
118	7	425223	4645026	10	15	2008	Traces
119	29	429715	4634298	4	4	2009	Footprint on mud
120	30	430052	4634333	4	9	2009	Footprint on mud
121	31	430166	4636718	9	21	2009	Footprint on mud
122	32	430101	4636665	9	23	2009	Scat
123	33	426916	4635875	10	6	2009	Scat
124	34	420770	4659547	10	27	2009	Scat
125	35	416897	4665598	11	9	2009	Scat
126	44	430569	4639240	10	15	2009	ND
127	36	418214	4644322	4	16	2010	Sighting
128	37	417982	4645744	4	18	2010	Sighting
129	38	417422	4645076	5	25	2010	Stones over turned
130	39	418568	4649772	6	15	2010	Sighting
131	40	417460	4644645	8	2	2010	Stones over turned
132	41	420075	4642588	8	18	2010	Predation
133	42	426257	4644027	8	20	2010	Predation
134	43	424692	4648547	8	13	2010	Sighting
135	138	421850	4662744	10	21	2010	Sighting

Appendix 7: Summarized data for the four kernels

Kernels	No. of records	Year /No. of observations	Note	Season	
A	11	2002 - 1, 2003 - 4 2004 -1, 2010 - 5	Footprint, scat, damage, sightings overturned stones , predation	Winter - 0 Spring - 3 Summer-4 Autumn -3	
B	10	1999 -1 2006 -6 2008 -1	Tracks on the snow Excavation, sightings,	Winter - 6 Spring - 0 Summer - 2	

		2010 -2	Scat, predation traces	Autumn - 1	
C	28	1996 - 4 1997 -1 2000 -1 2001 -1 2003 -1 2004 -1 2006 -6 2007 -4 2008 -5 2009- 4	Tracks on the snow, Sighting, scat, hair, traces on mud	Winter - 8 Spring - 8 Summer - 2 Autumn-10	
D	7	1999 -3 2006 -4	Damage to garden Scratches on attempted predation	Autumn -7	On chicken
No kernel	6	1999 -2 2003 -1 2004 - 3	Sighting and damage	Winter - 2 Spring - 3 Autumn - 1	Damage to livestock