Beech Expansion: Pattern, Process & Prediction

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by

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Abstract

Beech, Dwarf Pine, Shrub and Grass were mapped with the help of Landsat TM satellite images taken in 1987 and 2003 respectively and ground truthing in 2005 within the central part of Majella National Park, Italy. The two image maps were overlaid in GIS software to identify changes, especially Beech expansion. Beech both in the study area and elsewhere had been reported to expand into abandoned farmland since the end of the Second World War. The results revealed an average rate of increase in Beech of 0.93%/year. Logistic regression models were used to examine the historic Beech cover changes and to calculate probabilities of future Beech expansion into abandoned farmland. Three explanatory variables were examined, namely, land parcel size, soil type and elevation. The most influential variables for Beech expansion showed to be soil type and elevation. Therefore these two variables were further modelled together to create a combined logistic regression model. The combined model was validated by the Receiver Operating Characteristic (ROC) method and found to be successful (ROC=70.2%) in modelling Beech expansion. In general areas located on soils with colluvuial and moraine deposits and in lower elevations were more likely to be covered by expanding Beech. These results may be used to project the probabilities of Beech expansion spatially.

To grandpa, **Edwin Muwamba (1914 – 2005)**

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List of abbreviations

CBD	Convention of Biological Diversity
DBH	Diameter at breast height
DEM	Digital elevation model
GIS	Geographical information systems
GPS	Global positioning system
LRMs	Logistic regression models
NP	National park
PCC	Proportion correctly classified
ROC	Receiver operating characteristic
RS	Remote sensing
TM	Thematic Mapper

1. Introduction

1.1. Background

Detecting and monitoring landscape changes is an important issue of landscape ecology(Hsu and Cheng, 2000), natural resources conservation (Goldsmith, 1991) and management (Salem, 2003). Direct observations by satellite remote sensing (RS) of land cover changes allow the identification of major processes of change.

To grasp the complexity of landscape mosaics and changes to them, fine scale land cover and socio-economic data are required. Collecting this information globally is a daunting task and therefore it is necessary to focus attention on a sample of areas, for which remote sensing and field observations could be collected (Mertens, 1999). In a similar manner (Puumalainen et al., 2003) states that change detection needs more detailed monitoring at landscape and stand level rather than national or regional level as only very general conclusions can be drawn from the latter and also suggests the efficient use of Geographic Information Systems (GIS) techniques in monitoring forest ecosystems.

Detailed studies of selected areas should lead to the identification of generic trajectories and processes of change, which could then be carefully generalized at broader scales. land cover change detected by RS and GIS approaches most often lead to a good perception of the spatial dimensions of land cover change processes or of their exact region of influence than field based studies (Mertens, 1999).

Sources of data for land cover change detection studies vary in spectral, spatial and temporal resolution. When available, high resolution colour aerial photographs are used to detect large-scale (local) changes, or more frequently, for assessing accuracy of small-scale (regional) changes identified from lower resolution satellite data. The effectiveness of satellite data for detecting different types of forest changes depends to a large extent upon the spatial resolution of the satellite sensor which can range from 10m (SPOT panchromatic) to 1km (NOAA AVHRR) (Michener, 1996). For example, SPOT VGT (1km resolution) and NOAA AVHRR (1km resolution) were used to detect large-scale forest cover change in Canada (Fraser et al., 2005), SPOT XS (20m resolution) was used to study forest regeneration dynamics of tropical forests of the Central African Republic (De Wasseige and Defourny, 2004) and, Landsat TM (30m resolution) and Landsat MSS (80m resolution) were used to detect land use and land cover dynamics in the Ecuadorian Amazon (Messina and Walsh, 2001).

Various analytical approaches differing in complexity, computational intensity and ease of interpretation have been employed in change detection studies. Some of the most common methods are post classification change detection differencing, spectra-temporal change, data transformation (Normalised Difference Vegetation Index (NDVI) and image differencing (Michener, 1996).

Observations derived from land cover change detection processes can then be used to develop spatially-related statistical models. These models can be used to predict where land cover changes may occur next. Such predictive information is essential to support the implementation of appropriate policy responses to, for example land degradation that may lead to the loss of important resources. Models are built to describe the relationship between the response variable e.g. forest cover change and the explanatory variable. Multivariate analysis is used to determine the variables most closely associated in space with the response variable (Mertens, 1999).

A widely used statistical method in modelling probability is logistic regression analysis Hosmer and Lemeshow, 1989; Collet, 1991 cited by (Jalkanen and Mattila, 2000). Use of logistic regression is common, for example, in epidemiological studies Breslow and Day, 1980; Kleinbaum et al., 1982, cited by (Jalkanen and Mattila, 2000).Logistic regression models (LRMs) have also been used in natural resources and landscape ecology research, and in addition have been reported to provide better fitting models for various ecological phenomena Morrison et al., 1998 cited by (Hashimoto et al., 2005).

In land cover change studies LRMs have been used to predict deforestation in Carrasco Province, Bolivia (van Gils and Loza, 2005), to analyse landscape dynamics of Liukuei ecosystem management area, Taiwan (Hsu and Cheng, 2000) and to predict the probability of native Grassland destruction and degradation in Australia (Williams et al., 2005). LRMs typically seek to provide the user with a statistical relationship between the response and a series or explanatory variables for use in predicting the probability of vegetation cover changes, species occurrence or estimating numbers of an organism at new locations (Guisan et al., 2002).

Majella National Park (NP) in Italy, covers an area rich in biological diversity .The park hosts 45% and 36% of the animal and plant species respectively, present in Italy (Majella National Park, 2005). Over the past years the NP has experienced increases in forest cover, as is the case for Italy as a whole (FAO, 2001). This has lead to a reduction in mountain pasture and farmland and an increase in biomass per hectare (Colletti and Venzi, 1999). The change of mountain landscape into forest is a trend that is occurring over large areas of Mediterrrenean Europe (Debussche et al., 1999) and is considered evidence of a series of socio-economic changes that are typical of this territory linking to the exodus (Nicolini et al., 2002) of rural residents from these areas, particularly after world war II.

This study focuses on the expansion of Beech (*Fagus Sylvatica*) in the central portion of Majella National Park. Because of its longevity, widespread distribution and climatic sensitivity, Beech is considered the most promising species for biological monitoring on the status of European temperate forests (Piovesan et al., 2005). This species is of importance to the ecology of the NP, providing food in the form of masts/nuts to many wild ungulates such as Wild boar, Roe and Red deer which in turn are preyed upon by wolves and bears (wildlife species of great touristic value to the NP). Because of their closed canopy and homogenous nature, Peters 1997 cited by (Ke, 1999), the expansion of Beech species in Majella NP also poses a possible risk to lower herbaceous plant (shade-intolerant) species found in the Park.

(Fabbio, 2003) in a study on silvicultural management and biodiversity in Europe states that in general information on biodiversity on the continent is lacking. Limited amounts of data in Mediterranean landscapes (Mouillot et al., 2005) and incomplete knowledge on the state of biodiversity and of pressures and trends affecting biodiversity handicap protection efforts in many European countries. Therefore good data and appropriate indictors are necessary to assist policy making and monitoring, to understand the causes of changes in biodiversity and to better implement protection strategies. Furthermore, indicators are needed to monitor the developments in protected areas (Puumalainen et al., 2003).

Quantifying the ongoing land cover changes and, further understanding the process of Beech expansion and its association with both physical and socio-economic factors through LRMs, could help fill information gaps, increase knowledge on the state of biological resources and provide future forecasts of Beech expansion in Majella NP. This information could further be of importance to planners and decision-makers for exploring management options and developing monitoring and protection strategies for the NP.

This study aims to determine and quantify the changes in land cover in the central portion of Majella NP from 1987 to 2003 and further focuses on Beech expansion with a view to model this process using a combined LRM.

1.2. Research problem and justification

Limiting amounts of data and incomplete knowledge on the state of biodiversity and pressures and trends affecting it handicap protection efforts in Europe (Puumalainen et al., 2003). The landscape changes currently occurring in Italy (Majella NP) and the Mediterranean as a whole may have both biological and ecological consequences (e.g. spread of woodland species (forest expansion), threat against open habitat species, fires regimes modification (Debussche et al., 1999). With regards to the expansion of forest , this to a certain extent is also viewed as a threat by the (UNECE, 2000) which recognizes the homogenous nature of some of the European tree species e.g. Beech and how this impacts negatively on forest diversity.

Italy as a signatory to the Convention of Biological Diversity (CBD) is obliged to conserve and sustainably use biodiversity in the country. Majella NP by virtue of being a designated protected area takes up this responsibly.

To address the potential effects on biodiversity that land cover changes may cause, particularly Beech expansion, authorities of the Majella NP require more than expert judgment. Quantifying the ongoing land cover changes and, further understanding the process of Beech expansion and its association with both physical and socio-economic factors, could help update and fill information gaps, increase knowledge on the state of biological resources and provide evidence on the process and factors influencing it.

The application of change detection methods will provide for quantitative data on land cover dynamics quickly and cost effectively in the study area. The use of LRMs in predicting Beech expansion, if found to be successful could be adopted as a management tool, to help understand and monitor Beech forest expansion. This knowledge could further be incorporated into the local planning, management and protection of biodiversity in Maiellla NP.

1.3. Research objective

1.3.1. General objective

- To detect and quantify land cover and land cover changes between 1987 and 2003 with a focus on Beech expansion and, further analyse the physical and social factors/variables that influence Beech expansion in the central portion of Majella NP.

1.3.2. Specific objectives

- To determine and quantify the land cover and land cover changes between 1987 and 2003.
- To determine the increase in Beech between 1987 and 2003.
- To determine the average rate in Beech expansion between 1987 and 2003.
- To establish the explanatory variables that are significantly associated with Beech expansion.
- To determine the linkages between each explanatory variable with Beech expansion.
- To predict the probability of Beech expansion using a LRM of change.

1.4. Research questions

- What are the land cover changes between 1987 and 2003?
- What areas does each land cover type and land cover change occupy?
- What is the increase in of Beech between 1987 and 2003?
- What is the average rate of Beech expansion between 1987 and 2003?
- Which explanatory variables are associated to Beech expansion?
- Which explanatory variables are significant predictors of Beech expansion?
- Can a good prediction of the probability of Beech expansion be made from the significant predictors using a combined LRM of change?

1.5. Hypotheses

Hypothesis 1

H_o: The distribution of areas that convert to Beech is the same for small, medium and large land parcels.

H_a: The distribution of areas that convert to Beech is different for small, medium and large land parcels.

Hypothesis 2

H_o: The distribution of areas that convert to Beech is the same for different soil types.

H_a: The distribution of areas that convert to Beech is different for different soil types.

Hypothesis 3

H_o: The distribution of areas that convert to Beech does not differ with differences in elevation.

H_a: The distribution of areas that convert to Beech differs with differences in elevation.

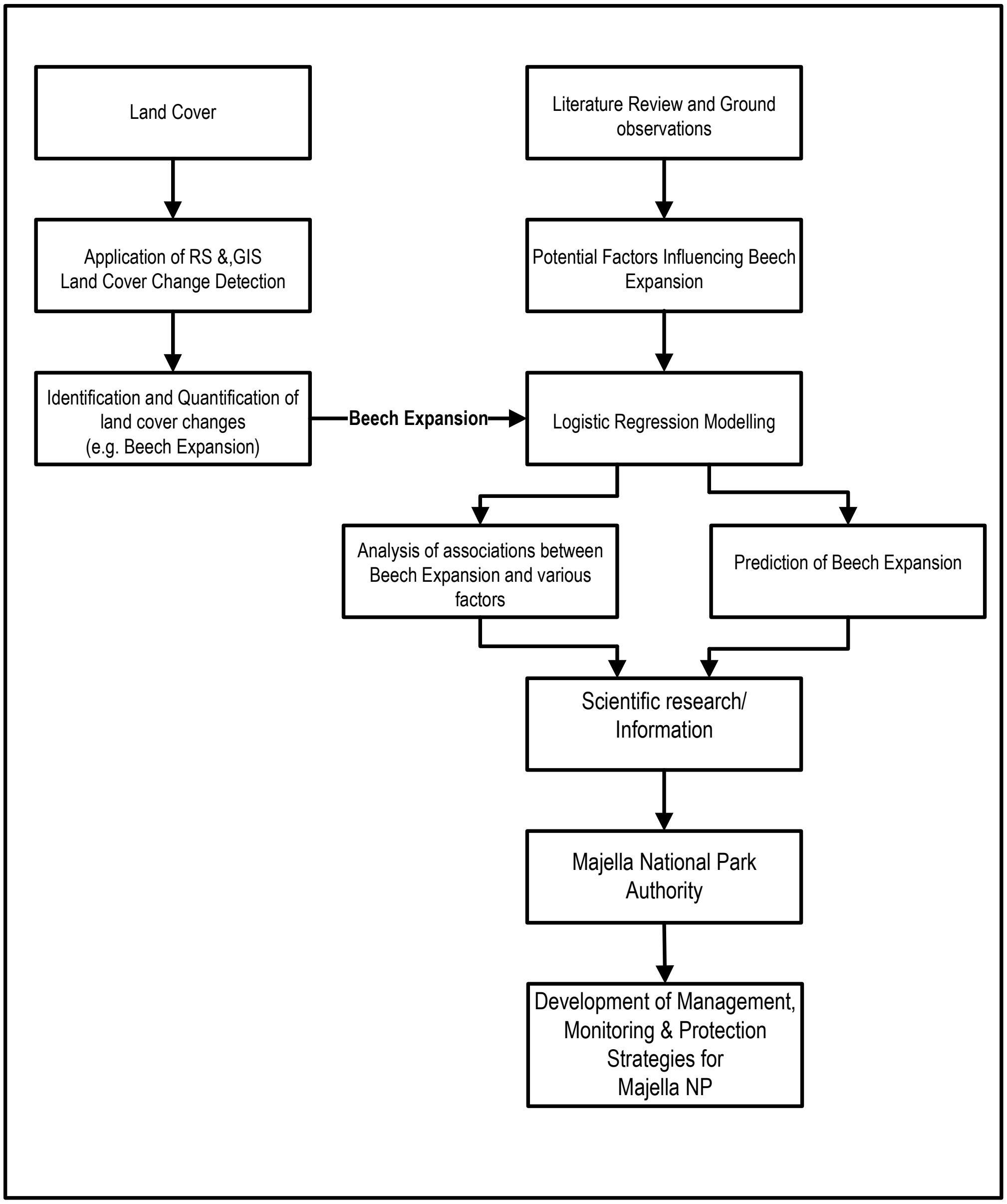


Figure 1-1: Conceptual Framework of Research (Adapted from Phong, 2004).

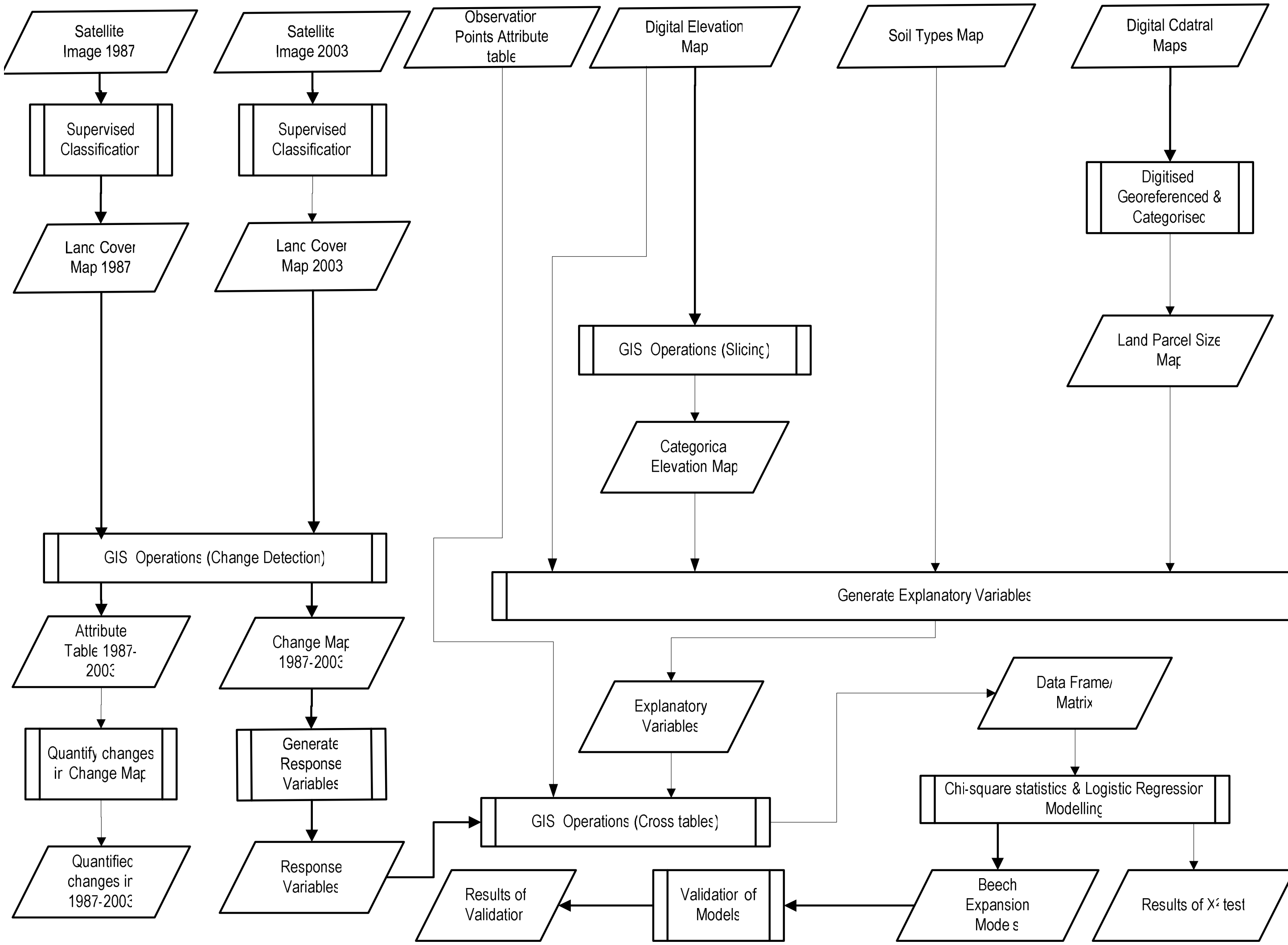


Figure 1-2: Research Approach Flowchart

2. Definitions and Concepts

2.1 Definitions

Afforestation: Afforestation is the establishment of trees/forests by natural succession or planting on an area that has lacked forest cover for a very long time or has never been forested (Ministry of Forests and Range British colombia, 2006).

Beech expansion: The (UNECE, 2000) defines forest expansion as the afforestation or conversion of other wooded land to forest. This study adopts this definition for Beech expansion.

Climax community: A climax community is a relatively stable plant community that is perpetuated through adequate reproduction under prevailing environmental conditions.

Land cover: Land cover is the observed (bio) physical cover on the Earth's surface (FAO, 2001).

Variable: A variable is any characteristic of an individual. A variable can take different values for different individuals (Moore and McCabe, 1998).

Response variable: A response variable measures an outcome of a study.

Explanatory variable: An explanatory variable explains or causes changes in the response variable.

2.2 History of Forests in Italy

The barbarian invasions of the 3rd, 4th and 5th century AD caused the abandonment of large fertile areas previously cultivated by the Romans; leading to a succession of forests taking over of these areas. In addition feudal lords valued these woodlands as hunting preserves creating a favorable environment for their sustainability. With the passage of centuries this favorable conditions were modified due to the repeated division of land, progressive restriction of rights of feudal lords and increasing population. This necessitated the replacement of vast forests by agricultural fields, though some forests on monastic lands survived encroachment.

In the small urban centres that began to take shape about the 11th century AD, the importance of forest production as well as the defenses they provided against avalanches and landslides, was recognised in municipal ordinances. Even so war and other abuses brought enormous destruction.

Increasing population, lack of adequate regulation and the abolition of feudal rights in the Kingdom of Naples at the beginning of the 19th century AD, contributed towards the further reduction of forest area in Italy and when the country was united as a Kingdom (1870) it faced an extremely serious forest situation .

Currently in Italy, like in other European countries, particularly after world war II this trend has reversed and what is being observed now is an increase in forested areas (Nicolini et al., 2002).

2.3 Beech forest

Beech forest (*Fagus sylvatica*) represents the most important forest community in natural forested landscapes in Europe, (Peter, 1996 cited by (Oheimb, 2005). Beech stands in Europe have commonly been managed following high-forest silvicultural systems so that stands with trees older than a century are not uncommon over the landscape, Dittmar et al., 2003 cited by (Poivesan, 2005).

Beech trees are broad-leaved and deciduous in nature i.e. their leaves fall off or shed seasonally to avoid adverse weather conditions or drought. Beech trees can grow to heights of 40m (Archibold, 1995) with a spread of 20m. They are dominant species, long-lived and have a competitive vigor that is not matched by any other deciduous tree species in Europe (Ulrich and Rohrig, 1991). In addition Beech trees are considered to be shade or deep shade-tolerant often occurring as canopy trees in moist habitats Watt 1923, Baker 1950, Nakashizuka & Numata 1982, Hara 1987, Canham 1988,1990, Cao 1995, Grubb et al.,1996, Peters 1997, cited by (Ke, 1999). In Europe, Beech often alone dominates the forests with little or no undergrowth, or co-dominates in mixed forests with *Abies alba*, *Picea abies*, *Quercus petraea* and *Quercus robur* Peters 1997 cited by (Ke, 1999). Because of its dominant nature Beech has been known to replace Oaks on well-drained loamy soils, but due to clearing in the past for agriculture this species is generally limited to chalk and limestone areas in certain parts of Europe (Archibold, 1995).

Italian Beech forests are present over several phytoclimatic regions, from the Mediterranean region, at the southern latitudinal limit of species, to the beginning of boreal forests Pignatti, 1998 cited by (Poivesan, 2005).Beech forests and deciduous oak woodlands together make up ~30% of the total area of land occupied by broad-leaved species in Italy (M'Hirit, 1999).

Beech forests in the study area range from elevations of 1000m to 1800m, with a mean height of 13m (Poivesan, 2005),for the whole of Majella NP Beech forests range from 900m to 1900m (Ponziani, Personal Communication). Beech forests are exploited for firewood, timber, mushrooms, hunting, recreation and grazing. Ecologically they are used for water management and form an important link in ecological food chains e.g. wild boars (*Sus scrofa*) (Appendix I) in general depend on energy (carbohydrate and fat) rich foods such as Beech and oak masts/nuts which promote reproduction and maintenance of good physical conditions in these species (Massei, 1996). Other wild ungulates such as Red and Roe Deer also feed on Beech and oak masts. These in turn are preyed upon by bears (*Ursus arctos marsicanus*) and wolves (*Canis lupus*) (Appendix II), which are protected animals species in Italy and are of high touristic value to Maiella NP. Wolves particularly prey intensively on the young ungulates of Roe deer, Red deer and wild boar (Mattioli, 2004). In addition Beech forests form suitable habitats for bears in the study area.

2.3.1 Beech expansion

(FAO, 2001), forest statistic show that from 1990 to 2000 Italian forest cover increased from 9.708, 000ha to 10,003,000 ha at an average rate of 0.3%/year. Data on the percentage of the total increase in Beech forest only was not available. None the less reports refer to the fact that their have been increases in forest cover and most of which are occurring in the rural mountain areas of Italy, particularly areas that have experienced a large rural exodus, leading to a reduction in agricultural activities, with a great loss of areas of mountain pasture and farmland (Colletti and Venzi, 1999).

2.4 Land abandonment

A phenomenon that is closely linked with land abandonment is spontaneous afforestation (Hunziker, 1995). Most often former mosaics of forests and farmland end up wholly in forest Hladnik, 2005 cited by (Kobler, 2005). Marginalisation of agriculture and spontaneous afforestation of abandoned land due to structural, demographic and social reasons are pressing issues in several regions of the EU. Often farmers cease to use land because of high costs due to remoteness, difficult access, land of poor quality, steep slopes or high labor requirements, or whether farmers' age and health prohibit use of land further from the homestead (Kobler, 2005). According to (MacDonald et al., 2000) agricultural land abandonment reflects a post war trend in western and southern Europe of rural depopulation to which isolated and poorer areas are most vulnerable. Italy is no exception to this problem, as a result of the inadequacy of incomes, the limited availability of services, many rural residents have been abandoning the mountainous areas since the 1960's (Nicolini et al., 2002).

Majella NP has two major aspects integrated into it, agriculture and conservation. The average farm size ranges from 3 - 21ha (Hunziker, 1995). In certain portions of Majella NP agricultural activities have stopped and previously cultivated lands lay abandoned and over grown with grass, shrub or trees. For this study it is assumed that all land parcels of 3 - 21ha in size are abandoned farm plots/parcels and because of the link associated with land abandonment and afforestation, land parcel size is considered as one of the potential explanatory variables that can predict Beech expansion. In a similar way (Kobler, 2005) used proportions of sizes of abandoned farms in order to model spontaneous afforestation.

2.5 Succession theory

Succession has often been narrowly defined as the change in species composition of a community through time. More broadly, it is the change in both composition of a community and structure (van der Maarel, 2004). Disturbance from fire and other natural factors, such as disease and hurricanes, periodically alters the nature of plant cover in an area. The development of plant cover is controlled by the competitive interactions of the species and their effect on the environment. (Archibold, 1995). Each change over time may be presented as a transition from one state to another over a time interval, each transition occurs within a certain probability (Ricklefs, 1990).

Table 2-1: General characteristics of plants associated with early and late succession stages (adapted from Ricklefs (1990)).

	Early succession	**Late succession**
Adult longevity	short-lived	long-lived
Growth rate	rapid	slow
Size at maturity	small	large
Root: shoot ratio	low	high
Shade tolerance	low	high
Number of seeds	many	few
Seed size	small	large
Seed viability	long	short
Seed dispersal	long distance	short distance

Table 2-1 illustrates the general characteristics of plants associated with the early and late stages of succession. As mentioned earlier Beech trees are generally long-lived, have slow growth rates, are Receiverly large in size, growing to heights of over 20m and there saplings have a high shade tolerance. These and other factors characterise Beech trees as late successional tree species (Oheimb, 2005).

Generally in Majella NP what is observed in mid elevation zones is a gradual encroachment of shrubby species over grassland and/or herb occupied areas followed by the establishment of a few tree species at sapling or scrub level. These young tree species lead towards young woodlands with a few patches of grass and shrub, which further extend towards more mature single species forests. The stress caused by late successional species is quite evident in Beech succession processes. Shrub such as *Juniperus communis* experience loss of leaves and discolouring when located under the canopies of Beech trees.

2.6 Image Classification

Digital image classification is the process of assigning pixels to classes. In most cases each pixel is treated as an individual unit composed of values in several spectral bands. By comparing pixels to each other and to pixels of known identity, it is possible to assemble groups of similar pixels into classes that match an informational category of interest to the user (Jenson, 1996). There are basically two types of image classification methods. These are unsupervised and supervised methods (Bakker et al., 1999). In this study the supervised classification method is applied.

2.6.1 Supervised classification

One of the main steps in image classification is the 'partitioning' of the feature space. In a supervised classification this is realised by an operator who defines the spectral characteristics of the classes by identifying sample areas (training areas). Supervised classification requires that the operator be familiar with the area of interest. The operator is required to know where to find the classes of interest in the area covered by the image. This information can be derived from ‘general area knowledge’ or from field observations (Bakker et al., 1999).

2.6.2 Classification accuracy

The final stage in images classification is the validation of the classification. The most common approach to the assessment of classification accuracy is to check the classification against “Ground truth” collected at sample points on the ground. The resulting data are organised in a confusion or error matrix from which the overall accuracy and the accuracy of individual classes can be calculated. In terms of the proportion correctly classified (PCC) sample points.

The overall accuracy is computed by dividing the sum of all correctly classified points by the total number of sample points. The PCC for a particular class is calculated by dividing the number of correctly classified points in that class by the number of points in the reference data. The resulting value is a measure of the omission error. A similar calculation resulting in the error of commission is calculated by dividing the total number of incorrectly classified points for that class by the number of points in the image interpretation.

Omission and commission errors are also known, respectively as “producer’s accuracy” and “user’s accuracy”. The producer’s accuracy indicates the risk that the work has to be repeated to meet user’s requirements. The user’s accuracy assesses the probability that a class shown at a point on the map or classified image actually indicates what is present on the Ground.

2.7 Change Detection

Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times. Essentially, it involves the ability to quantify temporal effects using multi-temporal data sets (Singh, 1989). Many change detection methods have been developed for various applications such in natural resources and environmental monitoring. For this study the post-classification change detection method is be applied.

2.7.1 Post-classification change detection method

The Post-classification is among the most widely applied techniques for change detection and involves firstly the classification of two multi-temporal images taken at different dates. The maps are then overlaid in a GIS environment and the categories of change and the areas they cover are extracted through the direct comparison of the classification results.

2.8 Pearson's Chi-squared test

The chi-squared test was invented by the English statistician Karl Pearson in 1900. It is the oldest inference procedure still used in its original form (Moore and McCabe, 1998). It is a useful statistical tool for testing null hypotheses i.e. It gives evidence against the same in order to prove the alternative hypothesis true. The chi-squared test is a measure of how much observed cell counts in a two way table diverge from the expected cell counts. The formula for the test is

$$\boxed{X^2 = \frac{\sum(\text{observed count} - \text{expected count})^2}{\text{expected count}}} \tag{1}$$

2.9 Logistic regression model

A wide range of land use and land cover models have been developed. They include the logistic regression model, dynamic systems model, spatial simulation model and linear planning model (Kobler, 2005).

The logistic regression model is applied to response variables with only two possible outcomes. When using this model we think in terms of a binomial model for the two possible values of the response variable and use one or more explanatory variables to explain the probability of success. Logistic regression works with odds rather than proportions, which is the ratio of proportions for the two possible outcomes. The odds are transformed using the natural logarithm resulting in what is called the log-odds. The log-odds is modelled as a linear function of the explanatory variable/s (Moore and McCabe, 1998):

$$\boxed{\nu = \log\frac{\rho}{1-\rho} = \beta_0 + \sum(\beta_i * X_i)} \tag{2}$$

Where ν is the linear predictor, ρ is the binomial proportion, X_i (i=1… ρ) is the explanatory variable, β_0 and β_i are the parameters of the model.

The logit link function transforms the linear predictor into fitted probabilities.

$$\boxed{\rho = \frac{\exp(\nu)}{1+\exp(\nu)}} \tag{3}$$

2.9.1 Model Evaluation

To evaluate a logistic regression model as advised by (Menard, 1995) three things must be examined:

- The relationships/associations between explanatory and response variables.
- How well the overall model works (with all the significant variables).
- Which variables contribute more to the prediction of the response variables?

The model can then be validated. The ROC (Receiver Operation Characteristics) curve is a known technique that is used to validate models so as to predict the accuracy of the model. In land cover change models the ROC curve validates a model's ability to specify location, while maintaining the freedom from committing to a specific quantity of change (Pontius, 2001). The ROC produces a quantitative measure that may be translated into a grading system on a 0 to 1 scale (Rossiter and Loza, 2005).

ROC < 0.6 = poor model
0.6 – 0.7 = pass
0.7 – 0.8 = good model
0.8 – 0.9 = very good model
0.9 =< ROC= excellent model

The ROC curve is plot of the sensitivity (proportion of true positives) of the model prediction against the complement of its specificity (proportion of false positives), at a series of thresholds for a positive outcome. The ROC curve can be summarised by the area under the curve (the quantitative measure), computed by the trapezoidal rule (Rossiter and Loza, 2005):

$$\boxed{A = \sum \left[(x_{i+1} - x_i) * \left(\frac{y_{i+1} + y_i}{2}\right) \right]} \qquad (4)$$

Where i are the thresholds where the curve is computed.

3. Methods and Materials

3.1. Study area

Majella NP is located in the Abruzzo region of Italy (figure 3-1) east of the Italian capital, Rome. It is approximately 74,095 ha in size and is made up of a combination of 3 provinces, Pescara, Aquila and Chieti. The park was established in 1991 and consists of 6 mountain communities, Peligna, Alto Sangro and Altopiano delle Cinquemiglia, Majella and Morrone, Majelletta, Aventino-Medio Sangro, and Medio-Sangro.

The study area is located within the confines of Majella NP in the municipalities of Sant’Eufemia and Pacentro. It covers an area of approximately 5,316ha (7% of the total park area). The geographic location of the study area is 42°07’59”N, 13°59’40”E and 42° 08’01”N, 14°04’58”E and it is within the Orta valley.

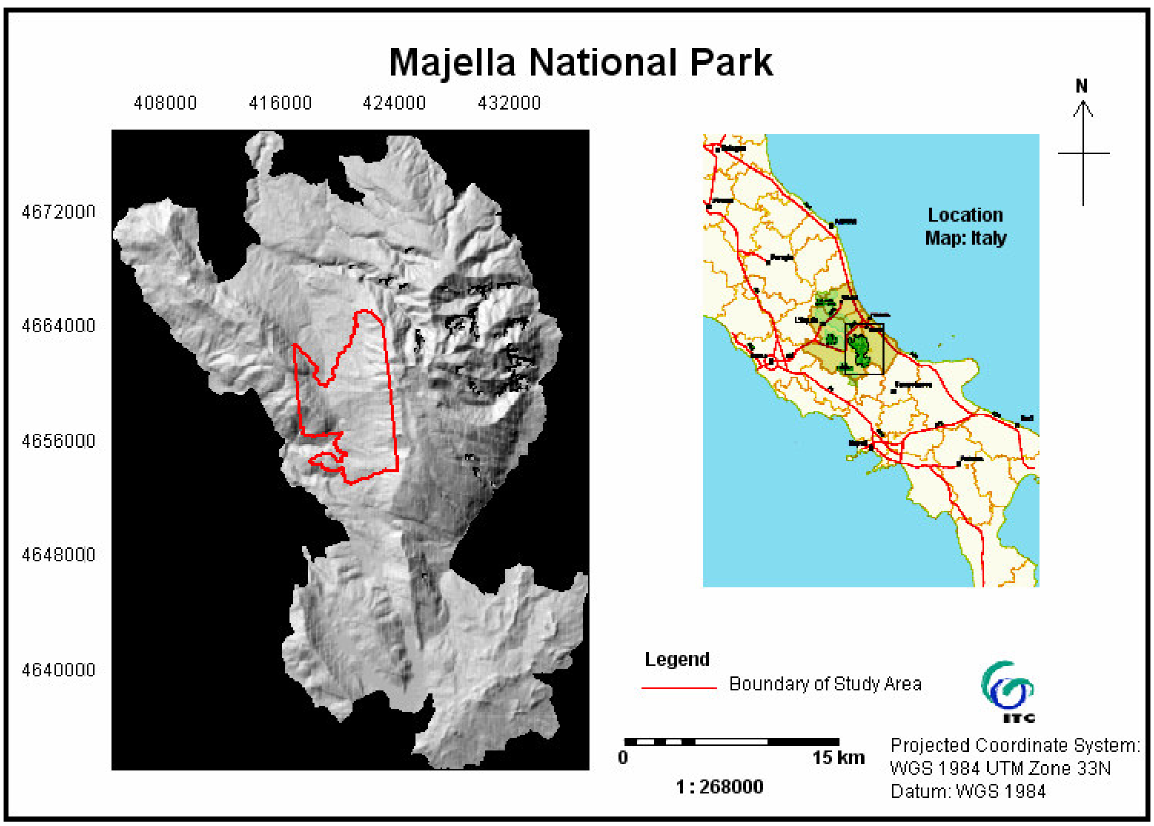


Figure 3-1: Location Map of Study area within the Majella NP (Adapted from the Majella NP Website, 2005)

3.1.1. Climate

Majella NP is located a few kilometres from the Adriatic Sea and for this reason experiences a warm temperate Mediterranean climate which is generally characterised by mild, wet winters and dry summers.

3.1.2. Landscape

The landscape of Majella NP is mountainous characterised by deep valleys and canyons. The area has more than 60 mountain peaks of which 30 are 2000m in height above mean sea level. The highest peak being that of Mount Amaro which is at 2793 m mean sea level (Majella National Park, 2005).

The studyarea is covered by grasslands, forests and woodlands. The Garrigue and Marquis are found at the lower eastern border of Majella NP. The former which consists of scattered bushes, bare patches of rock outcrops, bare soil, stony ground and grasses and the latter which consists of shrub populations and low tree cover (Wamunyima, 2005). The main forest types in the area are of a deciduous temperate nature.

Figure 3-2: Photograph of portion of study area taken at the end of the summer season shifting towards autumn as shown by the yellowing of the Beech. In the backGround is the Majella, mountain September 2005.

3.1.3. Vegetation

There are various vegetation types distributed within Majella NP. In zones of the park where land was previously cultivated and has since been abandoned Grassy and Shrubby vegetation can be observed. The dominant species being *Brachypodium pinnatum*, *Juniperus communis* and *Prunus spinosa.* These areas may be occasionally grazed (Ponziani, Personal Communication).

Riparian vegetation can be found along water bodies in the lower zones of the NP, characterised by *Populus* and *Salix sp*. At foot slopes and within canyons of the park at altitudes of between 300m to 900m-1000m (Conti, 1998) mixed forest dominated by *Quercus* sp. such as *Quercus pubescens* and *Quercus cerris* are present. Other less dominant trees species present in this zone are *Fraxinus ornus*, *Acer campestre, Acer opalus*, and *Ostrya carpinifoilia* (Majella National Park, 2005).

Extending between 900m and 1900m are Beech (*Fagus sylvatica*) forests (figure 3-3) forming extensive woods of almost pure formation associated with limestone enriched soils (Ponziani, Personal Communication) Beech (*Fagus sylvatica*) is the dominant tree in the study area. The Beech forests consist of Beech trees of which some are coppiced. Associated with the Beech forests are *Acer opalus*, *Acer pseudoplatanus*, *Taxus baccata*, *Ilex aquifolium*.

Above 1800m are *Pinus mugos* coniferous shrubland that extends towards the upper (sub-alpine) Grasslands. The *Pinus mugos* stretch up in strips colonising poor soils and associated to them are *Silene pusilla, Hieracium prenanthoides* and *Hieracuim villosum*. In addition the Majella NP also has forest plantations consisting *Pinus nigra* and *Abies sp.* (Ponziani, Personal Communication).

As for herbaceous plant species the study area is host to a large number of which some are endemic such as; the Rock Artemisia (*Artemesia eriantha* Ten.) endemic to the Apennines and Maritime Alps, the Abruzzo ciombolino (*Cymbalaria pallida* Wettst.), endemic to the Abruzzo region and the Neapolitan Bellflower (*Campanula fragilis Cyr.*), endemic to the Abruzzo region (Majella National Park, 2005).

Figure 3-3: A) The peripheral of a non-coppiced Beech forest in Majella NP, (B) The interior of a non-coppiced Beech Forest in Majella NP (September 2005)

3.1.4. Land Tenure

The study area is made up of three major land tenure regimes i.e. Stateland, Municipal (communal) Land and Private Holdings. State and Municipal Land may be leased out for agricultural purposes.

Stateland is partly managed by the Italian Forestry Services. Within the Private Holdings there are further distinctions i.e. Small Peasant Holdings, Baronial Estates and Church estates. The small peasant holdings are fragmented to the level that individual holdings are below viable farm size.

3.1.5. Management Zones

Majella NP is divided into 3 Management Zones (Appendix III) as follows:

Zone A: Intergral Reserve (Reserva Integrale)
This zone forms parts of the park that are of ecological and tourist importance such as forested areas, mountain peaks and water systems etc.

Zone B: Area of general activities (Riserva generale orientate)
This zone forms the bulk of the areas designated for socio-economic activities such as farming and grazing, etc.

Zone C: Protected Area (Area di Protectezione)
This zone acts as a protective buffer to the integral reserve.

3.1.6. Population

As was mentioned earlier the study area embraces two municipalities Sant'Eufemia a Majella and Pancentro. These municipalities, like the rest of Majella NP, have experienced a negative population trend, mainly due to rural-urban migration accelerated after the end of the second world war (Barbero, 1990). Figure 3-4 below gives population estimates for the Pacentro and Sant'Eufemia a Majella from 1951 to 1997 (Source: Majella NP Authority, 2005).

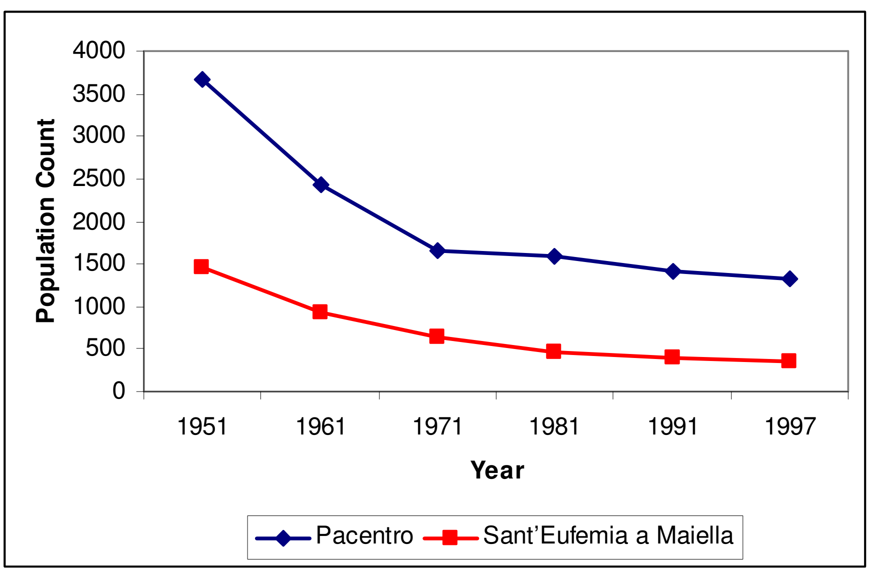


Figure 3-4: Line graph showing population trends per municipality (1951-1997)

3.2. Materials Used

Table 3-1 Digital data that was available for the study

Data	Source
Digital Cadastral Maps of Sant'eufemia a Majella and Pacentro Municipalities	Sant'eufemia a Majella Municipal Council
Digital Elevation Map of Majella NP	ITC BioFRAG Project
Digital Soil Map of Majella NP	Majella NP Authority
Multi-spectral satellite Images Aster June 2001, Landsat 5TM August 1987 and 7TM August 2003	ITC
Orthophotos 2000 of Majella NP	Italian National Cadastral Office

3.2.1. Satellite Image Pre-processing

In the satellite image pre-processing stage the Landsat 5 TM (1987) and Landsat 7 TM (2003) images were georeferenced to the coordinate system of the Aster 2001 image (WGS84, UTM projection, zone 33 north). The georeferencing was carried out using the image to image co-registration method in ERDAS version 8.7 RS/GIS software. The satellite images were also resampled to a common resolution (34m). These steps were taken in preparation for the supervised classification which was also carried out in ERDAS.

3.2.2. Sampling

The field work was carried from 3rd September to 3rd October, 2005 and the main objective was to collect data required for training and validation in the classification of the Landsat 7TM (2003) image. In addition to this other data in the form of digital maps and literature related to the study were collected.

To create the observation points for the study area an existing classified image was used as a reference. The existing map had the following classes: Beech forest, Oak woodland, Shrub and Grass land areas. Using ArcGIS version 9, random points were generated from the classified map. The points were then displayed as a point map with an attached attribute table showing the coordinates per given point. Ideally for each randomly selected observation point four other observations were made approximately 30m north, south, west and east of the original point. Due to the harshness of the terrain this was not always possible and hence modifications were made where necessary resulting in 102 observation points.

A GPS was used to locate the observation points and observations made at each point were entered into a data sheet (Appendix IV). The observation points (Appendix V) are shown in figure 3-5 below.

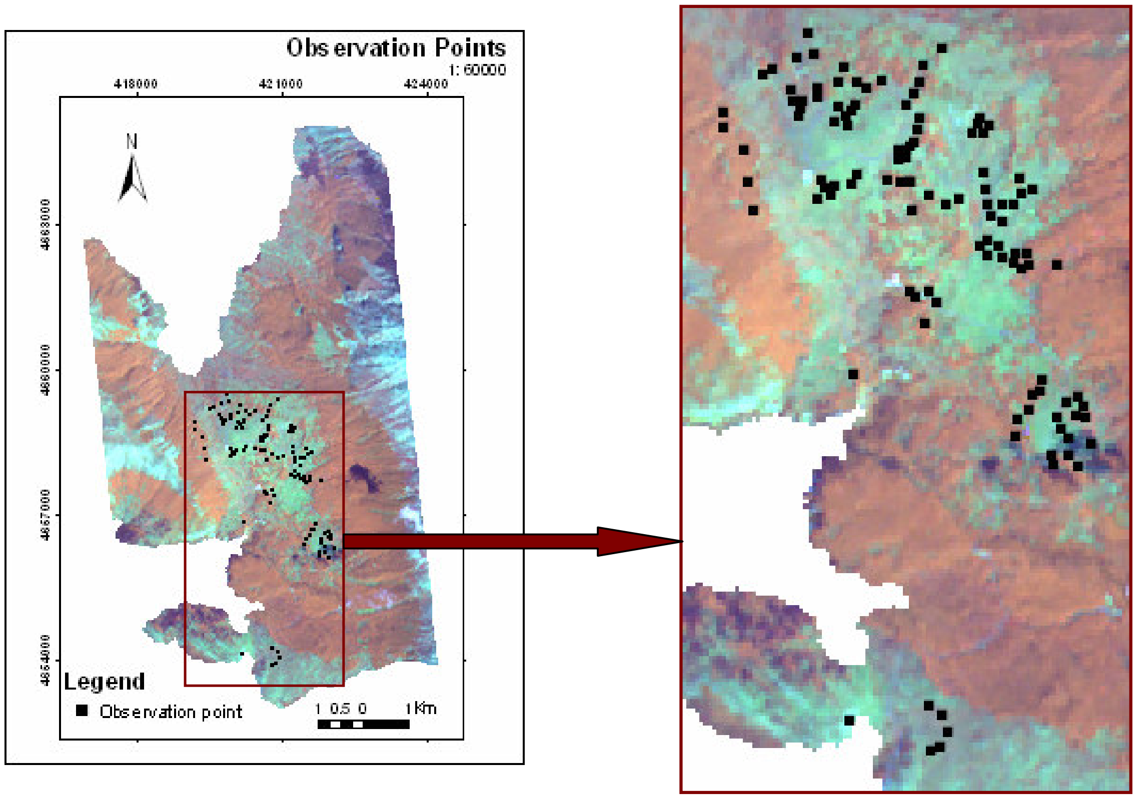


Figure 3-5 Field observation points displayed on Landsat 7TM Image August 2003, RGB (4, 5, 2)

3.2.3. Digital Image Classification

3.2.3.1. Land Cover Classes

For the supervised satellite image classification five cover classes were originally defined and are described below;

Beech: This cover class represents extensive forests of almost exclusively Beech (*Fagus sylvatica*) trees with heights of above 8m, including isolated colonies of Beech trees and Beech scrubs of height of between 4 to 8 m, with crown cover over 40%.

Oak: This cover class represented areas of mature Oak woodland and scrubland dominated by *Quercus pubenscen*, with heights above 3m, and crown cover of over 40%.

Shrub: This cover class represented non-Beech scrub species and Shrub species such as *Juniperus* communis, *Prunus* spinosa and *Pteridium* aquilinum with heights ranging from 1m to 4m and cover above 40%.

Dwarf Pine: This cover class represented *Pinus mugos* coniferous shrub. In the study area these species are found only locally in the north eastern high altitude alpine areas.

Grass: This cover class represented areas of grassland dominated by Festuceti, Xerobrometi, Brachipodieti and Seslerieti (Ponziani, Personal Communication)with cover of over 40%.

Bare Ground: This cover class represented rocky alpine areas and areas of minimal grass cover (< 40%) or completely no grass cover.

3.2.3.2. Supervised Classification Landsat TM satellite images

For the supervised classification the georeferenced Landsat 7 TM (2003) image was used. 51 samples were taken out of the 102 observation made to train the image. Using the signature editor in ERDAS the above mentioned classes were assigned signatures.

The classification was then run using the maximum likelihood classifier. During the classification it became clear that the separation of Oak and Beech classes was not possible, this was also observed in feature space (Appendix VI, figure 8-1). A decision was made to cut out the portion of the images were the oak woodland was prominent.

The separation was done using elevation because it is known that the two tree species are limited to certain elevation belts. The average upper elevation limit for Beech and Oak in Italy is 2000m and 1200m respectively (Pignatti, 1982). Conti 1998 states the upper elevation limit for Oak between 900m and 1000m for the Abruzzo region. A limit of 1000m was set as the highest elevation point observed for Oak in the study area was 946m. Using the 'iff" statement in Ilwis Academic GIS software the image was limited to an elevation of above 1000m.

The 2003 Landsat image was then subjected to a final classification limited to four classes, Beech, Dwarf Pine, Grass, Shrub and Bare Ground. The classified map was then assessed for accuracy in ERDAS using the remaining 51samples from the observations made on the ground. The assessment was run and the results reviewed. The 1987 image was also subjected to a supervised classification but due to lack of field observations for that year was not assessed for accuracy. For better visualisation the two images were filtered using the nearest neighbor filter (Bakker et al., 1999).

3.2.4. Change Detection

To create a map depicting land cover change, particularly conversion to Beech cover over time the post classification change detection method was applied. The classified images representing different points in time were crossed (using the matrix function) in ERDAS resulting in a change map showing the various categories of land cover change that occurred from 1987 to 2003. Using the accompanying cross table the change map was recoded to depict the following classes: Change to Beech, Change to other, No change Beech and No change other. Other representing other cover types such as Shrub, Grass etc. The change map was then imported into Ilwis and rastersized.

3.2.5. Logistic Model of Change

In order to analyse the potential variables (socio-economic and physical) that influence conversion to Beech a logistic model of change was applied using the 'R' programming software package.

To begin with all the explanatory variable maps were created (Appendix VII). The land parcels size map was created in ArcGIS using a digital cadastral dataset of Sant'Eufemia a Majella and Pacentro Municipalities. The land parcels map was catergorised as follows:

Small land parcels	: 3 - 21ha (agricultural land)
Medium land parcels	: 21 - 77ha
Large land parcels	: 77- 300ha

The soil type map was created from an existing digital soil map of the Majella NP. The soil map was clipped to the study area. The different soils were catgorised from A to F. Appendix VIII gives information on the characteristics of each soil type represented in the soil type map.

Two elevation maps were created using a DEM of Majella NP. One map represented the elevation in a quantitatively and the other in a categorically. The quantitative map was used in the logistic model and the categorical map was used in the Chi-squared test. The quantitative map was catergorised as follows:

< 1000m	: Extremely low elevation
1300m – 1400m	: Low elevation
1400m – 1800m	: High elevation
1800m – 2000m	: Very high elevation
2000m <	: Extremely high elevation

A sample point map with 1212 points was also produced in ArcGIS. The sample points were produced randomly and provided for the sample set to be analysed in 'R' programming software. All the created maps were then imported into Ilwis, rastersized and crossed with the change raster map to create a matrix (data frame). The data frame was them imported to 'R' for modelling. Appendix IX displays the programming script created in 'R' and used to model Beech expansion. Table 3-2 gives a summary of the explanatory variables used in the Logistic regression analyses.

Table 3-2: Summary of explanatory variables

Explanatory variable	**Quantitative (Q) or Categorical (C)**	**Socio-economic (S) or Physical (P)**	**Unit**	**Map used to generate the variable**
Elevation	QL & C	P	Metres	DEM
Soil type	C	P	Soil type unit (A to F)	Digital soil map
Land parcel size	C	S	Land parcel size units (small to large)*	Digital cadastral maps

One of the main objectives of the study was to predict the probability that an area (sample point) will convert to Beech cover, meaning that areas where this was impossible had to be excluded from the sample set. Therefore points representing areas that already had established Beech Forest (No change Beech) were excluded from the sample set, leaving .a total of 714 points for the statistical analyses. A general statistical assessment of the data was first made, followed by the Chi-squared test for each explanatory variable to found if they are associated to Beech expansion (response variable). After that the associations between explanatory variables were explored.

The Chi-squared test was used to asses associations between land parcel size and soil type and linear models were used to asses associations between elevation, land parcel size and soil type. Their associations were then visualised with the two way table and Boxplot respectively. After this each variable was modelled separately using logistic regression and the results were plotted for visualisation purposes.

The resulting significant explanatory variables which had a weak association with each other were then modelled together to form a combined logistic model. All the created models were then validated using the ROC method and these results were analysed in order to assess the success of each model in predicting Beech expansion.

4. Results

4.1. Quantifying land cover change

4.1.1. Classification accuracy

Table 4-1 shows the results of the accuracy assessment applied to the classified 2003 Image using the Confusion Matrix:

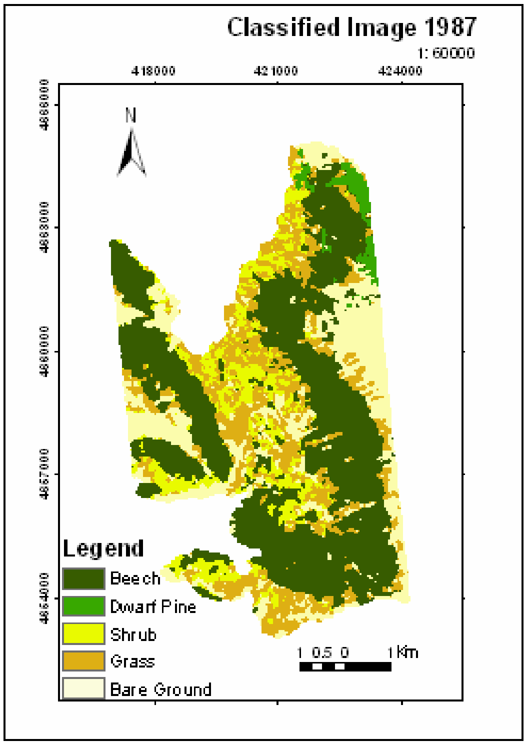
Table 4-1: Confusion Matrix and Kappa Statistics

Cover Class	**Beech**	**Shrub**	**Grass**	**Tota l**	**Error of Commission (%)**	**User Accuracy (%)**
Beech	16	1	0	***17***	5.88	94.12
Shrub	4	12	3	***19***	36.84	63.16
Grass	2	6	7	***15***	53.33	46.67
Total	***22***	***19***	***10***	***51***		
Error of Omission	27.27	36.85	30.00			
Producer Accuracy (%)	72.73	63.15	70.00			
Overall Classification Accuracy (%)	68.63					

As mentioned on page 23, 51 ground observations points were used in the accuracy assessment of the 2003 Landsat TM image. The results produced a user accuracy of about 94% in the Beech class. This was the highest user accuracy recorded. The lowest was recorded in the Grass class (about 47%). This was expected as during signature recognition feature space revealed the inseparability of the Shrub and Grass classes (Appendix IV, figure 19), illustrating that Shrub and Grass in the study area have reflectance values common to both. The overall classification was found to be about 69%.

4.1.2. Classification of Landsat TM Images

Two classified Landsat TM satellite images representing the August 1987 and August 2003 were produced. The classified images were limited to five cover classes and are displayed below (figures 4-1 and 4-2).



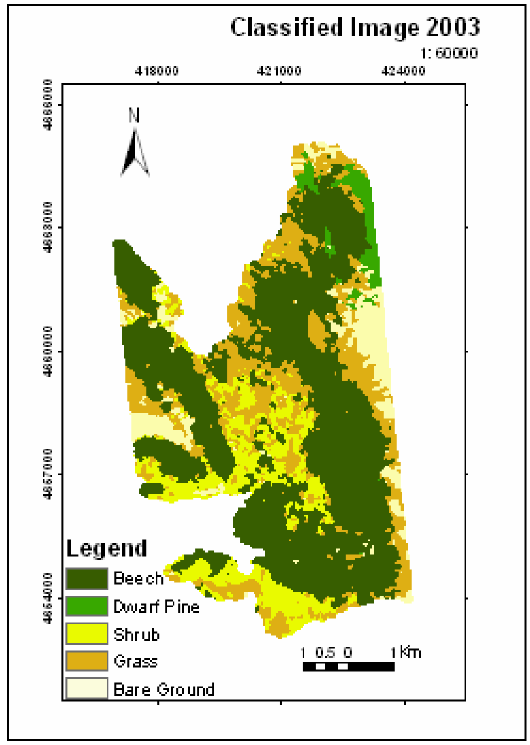


Figure 4-1& 4-2: Classified Landsat TM Satellite Images August 1987 and August 2003. Using supervised classification techniques and general area knowledge

A preliminary visual comparison of the two classified images shows that the areas representing Bare Ground seem to have reduced from 1987 to 2003. This is very visible in the central portion of the study area where almost all the Bare Ground was replaced by either Shrub or Grass in 2003. Turning to the two main Beech belts running across the western and eastern mountain ridges of the study area the reduction or complete closure of gaps was quite evident in both. In addition an expansion of the fringes of the eastern Beech belt was also apparent. This was also true for areas covered with Dwarf Pine. In 1987 the spread of Shrub and Grass seemed more or less even, across the central region of the study area. In 2003 where the majority of the Shrub was concentrated in the central and southern parts of the study area and the Grass was more abundant in the northern parts.

4.1.2.1. Cover Classes in 1987 and 2003

In addition to producing the classified images, the areas occupied by each cover class were quantified and are displayed in Table 4-2 and Figure 4-3 below.

Table 4-2: Area of each cover class for August 1987 and August 2003

Cover Class	1987		2003		Increase ha	Decrease ha	Increase		Decrease	
	ha	%	ha	%			ha/Yr	%	ha/Yr	%
Beech	2375.12	44.67	2729.78	51.34	354.66	-	22.17	0.93	-	-
Dwarf Pine	95.83	1.80	134.10	2.52	38.26	-	2.39	2.50	-	-
Shrub	638.57	12.02	696.02	13.09	57.45	-	3.59	0.56	-	-
Grass	1086.76	20.44	1219.00	22.93	132.25	-	8.27	0.74	-	-
Bare Ground	1120.51	21.07	537.89	10.12	-	674.29	-	-	42.14	3.76
Total	5316.79	100	5316.79	100	582.62	674.29	-	-	-	-

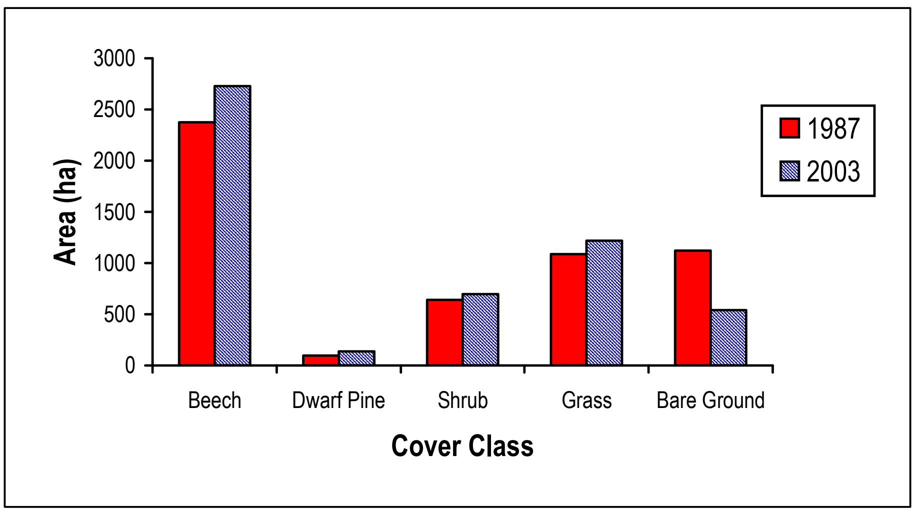


Figure 4-3: Area in of each cover class for August 1987 and August 2003 in chart format

In table 4-2 above the results show that for every cover class except Bare Ground there was an increase from 1987 to 2003 in total area covered by each class. The largest increase was in the Dwarf Pine class where there was an increase of about 40% (refer to figure 4-3 to visualise the increase) at an average rate of about 3ha/year. Beech recorded an increase of about 15% at an average rate of 22ha/year. The remaining cover classes' Shrub and Grass recorded increases below 13%. The lowest increase being that of the Shrub cover class.

The increased cover of the vegetation classes was at the expense of Bare Ground which decreased from about by 60% 21% at and average rate of 42ha/year. These results tally with the preliminary assessment made in the first part of section 4.2.

4.1.2.2. Land cover change for 1987 and 2003

The resulting map below (figure 4-4) illustrates the cover changes that occurred in the study area.

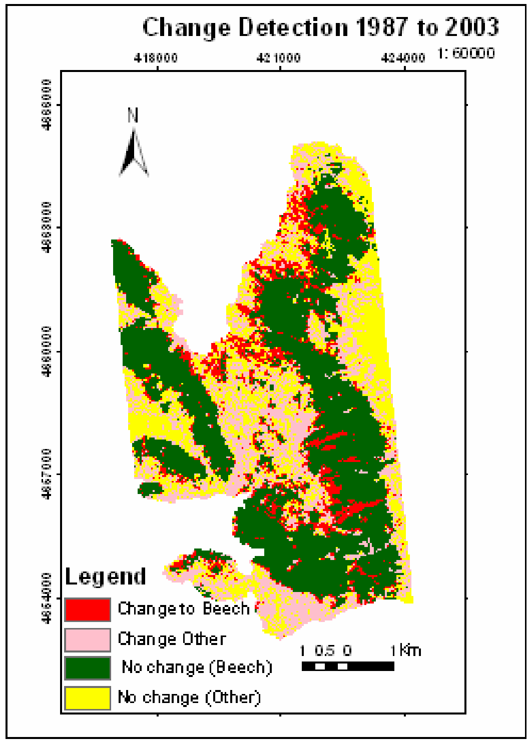


Figure 4-4: Cover Change from August 1987 and August 2003 using the Post-Classification Change Detection Technique.

The changes and non-changes detected revealed the following categories of change shown in table 4-3.

Table 4-3: Cover changes from August 1987 to August 2003.

Category	Cover Changes (1987 to 2003)	Change ha	Change %	Rate of Change ha	Change Class
1	Dwarf Pine to Beech	2.77	0.05	0.17	Change to Beech
2	Shrub to Beech	239.99	4.51	15.00	
3	Grass to Beech	240.33	4.52	15.02	
4	Beech to Dwarf Pine	25.78	0.48	1.61	Change to Other
5	Beech to Shrub	34.33	0.65	2.14	
6	Beech to Grass	51.67	0.97	3.23	
7	Beech to Bare Ground	16.65	0.31	1.04	
8	Dwarf Pine to Grass	2.43	0.05	0.15	
9	Dwarf Pine to or Bare Ground	1.39	0.03	0.09	
10	Shrub to Dwarf Pine	3.93	0.07	0.25	
11	Shrub to Grass	160.11	3.01	10.00	
12	Shrub to Bare Ground	3.01	0.06	0.19	
13	Grass to Dwarf Pine	5.32	0.10	0.33	
14	Grass to Shrub	261.26	4.91	16.33	
15	Grass to Bare Ground	18.61	0.35	1.16	
16	Bare Ground to Dwarf Pine	9.83	0.18	0.61	
17	Bare Ground to Shrub	168.89	3.18	10.56	
18	Bare Ground to Grass	443.56	8.34	27.72	
Total (Change)		1689.86	-	-	-
19	Beech To Beech	2246.69	-	-	No Change (Beech)
20	Dwarf Pine to Dwarf Pine, Shrub to Shrub, Grass to Grass or Bare Ground to Bare Ground	1380.26	-	-	No Change (Other)
Total (No Change)		3626.95	-	-	-

Table 4-3 displays the areas represented by each cover change category. The largest change was from category 18 which resulted in ~444ha of Bare Ground converting to Grass. Other considerably large changes were recorded in category 14, Grass to Shrub (~261ha). Conversion to Beech from other cover types recorded a total area of ~483ha and a total of ~128ha was converted from Beech to other classes. The lowest change was recorded in category 9 where ~1ha of Dwarf Pine converted to Bare Ground. A total of ~2247ha and ~1380ha of Beech and other cover classes respectively remained unchanged.

4.2. Analysing associations of exaplanatory variables with Beech expansion

A total of 714 randomly created sample points were used to analyse the conversion of other cover types to Beech from August 1987 to August 2003, out of these points 204 (~29%) sample points converted to Beech.

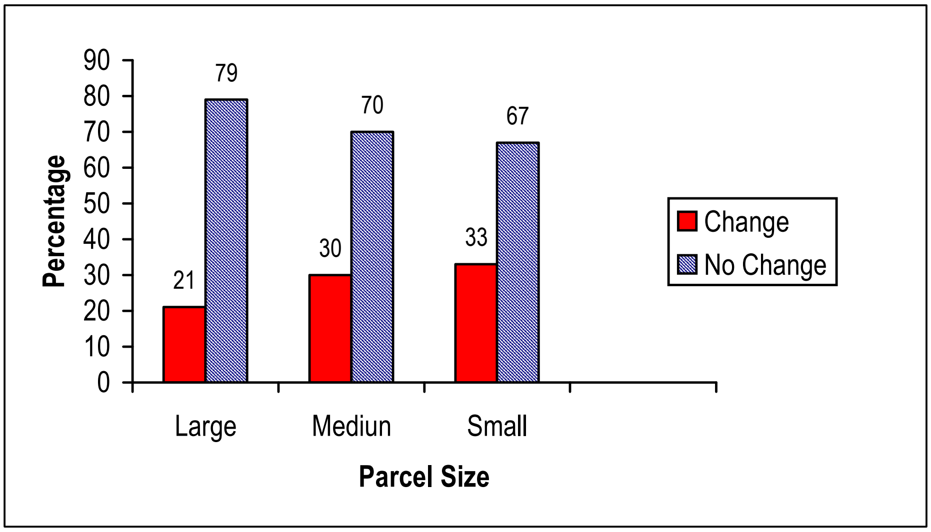


Figure 4-5: Bar graph showing the percentage of sample points per land parcel size that converted to Beech (Change) and did not convert to Beech (No Change).

The cross-classification of Beech change and land parcels in figure 4-5 shows that the number of sample points that did or did not convert to Beech per land parcel size as a percentage. The highest percentage of change (33%) was in the small parcels class and the lowest proportion of change was in the large parcels class (21). It is also observed that the differences in the percentages of sample points that changed are not very wide particularly for medium and small sized land parcels. Therefore it can be said that for some reason or another conversion to Beech happens more often in small and medium sized parcels than large ones. Appendix X, figure 8-3 shows the actual counts of changed and unchanged sample points per land parcel class.

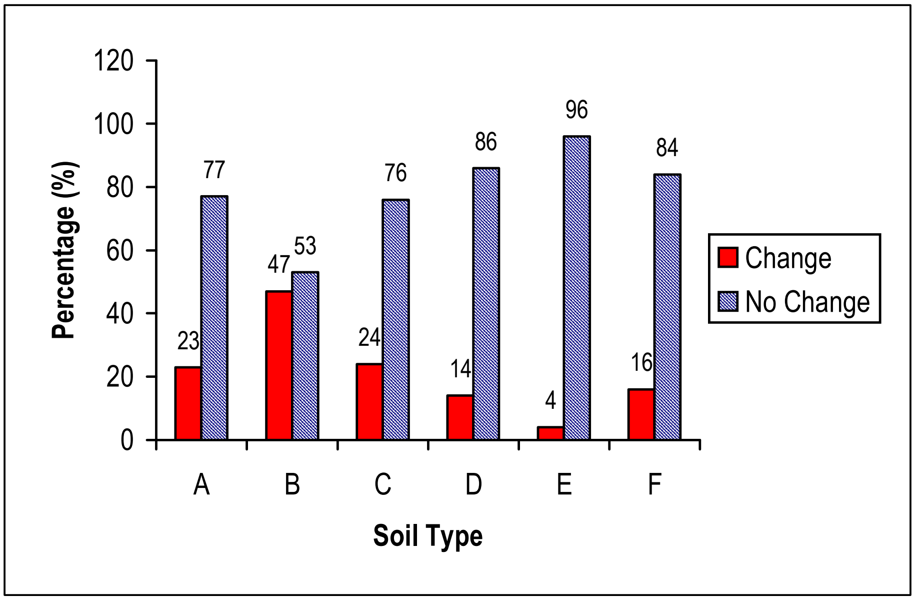


Figure 4-6: Bar graph showing the percentage of sample points per soil type that converted to Beech (Change) and did not convert to Beech (No Change).

The results in figure 4-6 show the different percentages of changed and unchanged sample points for each class of soil type. The highest percentage of change (47%) was in soil type B and the lowest proportion of change (4%) was in soil type E. These results show us that due to some reason conversions to Beech are more likely in soil type B than any of the other soil types. Appendix X, figure 8-4 shows the actual counts of changed and unchanged sample points per soil type.

4.2.1. Pearson's Chi-squared test

The Pearson's Chi-squared test was applied to the explanatory variables (land parcel size, elevation and soil type) and the results are shown in table 4-4 below.

Table 4-4: Summary Chi-square statistics for parcels size, elevation and soil type.

Classified Variable	Degrees of freedom (df)	Chi-square (X^2)	P-value
Parcel Size	2	10.3427	0.005677
Elevation	5	39.9128	1.555e-07
Soil Type	5	75.9667	5.846e-15

The results in table 4-4 show that the categorical variable soil type had a highest Chi-square distribution. These results show that all three variables are significantly associated with the conversion of an area to Beech at a significance level of 0.05. It can also be said that all three variables provide evidence against the null hypotheses (stated on page 5) as they all have p-values of less than 0.05, though evidence against the null hypothesis is clearly strongest for soil type. Therefore in all three cases the null hypothesis is rejected.

4.2.2. Logistic Regression Models (LRMs)

4.2.2.1. Investigating associations between the explanatory variables land parcel size and soil type

A two-way table and Pearson's chi-squared test were used to assess the possible association between land parcel size and soil type .The results are given on the next page.

Table 4-5:(a) Total number of samples per combination, (b) Proportion of samples that converted to Beech per combination and (c) Summary of Chi-squared test

(a)

Land Parcels	Soil Type						Total
	A	B	C	D	E	F	
Large parcels	74	33	2	11	54	57	**231**
Medium parcels	4	30	2	3	9	28	**76**
Small Parcels	33	193	140	0	5	36	**407**
Total	**111**	**256**	**144**	**14**	**68**	**121**	714

(b)

Land Parcels	Soil Type					
	A	B	C	D	E	F
Large parcels	0.16	0.64	0.5	0.18	0.06	0.16
Medium parcels	0.5	0.60	1	0	0	0.04
Small Parcels	0.33	0.42	0.23	0	0	0.25

(c)

Classified Variables	Degrees of freedom (df)	Chi-square (X^2)	P-value
Land parcels size & Soil type	10	337.402	<2.2e-16

Table 11a shows the total number of samples per combination of land parcel class and soil types. It is clear that that the combination of small parcels and soil type D is not present in the sample. Soil type D is limited more to the large parcels and less to the medium parcels. Similarly we could say that soil type C is limited to the small parcels as only two points were found in both the medium and large parcels.

Table 11b shows the proportions of converted sample points per combination of land parcel class and soil type. We see that soil type D combined with the medium parcels had no sample points that converted to Beech cover. This is similar for soil type E when combined with small and medium parcels.

The highest proportion of sample points that converted to Beech cover was found in the combination of small land parcels and soil type B.

The Chi-squared test gives a very large value of X^2 (table 11c), statistically this shows that parcel size and soil type are strongly associated, though caution is taken when accepting this result as some combinations had very few if any samples counts to make a good assessment from, none the less by overlaying the land parcels on to the soil map of the study area it was observed that certain soil types are limited to certain parcels sizes. Such an association can lead to wrong interpretations of the predictive power of any one of these variables as their effects on conversion to Beech cover may be mixed together, therefore they can not be modelled together. These two variables can be said to be confounded.

land parcel size, soil type and elevation

Classified Boxplots and Linear models were used to assess the possible association between the two categorical variables and elevation. The results are given below.

Elevation vs. land parcel size

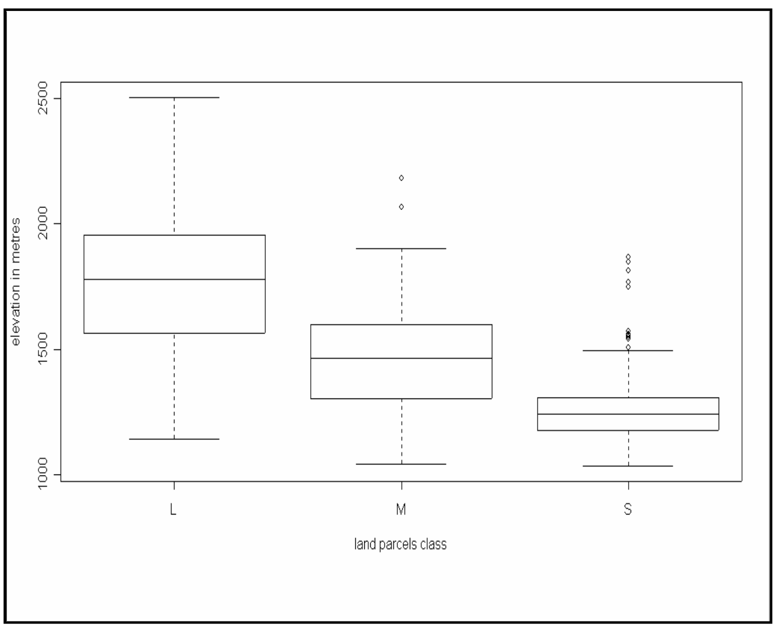


Figure 4-7: Classified Boxplot of elevation grouped by land parcel size.

Table 4-6: Summary of linear model for elevation and land parcel size.

Land parcels class	Estimate	Std. error	T value	Pr(>|t|)
Large parcels: L (Intercept)	1749	13.5	129.2	<2e-16
Medium parcels: M	-280	2.2	-10.3	<2e-16
Small parcels: S	-493.4	17	-29.1	<2e-16

Adjusted R^2: 0.543, **df:** 711, **p-value:** <2e-16

In figure 4-7 we see that large parcels were generally found above elevations of about 1100m. The medium and small parcels were limited to lower elevations (below ~1900m and ~1600m respectively). In addition in Table 4-6 the adjusted R^2 of the linear model for elevation and land parcel size was given as 0.543. These results show that there is an association between land parcel size and elevation and that the association can be said to be significant i.e. above 0.5 and therefore elevation and land parcels were not modelled together.

Elevation vs. soil type

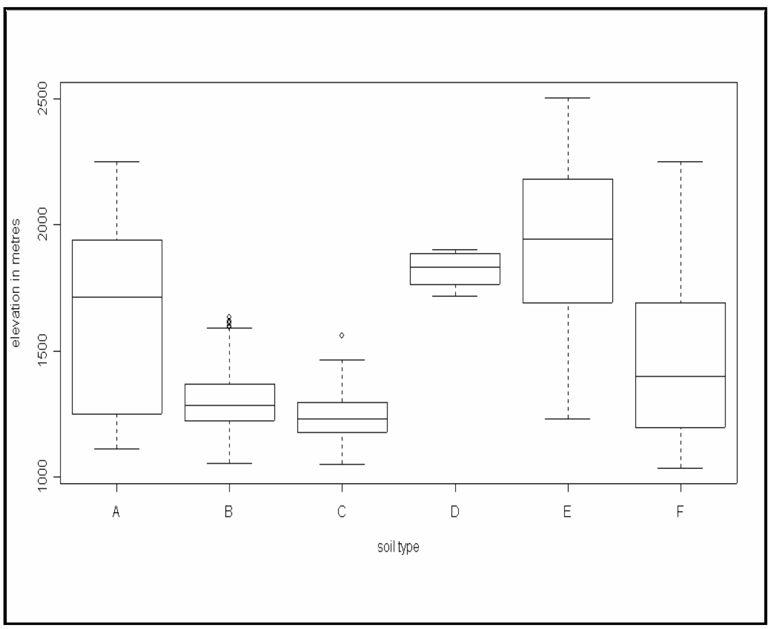


Figure 4-8: Classified Boxplot of elevation grouped by land parcel size

Table 4-7: Summary of linear model for elevation and soil type

Soil type class	Estimate	Std. error	T value	Pr(>|t|)
Soil A (Intercept)	1627	21	77.56	<2e-16
Soil B	-319.3	25.1	-12.71	<2e-16
Soil C	-382.5	27.9	-13.70	<2e-16
Soil D	190.7	62.7	3.04	0.0024
Soil E	291.8	34	8.57	<2e-16
Soil F	-171.5	29	-5.9	5.5e-09

Adjusted R^2: 0.473, **df:** 708, **p-value:** <2e-16

In figure 4-8 we see that soil type E has the widest spread of distribution (from about 1300m to 2500m) and soil type D has the narrowest spread of distribution (from ~1700m to ~1900m). Soil type B and C are only found in areas of lower elevation (below ~1600m and ~1500m respectively). The remaining soil types can be said to be found in both low and high elevations, with soil type E being the only soil type found above 2300m. In addition in table 4-7 the adjusted R^2 of the linear model for elevation and soil type was given as 0.473. These results show that there is an association between elevation and soil type, although the association is less significant than that of elevation and land parcel size i.e. below 0.5. Because of the moderately low significance in association of elevation and soil type it was considered justifiable to model conversion to Beech using both variables.

4.2.2.2. The Logistic model of change for each predictor variable

The three explanatory variables land parcel size, soil type and elevation where each subjected to logistic regression. This meant that they took up the role of predictor variable in each respective model. The results were as follows:

Logistic model of change predicted by land parcel size

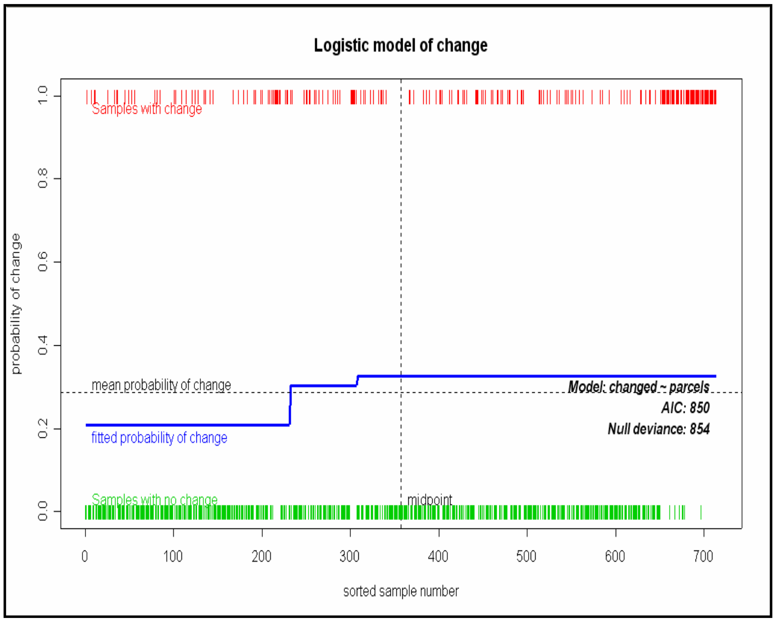


Figure 4-9: Logistic model of change predicted by land parcel size

Table 4-8: Summary of logistic model of change predicted by land parcel size.

Land parcels category	Estimate	Std. error	Z value	Pr(>|z|)	Odds ratio
Large parcels: L (Intercept)	-1.338	0.162	-8.25	<2e-16	0.262
Medium parcels: M	0.503	0.298	1.69	0.0908	1.654
Small parcels: S	0.616	0.194	3.18	0.0015	1.852

Figure 4-9 shows the results of the logistic model predicted by land parcel size as a plot. The fitted probabilities for each land parcel class are close to the mean probability of change (0.286). This means that the predictive powers of each land parcel category are not very different from each other. The largest difference from the mean probability was recorded in the large parcels class.

Table 4-8 gives the summary statistics of the model. The model generally shows the dependency of conversion to Beech on the three land parcel categories. The results show that both medium and small sized parcels have a positive association with conversion to Beech. The predicted odds that a sample will convert to Beech generally increases with a shift to a lower (smaller sized) land parcel category. The rate of increase is given by the slopes of the model, for example the slope (odds ratio) given by large and small parcels is 1.852. This means that the odds of a sample point converting to Beech predicted by large parcels increases by 1.852 times when predicted by small parcels. Using a significance level of 0.05 we further see that of the three predicted odds only those predicted by large and medium parcels are significant i.e. likely to be reliable predictions.

Logistic model of change predicted by soil type

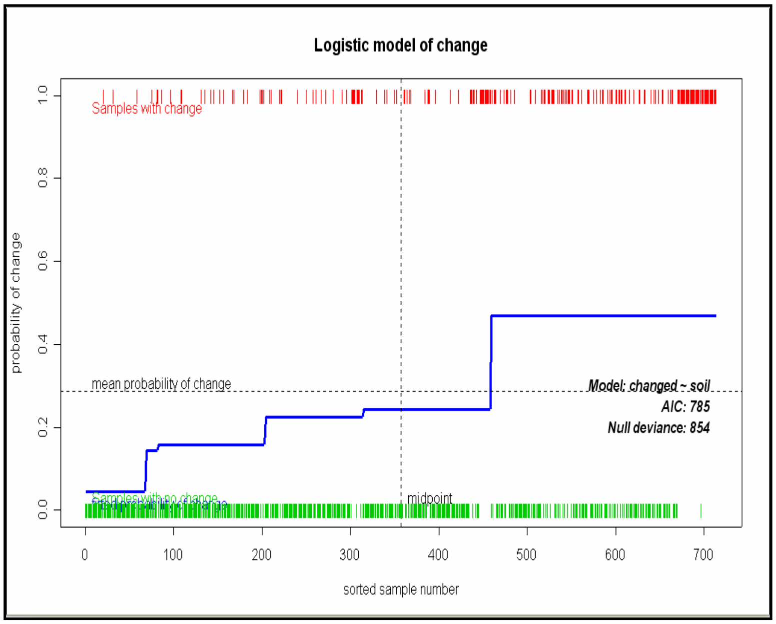


Figure 4-10: Logistic model of change predicted by soil type size.

Table 4-9: Summary of logistic model of change predicted by soil type.

Soil type	Estimate	Std. error	Z value	Pr(>|z|)	Odds ratio
Soil A (Intercept)	-1.2355	0.2272	-5.44	5.4e-08	0.291
Soil B	1.1103	0.2594	4.28	1.9e-05	3.035
Soil C	0.0995	0.2990	0.33	0.7393	1.105
Soil D	-0.5563	0.7968	-0.70	0.4851	0.573
Soil E	-1.8403	0.6327	-2.91	0.0036	0.159
Soil F	-0.4451	0.3377	-1.32	0.1876	0.641

Figure 4-10 shows the results of the logistic model predicted by soil type as a plot. The fitted probabilities for each soil type differ from the mean probability of change (0.286). The noticeable differences from the mean probability were recorded in soil types B and E. Soil type B was higher than the mean probability of change and soil type E was lower. The highest probability for a sample point to convert to Beech was given by soil type B and the lowest probability was given by soil type E.

Table 4-9 gives the summary statistics of the model. The model generally shows dependency of conversion to Beech on the six soil types. The results show that only soil type B and C have a positive association with conversion to Beech. The predicted odds that a sample point will convert to Beech are highest for soil type B and lowest for soil type E. This means that for some reason or another conversion to Beech is more likely in soil type B than E. Focusing on the highest and lowest predictions it is observed that the odds of a sample point converting to Beech cover increase by about 3 times when predicted by soil type B. When the odds of a sample point converting to Beech are predicted by soil type F there is a decrease of about 0.2 times in the odds. Using a significance level of 0.05 we further see that of the six predicted odds only those predicted by Soil type A, B and E are significant i.e. likely to be reliable predictions.

Logistic model of change predicted by Elevation

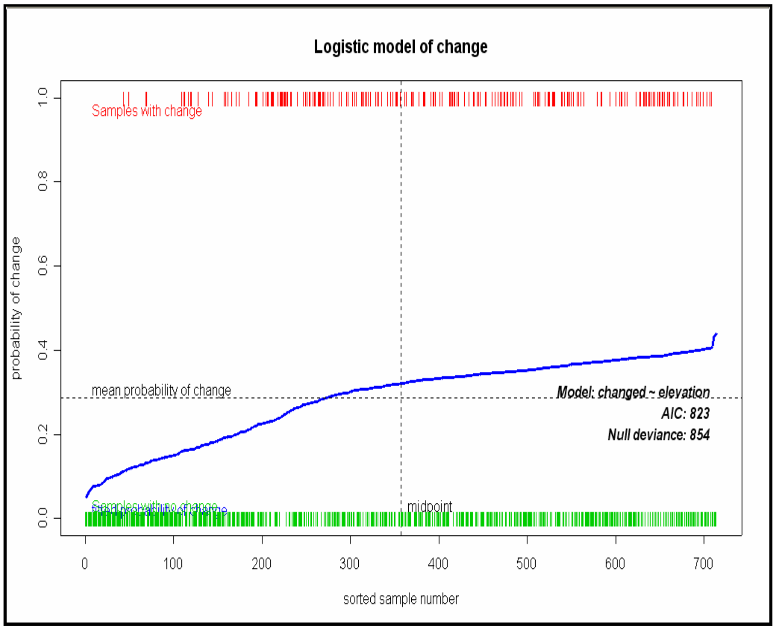


Figure 4-11: Logistic model of change predicted by elevation.

Table 4-10: Summary of logistic model of change predicted by elevation

Continuous variables	Estimate	Std. error	Z value	Pr(>|z|)	Odds ratio
(intercept)	1.678531	0.475861	3.53	0.00042	5.358
elevation	-0.001854	0.000344	-5.40	6.9e-08	0.998

Figure 4-11 shows the results of the logistic model predicted by elevation as a plot. The fitted probabilities at different elevations differ from each other and we further see that with decrease in elevation there is an increase in the probability of a point to convert to Beech.

Table 4-10 gives the summary statistics of the model. The model generally shows dependency of conversion to Beech on elevation. The results show that elevation has a negative association with conversion to Beech. The predicted odds that a sample point will convert to Beech generally decrease with increase in elevation. This means that conversions are more likely at lower elevations than higher ones. The rate of this model is 0.998. This means that for every unit increase in elevation the odds decrease by 0.998 times. Using a significance level of 0.05 we further see that the predictions are very significant i.e. more likely to be reliable predictions.

4.2.2.3. The combined logistic model

Only the predictor variables (soil type and elevation) were combined additively to form one model. This additive combination was considered justifiable as the association between the two variables was not very strong. Land parcels size was removed because it showed a strong association with soil type and also because it had a stronger association with elevation than soil type.

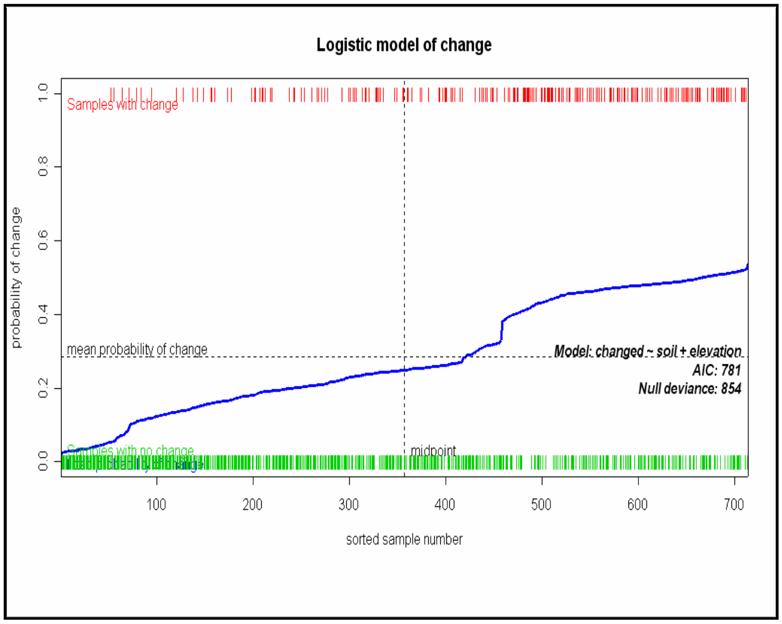


Figure 4-12: Combined logistic model of change predicted by soil type & elevation

Table 4-11: Summary of combined logistic model of change predicted by soil type and elevation.

Variables	Estimate	Std. error	Z value	Pr(>|z|)	Odds ratio
(Intercept)	0.500858	0.745665	0.67	0.5018	1.650
Soil B	0.799463	0.285956	2.80	0.0052	2.224
Soil C	-0.282016	0.334117	-0.84	0.3986	0.754
Soil D	-0.311664	0.806425	-0.39	0.6991	0.732
Soil E	-1.540892	0.645858	-2.39	0.0170	0.214
Soil F	-0.624735	0.348133	-1.79	0.0727	0.535
elevation	-0.001091	0.000455	-2.39	0.0166	0.999

In figure 4-12 we see the logistic model predicted by soil type and elevation. The model ranges from a probability of about zero to 0.5.

Table 4-11 gives the summary statistics of the combined logistic model. The results show that soil type A and B have a positive association with conversion to Beech. We also see that soil type A now has a positive association with conversion to Beech and soil type C now has a negative association with the same. This means that the combining of soil and elevation into one model has somehow reversed their association. The predicted odds that a sample point will convert to Beech is still highest in soil type B but the combination with elevation has lowered the odds. The lowest odds are predicted by soil type E and it has experienced a slight increase in predicted odds. The odds predicted by elevation are more or less the same i.e. not strongly affected by the combination. Using a significance level of 0.05 we further see that the predictions of odds by soil type B and F, and elevation are significant i.e. more likely to be reliable predictions. Though each of their predictions have less significance than before.

Statistical model for conversion to Beech

The statistical model for the combined logistic model is given as;

$$\boxed{P = 0.500858 + 0.7994463X_0 - 0.282016X_1 - 0.311664X_2 - 1.540892X_3 - 0.624735X_4 - 0.001091X_5} \quad (5)$$

Where,
P= the probability of conversion to Beech
X_0 = soil B
X_1 = soil C
X_2 = soil D
X_3 = soil E
X_4 = soil F
X_5 = elevation

4.2.2.4. Evaluation of logistic regression models

After modelling, each model was evaluated and then validated using the “Receiver Operating Characteristc (ROC).The results were as follows:

Table 4-12: Summary of model validation results.

Model	ROC	AIC	Deviance
Land Parcel size	0.5618	850	0.0125298
Elevation	0.5932	823	0.0411021
Soil type	0.6940	785	0.0948389
Combined (elevation + soil type)	0.7020	781	0.1017000

ROC Grading: ROC < 0.6 = poor model
0.6 - 0.7 = pass
0.7 - 0.8 = good model
0.8 - 0.9 = very good model
0.9 = < ROC = excellent model

The results in table 4-12 show that the combined logistic model has the highest area under the ROC curve. This suggests that the combined model is more successful than the other models in predicting the points that did and did not convert to Beech. AIC values also suggest that a combination of elevation and soil type creates a better model for conversion to Beech than models of individual predictor variables. The deviances for each model are also shown; the combination of soil type and elevation explains about 10% of the variability in the model and when compared to the deviances of the other models the combined logistic model is the most accurate. Taking all these factors into consideration the combined logistic model can be said to be the better model out of the four models in predicting conversion to Beech.

5. Discussion

5.1. Quantifying land cover change

Five classes were assigned to the two Landsat TM images for 1987 and 2003 during the classification process i.e. Beech, Dwarf Pine, Shrub, Grass and Bare Ground. The overall accuracy of the classification was found to be 69% for the 2003 image. This result was found to be acceptable seeing that the class of most interest (Beech) scored a very high individual accuracy (94%). Further the confusion matrix revealed confusion particularly between Shrub and Grass classes. This was due to the fact that both classes had almost the same range of spectral values and hence were not very separable in feature space (Appendix X, figure 8-4). None the less it was important to classify the two classes separately so as to get the conversion dynamics of these two vegetation types. This problem of mixed pixels is inherent to image classifications (Bakker et al., 1999) and hence forth cannot be avoided.

In an effort to make the classifications of the 1987 and 2003 images more comparable, images taken in the same month (August) were chosen. This allowed for the comparison and classification of the two images under the same seasonal (summer) conditions as different seasons imply different vegetational conditions i.e. the same species may have different spectral characters in different seasons.

Referring to the classified images it could be seen that gap closure within established Beech forest and expansion at forest fringes was prominent. The gaps within forested areas were probably areas once used for logging or roads to mountain pastures. It must be mentioned that during the field expedition it was observed that logging activities were taking place in the study area at both small and large levels, though this is not proof that the gaps are indeed past logging areas. Information on the exact points of current logging and regulations applied to this activity was not available during the study.

The classified images also illustrated the reduction in Bare Ground from 1987 to 2003, particularly in the central portion of the study area. This could be attributed to vegetative successive processes. The creation of a ploughed field or its abandonment invites a host of plants species particularly adapted to be good invaders (Ricklefs, 1990). In the case of the study area the central portion forms the bulk of small sized land parcels (3-21ha) previously used for cropping and now abandoned. It is unlikely that the bare portions of land in the 1987 classified map are the exposed surfaces of ploughed fields, but are most probably abandoned fields covered with dried out grasses caused by hot weather conditions.

The field observation data used in the classification and accuracy assessment was collected in September 2005. Despite a difference of two years with the 2003 Landsat 7TM image it was justifiable to do this as the main process being captured (Beech expansion) is slow. This justification is backed by (Mosello et al., 2002) who observed changes in both Beech forest and Oak woodland in Italy over a period of 6-7 years and found the changes to be of very low significance, Mosello suggested a longer survey time to evaluate trends in these forest ecosystems. As for the classified 1987 Landsat image the accuracy was not assessed due to lack of observation data.

5.1.1. Land cover change analysis

In general the results of the image classification showed that between 1987 and 2003 Beech increased by ~355ha (15%) at an average rate of ~22ha/yr (0.93%/yr).This result was second to the increase in Dwarf Pine cover which was about ~38ha (40%) at an average rate of ~2ha/yr (2.5%/yr). (Mouillot et al., 2005) in a study on Mediterranean forest expansion in Corsica, Southern France found an average forest expansion of 0.59%/yr and further mentions that an average forest expansion of 1%/yr is a common value in many of the Mediterranean forest ecosystems. The results from this study agree with the usually observed forest expansion rate in the Mediterranean regions i.e. 0.93%/yr compared to an average value of 1%/yr generally observed. The results also show that Beech is a slow growing species. This view is shared by (Oheimb, 2005) who observed that the regeneration of Beech occupied a long time span even on a very small spatial scale.

In terms of coverage Beech occupied ~2375ha (45%) of the study area and by 2003 increased to ~2730ha (51%). Other vegetation cover types such as Shrub and Grass also experienced increases in cover from 1987 to 2003. It can be said that in the study area most of the vegetation cover change processes seem to favour an overall increase in vegetation cover be it Beech, Shrub or Grass.

The most prominent land cover changes from 1987 to 2003 where those that indicated conversion from Bare Ground and conversion to Beech. About 622ha (37%) of the total change that occurred in the study area represented conversions from Bare Ground to other land cover types, conversions to Beech represented ~483ha (29%). It was also observed that conversions to Beech happened at the expense of both Grass and Shrub. This result was in agreement with a similar study by (Mouillot et al., 2005) where Mediterranean forest dynamics were studied in Corsica, France. Mouillot found that from 1960-1990 forests increased at the expense of shrubland and grassland (9.3% and 5.6% respectively). This is not surprising as Grass and Shrub generally constitute early and mid-successional vegetation types in forest succession processes.

From the classified images we see that in 1987 Bare Ground was visible within the central portion of the study area and by 2003 these areas had been converted to other cover types such as, Grass, and Shrub. As mentioned before the central portion of the study area forms the bulk of small sized land parcels. These parcels were in the past crop fields and have since been abandoned and hence provide the opportunity to observe successional processes (Ricklefs, 1990). Similarly (Hunziker, 1995) links land abandonment to spontaneous reaforrestation and refers to this process as old-field succession. Similarly (MacDonald et al., 2000) states that in mountain zones where abandonment is taking place, the environmental processes usually involve encroachment of vegetation onto and field sites, loss of Grassland to scrub and forest, and loss of woodland clearings.

Generally it can be said that vegetation succession activities indirectly promote Beech expansion, most of which most probably begin on Bare Ground in this case abandoned farmland, which are first invaded by lower plant species (grasses, herbs and shrub) leading towards higher plant tree species like Beech, which is a late-successional species (Piovesan et al., 2005). This process probably dates back to the 1950’s and 60’s when emigration of local inhabitants to the area began and has been on going ever since.

5.2. Analysis of association between Beech expansion and the explanatory variables

The Chi-squared test showed that land parcel size, elevation and soil type all had significant associations ($p < 0.05$) with Beech expansion. Therefore In all three cases the null hypothesis was rejected and it can be said that there are differences in distribution of areas the converted to Beech with differences in soil type, elevation and land parcel size.

Soil type had the highest significance ($p= 5.846e^{-15}$) between the three and this could be attributed to the fact that soils provide a direct nutritional link to plant species. Generally soils are considered important determinants of forest dynamics (Mouillot et al., 2005). Elevation though not as direct a link as soil determines the geographical variation in temperature, thus altering the atmospheric conditions in which a plant can exist. To a certain extent these two variables dictate the distribution of Beech in the study are as it is known that these species are limited to an elevation belt of between 1000m and 1800m and thrive in soils rich in chalk or limestone but can also grow on light soils of a sandy or loamy nature(Forestry, 1968).

Land parcels size had the lowest significance ($p=0.005677$) with Beech expansion. Its association with Beech expansion is not direct i.e. not of a causal nature. This is because land parcels in themselves may have underlying variables that directly promote Beech expansion. For example the land use activity within a particular parcel, is it abandoned, is it grazed or forested? The management and commercial activities attached to the land parcels. All these lurking variables may some how work together and provided a suitable environment within that land parcel for the process in question. It therefore can be said that lurking variables dictate its association with Beech expansion.

From the signs and magnitudes of the estimated coefficients displayed in the summaries of the individual LRMs, the effects or influence of each explanatory variable on Beech expansion can be inferred. From these results it was observed that for land parcels, small sized parcels had the highest odds that an area would convert to Beech. The association of small land parcels and prediction of Beech expansion was found to be positive implying that small parcels are more likely to convert than medium or large sized parcels. This could be because the small parcels take up the largest portion of area in the study area that is available for Beech establishment e.g. most of the large and medium sized parcels are covered by Beech forest or rock.

In the case of the explanatory variable soil type, it was observed that soil type B had the highest odds of an area converting to Beech. This could be explained by the fact that soil type B provides a better nutritional environment for Beech trees that encourages seed germination and seedling establishment. It consists of colluvial and moraine deposits with debris. Moraine deposits in particular which are glacial materials consist of clay, sand and gravel. Beech can grow well on in sandy, loam and clay soils (Treehelp.com- Tree Care Made Easy, 2006). Beech Soil type E had the lowest odds and a negative association with conversion and this implies that soil type E is less suited for Beech establishment.

Elevation had a strong negative association with conversion to Beech cover that is to say it had a significant effect on the process. Similar results were obtained in a study by (Hsu and Cheng, 2000) in which elevation was found to be a significant variable in predicting landscape changes in Vietnam. It is known that areas ranging between 1400m and 1800m in the study area are more or less covered by Beech. This means that the only available areas left for Beech to be established are below 1400m as Beech cannot grow beyond 1800m as climatic conditions are not suitable. The results from the model imply that lower elevations provide better climatic conditions for Beech to grow in, but land in which Beech is to be established must first be available, hence the abandoned farmlands.

The combined logistic model (soil type and elevation) predicted highest for soil type B and this could be attributed to the same reasons earlier mentioned, though combining Soil type B with elevation seemed to lower its predictive powers slightly. In general the results of the combined logistic model imply that soil type B has a very strong influence on the conversion of an available area to Beech. Elevation maintained more or less that same predictive power implying that combining it with soil does not have much of an effect.

The highest area (70.2%) under the ROC curve was recorded by the combined logistic model and the lowest area was recorded by the land parcel size model. Though it must be mentioned that soil type on its own made a slightly good single predictor variable. The combined model was graded as a good model meaning it was quite successful in predicting the probability of conversion to Beech cover.(Pontius, 2001) recorded an area of 65% for his logistic model and (van Gils and Loza, 2005) an area of 71.5%. Though the results of the ROC curve were good there is room for improvement by fitting more explanatory/predictor variables generally known to be linked to Forest expansion or land cover change e.g. slope, distances to natural forests and distances to roads have been used by (Hsu and Cheng, 2000) in analysing landscape changes and were found to be good predictors under the set conditions.

The land parcels model was rated as a poor model implying that though land parcel size has a strong association with conversion to Beech cover; it does not really cause it or have influence over it and hence can be referred to as a weak predictor of the process. This is where the issue of lurking and confounding variables takes effect. (Moore and McCabe, 1998) emphasizes this point by stating that “Even when a strong association is present, the conclusion that the association is due to a causal link between the variables is often elusive”.

It can be said that the combined logistic regression model can give a good prediction of Beech expansion in the study area.

6. Conclusions & Recommendations

Land cover changes between 1987 and 2003 were detected with a focus on Beech expansion. The physical and social factors influencing Beech expansion were also analysed resulting in the following conclusions:

- Research question 1: What are the land cover changes between 1987 and 2003?

  ☑ 18 categories of land cover changes were detected and the largest change was from bare ground to grass (444ha) and grass to shrub (261ha)

  ☑ Conversion from other cover types to Beech recorded a total of 483ha.

- Research question 2 & 3: What is the increase and average rate of increase in of Beech between 1987 and 2003?

  ☑ The image classification showed that between 1987 and 2003 Beech increased by 355ha at an average rate of 1%/year.

- Research question 4: Which explanatory variables are associated to Beech expansion?

  ☑ The Chi-squared test showed that land parcel size, elevation and soil type all had strong association with Beech expansion and the strongest association was observed in the variable soil type.

- Research question 5: Which explanatory variables are significant predictors of Beech expansion?

  ☑ Soil type and to a lesser extent elevation were found to be significant predictors variables and when combined there predictive powers were increased.

- Research question 6: Can a good prediction of Beech expansion be made from the significant predictors using a combined LRM of change?

  ☑ Soil type and elevation when combined to model Beech expansion using logistic regression produced a good approximation of Beech expansion.

To improve the model I recommend that other variables which were not considered in this study because of time constraints could be taken into consideration such as land use, rainfall, radiation, slope, etc.

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Appendices

Appendix I : Summary wild boar (*Sus scrofa*)

The Wild Boar (Sus Scrofa L. 1758) also known as the European wild boar is the largest of wild pigs and can be found in all continents, except Antarctica, partly due to it's original widespread distribution and then to subsequent translocations imposed by man (d'Huart,1991; Herrero et al 2005). During the last two decades, populations of the wild boar in Europe have increased considerably and the species has expanded into new areas over the entire continent (Geisser and Reyer, 2005). In Mediterranean countries such as Spain the increase in population numbers and expansion in range of wild boar has been influenced by the abandonment of large cultivated areas and reafforesation (Vericad 1970; Telleria and Sáez-Royuela 1985; Abáigar 1990, Abáigar 1994). In many places in Europe a similar trend is observed (Telleria and Sáez-Royuela 1985; Erkinaro et al., 1982; Abáigar 1994).The wild boar is bristly haired, grizzled, blackish or brown in colour, and stands up to 90cm tall at the shoulder. Except for old males which are solitary, wild boars live in groups. They are swift, nocturnal and omnivorous. They posses sharp tusks, and although they are normally not aggressive, they can be dangerous (Encyclopedia Britannica 1994).Wild boar species present in the Abruzzo region of Italy are not of the typical Italian species known as "maremmana", but are of Eastern Europe lineage (Ponziani, Personal Communication)

Wild boars are heavily hunted, partly because they are highly prized and in part because they cause crop damage (Vassant et al., 1992; Herrero et al 2005). Despite their abundance and the availability of samples (obtained from hunting activities), the knowledge of wild boars in different environments can be considered scarce. In Europe some studies on their food habits have been carried out in Mediterranean areas, in agricultural and marsh land areas of Eastern Europe and in Mountainous environments such as the Alps. These studies have been important because wild boars impact on the biocenosis on which they feed both above and underGround (by rooting), for example they can affect Ground nesting birds, soft and hard mast distribution, soil invertebrates or plant roots. They can have impacts on communities, tree regeneration or vegetation composition. Due to the effects they have on various components of various ecosystems they inhabit wild boars are considered an important element of mountain ecology (Herrero et al 2005). This view is shared by (Ponziani, Personal Communication), he expresses in his report that the importance of the wild boar for nature balance must not be downgraded. In fact when rooting for tubers, the wild boar ploughs the Ground, promoting the germination of seeds. It controls an increasing number of reptiles and eliminates damaging insects (Imenopteries and Coleopteries). The wild boar is also important because its puppies are predated by wolves and because it is an important agent in the dispersal of plant diaspores within and between European temperate forests patches (Heinken et al., 2005).

Habitat requirements of wild boars

In general habitat use by wild boars is determined by food availability, shelter and weather conditions (Leaper et al., 1999). They select habitats that offer high-energy food, cover from predators (hunters included) and avoid areas where weather conditions may be extreme (Singer et al., 1981; Leaper et al 1999). During hot summers wild boars prefer shady places as they lack sweat glands, they need to thermoregulate by wallowing in cool area (Saunders & Kay, 1991; Leaper et al 1999).

Deciduous woodlands provide optimal habitat for wild boar and oak and/or Beech woodlands are the most suitable given the preferred natural foods of wild boar are acorn and Beech masts (Worrel and Nixon, 1991; Leaper et al 1999).

Wild boars of the Italian Alps prefer woody habitats and in particular those which tend to be more natural such as broad-leaved mature woods, old coppices and mixed woods that provide food and shelter for them. Seasonal differences in habitat selection by wild boars are influenced by changes in food and shelter availability and to particular requirements e.g. reproductive and farrowing periods (Meriggi and Sacchi, 2001). In Camargue, France and in the Great Smokey Mountains National Park, USA the use of habitat by wild boars appeared to be affected by the availability of energy rich foods such as acorns and Beech mast, as well as crops (Singer et al., 1981; Dardallion, 1987)

Feeding requirements of wild boars

The wild boar though omnivorous is predominately herbivorous with plant material forming the bulk of its diet (Leaper et al., 1999). The lesser portion of its diet consists of soil invertebrates and invertebrates (Herrero et al 2005). Among these are insects, earthworms, birds, mammals, amphibians, reptiles, gastropods and myriapods (Schley and Roper, 2003).

Wild boars in general depend on energy rich foods throughout their range, irrespective of habitat and latitude ((Massei, 1996)). Carbohydrate and fat rich foods such as Beech and oak masts and chestnuts are essential for reproduction and maintenance of good physical condition (Massei, 1996)).

In a resent paper by Herrero et al., 2005, the food strategy of wild boar in the Pyrenees, Spain was investigated. The diet and food alternatives of wild boar during autumn and winter were analysed based on stomach–content analysis. The results revealed that plant material was the most important item in wild boar diet. The aerial parts (mainly hard mast) of plants were consumed more than the underGrounds parts. Amongst these in order of abundance and frequency were Beech nuts (Fagus sylvatica), acorns from oak (Quercus humilis) and holm oak (Quercus ilex), and bracken (Pteridium aquilium) roots, which represented 70. 7% of the total volume of food items found in wild boar stomachs. Oak and Beech masts being of high carbohydrate content provided for the energy requirements of wild boars particularly during critical seasons (the end of winter). This was in agreement with a similar study carried out in central Italy (Massei, 1996) indicating that 86.3% of wild boar diet consisted of plant material i.e. acorns, olives pine-seed and graminoids were consumed the most . Energy rich food such as acorns, olives and pine-seeds were consumed in relation to availability and in there absence graminoids, forbs and junipers were consumed and thus regarded as alternative, less preferred foods.

Appendix II : Summary wolf (*Canis lupus*)

The wolf (Canis lupus) has been extirpated in most of Western Europe in the last century, but maintained viable populations remain in Spain, Portugal and Italy, (Boitani and Ciucci, 1993, Francisci and Gubert 1993; Petrucci-Foseca and Promberger 1993; (Mattioli, 2004)). Even in these countries, wolves have faced impoverished ecological conditions, generally characterised by the destruction of their natural prey: wild ungulates, thus turning to domestic livestock for food requirements (Mattioli et al, 1995). In Italy the wolf population is believed to have reached its minimum in the early 1970’s, when about 100 wolves were estimated, mostly in the central southern portion of the peninsula (Zimen & Boitani, 1975; Corsi et al, 1999). In 1976 full legal protection was awarded to the wolf in Italy. This increased the acceptance of the wolf and in addition a significant increase of wild ungulate populations favoured an increase of wolf populations. This led to the recolonisation of large areas of former distribution range (Boitani, 1992; Corsi et al, 1999). This process is further encouraged by rural depopulation in the last few decades which has decreased human-carnivore conflicts and allowed the regeneration of natural vegetation (Bunce et al 1998; Mladenoff eat al., 1997;Cayuela, 2004) resulting in substantial increases in potential wild prey such as wild boar, roe deer and red deer (Palacios, 1997; Telleria and Sáez-Royuela, 1984; Cayuela, 2004). In spite expanding trends, the population viability of the wolf is still threatened by small population size and significant adult mortality caused by illegal hunting (Boitani and Ciucci, 1993; Corsi et al, 1999). The species has recently been confirmed as “endangered” (Pinchera et al., 1997; Corsi et al, 1999).

Majella N.P. is inhabited by 25 wolf packs made up of 4-5 individuals. The wolf is considered an important species in the park as it is at the top of the alimentary food chain and for this reason wild ungulates have been reintroduced to the park. This has increased the survival of the wolf due to the availability of better nutrition (Ponziani, Personal Communication).

Habitat requirements of wolves

The wolf is rather a generalist in terms of habitat requirements (Carroll et al., 1999; Cayuela, 2004). Studies have shown that factors such as; wild prey abundance, human presence and forest cover play an important role in determining habitat suitability for wolves (Massolo and Meriggi, 1998). Wild prey abundance and size have been found to be strongly related to high wolf density (Appollonio et al., 2004) and human presence has been reported to determine the probability of wolf population persistence and continued expansion (Blanco and Cortés, 2002; Cayuela, 2004).

Feeding requirements of wolves

The wolf is carnivorous and in Italy mainly preys off wild ungulates. In a study by Mattioli et al, 1995 wild ungulates accounted for more than 92% for both frequency and occurrence in the scats of 240 wolves inhabiting the northern Apennines. It was further observed that during the study period there was a decrease in the consumption of Roe deer and an increase in the consumption of wild boar. Wolves tend to predate more intensively on the young ungulates (Gazzola et al., 2005) of Roe deer, Red deer and wild boar (Mattioli et al, 1995). Similarly Pezzo et al., 2003 reported that ungulates represented the bulk of the wolves’ diet of which the most important prey was found to be wild boar. In addition it was observed that wolves preferred wild ungulates to domestic livestock, despite high livestock densities in the study area.

Appendix III: Majella national park zonation map

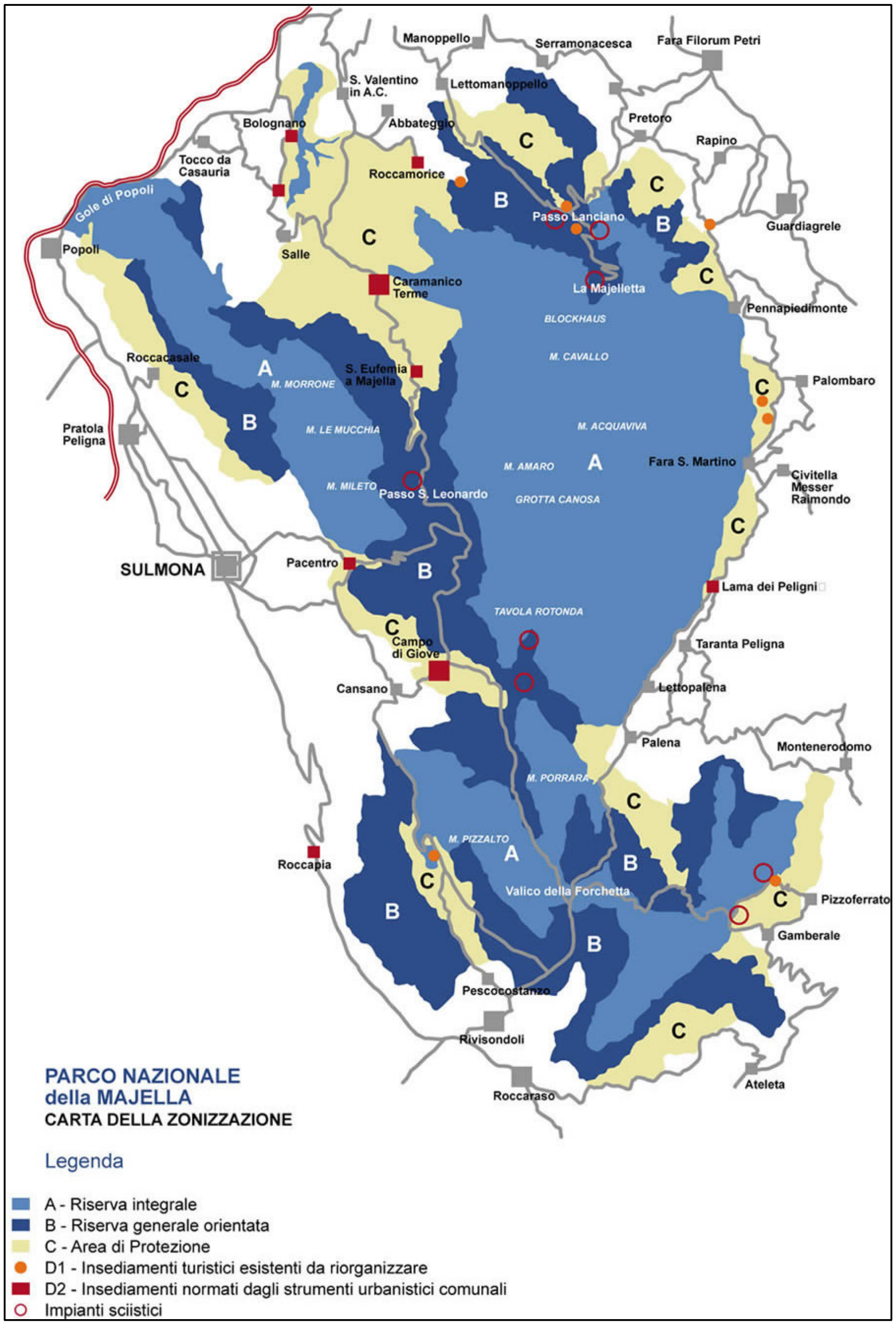


Figure 0-1 : Map illustrating the Majella national park management zones (source: Majella National Park, 2005).

Appendix IV : Field data sheet

Majella fieldwork sheet- September 2nd – October 3rd 2005

Data	Investigator	Sample ID	X coordinates	Y coordinates
Altitude (m)	Landform			
CLASS ID	BF:	OW:	SL/SC:	GL:

Vertical Projection of Canopy Cover of all Veg in Sample Plt			
Tree canopy (%)	Shrub/scrub (%)	Grass canopy (%)	Other (%) Litter, Rock, Soil, Herb etc

Analysis/ Vegetation layer

TREE CANOPY COVER (%) :				
No	Dominant Sp.	Height(m)	Mean DBH (cm)	% Canopy Cover
1				
2				
Remarks:				

SCRUB CANOPY COVER(%):			
No	Dominant Sp.	Height(m)	% Canopy Cover
1			
2			
Remarks:			

SHRUB CANOPY COVER (%):			
No	**Dominant Sp.**	**Height(m)**	**% Canopy Cover**
1			
2			
Remarks:			

GRASSLAND CANOPY COVER (%) :			
No	**Dominant Sp.**	**Height(m)**	**% Canopy Cover**
1			
2			
Remarks:			

GROUND COVER (%)				
Grass Cover(%)	**Herbs & Moss (%)**	**Rocks (%)**	**Bare Soil (%)**	**Litter(%)**

Appendix V : Observation (OBS) points table

OBS#	X	Y	OBS#	X	Y	OBS#	X	Y
1	419916	4658994	45	420717	4659124	89	420787	4657487
2	419923	4659075	46	420752	4659249	90	420686	4657441
3	420079	4659112	47	420896	4659379	91	420644	4657475
4	420220	4658939	48	422886	4649190	92	420760	4657236
5	420304	4659069	49	421051	4651880	93	421956	4656660
6	420428	4659131	50	421036	4651957	94	421992	4656581
7	420225	4659124	51	420992	4652040	95	422008	4656492
8	420129	4659243	52	420986	4652120	96	421942	4656511
9	419897	4659333	53	420976	4652199	97	421873	4656606
10	419843	4659495	54	421059	4652215	98	419044	4660851
11	419755	4659313	55	421132	4652230	99	418994	4660836
12	419344	4658589	56	421163	4652145	100	418924	4660814
13	419189	4658768	57	421119	4652107	101	418948	4660769
14	419188	4658888	58	421080	4652077	102	419004	4660736
15	419496	4659175	59	421127	4651986			
16	419563	4659221	60	421165	4651913			
17	420564	4658334	61	421196	4651823			
18	420458	4658358	62	421129	4651807			
19	420648	4658338	63	421102	4651886			
20	420648	4658338	64	421224	4658403			
21	420660	4658113	65	421234	4658280			
22	421462	4657783	66	421242	4658156			
23	421561	4657771	67	421276	4658075			
24	421575	4657693	68	421358	4658025			
25	421511	4657656	69	421024	4658208			
26	421459	4657696	70	420919	4658165			
27	420197	4656832	71	420787	4658226			
28	421257	4658780	72	420224	4658394			
29	421190	4658836	73	420185	4658323			
30	421174	4658799	74	419973	4658299			
31	421223	4658713	75	419945	4658349			
32	421128	4658725	76	420045	4658301			
33	419372	4658341	77	420024	4658232			
34	419413	4658111	78	419926	4658202			
35	421763	4656125	79	420134	4658850			
36	421953	4656113	80	420187	4658894			
37	422062	4656287	81	420053	4658807			
38	421467	4656349	82	420078	4658920			
39	420636	4658620	83	420161	4658786			
40	420677	4658647	84	421337	4657830			
41	420695	4658751	85	421247	4657761			
42	420714	4658838	86	421194	4657828			
43	420606	4658938	87	421359	4657743			
44	420672	4659024	88	420844	4657387			

Appendix VI: Feature space plot

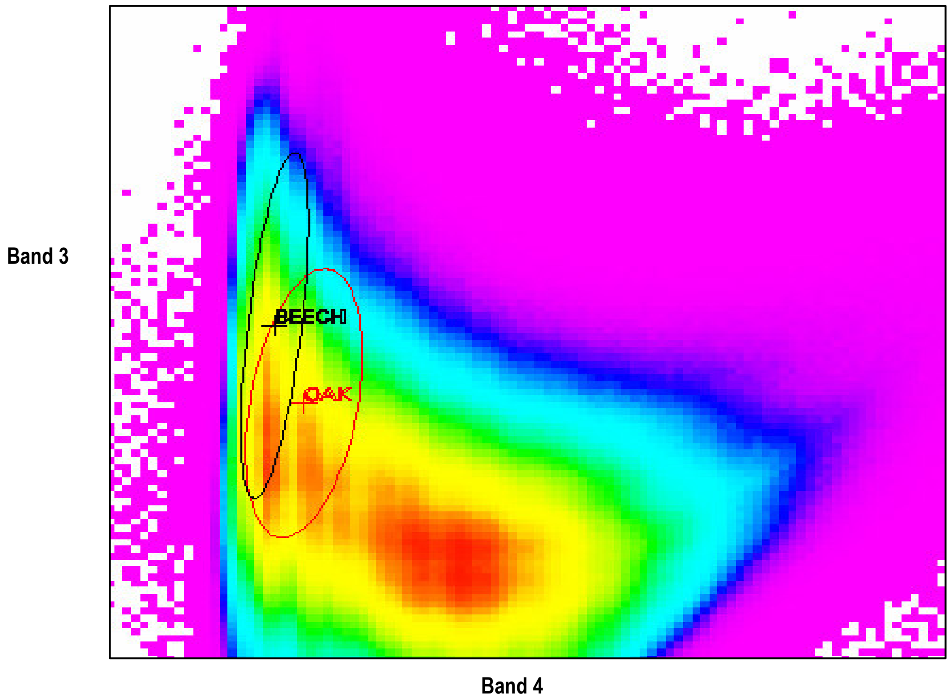


Figure 8-1: Feature space scatter plot showing the spectral signatures of Beech and oak using Landsat 7TM 2003 bands 3 and 4. Feature space shows that some of the pixel spectral values of Beech are also common to oak.

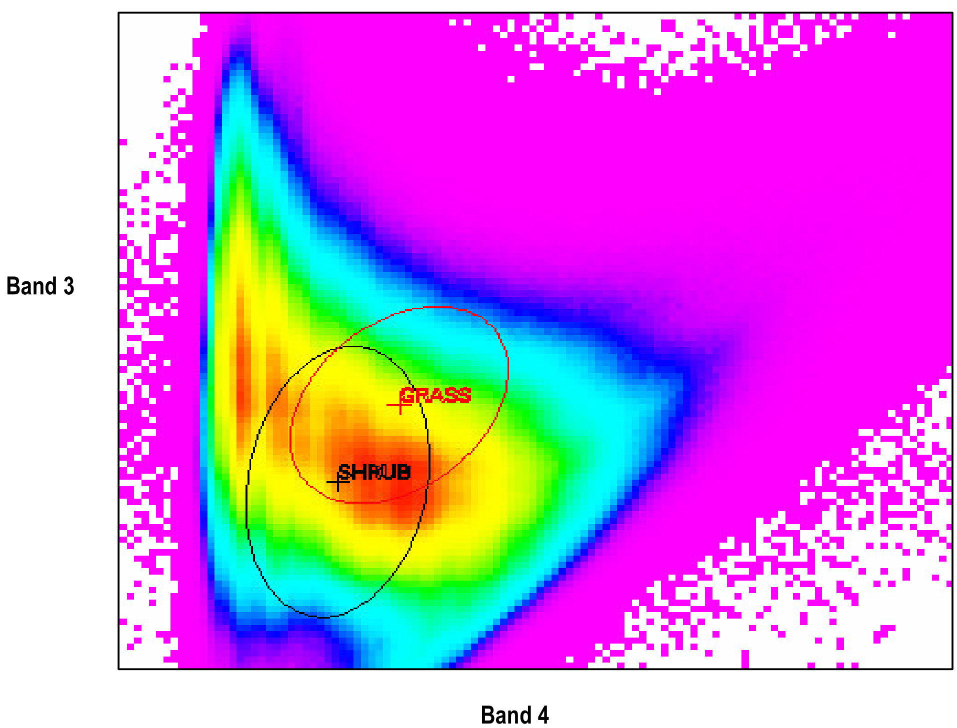
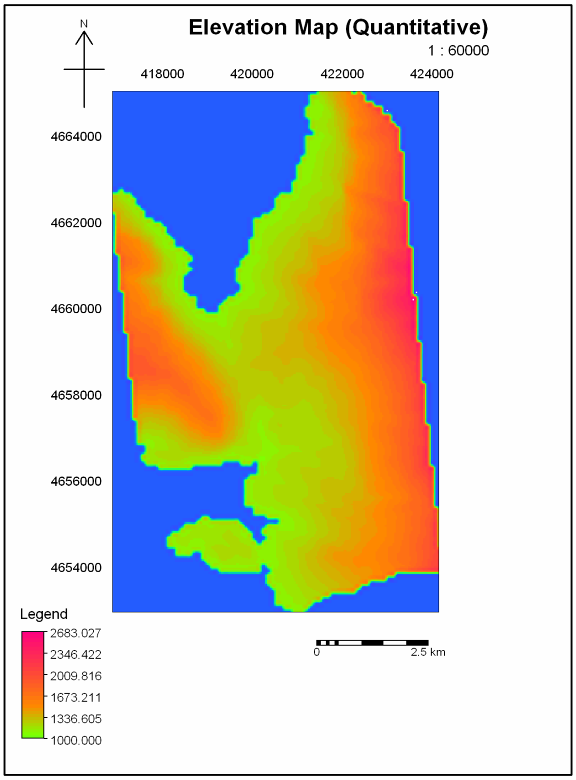
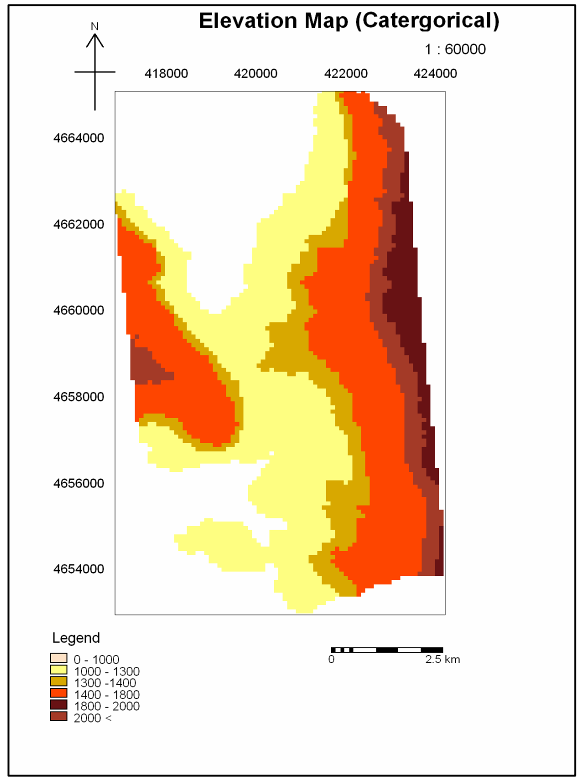
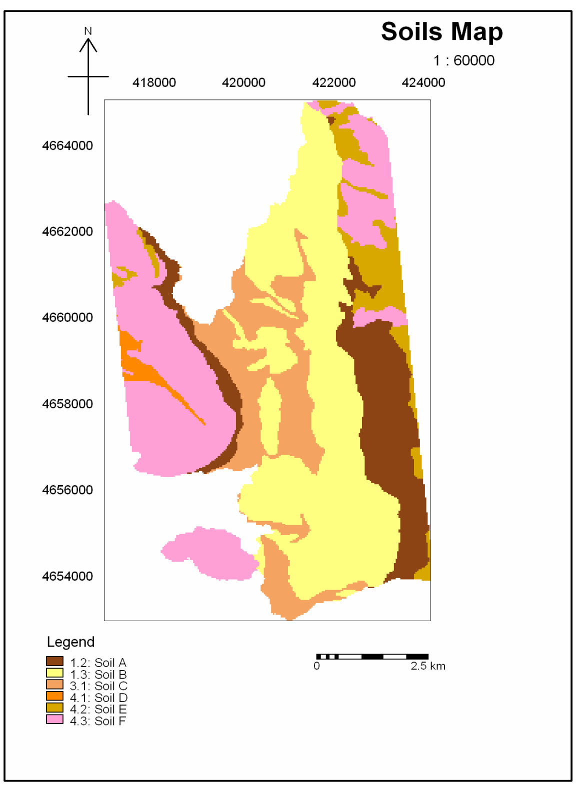


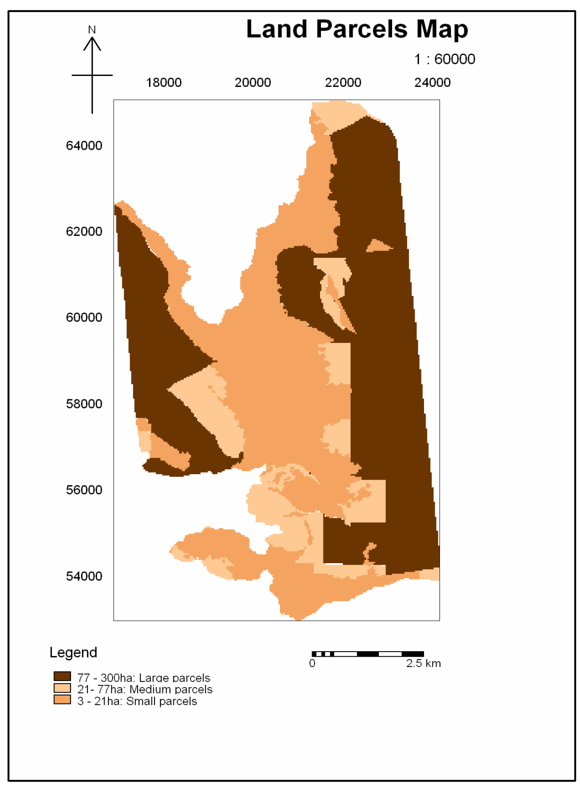
Figure 8-2: Feature space scatter plot showing the spectral signatures of Shrub and Grass using Landsat 7TM 2003 bands 3 and 4. Feature space shows that some of the pixel spectral values of Beech are also common to oak.

Appendix VII : Explanatory variable maps









Appendix VIII : Descriptive soil legend for Majella NP

Soil-landscape legend, Majella National Park
(Notes by translator: soil descriptions ommitted; soil types from USDA Soil Taxonomy 1975)

1 -Continental Plio-Quaternary Units

Debris, alluvial cone, fluvial and colluvial deposits, moraine deposits, paleosols on residual deposits (Terra Rossa) and fluvial deposits.

1.2 (SOIL A)-Slope areas covered by recent or current debris and alluvial cone and/or moraine deposits. The morphology is regular (smooth) and the slope goes from moderately sloping to steep. (Typic Rendolls)

1.3 (SOIL B)-Slope areas covered by colluvial deposits mixed with debris and/or moraine deposits, over residuum. The surface morphology is irregular and the slopes are mostly steep. The dominant processes are superficial and deep gravitational phenomena (mass movements). (Typic and Aquic Eutrochrepts)

3 -Terrigenous Units.

Alternating beds of sandy pelites, multi-coloured claystones and calcareous arenites

3.1 (SOIL C) -Hilly relief mostly composed of clay-marl, with alternations of sandy levels. Morphology is gently undulating to undulating, with slopes from strongly sloping to steep subject to superficial landslide processes. Local badland formation. (Typic Eutrochrepts, inclusions of Aquic Eutrochrepts)

4 -Limestone units of the continental platform and slope.

Includes transitional units from limestone to marl.

4.1 (SOIL D) - High-altitude areas (ridges, mountain tops and highest parts of the slopes) of relief, with slope from gently sloping to moderately steep; locally active karst processes. (Lithic Rendolls)

4.2 (SOIL E) -Slopes with irregular morphology with very steep slopes. Landslide and ice-induced (cryoclastic) phenomena prevail. Many rock outcrops, therefore irregular slope shape with local cliffs (Lithic Udorthents and Lithic Rendolls)

4.3 (SOIL F) -Slopes with morphology and profile mostly regular and slope from steep to very steep. (No soil type given)

Appendix IX : 'R' Script for statistical methods

```
R : Copyright 2004, The R Foundation for Statistical Computing
Version 2.0.1  (2004-11-15), ISBN 3-900051-07-0

[Previously saved workspace restored]

> dset<-read.csv("Matrix1218R3.csv")
> str(dset)
`data.frame':   1212 obs. of  4 variables:
 $ change   : Factor w/ 4 levels "BB","OB","OO",..: 1 4 3 3 2 1 1 1 1 4 ...
 $ parcels  : Factor w/ 3 levels "L","M","S": 3 1 3 1 1 2 1 1 1 3 ...
 $ soil     : Factor w/ 6 levels "A","B","C","D",..: 2 5 3 1 6 6 1 1 6 6 ...
 $ elevation: int  1510 1660 1120 1940 1720 1500 1880 1750 1290 1170 ...
> attach(dset)
> changed2<-!(change=="BB"|change=="OO")
> table(changed2)
changed2
FALSE  TRUE
  795   417
> round(sum(changed2)/length(changed2),3
+ )
[1] 0.344
> changed3<-!(change=="BB"|change=="OO"|change=="OX")
> table(changed3)
changed3
FALSE  TRUE
 1008   204
> round(sum(changed3)/length(changed3),3)
[1] 0.168
> dc<-dset[substring(as.character(change),1,1)=="O",]
> str(dc)
`data.frame':   714 obs. of  4 variables:
 $ change   : Factor w/ 4 levels "BB","OB","OO",..: 4 3 3 2 4 4 3 3 3 3 ...
 $ parcels  : Factor w/ 3 levels "L","M","S": 1 3 1 1 3 1 3 1 3 2 ...
 $ soil     : Factor w/ 6 levels "A","B","C","D",..: 5 3 1 6 6 1 3 1 6 6 ...
 $ elevation: int  1660 1120 1940 1720 1170 2030 1560 1780 1190 1670 ...
> detach(dset);attach(dc)
> changed<-!(change=="BB"|change=="OO"|change=="OX")
> dc<-cbind(dc,changed)
> str(dc)
`data.frame':   714 obs. of  5 variables:
 $ change   : Factor w/ 4 levels "BB","OB","OO",..: 4 3 3 2 4 4 3 3 3 3 ...
 $ parcels  : Factor w/ 3 levels "L","M","S": 1 3 1 1 3 1 3 1 3 2 ...
 $ soil     : Factor w/ 6 levels "A","B","C","D",..: 5 3 1 6 6 1 3 1 6 6 ...
 $ elevation: int  1660 1120 1940 1720 1170 2030 1560 1780 1190 1670 ...
 $ changed  : logi  FALSE FALSE FALSE  TRUE FALSE FALSE FALSE FALSE FALSE FALSE FALSE  TRUE
...
> t<-table(parcels,changed)
> t
       changed
parcels FALSE TRUE
      L 183    48
      M  53    23
      S 274   133
> round(t/apply(t,1,sum),2)
       changed
parcels FALSE TRUE
      L 0.79  0.21
      M 0.70  0.30
      S 0.67  0.33
> chisq.test(t)
        Pearson's Chi-squared test
data:  t
X-squared = 10.3427, df = 2, p-value = 0.005677
> t2<-table(soil,changed)
> t2
    changed
soil FALSE TRUE
   A  86    25
   B 136   120
   C 109    35
   D  12     2
   E  65     3
   F 102    19
> chisq.test(t2)
        Pearson's Chi-squared test
data:  t2
X-squared = 75.9667, df = 5, p-value = 5.846e-15
Warning message:
```

```
Chi-squared approximation may be incorrect in: chisq.test(t2)
> round(t2/apply(t2,1,sum),2)
    changed
soil FALSE TRUE
   A 0.77  0.23
   B 0.53  0.47
   C 0.76  0.24
   D 0.86  0.14
   E 0.96  0.04
   F 0.84  0.16
> glm.parcels<-glm(changed~parcels,family=binomial)
> summary(glm.parcels)
Call:
glm(formula = changed ~ parcels, family = binomial)
Deviance Residuals:
   Min      1Q  Median      3Q     Max
-0.890  -0.890  -0.683   1.496   1.773
Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)   -1.338      0.162   -8.25   <2e-16
parcelsM       0.503      0.298    1.69   0.0908
parcelsS       0.616      0.194    3.18   0.0015
 (Dispersion parameter for binomial family taken to be 1)
    Null deviance: 854.33  on 713  degrees of freedom
Residual deviance: 843.62  on 711  degrees of freedom
AIC: 849.6
Number of Fisher Scoring iterations: 4
> 1-(glm.parcels$deviance/glm.parcels$null.deviance)
[1] 0.0125298
> logit.plot<-function(model, dframe, title="Logistic model of change") {
+ sf<-sort(model$fitted, index=T)
+ plot(sf$x, ylim=c(0,1), type="l", col=4, lwd=3,
+ xlab="sorted sample number", ylab="probability of change")
+ text(0,min(model$fitted)-.03,
+ "fitted probability of change",col=4,pos=4)
+ title(title)
+ abline(h=mean(model$fitted),lty=2)
+ text(0,mean(model$fitted)+.02,
+ "mean probability of change", pos=4)
+ abline(v=length(dframe$changed)/2,lty=2)
+ text(length(dframe$changed)/2,.03,"midpoint",pos=4)
+ # show actual points changed as vertical bars at the index
+ # this should be denser towards the extremes
+ points(1:length(dframe$changed),dframe$changed[sf$ix],
+ pch="|",cex=1,col=ifelse(dframe$changed[sf$ix],2,3))
+ text(0,.03,"Samples with no change",col=3,pos=4)
+ text(0,.97,"Samples with change",col=2,pos=4)
+ # print model and fit
+ text(length(dframe$changed),0.30,paste(
+ "Model:", model$formula[2], model$formula[1], model$formula[3],sep=" "),
+ pos=2,font=4)
+ text(length(dframe$changed),0.25,paste(
+ "AIC:", round(summary(model)$aic,0), sep=" "),
+ pos=2,font=4)
+ text(length(dframe$changed),0.20,paste(
+ "Null deviance:", round(summary(model)$null.deviance,0),sep=" "),
+ pos=2,font=4)
+ }
> logit.plot(glm.parcels,dc)
> glm.soil<-glm(changed~soil,family=binomial)
> summary(glm.soil)
Call:
glm(formula = changed ~ soil, family = binomial)
Deviance Residuals:
   Min      1Q  Median      3Q     Max
-1.125  -0.746  -0.584   1.231   2.498
Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -1.2355     0.2272   -5.44  5.4e-08
soilB         1.1103     0.2594    4.28  1.9e-05
soilC         0.0995     0.2990    0.33   0.7393
soilD        -0.5563     0.7968   -0.70   0.4851
soilE        -1.8403     0.6327   -2.91   0.0036
soilF        -0.4451     0.3377   -1.32   0.1876

(Dispersion parameter for binomial family taken to be 1)
    Null deviance: 854.33  on 713  degrees of freedom
Residual deviance: 773.31  on 708  degrees of freedom
AIC: 785.3

Number of Fisher Scoring iterations: 5
```

```
> 1-(glm.soil$deviance/glm.soil$null.deviance)
[1] 0.0948389
> logit.plot(glm.soil,dc)
> glm.elevation<-glm(changed~elevation,family=binomial)
> summary(glm.elevation)
Call:
glm(formula = changed ~ elevation, family = binomial)
Deviance Residuals:
   Min      1Q  Median      3Q     Max
-1.079  -0.918  -0.667   1.382   2.090
Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)  1.678531   0.475861    3.53  0.00042
elevation   -0.001854   0.000344   -5.40  6.9e-08

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 854.33  on 713  degrees of freedom
Residual deviance: 819.21  on 712  degrees of freedom
AIC: 823.2
Number of Fisher Scoring iterations: 4
> 1-(glm.elevation$deviance/glm.elevation$null.deviance)
[1] 0.0411021
> logit.plot(glm.elevation,dc)
> length(glm.parcesl$fitted)
Error: Object "glm.parcesl" not found
> length(glm.parcels$fitted)
[1] 714
> summary(glm.parcels$fitted)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  0.208   0.208   0.327   0.286   0.327   0.327
> sum(glm.parcels$fitted>0.2)
[1] 714
> summary(glm.parcels$fitted>0.2)
   Mode    TRUE
logical     714
> summary(glm.parcels$fitted>0.3)
   Mode   FALSE    TRUE
logical     231     483
> sum(changed)
[1] 204
> sum((glm.parcels$fitted> 0.3) & changed)
[1] 156
> (sens.p<-sum((glm.parcels$fitted > 0.3) & changed)/sum(changed))
[1] 0.764706
> summary(glm.parcels$fitted>0.32)
   Mode   FALSE    TRUE
logical     307     407
> summary(glm.parcels$fitted>0.25)
   Mode   FALSE    TRUE
logical     231     483
> sum(!changed)
[1] 510
        (list) object cannot be coerced to double
> sum((glm.parcels$fitted < 0.3) & (!changed))
[1] 183
>  sum((glm.parcels$fitted< 0.3))
[1] 231
> (spec.p<-sum((glm.parcels$fitted < 0.3) & (!changed))/sum(!changed))
[1] 0.358824
> (fp.p<-sum((glm.parcels$fitted > 0.3) & !changed)/sum(!changed))
[1] 0.641176
> spec.p+fp.p
[1] 1
> (fn.p<-sum((glm.parcels$fitted < 0.3) & changed)/sum(changed))
[1] 0.235294
> sens.p+fn.p
[1] 1
> length(glm.soil$fitted)
[1] 714
> summary(glm.soil$fitted)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 0.0441  0.1570  0.2430  0.2860  0.4690  0.4690
> sum(glm.soil$fitted>0.3)
[1] 256
> sum(changed)
[1] 204
> sum((glm.soil$fitted > 0.3) & changed)
[1] 120
> (sens.s<-sum((glm.soil$fitted > 0.3) & changed)/sum(changed))
[1] 0.588235
> sum(!changed)
```

```
[1] 510
> sum((glm.soil$fitted < 0.3))
[1] 458
> sum((glm.soil$fitted < 0.3) & (!changed))
[1] 374
> (spec.s<-sum((glm.parcels$fitted < 0.3) & (!changed))/ sum(!changed))
[1] 0.358824
> ((fp.s<-sum((glm.soil$fitted > 0.3) & !changed)/sum(!changed))
+ )
[1] 0.266667
> spec.s + fp.s
[1] 0.62549
> (spec.s<-sum((glm.soil$fitted < 0.3) & (!changed))/ sum(!changed))
[1] 0.733333
> spec.s + fp.s
[1] 1
> (fn.s<-sum((glm.soil$fitted < 0.3) & changed)/sum(changed))
[1] 0.411765
> sens.s+fn.s
[1] 1
> length(glm.elevation$fitted)
[1] 714
> summary(glm.elevation$fitted)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 0.0491  0.2060  0.3210  0.2860  0.3620  0.4410
> sum(glm.elevation$fitted>0.3)
[1] 416
> sum(changed)
[1] 204
> sum((glm.elevation$fitted > 0.3) & changed)
[1] 138
> ((sens.e<-sum((glm.elevation$fitted > 0.3) & changed)/sum(changed))
+ )
[1] 0.67647
> sum(!changed)
[1] 510
> sum((glm.elevation$fitted < 0.3))
[1] 298
> sum((glm.elevation$fitted < 0.3) & (!changed))
[1] 232
> (spec.e<-sum((glm.elevation$fitted < 0.3) & (!changed))/ sum(!changed))
[1] 0.454902
> (fp.e<-sum((glm.elevation$fitted > 0.3) & !changed)/sum(!changed))
[1] 0.545098
> spec.e + fp.e
[1] 1
> (fn.e<-sum((glm.elevation$fitted < 0.3) & changed)/sum(changed))
[1] 0.323529
> sens.e+fn.e
[1] 1
> plot.quad <- function(model, dframe, threshold=0.2, title="Model success") {
+ sf<-sort(model$fitted, index=T)
+ # leave extra space at bottom for diagnostics, no slop on x axis
+ par(mar=c(8,4,4,2)+.1); par(col.sub="blue"); par(xaxs="i", yaxs="r")
+ plot(sf$x, ylim=c(0,1), type="l", col=4, lwd=3,
+ xlab="sorted sample number", ylab="probability of change")
+ abline(h=c(0,1), lty=1)
+ # show threshold and its crossover point
+ abline(h=threshold,lty=2); text(0,threshold+.02, "threshold", pos=4)
+ crossover <- sum(model$fitted < threshold)
+ abline(v=crossover,lty=2)
+ text(crossover,.05,"crossover",pos=4)
+ text(crossover, threshold-.03,
+ "fitted probability of change",col=4,pos=4)
+ # show actual points changed as vertical bars at the index
+ # colours differ with false /true predictions
+ points(1:length(dframe$changed),dframe$changed[sf$ix],
+ pch="|",cex=1,
+ col=ifelse((dframe$changed[sf$ix] == (sf$x>threshold)),3,2))
+ right <- length(sf$x)*.7
+ # compute proportions
+ tn <- sum(!dframe$changed[sf$ix] & (sf$x<threshold))
+ fn <- sum(!dframe$changed[sf$ix] & (sf$x>=threshold))
+ tp <- sum(dframe$changed[sf$ix] & (sf$x>=threshold))
+ fp <- sum(dframe$changed[sf$ix] & (sf$x<threshold))
+ text(0,.1,paste("True negatives:",tn), col=3,pos=4)
+ text(right,.1,paste("False negatives:", fn), col=2,pos=4)
+ text(right,.9,paste("True positives:", tp), col=3,pos=4)
+ text(0,.9,paste("False positives:", fp), col=2,pos=4)
+ title(main=title)
+ title(sub=paste("Sensitivity:", round(tp/(tp+fp),4), ";
+ Specificity:", round(tn/(tn+fn),4)), line=6)
```

```
+ }
> plot.quad <- function(model, dframe, threshold=0.3, title="Model success") {
+ sf<-sort(model$fitted, index=T)
+ # leave extra space at bottom for diagnostics, no slop on x axis
+ par(mar=c(8,4,4,2)+.1); par(col.sub="blue"); par(xaxs="i", yaxs="r")
+ plot(sf$x, ylim=c(0,1), type="l", col=4, lwd=3,
+ xlab="sorted sample number", ylab="probability of change")
+ abline(h=c(0,1), lty=1)
+ # show threshold and its crossover point
+ abline(h=threshold,lty=2); text(0,threshold+.02, "threshold", pos=4)
+ crossover <- sum(model$fitted < threshold)
+ abline(v=crossover,lty=2)
+ text(crossover,.05,"crossover",pos=4)
+ text(crossover, threshold-.03,
+ "fitted probability of change",col=4,pos=4)
+ # show actual points changed as vertical bars at the index
+ # colours differ with false /true predictions
+ points(1:length(dframe$changed),dframe$changed[sf$ix],
+ pch="|",cex=1,
+ col=ifelse((dframe$changed[sf$ix] == (sf$x>threshold)),3,2))
+ right <- length(sf$x)*.7
+ # compute proportions
+ tn <- sum(!dframe$changed[sf$ix] & (sf$x<threshold))
+ fn <- sum(!dframe$changed[sf$ix] & (sf$x>=threshold))
+ tp <- sum(dframe$changed[sf$ix] & (sf$x>=threshold))
+ fp <- sum(dframe$changed[sf$ix] & (sf$x<threshold))
+ text(0,.1,paste("True negatives:",tn), col=3,pos=4)
+ text(right,.1,paste("False negatives:", fn), col=2,pos=4)
+ text(right,.9,paste("True positives:", tp), col=3,pos=4)
+ text(0,.9,paste("False positives:", fp), col=2,pos=4)
+ title(main=title)
+ title(sub=paste("Sensitivity:", round(tp/(tp+fp),4), ";
+ Specificity:", round(tn/(tn+fn),4)), line=6)
+ }
> plot.quad (glm.parcels,dc)
NULL
> plot.quad (glm.soil,dc)
NULL
> plot.quad (glm.elevation,dc)
NULL
> roc <- function(model, dframe, steps=20) {
+ roc<- data.frame(pts = seq(0, 1-(1/steps), by=1/steps), sens = 0, spec=0);
+ for (i in 0:steps) {
+ thresh <- i/steps;
+ roc$sens[i] <- sum((model$fitted >= thresh) &
+ dframe$changed)/sum(dframe$changed);
+ roc$spec[i] <- sum((model$fitted < thresh) &
+ !dframe$changed)/sum(!dframe$changed)
+ }
+ return(roc)
+ }
> roc.area <- function(roc) {
+  area <- 0;
+ for (i in 1:(length(roc$pts)-1))
+ area <- area + ((1 - roc$sens[i+1]) - (1 - roc$sens[i]))*
+ ((roc$spec[i+1] + roc$spec[i])/2);
+          return (area)
+ }
> plot.roc<-function(r,title="ROC curve") {
+ old.par<-par(no.readonly=TRUE); on.exit(par(old.par))
+ par(xaxs="i", yaxs="i")
+ plot(1 - r$sens, r$spec, xlim=c(0, 1), ylim=c(0,1), type="l",
+ xlab="(1 - sensitivity): false positive rate",
+ ylab="specificity: true positive rate",
+ col="blue", lwd=2);
+ points(1 - r$sens, r$spec, pch=20, cex=2, col="blue");
+ abline(0, 1, lty=2);
+ segments(1-r$sens, 1-r$sens, 1-r$sens, r$spec, lty=2)
+ text(0, 0.9, paste("Area under ROC:",round(roc.area(r),4)), pos=4)
+ title(main = title)
+ }
> rp<-roc(glm.parcels,dc)
> roc.area(rp)
[1] 0.561765
> plot.roc(rp,"ROC for prediction by land parcels")
NULL
> rs<-roc(glm.soil,dc)
> roc.area(rs)
[1] 0.694002
> plot.roc(rs,"ROC for prediction by soil type")
NULL
> re <-roc(glm.elevation,dc)
```

```
> roc.area(re)
[1] 0.59319
> plot.roc(re,"ROC for prediction by elevation")
NULL
> t.ps<-xtabs(~parcels + soil,dc)
> t.t<-xtabs((change==T) ~ parcels + soil,dc)
> t.t<-xtabs((changed==T)~ parcels + soil,dc)
> t.f<-xtabs((changed==F)~ parcels + soil,dc)
> t.ps;t.t;t.f
       soil
parcels A   B   C   D   E   F
      L  74  33   2  11  54  57
      M   4  30   2   3   9  28
      S  33 193 140   0   5  36
       soil
parcels A  B  C  D  E  F
      L 12 21  1  2  3  9
      M  2 18  2  0  0  1
      S 11 81 32  0  0  9
       soil
parcels A   B   C   D   E   F
      L  62  12   1   9  51  48
      M   2  12   0   3   9  27
      S  22 112 108   0   5  27
> round(t.t/t.f,3)
       soil
parcels A     B     C     D     E     F
      L 0.194 1.750 1.000 0.222 0.059 0.188
      M 1.000 1.500   Inf 0.000 0.000 0.037
      S 0.500 0.723 0.296       0.000 0.333
> sum(t.t)/sum(t.f)
[1] 0.4
> par(mfrow=c(1,1))
> plot(elevation~parcels,xlab="land parcels class",
+ ylab="elevation in metres")
> plot(elevation~soil,xlab="soil type",
+ ylab="elevation in metres")
> lm.r<-lm(elevation~parcels);summary(lm.r)
Call:
lm(formula = elevation ~ parcels)
Residuals:
    Min      1Q  Median      3Q     Max
-605.97  -93.58   -9.27   91.33  755.03
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   1749.0       13.5   129.2   <2e-16
parcelsM      -280.7       27.2   -10.3   <2e-16
parcelsS      -493.4       17.0   -29.1   <2e-16
Residual standard error: 206 on 711 degrees of freedom
Multiple R-Squared: 0.544,      Adjusted R-squared: 0.543
F-statistic:  424 on 2 and 711 DF,  p-value: <2e-16
> lm.r2<lm(elevation~soil);summary(lm.r2)
Error: Object "lm.r2" not found
> lm.r2<-lm(elevation~soil);summary(lm.r2)
Call:
lm(formula = elevation ~ soil)
Residuals:
   Min     1Q Median     3Q    Max
-688.8 -113.5  -14.5  135.5  793.5
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   1627.0       21.0   77.56  < 2e-16
soilB         -319.3       25.1  -12.71  < 2e-16
soilC         -382.5       27.9  -13.70  < 2e-16
soilD          190.7       62.7    3.04   0.0024
soilE          291.8       34.0    8.57  < 2e-16
soilF         -171.5       29.0   -5.90  5.5e-09

Residual standard error: 221 on 708 degrees of freedom
Multiple R-Squared: 0.476,      Adjusted R-squared: 0.473
F-statistic:  129 on 5 and 708 DF,  p-value: <2e-16
Call:
>  glm.se2<-glm(changed~soil+elevation,family=binomial)
> summary(glm.se2)
Call:
glm(formula = changed ~ soil + elevation, family = binomial)
Deviance Residuals:
   Min      1Q  Median      3Q     Max
-1.243  -0.777  -0.599   1.185   2.418
Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)  0.500858   0.745665    0.67   0.5018
```

```
soilB        0.799463   0.285956    2.80   0.0052
soilC       -0.282016   0.334117   -0.84   0.3986
soilD       -0.311664   0.806425   -0.39   0.6991
soilE       -1.540892   0.645858   -2.39   0.0170
soilF       -0.624735   0.348133   -1.79   0.0727
elevation   -0.001091   0.000455   -2.39   0.0166
 (Dispersion parameter for binomial family taken to be 1)
    Null deviance: 854.33  on 713  degrees of freedom
Residual deviance: 767.44  on 707  degrees of freedom
AIC: 781.4
Number of Fisher Scoring iterations: 5
> 1-(glm.se2$deviance/glm.se2$null.deviance)
[1] 0.101700
> logit.plot(glm.se2,dc)
NULL
> plot.quad(glm.se2,dc)
NULL
> plot.roc(rall4,"ROC for parcels,soils,elevation")
NULL
> plot.roc(rse,"ROC for soils and elevation")
NULL
> rse2<-roc(glm.se2,dc)
> roc.area(rse2)
[1] 0.701956
> plot.roc(rse2,"ROC for soils and elevation")
NULL
> t<-table(elevcont,changed)
> t
        changed
elevcont FALSE TRUE
     ext  47     1
     h   107    54
     l     4     0
     mh   66    30
     ml  227   115
     vh   59     4
> round(t/apply(t,1,sum),2)
        changed
elevcont FALSE TRUE
     ext 0.98  0.02
     h   0.66  0.34
     l   1.00  0.00
     mh  0.69  0.31
     ml  0.66  0.34
     vh  0.94  0.06
> chisq.test(t)

        Pearson's Chi-squared test

data:  t
X-squared = 39.9128, df = 5, p-value = 1.555e-07

Warning message:
Chi-squared approximation may be incorrect in: chisq.test(t)
>
```

Appendix X: Tables for sample points used in 'R'

Table 8-3: Table showing the number of sample points that changed and did not change per land parcel size.

Land Parcel Class	Change to Beech	No Change
Large Parcels	48	183
Medium Parcels	23	53
Small Parcels	133	274

Table 8-4: Table showing the number of sample points that changed and did not change per soil type.

Soil Type	Change to Beech	No Change
Soil A	25	86
Soil B	120	136
Soil C	35	109
Soil D	2	12
Soil E	3	65
Soil F	19	102