Tree Line Change in Majella, Italy: Trends, Causes and Predictions

Li Dai
March, 2010

Course Title:	Geo-Information Science and Earth Observation for Environmental Modelling and Management
Level:	Master of Science (Msc)
Course Duration:	September 2008 - March 2010
Consortium partners:	University of Southampton (UK) Lund University (Sweden) University of Warsaw (Poland) International Institute for Geo-Information Science and Earth Observation (ITC) (The Netherlands)
GEM thesis number:	2010-11

Tree Line Change in Majella, Italy: Trends, Causes and Predictions

by

Li Dai

Thesis submitted to the International Institute for Geo-information Science and Earth Observation in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation for Environmental Modelling and Management

Thesis Assessment Board

Chairman: Prof. Dr. A.K. (Andrew) Skidmore
External Examiner: Dr. Petter Pilesjö
First Supervisor: Dr. H.A.M.J. (Hein) van Gils
Second Supervisor: Dr. D.G. (David) Rossiter

UNIVERSITY OF TWENTE.

ITC FACULTY OF GEO-INFORMATION SCIENCE AND EARTH OBSERVATION

Disclaimer

This document describes work undertaken as part of a programme of study at the International Institute for Geo-information Science and Earth Observation. All views and opinions expressed therein remain the sole responsibility of the author, and do not necessarily represent those of the institute.

Abstract

High-altitude forests are sensitive to climate change, especially in the location of the tree line. In the course of 20th century, tree line change was observed in most parts of the world. This study aims to quantify the process and explain the causes of tree line change between 1954 and 2007 in 28.7 km^2 study area within Majella National Park, Italy, as well as predicting future changes. Dwarf pine (*Pinus mugo* L.) is the species dominates the tree line in the study area. Panchromatic aerial photos of 1954 and colour aerial photos of 2007 were accurately (weighted Kappa = 0.8) classified by the object-oriented method, and the change in the period was determined by map overlay. Vertical expansion was primary down slope. Most expansion was lateral and concentrated between 1700 and 2300 m elevation.

Changes were analyzed for two plots, but only one plot was further analyzed for statistical modelling and prediction. Causes of dwarf pine expansion were inferred from logistic regression models implemented as generalized linear models in the R computing environment. Six explanatory variables showed significant relation to expansion: altitude, historical grazing, distance to historical beech, proximity to historical dwarf pine, 10 m neighbourhood effect of beech, and 70 m neighbourhood effect of dwarf pine. The model with these six variables successfully describes expansion (area under ROC curve is 0.87). Considering the variables identified for the final model, and the mostly lateral and downward change, expansion of dwarf pine in this plot was primarily driven by land use change, i.e. abandonment of alpine summer grazing. If the current trend continues, it is predicted to be a 47 m upwards shift of tree line by 2060 at the 0.6 probability threshold.

Key word: tree line change, climate change, livestock grazing, dwarf pine, object-oriented classification, aerial photo, logistic regression, neighbourhood effect, R, generalized linear model

Acknowledgements

I sincerely thank my supervisors, Dr. Hein van Gils and Dr. David Rossiter, who supported me for more than half a year to finish this thesis. Deep gratitude to both of you, especially for the excellent suggestions and perceptive comments.

Special thanks to Dr. Anton Vrieling, Drs. Eduard Westinga and the staffs of Italian Majella Natianl Park for the help during the field work.

Several people contributed to the technique part of my work. I really appreciated the valuable time and expertise from Dr. Tiejun Wang, Mr. Gerard Reinink, Ms. Muditha Heenkenda, Mr. Sokhon Phem and Ms. Shruthi Chalapathi. Dr. David Rossiter deserves a mention again because of the great contribution of using logistic model and R codes in this work.

I'm also grateful to EU Erasmus Mundus programme, to the four universities in GEM course: the University of Southampton (UK), Lund University (Sweden), University of Warsaw (Poland) and ITC (Netherlands). Thanks all the professors, lecturers and course coordinators in these four universities.

Also, I would like to express gratitude to all the lovely GEMs 2008, and my friends for having the wonderful time together throughout the GEM course.

Lastly, my heartfelt appreciation goes to my family, the encouragement from you makes the accomplishment of my work possible.

Table of contents

List of figures

List of tables

Appendices

1. Introduction

1.1. Tree line change

1.1.1. Forest and tree line

Forest covers around one third of the total land area in the world (FAO, 2005), and is one of the key components in the biosphere. It adjusts atmospheric and hydrological cycles, acts as sources of food, industrial material, and has a close relation to fauna and vegetation (McMahon et al., 2009). The change of forest influences the environment, for example, the frequency of natural disasters, as well as its socio-economic function (FAO, 2005). Accordingly, study of forest and its change is crucial especially in view of climate change.

Forest dynamics at high altitude are obvious under climate change because the harsh environmental conditions are sensitive to many drivers, and these factors limit the highest altitude for certain species survival. There are many definitions relating to the highest growing limit of the tree, such as tree line, timber line, tree species line, tree limit and tree line ecotone, which are applied in different studies (Kullman, 2001, Korner and Paulsen, 2004, Holtmeier, 2009). In this study, the place of "elevation (m a.s.l) of the uppermost individual of a specific tree species with a minimum height of 2 m" is adopted as tree line (Kullman, 2001). The transaction from upper closed forest to the upper growing limit for specific species, in reality, is not always a line, but is a density or height reducing zone mixed with shrub, which is called tree line ecotone or tree line park land (Korner and Paulsen, 2004, Zhang et al., 2009) (Figure 1).

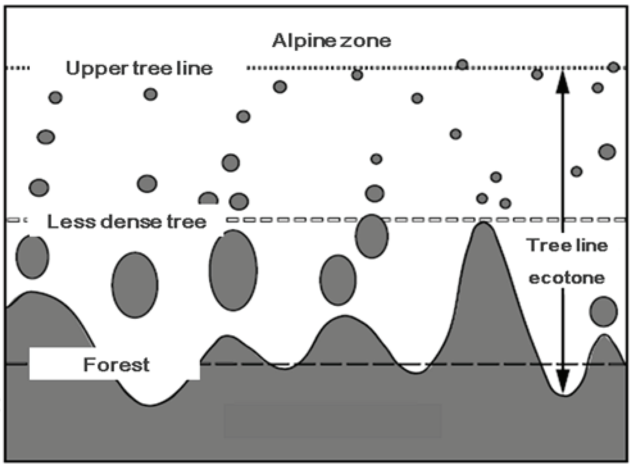


Figure 1 Schematic representation of tree line and forest (Modified from Korner and Paulsen, 2004)

Further, Holtmeier (2009) defined four categories of tree line from a global view (Figure 2). For type a, b and d in Figure 2, there are mainly two kinds of land cover: forest and low vegetation, while the Krummholz belt involves in c type of tree line ecotone. Krummholz belt is often formed by dense, prostrate woody species, such as dwarf pine (*Pinus mugo*, L.), which dominates tree line ecotone. This belt exists in the "Alps, the Dinaric Alps, Carpathian Mountains, Japan, Sikhote Alin Mountains, Sachalin and Kamchatka" (Holtmeier, 2009), and has been directly used for tree line study as it fringes tree line ecotone (Dullinger et al., 2005, Wild and Winkler, 2008).

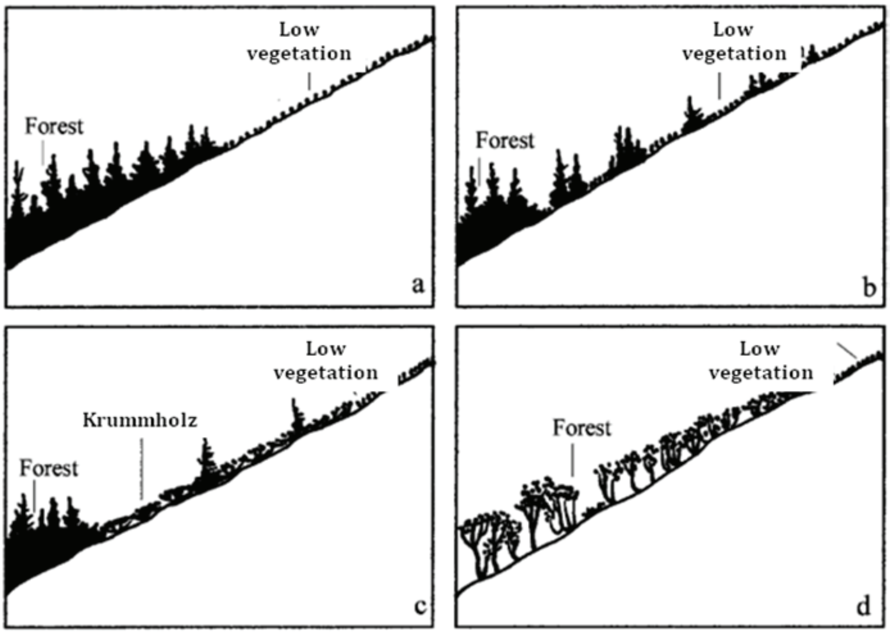


Figure 2 Four types of tree line: a. abrupt forest limit bordering with alpine low vegetation; b. tree line with a transition zone (ecotone); c. a Krummholz belt above the upright growing forest; d. gradual transition with same species from high to low stemmed trees (Modified from Holtmeier, 2009).

1.1.2. Tree line change and influence

In the twentieth century, observed tree line change, especially alpine tree line shift, is common around the world (Danby and Hik, 2007, Zhang et al., 2009). Between late 19th and late 20th century, multispecies elevational tree-limit moved up more than 100 m in Swedish Scandinavian mountain without time lag (Kullman, 2001). Melanie et al. (2009) examined more than 200 tree line studies carried out in 166 site worldwide, mainly alpine tree line in America and Europe, and found advances at about 52% of all these sites since 1900 AD. Besides, tree line change in the Alps is also significant (Rolland et al., 1998, Paulsen et al., 2000), such as in Switzerland (Gehrig-Fasel et al., 2007).

However, the changes are not uniform. Lloyd and Fastie (2002) observed decreased tree growth in some part of the Alaska Range. Tree line advanced at different speed in north-facing and south-facing slope in the northern Scandinavian mountain range in Sweden (Karlsson et al., 2007). Also, speed of change partly depends on temporal turnover length of each species (Lenoir et al., 2008). Hence, these changes are species specific and link to local physical or geographical condition (Zhang et al., 2009).

Changes of tree line and its ecotone have significant implication for global carbon cycle study, particularly for carbon sink calculation (Grace et al., 2001). Korner (1998) states that trees near tree line are more favourable for photosynthesis than trees in lower altitude in growing season in the temperate zone. This might help further understanding "the missing mid-latitudinal carbon sink and negotiations on carbon credits for 'reforestation'"(van Gils et al., 2008). Besides, the change of forest type in different elevation may subsequently modify biodiversity status. As richness of central-southern Apennines endemics rises along with increase of altitude in central Italy, the moving up of tree line will reduce biodiversity (Stanisci et al., 2005). Meanwhile, these changes extensively alter landscapes, as well as closely related stakeholders (Grace et al., 2001).

1.1.3. The reasons of tree line change

Tree growth and seed production, factors defining forest expansion, are constrained by temperature, precipitation, solar radiation, wind strength and soils nutrient condition (Grace et al., 2001, Liu et al., 2002, Hoch and Korner, 2009, Takahashi and Yoshida, 2009) . Temperature is one of the key factors which inhibit the upper vegetation distribution limit in alpine zone, especially the temperature during the growing season, the "warmest month" rule, lower threshold temperature for tissue growth, seasonal mean air temperature and root zone temperature have been used to explain the growing limit in the high altitude (Korner, 1998, Wieser et al., 2009).

In 20th century, climate change took place and will continue in the future (Pachauri and Reisinger, 2007). Temperature increase has been recorded in alpine zone as well. The Swiss Alps temperature increased 1℃ to 2 ℃ between 569 and 2500 m a.s.l, which is 0.7 ℃ higher the average increase of world, and the change accelerated after 1980s (Beniston et al., 1997). These changes of temperature lift up the thermal boundary of vegetation growth, and induce tree line variation (Korner, 1998, Melanie et al., 2009). In addition, Lenoir et al. (2008) calculated the rate of mountainous vegetation change caused by climate warming in west European mountain between 1905 and 2005.

Besides climate change, anthropogenic influence is another well discussed factor, such as land use change. Abandoned farm land and pasture with reduced grazing intensity are the favourable location for forest invasion below the potential natural tree line (Gehrig-Fasel et al., 2007, van Gils et al., 2008).

Land uses together with climate change have synergetic effect on tree line shift and its ecotone, as long as both of the factors jointly working at the same area, such as the northern Scandinavian forest and most places in the Alps (Theurillat and Guisan, 2001, Karlsson et al., 2007). Historically, a large number of studies deal with small area and emphasize on regional peculiarities, which could overshadow the broader climate change trend. Few studies have compared changes in relatively natural environment and the joint effects' surroundings of tree line and its ecotone. However, distinguishing between anthropogenic and climate influence can be complex if both of them have occurred in same place over a very long time (Motta and Nola, 2001).

1.1.4. Methods of tree line change research

Different methods have been applied to look into change around the tree line. Usually, detailed ground measurements and land use statistics are used (Kullman, 2001, Korner and Paulsen, 2004, Gehrig-Fasel et al., 2007). Models are also common approaches to assess the influencing factors of tree line or vegetation distribution, such as climate envelope modeling (CEM), succession model FORCLIM and GLM model (Guisan et al., 1998, Heiri et al., 2006, van Gils et al., 2008, van Zonneveld et al., 2009). In addition, plant physiology, such as the effects of seedlings' pre-establishment, is studied for determining upper limit changes of vegetation growth (Smith et al., 2009). Dendroecological methods are applied to analysis developing dynamic and influencing factors for tree line species (Motta et al., 2006, Palombo, 2009).

Remote Sensing (RS) images, especially the spaceborne RS, are not widely used for tree line change detection due to conflicts between the short time availability of satellite image (after 1970s) and the long term period of tree line change. Meanwhile, the response of vegetation to global warming around the tree line ecotone has been reported as increased forest density and increased radial and vertical growth rather than the upwards advancing of the tree line (Payette and Filion 1985, Kullman 2007), which means that the density change is a relatively faster process comparing detectable tree line change. Both the density and tree line location have close relationship with each other, and density indicates the actual and potential change of tree line. As single tree is hardly detectable by remote sensing method, classification of images is usable for studying tree line combined with density concept. The same principle is also applied for vegetation index computation from satellite image (Zhang et al., 2009).

Post classification change detection, data transformation and image differencing are suitable method for studying tree line and forest (Mas, 1997, Woodcock et al., 2001). Aerial photos, furthermore, are proper information sources due to their long backward study period and higher resolution which are good for global change research and historical change detection (Kadmon and Harari-Kremer, 1999, Okeke and Karnieli, 2006).

1.2. Dwarf pine

In the mountains of eastern, central and southern Europe, dwarf pine presently dominates the tree line (Dullinger et al., 2003, Dullinger et al., 2004, Boratynska et al., 2005) (Figure 3). Dwarf pine belongs to the family of Pinaceae, is also called as dwarf mountain pine, mountain pine and mugo pine, the scientific name is *Pinus mugo* (Pignatti, 1982). It is a long-lived shrubby vegetation type, and can reach 2 to 5 m tall of adult canopy height with flowering from May to July (Pignatti, 1982). The asymmetry of cones (Figure 3) is a unique feature for identification against related other sub-species, such as cembra pine (*Pinus cembra* L.). The primary way of reproduction is seed being distributed firstly by wind, secondly by birds and small mammals (Müller-Schneider, 1986). Occasionally, dwarf pine reproduces by layering (Wild and Winkler, 2008, Holtmeier, 2009). Most tree species reproduces at quite old age, but dwarf pine produces seed only after 10 years (Holtmeier, 2009). It prefers basic, calcareous or Dolomitic grounds, and distributes between 1500 and 2700 m in the valley of Italy, which highest growing place is beyond range of other arboreal vegetation (Pignatti, 1982).

Figure 3 Dwarf pine at the tree line and its cone (by Li Dai, September of 2009 in Majella National Park, Italy)

In its natural growing range, dwarf pine always set up thick, widespread and single dominant shrub land (Dullinger et al., 2003). However, it does not solely constitute vegetation between subalpine belts to upper tree line, it forms mixed woodland with European larch [*Larix decidua* (Mill.)], cembra pine (*Pinus cembra* L.) and European spruce [*Picea abies* (L.) Karst] in dry and continental valleys of the Alps (Carcaillet et al., 2009).

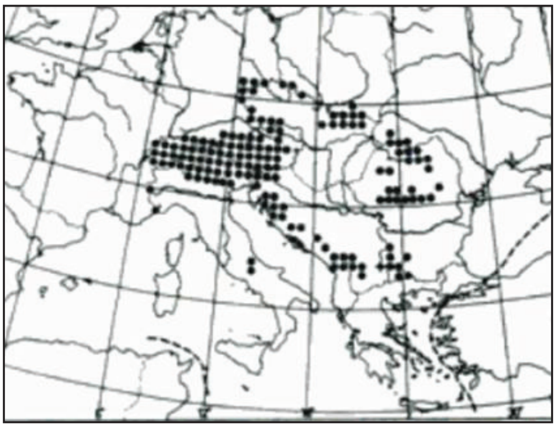


Figure 4 Distribution of dwarf pine in Europe. Black dots represent the occurrence of dwarf pine (Richardson, 1998)

Dwarf pine distributes in Alps, the Dinaric Alps, Carpathian Mountains and central–Apennines in Europe (Figure 4) (Holtmeier, 2009). It is a pioneer species, but is fragmented and isolated from other similar sub-species (Ali et al., 2006). One of the most geographically isolated location is in the upper elevations of the Abruzzian Apennines (Boratynska et al., 2005). Ali et al. (2006) estimated that there was wider spatial distribution in the occidental Alps in the past.

Dwarf pine expansion is common because of the climate change and human influence, for example, the changes of land use or abandonment of transhumance summer grazing (Dullinger et al., 2003, Bemigisha et al., 2008, Hoch and Korner, 2009, Palombo, 2009). Upward movement of dwarf pine is obvious. It can invade subalpine abandoned pasture land, pose threat to many herbaceous species (Dullinger et al., 2003, Palombo, 2009).

1.3. Research problem

Climate change has been observed in Italy in past 130 years, and is predicted to further rise a 3.5 ℃ in temperature before the year of 2100 (Brunetti et al., 2001). Beech (*Fagus sylvatica* L.) forest has expanded to sub-alpine grassland at annual rate of 0.5 % in the Majella National Park since 1975 (van Gils et al., 2008). Stanisci et al. (2005) predicted that climate change in Majella National Park would lead to tree line shift firstly in the eastward aspect. However, only few researches studied the change of shrubby vegetation near tree line, and even fewer concentrated on the dwarf pine as tree line species (Richardson, 1998, Dullinger et al., 2003, Boratynska et al., 2005, Carcaillet et al., 2009, Palombo, 2009).

There are two factors that potentially influence the tree line in Majella: climate and human activities change, but most previous studies have not separated the effect of the two factors.

Further, in terms of technique, automatic classification is more advanced than traditional visualized method since it is accurate and repeatable. Moreover, object-oriented classification can improve the problem of salt and pepper effect caused by traditional pixel based classification approach for very high resolution imagery (Pekkarinen, 2002, Yu et al., 2006). Application of object-oriented segmentation for both deciduous and conifer species shows high accuracy (Pekkarinen, 2002, Platt and Schoennagel, 2009). Nevertheless, this method is easier to apply for distinguishing objects with clear boundaries, which is less utilized in historical panchromatic photos. There are only a few studies about suitability of object-oriented classification method for historical Black and White (B&W) aerial photos (Hay et al., 2005, Elmqvist et al., 2008, Platt and Schoennagel, 2009).

Accordingly, three issues haven’t been solved: first, the change of shrubby tree line vegetation; second, suitability of object-oriented method for historical B&W aerial photo classification; third, differentiating influences of climate change and human impact to tree line change.

2. Method and materials

2.1. Study area: Majella National Park

The study area (28.7 km^2) is located in Majella National Park (NP) in Italy. The NP was established in 1991 inside Abruzzo region, and includes parts of 3 provinces. It is one of the largest protected lands in Europe, has area of approximately 740 km^2, and is the place where dwarf pine is highly geographically isolated (Boratynska et al., 2005). Majella Mountain is "a thrust-related, asymmetric, box-shaped anticline composed of carbonates of Lower Cretaceous–Miocene age, covered by a silicoclastic sequence of Upper Miocene–Middle Pliocene age" (Tondi et al., 2006).

Inside the park, dwarf pine mainly distributes between 1400 and 2400 m in the north of the Majella massif (Figure 5). So, two plots where have continuous dwarf pine were selected among these places as the study area (Figure 5 and Table 1). The altitude of study area goes around 1000 m since this study needs the comparison between dwarf pine and beech, also because some dwarf pine grows in avalanche chute.

Table 1 Information of study area

plot	location	Area (km^2)	altitude (m)	slope (degree)
1	**14°4'E 42°8'N ~ 14°6'E 42°6'N**	**11.7**	**1237-2640**	**0.5- 59.6**
2	**14°6'E 42°9'N ~ 14°9'E 42°7'N**	**17.0**	**986- 2594**	**0.3- 73.0**

Climatically, beech belt inside study area is marine west coast climate, and known as "snowy winters and humid for the absence of annual summer drought" (van Gils et al., 2008). The higher part where dwarf pine grows is "subalpine-alpine humid type" (Stanisci et al., 2005). According to the manage plan of the park, most parts of both plots are within the "integral reserve" area, where is protected area. Few places are included in "Area of general activities places", where is designed for socio-economic activities, such as grazing.

Within study area, the beech forest is the dominating natural landscape below dwarf pine and sub-alpine grass land (Figure 6). The highest growing altitude of dwarf pine is around 2450 m a.s.l in the tree line ecotone (Stanisci et al., 2005). Subalpine grassland and *Juniper nana* (L.) also occur within tree line ecotone. Although different types of tree line exist in Majella NP, c type of Figure 2 is the most common one inside study area. In particular, considering much shorter reproduction time (10 years) of dwarf pine comparing to beech (50 years) (van Gils et al., 2008), the change of dwarf pine is more observable in 53 years' study span. Therefore, the change of dwarf pine between 1954 and 2007 is the main indicator of tree line dynamics inside study area.

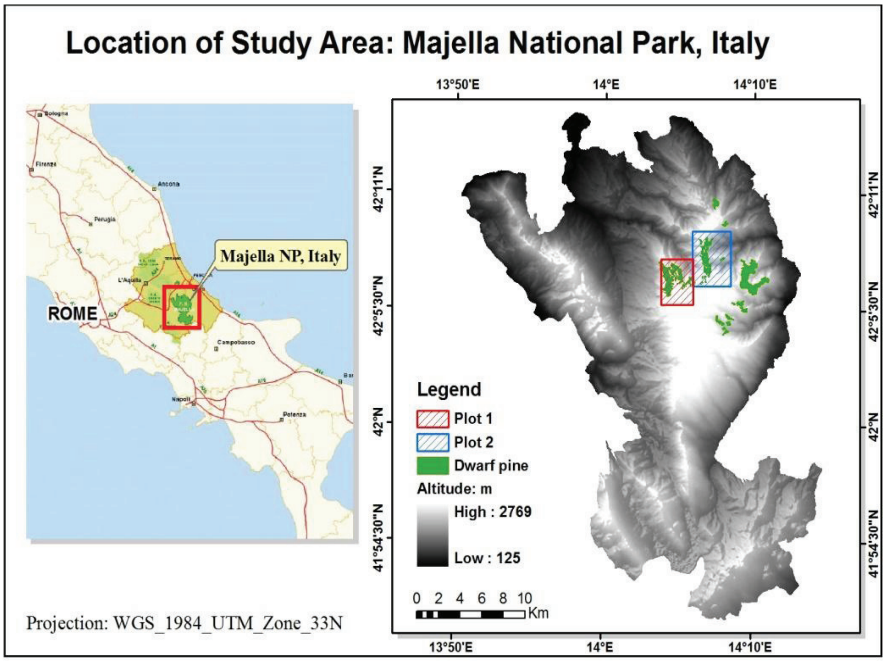


Figure 5 Location of study area. Plot-1 covers the top of mountain Rapina, Plot-2 covers the top of mountain Cavallo.
Location of Majella NP partly referenced information on website of Majella NP (Majella, 2009); the distribution of dwarf pine was referenced the land cover map (1999) from Majella NP; the DEM (1999) is from Majella NP.

In Majella NP, the human influences on dwarf pine were cutting and burn them to expand pasture land, or to create the cattle passages in the past. The livestock grazing started in Majella NP since about 2000 BC (Bemigisha et al., 2008). The grazing declined since 1950, and the speed of abandonment increased after 1995 because of establishment of the park.

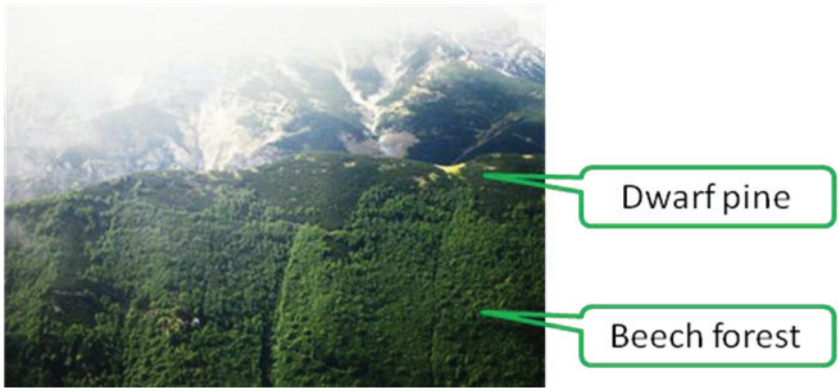


Figure 6 Beech and dwarf pine in the study area

2.2. Software and material

Software: ArcMap (version 9.3.1), ERDAS IMAGE 9.3, ERDAS LPS 9.3, ArcView 3.3, Definiens Developer 7, eCognition Developer 8, R (version 2.10.1) (R-Development-Core-Team, 2009), Tinn-R (version 2.3.4.2) and Microsoft Office 2007.

Material: all the original materials were used are shown in Table 2. They were utilized from field work preparation until statistical analysis.

Table 2 Material used in this study

Data	Year	Source	Data type	Resolution or others
DEM	**2008**	**ASTER**	**raster file**	**30 m**
Land cover map	**1999**	**Majella NP**	**vector file**	
Soil map	**1999**	**Majella NP**	**vector file**	
Aerial photos	**1954**	**Majella NP**	**panchromatic B&W photo**	**scale:1:33.000 size: 23*23 cm**
	2007	**Majella NP**	**digital colour photo**	**0.5 m WGS-1984-UTM-33N**
Grazing	**1999, 2007**	**Simone Angelucci, Majella NP**	**descriptive information**	
Geological map		**Majella NP**	**vector file**	**scale: 1:25.000**

2.3. Method

The working procedure is shown in Figure 7.

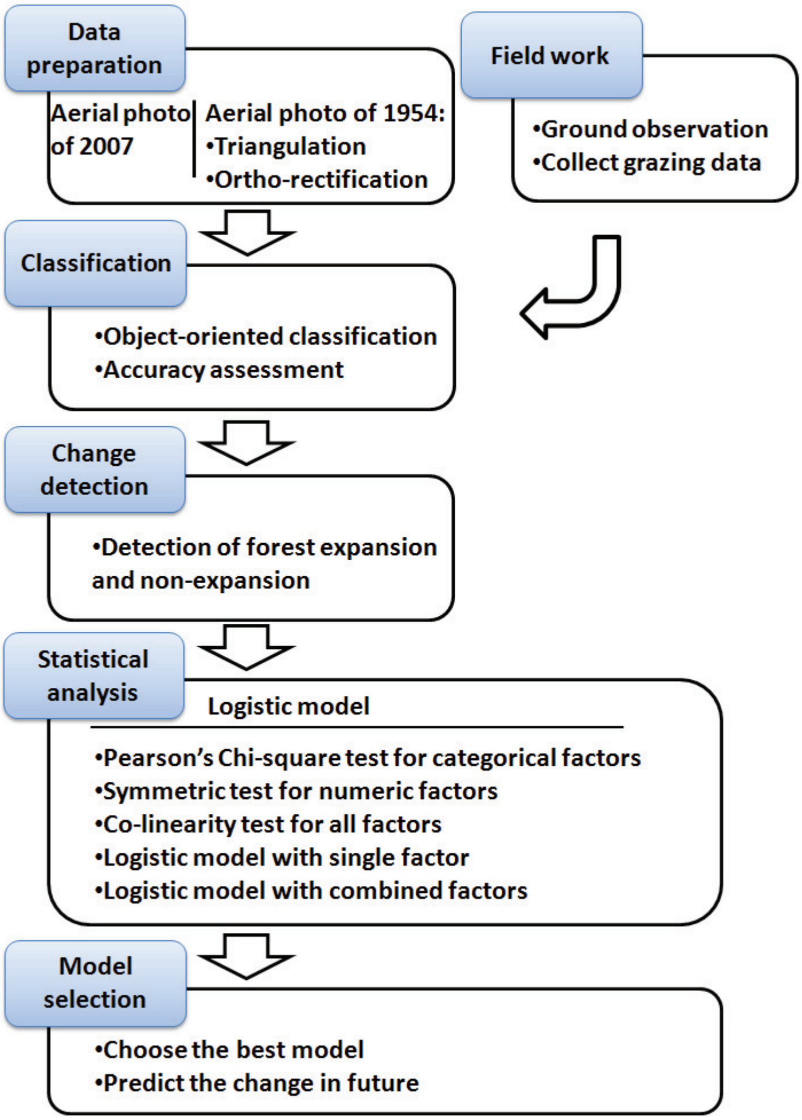


Figure 7 Work flow of the study.

2.3.1. Field work

Before going to the field, random points were generated within 30m buffer zone on both sides of the digitized hiking track with reference of the land cover map from

Majella NP (stratified simple random sampling). The detailed pre-field methods are as follows:

- digitize hiking track.
- create 30m buffer zone on each side of the hiking track.
- clip the land cover map with the buffer zone.
- generate the random points in every type of the land cover within the buffer zone.

Due to the accessibility within the study area, such as steep slope and day length limitation, there are two kinds of points' data collected in the field: firstly, the accessible random points generated in pre-field stage; secondly, points collected at least every 60 m along the hiking track where the random points are not accessible. Grazing information is also observed along the hiking track (Appendix II). The size of circular plot is 10 m in radius which is limited by the terrain condition. 111 points were collected in two plots (Figure 8).

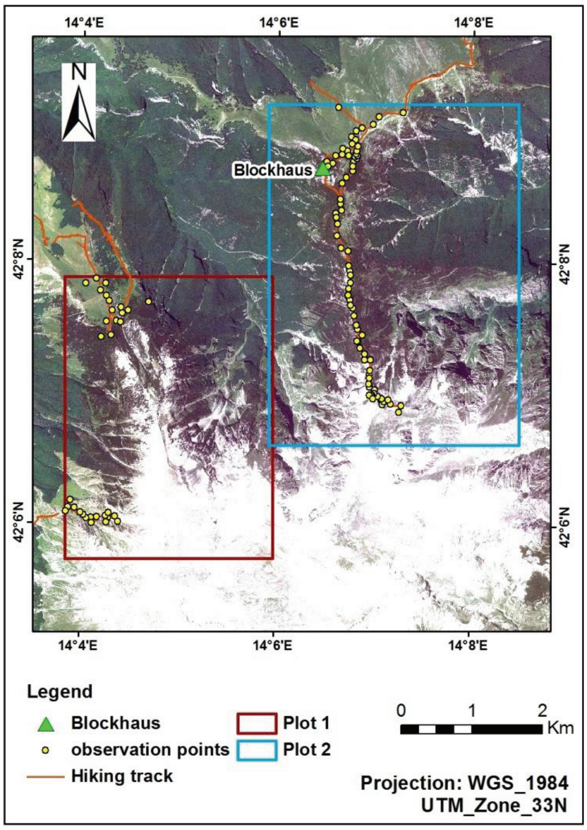


Figure 8 Field observation points in September, 2009. The background image is aerial photo of 2007.

The veterinarian of the park (Simone Angelucci) supplied secondary data of the type, number and location of live stock within study area in the year of 1999 and 2009 (Appendix I). Data before 1999 is unrecorded. Besides, around 200 sheep and goats near plot-1 and 1000 sheep and goats near plot-2 were observed with sheepherders and their dogs during the field work.

2.3.2. Preparation of aerial photos

Two kinds of aerial photos were utilized in this study: digital colour photo of 2007, and panchromatic photo of 1954. Six panchromatic photos were scanned with 1000 ppi (pixel per inch), which is scanning resolution. The formula of transferring scanning resolution (R_s) to ground resolution (R_g) is:

$$R_g\ (m) = \frac{M}{R_s\ (lines/m)} \qquad (2\text{-}1)$$

Where M is the scale number, for example, M is 33 000 if scale is 1:33.000 (Neteler and Mitasova, 2004). Since the unit of ppi is “lines/inch”, the calculation for this study should be:

$$R_g\ (m) = \frac{M}{R_s\ (lines/inch)} * 0.0254 \qquad (2\text{-}2)$$

Triangulation and ortho-rectification for 1954 photos were executed in LPS module in ERDAS using 2007 photo as reference image. After triangulation, “total image unit-weight RMSE (root mean square error)” indicates how well the result is. Lower the RMSE value, better the result of triangulation. Usually, RMSE is acceptable when it is smaller than 1.

Following, the 6 ortho-rectified photos were mosaicked by cropping 20 percent of each original photo, applying weighted cut line, automatic colour balancing and histogram matching with “mosaic tool” in LPS.

2.3.3. Land cover classification with object-oriented method

Definiens Developer 7 and eCognition Developer 8 were used for object oriented classification. Three parameters need to be set for multi-resolution segmentation: scale parameter, shape and compactness. Different values of these parameters were used for segmentation when distinguishing bare ground vs. non-bare ground, and different type of vegetations. The texture and “layer values”, such as brightness, green to red ratio, standard deviation, homogeneity and contrast were mainly used for classification. In addition, “position” value, for instance the distance to scene top border, was utilized to reduce the location influence.

Five classes were distinguishes in aerial photos of 2007: beech forest, dwarf pine, low vegetation, bare ground and shadow. The shadow in results of 2007 was not used for change detection. For the B&W photo of 1954, only forest and non-forest can be classified because there is no obvious difference between beech and dwarf pine without colour information, and also the same for bare ground and low vegetation.

UNFCCC (2001) define forest as “a minimum area of land of 0.05-1.0 hectares with tree crown cover (or equivalent stocking level) of more than 10-30 per cent with trees with the potential to reach a minimum height of 2-5 metres at maturity in situ”. By referencing this definition, definition of classes in this study are:

- beech forest: land of minimum 0.05 ha with more than 30 percent crown cover and more than 2 m height of mature beech tree;
- dwarf pine: land of minimum 0.03 ha with more than 30 percent crown cover and more than 1.5 m height of mature dwarf pine;
- low vegetation: minimum 0.03 ha with more than 30 percent crown cover and less than 1 m height of mature vegetation, including grass and herbs;
- bare ground: minimum 0.03 ha with less than 30 percent vegetation cover.

2.3.4. Accuracy assessment

The field observation points were used for accuracy assessment of 2007 aerial photo. For photos of 1954, 50 random points were generated for each plot using “hawths tool” since there is no ground observation available. Land cover type were assigned to each point by visual checking a circular area of 10 m radius around it,. If the colour is relatively uniformly dark, it is forest, otherwise it is non-forest (Platt and Schoennagel, 2009). For example, the land cover type should be forest for that point in Figure 9.

Accuracy assessment was carried out in R. Naïve measurement of agreement, such as user’s accuracy, producer’s accuracy, overall accuracy, and Kappa index of agreement were calculated using R code developed by Rossiter (2004). Meanwhile, considering the limitation of field observation (especially for 2007 aerial photo) that observed points can’t be evenly distributed in each class, the weighted Kappa was applied: after calculating the land cover percentage of each class in the classified photos, multiply this percentage with every mapped class in row of confusion matrix.

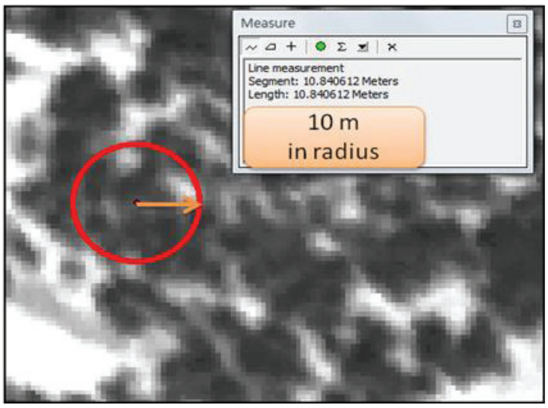


Figure 9 The example of classifying land cover type for reference point in 1954 photos

2.3.5. Land cover change detection

Change detection was done between aerial photo of 1954 and 2007 using raster calculator in ArcMap. The classes after change detection are in Table 3. Only dwarf pine forest expansion was analysed in next step.

Table 3 The land cover classes after change detection

Land cover of 1954	Land cover of 2007	Land cover after change detection
forest	**beech forest** **dwarf pine** **low vegetation** **bare ground**	**beech forest not changed** **dwarf pine not changed** **changed to low vegetation** **changed to bare ground**
non-forest	**Beech forest** **dwarf pine** **low vegetation** **bare ground**	**beech forest expansion** **dwarf pine expansion** **can't distinguish**

2.3.6. Statistically analysis of dwarf pine expansion

A logistic regression model was developed for plot-1 using the glm method of R with the binomial link function (Fox, 2002), adapting the procedures of Rossiter and Loza (2010). Two thousand random points were generated where is not dwarf pine in photo of 1954 to intersect with all potential variables shown in Table 4.

Before use any numeric variable in GLM model, the distribution was checked and it should be approximately symmetric. The numeric variables were transformed if its skewness was bigger than 0.5. For the variable which is left skewed, using logarithm function or descending the ladder of power (e.g. $\sqrt[2]{X}$ or $\sqrt[3]{X}$) to correct; if the variable is right skewed, ascending the ladder of power (e.g. x^2 or X^3) to improve it (Fox, 1997). A small offset was added to zero values to avoid undefined logarithms.

Variance Inflation Factor (VIF) was calculated to check co-linearity. The variable with biggest VIF should be eliminated if any of the VIF is bigger than 10 (Fox, 1997). Pearson's Chi-square test for categorical factors was done next. The modelling approach of GLM followed the approach of Rossiter and Loza (2010) and mainly used R code developed by them for analysis and visualization.

Akaike Information Criterion (AIC) is an index for comparing fit of alternative models with different number of variables: smaller the value, better the fit (Fox, 2002). The Receiver Operating Characteristic (ROC) curves "are used to judge the effectiveness of prediction for repeated binary decisions" (Burgman, 2005). The area under the curve (AUC) represents the overall accuracy of the predictor, and value of 0.5 for non-information, 1 for perfect prediction. Accordingly, model with highest AUC is the best comparing to other ones has same number of variables. If models have different number of variables, the one with the smallest AIC is better.

To account for neighbourhood effects, the neighbourhood function "nei" was calculated for both beech forest and dwarf pine of 1954. Buffer distance of 5, 10, 20, 30, 40, 70, 100, 200 and 300 m for dwarf pine, 10, 20, 30, 50, 70 and 100 m for beech were tested, and the one with highest AUC was chosen along with proper Pearson's Chi-square test result.

For selecting the better distance variables between cost distance and Euclidean distance, combined model with best neighbourhood factors selected in last step was applied, using the S formula language used to specify R models: "neighbourhood * distance – distance". This nested model means that distance is only considered as a predictor within each neighbourhood class, i.e. a different slope fits for the two classes, inside and outside the buffer (Fox, 2002).

After deciding on proper potential predictors, GLM model with single factor and combined factors were compared to choose the best fit model according to AIC and AUC.

Table 4 Potential variables for GLM model analysis

Factor		Value	Meaning	Note
Categorical variable	change	T	dwarf pine expansion	
		F	no dwarf pine expansion	
	terrain	A	canyon bottom	calculated in TPI tools in ArcView with default 4 classes type
		B	gentle slope	
		C	steep slope	
		D	ridgeline	
	nei	A	there was dwarf pine forest of 1954 in a rectangular window	several sizes of window were calculated from 5 m to 300 m
		B	there was no dwarf pine forest of 1954 in a rectangular window	
	graze	A	grazed in 1999	
		B	no grazing in 1999	
	inte	A	number of sheep and goats >=102.5(per km^2)	102.5 (per km^2) is the mean value
		B	number of sheep and goats <102.5 (per km^2)	
	geology			The map from Majella NP
	soil	A	moraine debris deposition on lower slope to glacial valleys	
		B	locally active karst processes on high mountain altitudes	
		C	landslide/ice-induced cryolastic phenomena with rock outcrops on irregular very steep slopes/cliffs	
		D	irregular steep slopes (No soil type given)	
	beech	A	beech forest in 1954	
		B	not beech forest in 1954	
	nei_bch	A	inside the certain rectangular plot, at least one pixel was beech forest in 1954	several sizes of window were calculated from 10m to 100m
		B	inside the certain rectangular plot, there is no pixel which was beech forest in 1954	

Numeric variable	asp		aspect (in radians, 0 radians is on the north)	
	slope		slope (in degree)	
	cd_pm		cost distance to the boundary of dwarf pine in 1954, slope is the cost layer	
	cd_bch		cost distance to the boundary of beech in 1954, slope is the cost layer	
	ld_pm		Euclidean distance to the boundary of dwarf pine in 1954	
	ld_bch		Euclidean distance to the boundary of beech in 1954	
	altitude		altitude	
	msol		mean solar radiation in a year	
	ssol		mean summer solar radiation(June, July and August)	
	wsol		mean winter solar radiation (November, December, January and February)	

2.3.7. Prediction

Prediction was only carried out in plot-1, and for time span of 53 years after 2007. New factors calculated for prediction were those selected in the best model. These were:

- cost distance from beech forest of 2007 with slope as cost layer;
- straight line distance from dwarf pine of 2007;
- neighborhood layer of beech forest of 2007 in 70 m rectangular window;
- neighborhood layer of dwarf pine of 2007 in 10 m rectangular window.

The new distance and neighbourhood layers were calculated based on classified photos of 2007, and in the way as mentioned in Table 4. Besides, using grazing map of 2009 (Appendix I).

The classified photo of 2007 was re-sampled to 10 m resolution, and dwarf pine in 2007 was masked out from it. After that, convert the raster to point, and use points to intersect with layer of predicting factors. For each point, probability of change was calculated according to the final model. Then, convert points to raster to get the prediction map.

3. Results

3.1. Data preparation of aerial photos

The resolution of scanned 1954 photos is 0.8 m by using the formula of (2-2). Total image unit-weight RMSE is 0.83 (pixel) after triangulation which is qualified for further analysis. The mosaic photos of 1954 are shown in Figure 10.

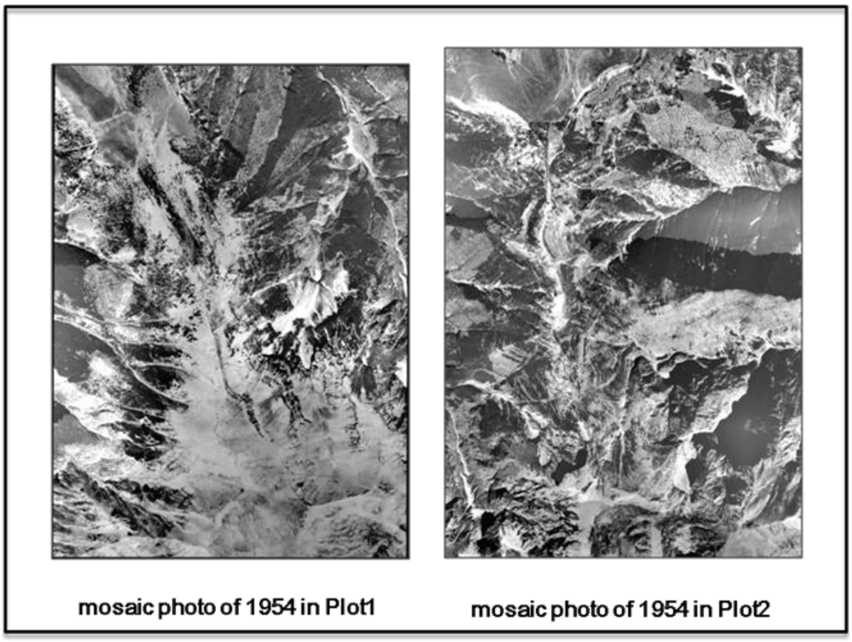


Figure 10 Mosaic aerial photos of 1954 for two plots

3.2. Classification

Aerial photos of two plots in 1954 and 2007 were classified and results are in Figure 11 and Figure 12. Shadow was detected for photos of 2007, but it was not used for change detection.

By visual evaluating Figure 11 and Figure 12, it is apparent that the dwarf pine forest expanded the gap within itself, as well as open places between dwarf pine and beech forest. The open ground was classified as non-forest in 1954, but it couldn’t be distinguished whether that is low vegetation or bare ground.

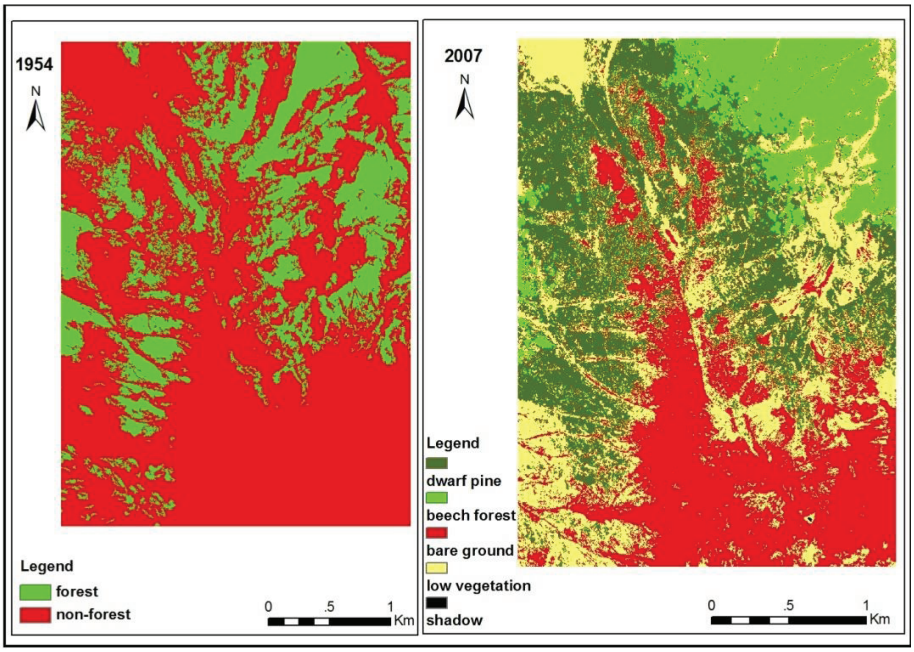


Figure 11 Land cover classification results of Plot-1 for year of 1954 and 2007. The shadow was only classified in 2007 aerial photos.

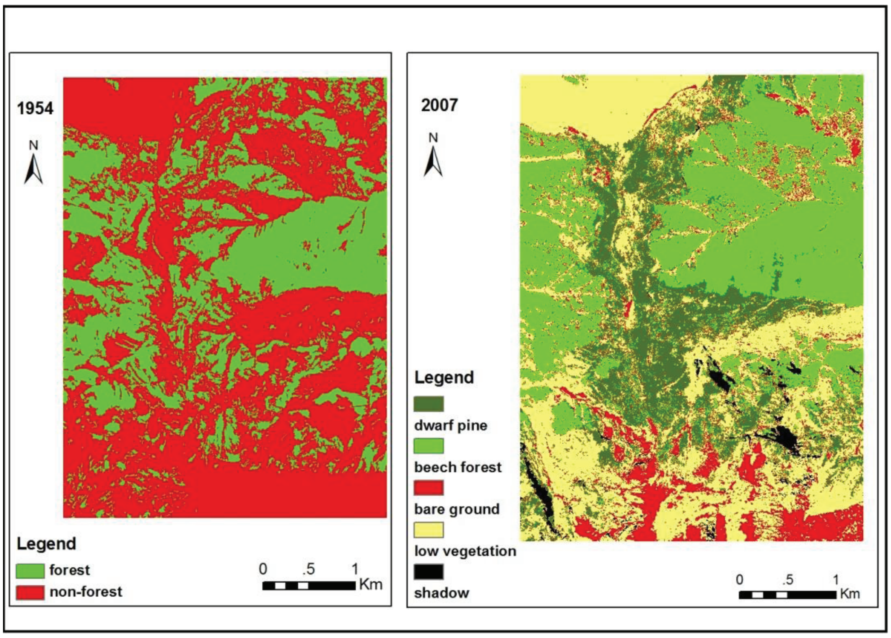


Figure 12 Land cover classification results of Plot-2 for year of 1954 and 2007. The shadow was only classified in 2007 aerial photos.

3.3. Accuracy assessment

The Naïve measurement of agreement, Kappa index of agreement and weighted kappa of classified photos are shown in Table 5 and Table 6. They show that the classified results are reasonably good, especially for photos of 1954. The overall and weighted kappa for plot-2 of 2007 indicate a lower accuracy, which might caused by no ground truth point of "beech forest" for plot-2. Since the research object is dwarf pine in this study, classified result of plot-2 in 2007 is still appropriate. Also, there is no big difference of accuracy between 1954 and 2007 photos.

Table 5 Accuracy assessment result for aerial photos of 2007

2007	class	% of whole plot	producer's accuracy	user's accuracy	overall accuracy	overall kappa	weighted kappa (overall)
plot-1	dwarf pine	0.25	0.8	1	0.88	0.82	0.81
	beech forest	0.18	1	1			
	bare ground	0.29	0.9	0.9			
	low vegetation	0.28	0.9	0.75			
	shadow	5×10^{-5}	NaN*	NaN*			
plot-2	dwarf pine	0.22	0.79	0.97	0.85	0.76	0.72
	beech forest	0.32	NaN*	NaN*			
	bare ground	0.12	0.81	0.81			
	low vegetation	0.33	0.96	0.74			
	shadow	0.02	NaN*	NaN*			

* "NaN" means there is no data available.

Table 6 Accuracy assessment result for aerial photos of 1954

1954	class	% of whole plot	producers' accuracy	user's accuracy	overall accuracy	overall kappa	weighted overall kappa
plot-1	forest	0.27	0.94	0.85	0.92	0.83	0.82
	non-forest	0.73	0.91	0.97			
plot-2	forest	0.42	0.93	0.87	0.94	0.85	0.85
	non-forest	0.58	0.94	0.97			

3.4. Change detection

Change detection was only performed for places where dwarf pine expanded or not (Figure 13). In both plots, dwarf pine forest expansion is not evenly distributed along forest boundary of 1954. The area of expansion is bigger than that of dwarf pine in 1954, but dwarf pine only accounts for less than one third of whole plots area in 2007 (Table 7). The expansion goes both downwards and upwards along altitude, nevertheless upwards expansion is only 3 m for plot-1 and 43 m for plot-2 (Table 7). The 3 m difference for plot-1 is so minus which can be neglected. Meanwhile, there are 124 m for plot-1 and 180 m for plot-2 dwarf pine expansion going to lower altitude.

Table 7 The area and altitude of dwarf pine expansion

Plot-1	Area (km^2)	Altitude (m)	***Plot-2***	Area (km^2)	Altitude (m)
no change	**1.25**	**1491-2588**	no change	**1.70**	**1317- 2395**
expansion	**1.65**	**1367-2591**	expansion	**1.96**	**1137- 2438**
whole plot	**11.66**	**1213-2640**	whole plot	**17.01**	**986- 2594**

3.5. GLM model

Two thousand random points were generated at beginning, but only 1993 points had valid value of all variable listed in Table 4.

Using symmetric test for all the numeric variables, skewness of “cd_pm”, “cd_bch”, “ld_pm”, “ ld_bch” and “wsol” was bigger than 0.5 and right skewed, and needed to be transformed. Therefore, “cdpm.l”, “cdbch.l”, “ldpm.l”, “ldbch.l” and “wsol.l” were calculated using logarithm for further analysis. In the meantime, three different solar radiations did not show significant influence to dwarf pine expansion using single variable GLM model. Consequently, they were not taken into account.

3.5.1. Selection of neighbourhood variables

The results of Pearson’s Chi-square test show all the neighbourhood variables are highly related to dwarf pine expansion. However, “nei70” is the best neighbourhood variable of dwarf pine because of its highest AUC (Table 8). The same reason for choosing “nei_bch_10” as the best neighbourhood variable of beech forest (Table 9). Although all the AUC in Table 9 are almost the same, the one of “nei_bch_10” is slightly better.

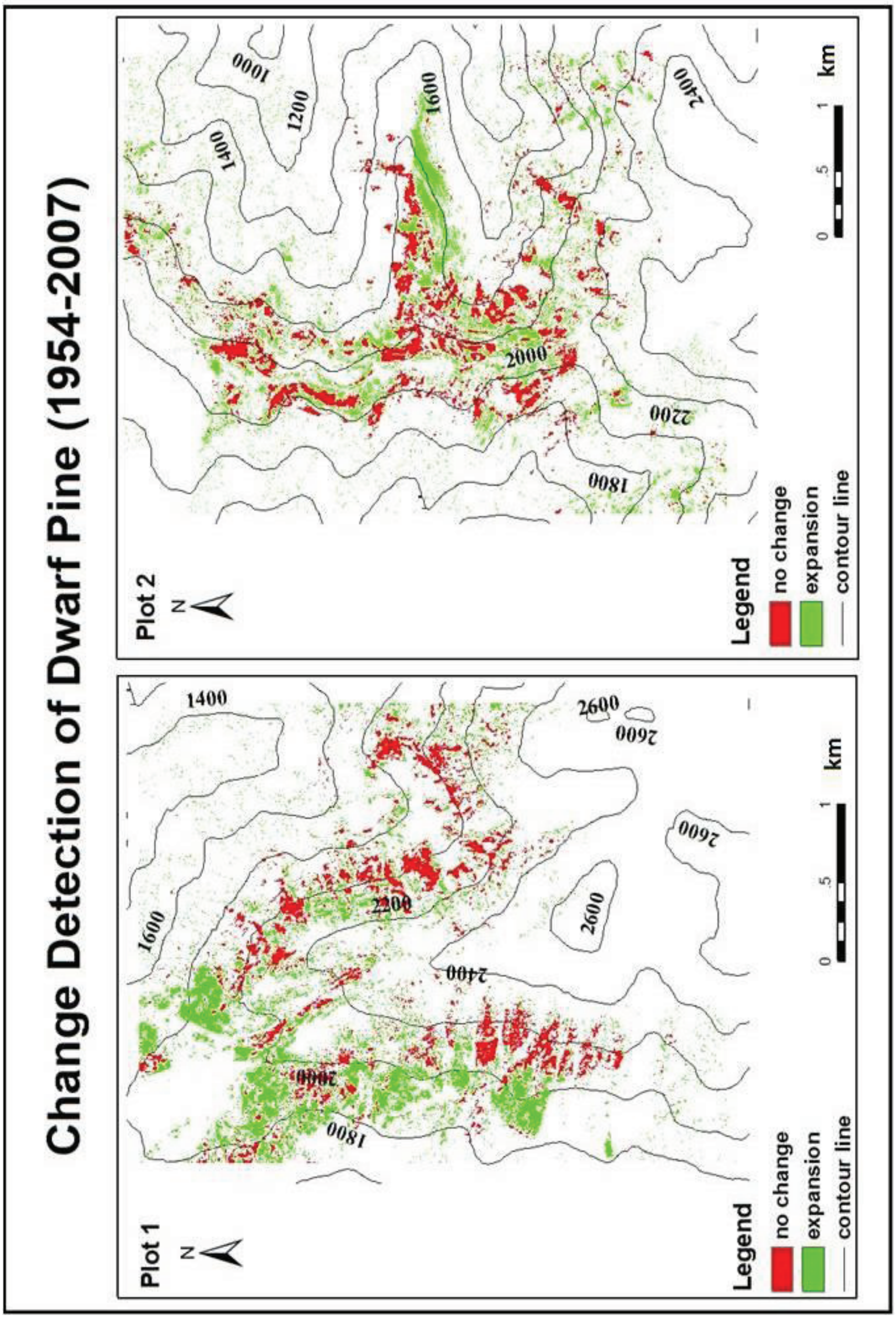


Figure 13 Result of land cover change detection

The "bch" variable, in addition, has less AUC value than "nei_bch_10", and principally, both of them include the place where beech forest grew in 1954. Therefore, "bch" variable is not considered.

Table 8 GLM model test for neighbourhood variables of dwarf pine in 1954

variable	AIC	AUC	variable	AIC	AUC
nei300	**1622.6**	**0.657**	nei30	**1585.7**	**0.714**
nei200	**1560.0**	**0.695**	nei20	**1610.2**	**0.690**
nei100	**1524.1**	**0.713**	nei10	**1684.4**	**0.630**
nei70	**1550.6**	**0.739**	nei5	**1732.6**	**0.584**
nei40	**1564.3**	**0.730**			

Table 9 GLM model test for neighbourhood variables of beech in 1954

factors	AIC	AUC	factors	AIC	AUC
nei_bch_10	**1705.4**	**0.598**	nei_bch_50	**1775.8**	**0.582**
nei_bch_20	**1728.7**	**0.596**	nei_bch_70	**1799.2**	**0.561**
nei_bch_30	**1753.9**	**0.593**	nei_bch_100	**1812.4**	**0.541**

3.5.2. Selection of distance variables

Combing the neighbourhood variables chosen last step, nested model indicates that Euclidean distance from dwarf pine (ldpm.l) and cost distance from beech forest (cdbch.l) are the better distance factors (Table 10 and Table 11).

Table 10 GLM model of selecting distance variables of dwarf pine

*nei70*distance-distance*		*AIC*	*AUC*
pm	cdpm.l	1426.2	0.808
	ldpm.l	1418.3	0.815

Table 11 GLM model of selecting distance variables of beech forest

*nei_bch_10*distance-distance*		*AIC*	*AUC*
nei_bch_10	cdbch.l	1259.7	0.859
	ldbch.l	1553.4	0.783

3.5.3. Co-linearity test

All the potential predictors, up to now, are chosen. There is no obvious co-linearity between variables since their VIF are not bigger than 10 (Table 12). Meanwhile, all the categorical variables are notably associated with forest expansion at the significant level of 0.05 (Table 13).

Table 12 The co-linearity test of the potential predictors

Variable	nei70	terrain	nei_bch_10	graze	inte	geology
VIF	**3.3**	**1.1**	**2.6**	**1.8**	**1.4**	**1.7**
Variable	soil	asp	slope	cdbch.l	ldpm.l	altitude
VIF	**1.5**	**1.1**	**1.3**	**8.2**	**4.3**	**2.6**

Table 13 Pearson't Chi-square test for the categorical variables

Variable	Chi-square	P-value	Variable	Chi-square	P-value
nei70	**261.2**	**< 2.2e-16**	inte	**10.6**	**0.001149**
terrain	**18.1**	**0.000419**	geology	**117.2**	**< 2.2e-16**
nei_bch_10	**75.6**	**< 2.2e-16**	soil	**43.3**	**2.12E-09**
graze	**126.0**	**< 2.2e-16**			

3.5.4. Selection of the best model

Some of the GLM models with single variable explain forest expansion quite well, taking "ldpm.l", "nei70" and "cdbch.l" as examples (Table 14). Table 15 lists models by their S formulas; this table shows that the AIC decreases rapidly comparing to single predictor. By reducing variables from model with all the potential factors, AIC continually reduces before model 8 and model 9 in Table 15. Although model 7 has the lowest AIC in Table 15, the significancy of each variable to forest expansion is higher in model 8. Additionally, change of AIC between model 7 and model 8 is truly minute. Therefore, model 8 in Table 15 is the best one for predicting dwarf pine expansion.

Table 14 The GLM models with single variables

Variable	AIC	AUC	Variable	AIC	AUC
graze	**1683.4**	**0.668**	nei70	**1550.6**	**0.739**
inte	**1808.7**	**0.530**	asp	**1820.8**	**0.504**
soil	**1780.4**	**0.599**	slope	**1814.2**	**0.558**
geology	**1676.7**	**0.643**	altitude	**1816.5**	**0.567**
nei_bch_10	**1705.4**	**0.598**	ldpm.l	**1446.0**	**0.815**
terrain	**1803.6**	**0.557**	cdbch.l	**1654.5**	**0.709**

Table 15 The GLM models with combined variables

Model: variables	AIC	AUC
1: full model (*)	**1229.6**	**0.874**
2: *-slope	**1228.2**	**0.875**
3: *-slope-aspect	**1226.3**	**0.875**
4: *-slope-aspect-geology	**1222.9**	**0.873**
5: *-slope-aspect-geology-soil	**1224.8**	**0.872**
6: *-slope-aspect-geology-inte	**1221.3**	**0.876**
7: *-slope-aspect-geology-inte-terrain	**1220.0**	**0.872**
8: *-slope-aspect-geology-inte-terrain-soil	**1222.2**	**0.871**
9: *-slope-aspect-geology-inte-terrain-soil-graze	**1235.1**	**0.867**

*full model is: changed ~ (nei_bch_10 * cdbch.l - cdbch.l) + (nei70 * ldpm.l - ldpm.l) + terrain + graze + inte + geology + soil + slope + asp_radians + altitude

The summary of final model is shown in Table 16 and Figure 14. Figure 14 and Figure 15 give two different views of the model success. First, Figure 14 shows the 1993 samples sorted by their probability of change; the blue curve is the cumulative proportion. The green and red bars show the actual true (changed) and false (not changed) samples. Ideally, the cumulative curve should be a shape square with the vertical component splitting the false (to the left) and true (to the right); in the less than ideal case, the success can be visually assessed by the concentration of the green lines to the right and the red to the left. Second, the Figure 15 shows the ROC curve. The ROC curve would be a triangle in ideal situation. The closer the curve comes to the left-hand border and then to the top border of the graph, the more accurate the model is. The

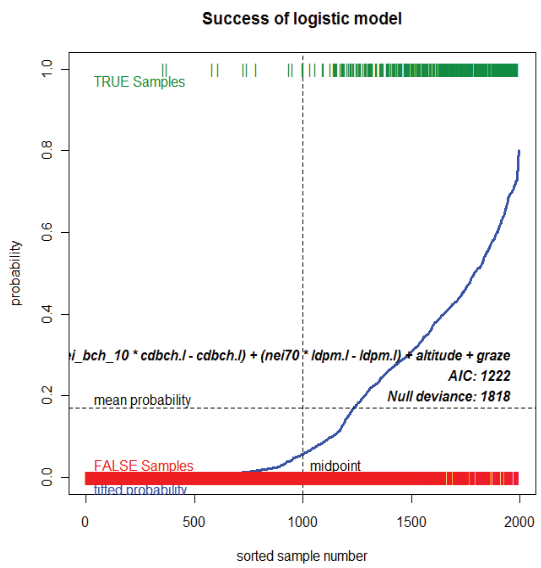


Figure 14 The graph of final logistic model

ROC curve in Figure 15 shows that the final model could effectively distinguish dwarf pine expansion with more than 87% success.

Table 16 The best model of dwarf pine expansion

Formula:
glm(formula = changed ~ (nei_bch_10 * cdbch.l - cdbch.l) + (nei70 * ldpm.l - ldpm.l) + graze + altitude, family = binomial)

Deviance Residuals:

Min	1Q	Median	3Q	Max
-1.79824	-0.51452	-0.14008	-0.04417	3.43649

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	-5.6487748	3.6035132	-1.568	0.116981	
nei_bch_10B	10.9262100	3.5993676	3.036	0.002401	**
nei70B	4.2869634	1.2374478	3.464	0.000531	***
grazeB	-0.6653373	0.1760591	-3.779	0.000157	***
altitude	-0.0008902	0.0003226	-2.759	0.005792	**
nei_bch_10A:cdbch.l	0.4993959	0.4558317	1.096	0.273267	
nei_bch_10B:cdbch.l	-0.3378933	0.0776030	-4.354	1.34e-05	***
nei70A:ldpm.l	-0.3011872	0.1120958	-2.687	0.007212	**
nei70B:ldpm.l	-1.3176106	0.3006158	-4.383	1.17e-05	***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Note for Table 16: The meaning of each variable is explained in Table 4. The value followed that is the size of window. For example, “nei_bch_10B” means the B type of neighbourhood effects of beech which is calculated in the window size of 10 m.

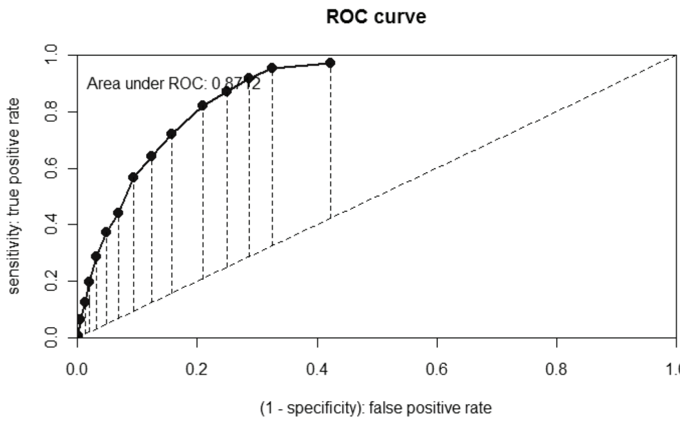


Figure 15 The ROC curve of the final model

By comparing the final model prediction at the threshold 0.18 (Figure 16 a), 0.5 (Figure 16 b) and 0.6 (Figure 16 c), there are more false negative and less false positive along with increasing of the threshold. Therefore, higher the threshold of probability, more places can’t be correctly modelled where actual changes were, and more conservative prediction the model makes. This may caused by lacking of some potential predictors. The threshold can be set according to the requirement of the users. If randomly set the probability threshold at 0.6, the final model shows only few false positives and more false negative (Figure 16 c).

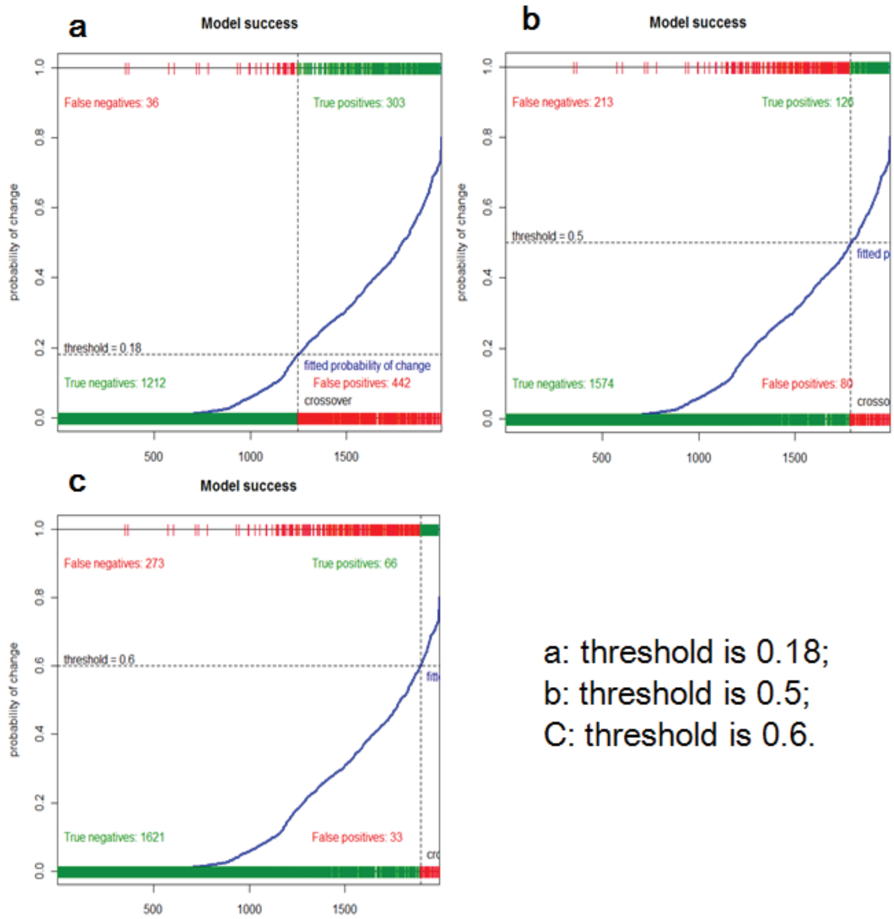


Figure 16 The success of final logistic model with different thresholds

In graph “c”, there are less false positives than false negatives

3.6. Prediction

The potential dwarf pine expansion in plot-1 was predicted using the final model, and under the circumstance that all the environmental factors will follow the same trend as last 53 years. The green colour represents places where has the high probability changed to dwarf pine in 2060 (Figure 17).

If assuming that places where the probability is bigger than 0.6 are going to expand, the altitude range of dwarf pine will between 1244 m to 2638 m in year of 2060. The highest altitude will be 47 m up comparing to year of 2007.

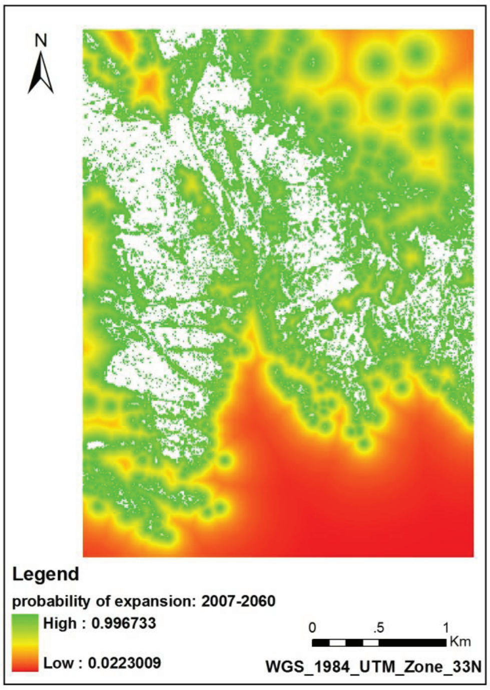


Figure 17 Prediction result of dwarf pine expansion in plot-1 from 2007 to 2060

4. Discussion

4.1. The object-oriented classication

One of disadvantages for the pixel based classification is depending on the spectral features of each pixel (Maggi et al., 2007), which could cause salt and pepper effect for very high resolution image (Yu et al., 2006). Although the resolution of photos is smaller than 1 m in this study, the classified results have relatively high accuracy using object-oriented method, which is similar with the studies done by Maggi et al. (2007) and Elmqvist et al. (2008). It shows that the object-oriented classification can overcome the drawback of pixel based method by considering neighbouring pixels.

However, the process is time consuming for choosing proper index of segmentation and criteria for each class (Hay et al., 2005). It can be improved by testing the algorithm and index in small area, and subsequently used in whole image. Nevertheless, the terrain inside study area is complicated, which causes one land cover type has more various spectral features in different slope and aspect, or similar to other land cover. In this case, the "position" value, such as "the distance to scene top border", was combined with texture and other layer values to successfully reduce the location influence.

Although the historical panchromatic photo has limited spectral information for classification, the results in this study show no big difference of accuracy between B&W and colour photos. Therefore, the object-oriented method is equally suitable for classifying both colour and historical panchromatic photos.

4.2. Dwarf pine expansion

According to the result of change detection and Table 7, expansion to upslope is much less than it's to down slope and laterally in 53 years. The area of lower altitude is either gap between dwarf pine and beech forest or continuous open land. Similar observation has been done in the central Alps where dwarf pine occasionally invaded deforested slopes or avalanche chute (Ronikier, 2009). Subalpine grass land is another place where dwarf pine usually invaded (Dullinger et al., 2003). The grass land and low vegetation located almost the same or lower altitudinal belt comparing to dwarf pine in study area, while the bare ground mostly distributed higher than dwarf pine in 2007 (Appendix III and Appendix IV). However, it is not easy to differentiate whether the open land is low vegetation or bare ground in aerial photo of 1954, so, the preferred invading place of dwarf pine can't be distinguished in this study.

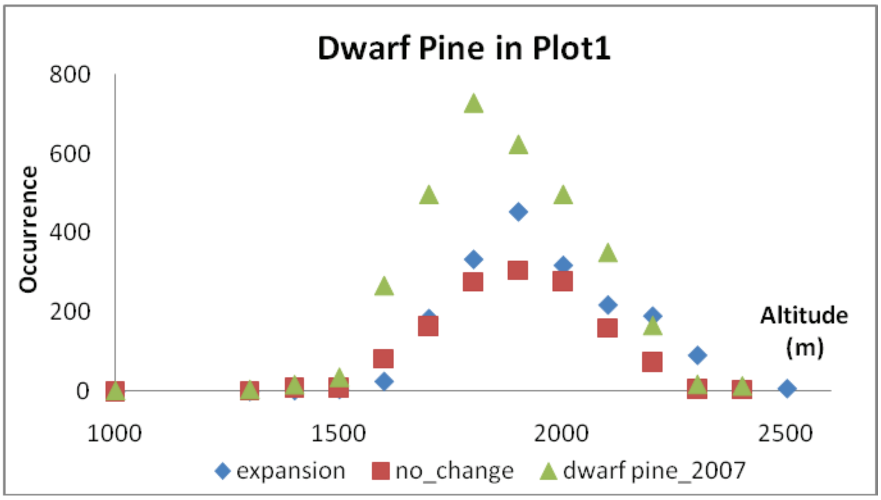


Figure 18 Altitudinal dwarf pine distribution and expansion pattern in plot-1

The "expansion" and "no_change" happened between year of 1954 and 2007; the unit for Y axis is the number of pixels after intersecting change detection result with DEM, and pixel size is 30 * 30 m.

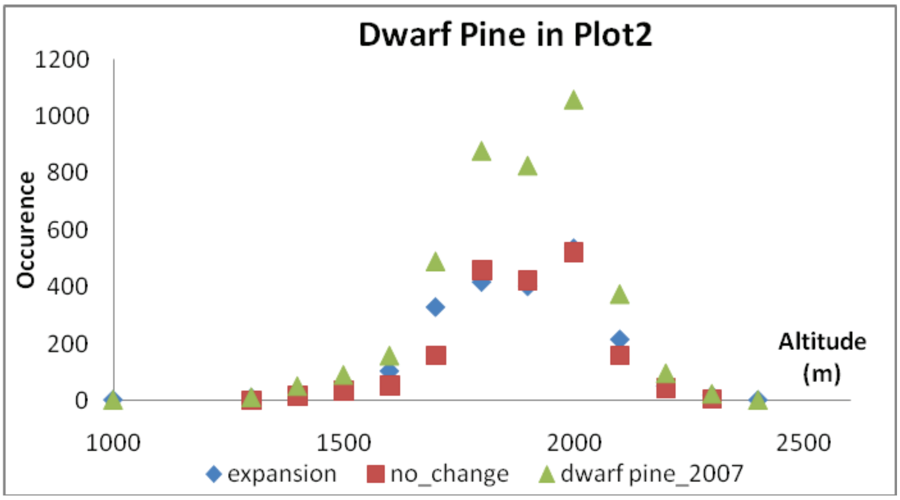


Figure 19 Altitudinal dwarf pine distribution and expansion pattern in plot-2

They are bi-modal distribution. The "expansion" and "no_change" happened between year of 1954 and 2007; the unit for Y axis is the number of pixels after intersecting change detection result with DEM, and pixel size is 30 * 30 m.

Expansion, besides, followed the the same altitudinal distribution pattern of dwarf pine in 1954 (Figure 18 and Figure 19). The main expansion of both plots took place between 1700 and 2300 m other than altitudinal expansion. This horizontal expansion might be caused by occasional layering and limited reproduction way by wind (Wild and Winkler, 2008, Holtmeier, 2009).

The distribution of dwarf pine in plot-2 is bi-modal and rested between 1900 to 2000 m (Figure 19), which means that environmental factors influencing dwarf growth is not only affected by altitude, but also by other natural elements, such microclimate or soil condition (Guisan et al., 1998).

4.3. The best fit model

The final model shows the probability of dwarf pine expansion increases along with following conditions:

- altitude decreasing;
- no beech forest in 1954 within 10 m rectangular window;
- livestock grazing in 1999;
- closer to (reduced cost distance to) beech forest in 1954, and there is no beech forest in 10 m rectangular window;
- no dwarf pine forest within 70 m rectangular window in 1954;
- closer to (reduced Euclidean distance to) dwarf pine in 1954.

The first two conditions are easy to interpret. Dwarf pine moved up in plot-2 in last 53 years, but that is not obvious in plot-1. The environmental condition is also less harsh in lower altitude comparing to the highest growing limit. Thus, expansion took place frequently in lower altitude among their altitudinal growing range.

Beech grows taller than 30 m, which can cause shade effect and reducing the survival for other species if they are not shade-preferred. So, new dwarf pine occurred less in beech forest and its 10 m buffer zone.

Among remaining factors in final model, grazing in 1999, cost distance to beech forest in 1954, and neighbourhood variable of dwarf pine forest in 1954 do not have direct explanation for dwarf pine expansion. Thus, they will be discussed separately.

Firstly, grazing in 1999. It is common to consider grazing as negative influence to dwarf pine expansion. However, the final model shows the positive influence of grazing in 1999. This may biased since the grazing map was sketched from dictation of the veterinarian in Majella NP, and there is no grazing record before

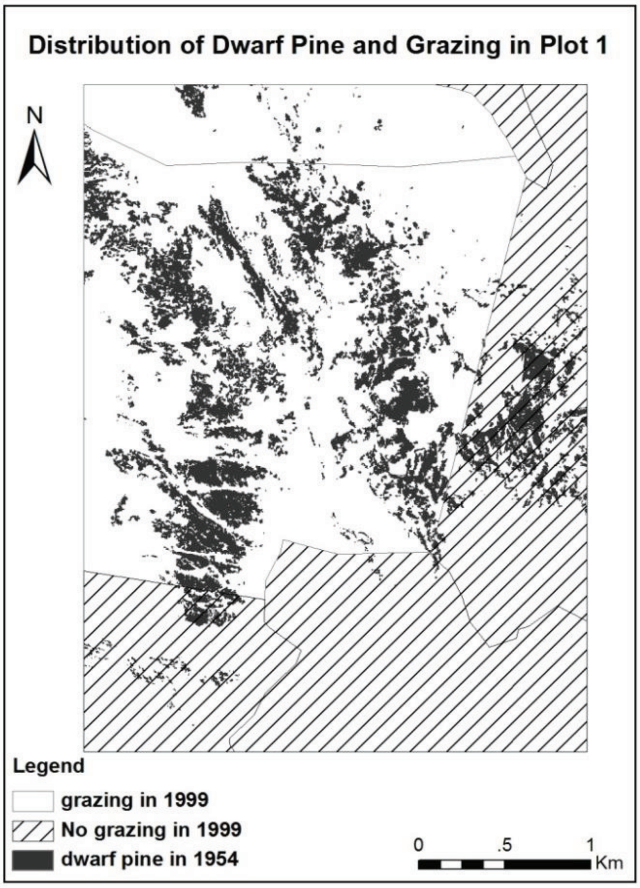


Figure 20 The spatial relation of dwarf pine and livestock grazing

establishment of the park. On the other hand, grazing places in 1999 cover most of the location of dwarf pine in 1954 (Figure 20), and the dwarf pine expansion is not far away from previous pines since the seed is mainly transmitted by wind (Müller-Schneider, 1986), which interprets this from distance point of view. Most importantly, grazing in the park decreased in alpine zone throughout the park after 1950s. According to the interview with the veterinarian, decreased grazing represents in form of reduced pasture land or less density of grazing. So, the decreased grazing might happen within grazing area of 1999, but that is not recorded, which explains reduced grazing positively influence dwarf pine expansion.

Secondly, cost distance to beech forest in 1954. The final model shows that the less expansion happens where shorter cost distance to beech forest outside the 10 m buffer of beech forest. Coincidently, cost distance of beech highly positively relates to straight line distance of dwarf pine, with correlation index of 0.74. Therefore, most places close to dwarf pine are also close to beech forest of 1954. This highly depends on their topologic relation.

Thirdly, neighbourhood variable of dwarf pine forest in 1954. Changes prone to happen where are outside 70 m buffer of dwarf pine forest in 1954. At the same time, closer to dwarf pine forest, higher probability to grow. Combining these two reasons, expansion still happens within the 70 m buffer, but it does not have to be inside the buffer. Change detection of plot-1 (Figure 13) also shows that the expansion is not evenly distributed along forest boundary in 1954. Another reason for this is the soil and terrain conditions might not homogeneous within this 70 m buffer.

In addition, shorter the distance to previous dwarf pine, higher the probability to change, which is the same as the distance effect to beech (van Gils et al., 2008). However, expansion responds differently to dwarf pine distance inside and outside the 70 m buffer of dwarf pine in 1954. According to the final model, the probability of expansion decreases four times faster outside the 70 m buffer along with increased distance (Figure 21). Therefore, the combined effect of neighbourhood function and distance is more suitable to explain dwarf pine expansion. This coincide with the lateral expansion shown in Figure 18 and Figure 19. The dwarf pine model done by Dullinger et al. (2003) also shows the importance of distance to seed source in Northern Calcareous Alps, Austria.

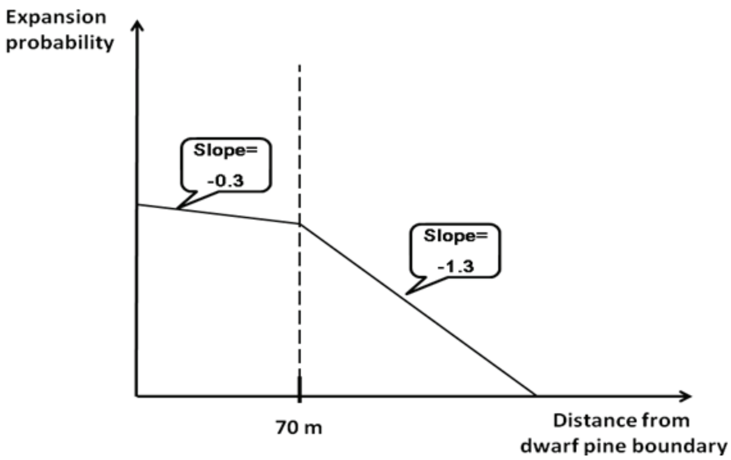


Figure 21 Sketched graph of expansion and distance to dwarf pine

Six of potential predictors were excluded from the final model, they are: slope, aspect, geology, grazing intensity, terrain and soil type. Logically speaking, they are variables which decide distribution of most vegetation (Guisan et al., 1998, Dullinger et al., 2003, Holtmeier, 2009). One of the reasons for their absence might be the overshadowing by other factors in small scale study, or in special alpine climate. On the other hand, the level of this study and these variables are not the same. This study is in local level, while these variables are in landscape level, for instance, the scale of geology map is 1:25.000. The study of beech forest expansion in Majella NP has the similar influences from incompatible level of predictors (van Gils et al., 2008). Further, resolution and quality are also possible causes. Slope was calculated from DEM which is 30 m in resolution. The grazing intensity, besides, is a sketched map, which might affect the accuracy.

4.4. Other factors influencing tree line change

Other factors also significantly influence the occurrence or expansion of dwarf pine. Wind, the main way for dwarf pine's seed dispersion, is one of such causes. The prevailing wind direction during seed release notably relates to dwarf pine recruitment (Dullinger et al., 2003). Also, prostrate growth of dwarf pine was observed in the study area (Figure 22) on extremely wind-exposed topography. The wind speed, consequently, is a key factor as well.

Figure 22 Prostrate dwarf pine in study area
(by Li Dai, September of 2009 in Majella, Italy)

Additionally, the interaction with other vegetation communities is a fundamental process for dwarf pine expansion. The canopy structure, canopy height and cover of different grass land provide diverse environment for new plant growth (Dullinger et al., 2003). In this study, only forest and non-forest were classified in photo of 1954, which makes considering interaction with grass land impossible. Meanwhile, the changing from beech forest to dwarf pine forest is not taken into account in this study, because it's hard to distinguish beech and dwarf pine in B&W photos. Moreover, the phenomenon that beech and dwarf pine mix in small area was observed during field work, which is also excluded in this study.

Temperature and micro-climate is equally important to other factors. Korner and Paulsen (2004) investigated the temperature of growing season at tree line, and got the conclusion that it is around +6 ℃. Therefore, once the climate changing lifts up the upper limit of temperature for growing, the dwarf pine expands upwards is also possible. Due to the micro-climate and local topography, climate warming might not increase temperature evenly for every spot. Therefore, even the highest altitude of dwarf pine doesn't change in plot-1, some expansion could still be caused by climate warming. Nevertheless, the simultaneous occurrence of climate changes and pasture abandonment obscure the change interpretation (Motta and Nola, 2001).

4.5. The reason of tree line change in the study area

Palombo (2009) studied dwarf pine in small scale in Majella NP, and found that there was no yearly average temperature increase in last 100 year. The evolution of dwarf pine in her study area was caused mainly by the abandonment of meadows, but also supported by the increase of spring temperatures recorded in the second half of the 20th century (Palombo, 2009). Therefore, although the seasonal temperature increase is possible in last 50 years (Stanisci et al., 2005), in view of the much faster lateral and downward expansion comparing to upward, and the final model highly relates to grazing, expansion of dwarf pine in study area is mainly driven by land use change, i.e. abandonment of grazing.

Meanwhile, beside the peculiar anthropogenic and natural influence, the tree line change is highly related to features of dwarf pine in study area, such as way of seed dispersal, mature age, preferred soil and ability of adaption to snow. It means that the tree line change is also species specific.

5. Conclusions and recommendations

Although it is time consuming for fine-tuning of parameters, the object-oriented method was able to precisely classify both high resolution colour and historical panchromatic photos. The “position” method combined with segmentation and classification algorithm tested in small area was useful to overcome the influence of terrain.

The dwarf pine expansion in 53 years can be successfully described using logistic model (area under ROC curve is 0.87). However, uncertainty in the image classification has an unavoidable unquantifiable effect on the logistic model. A problem with probabilistic predictor is the arbitrary selection of threshold. The higher the threshold, the more conservative the model predicts expansion. So, the threshold can be set according to the requirement of the user.

Total area of expansion is larger than that of dwarf pine in 1954. The distribution of the expanded followed the same pattern of historical dwarf pine. Most expansion was lateral and concentrated between 1700 and 2300 m elevation, and the tree line upwards shift is less than downwards in the time period. As tree line vegetation, the dynamics of dwarf pine is mainly driven by reduced livestock grazing associated with burning and cutting around the tree line. The contribution of climate change to tree line dynamics seems small based on the observed limited upward expansion, and still need to be discussed in further study. The conservative prediction shows 47 m upwards dwarf pine shift by 2060 using 0.6 probabilities as threshold. Consequently, the potential upper tree line shift can’t be neglected.

Lower altitude, decreased grazing, combination of reduced distance and 70 m neighbourhood effects of historical dwarf pine could jointly explain and predict dwarf pine expansion. The distance effects the expansion differently within and outside the 70 m neighbourhood of historical dwarf pine, which might influenced by the seed dispersal through wind and layering reproduction. This modelling approach includes spatial dependence of the response variables only via fixed neighbourhood predictor. It does not account for spatial dependence with other environmental variables. A more sophisticated approach to improve this is the auto-logistic model, which is a spatially explicit regression model.

Recommendation:

- Larger scale study area could be selected to compare with local research.

- Comparing to large scale, even smaller scale study can be implemented, such as counting seedlings on the ground or planting pine above tree line as experiment.
- Combine 3D model with DEM to interpret tree line change with more altitudinal information.
- Attaining reliable temperature is one of the obstacles in mountainous area. The conventional approach of combining data from weather stations at low altitude and a linear decrease of 0.6 ℃ every 100 m is unreliable, especially considering vegetation effects to micro-climate. Therefore, detailed temperature measurement or RS method such as Lidar or infrared is recommended. Although these methods still can't acquire the historical data, they can get the distribution pattern of temperature, or the relation between temperature and different slope, vegetation and aspect.
- Choose other images or photos between 1954 and 2007 to increase number of time intervals, and therefore deeper analyze the dynamics.
- More variables can be included to analysis the tree line and dwarf pine change, such as the snow cover, wind velocity and direction, micro-climate and topography.
- Auto-logistic model can be applied to consider spatial dependence of environmental factors.

6. References

Ali, A. A., Martinez, M., Fauvart, N., Roiron, P., Fioraso, G., Guendon, J. L., Terral, J. F. & Carcaillet, C. (2006) Fire and Pinus mugo Turra communities in the western Alps (Susa Valley, Italy) during the Lateglacial-Hollocene transition: an evidence of refugia area. *Comptes Rendus Biologies,* 329**,** 494-501.

Bemigisha, J. R., Skidmore, A. K. p. & Prins, H. H. T. p. (2008) Spectral and human sensors : hyperspectral remote sensing and participatory GIS for mapping livestock grazing intensity and vegetation in transhumant Mediterranean conservation areas. *ITC Dissertation;155.* Wageningen and Enschede, Wageningen University and ITC.

Beniston, M., Diaz, H. F. & Bradley, R. S. (1997) Climatic change at high elevation sites: An overview. *Climatic Change,* 36**,** 233-251.

Boratynska, K., Marcysiak, K. & Boratynski, A. (2005) Pinus mugo (Pinaceae) in the Abruzzi Mountains: high morphological variation in isolated populations. *Botanical Journal of the Linnean Society,* 147**,** 309-316.

Brunetti, M., Buffoni, L., Mangianti, F., Maugeri, M. & Nanni, T. (2001) Climate variations in Italy in the last 130 years. IN VISCONTI, G., BENISTON, M., IANNORELLI, E. D. & BARBA, D. (Eds.) *Global Change and Protected Areas.* Dordrecht, Springer.

Burgman, M. A. (2005) *Risks and decisions for conservation and environmental management* Cambrideg, UK, Cambridge University Press.

Carcaillet, C., Fauvart, N., Roiron, P., Terral, J. F. & Ali, A. A. (2009) A new, isolated and endangered relict population of dwarf pine (Pinus mugo Turra) in the northwestern Alps. *Comptes Rendus Biologies,* 332**,** 456-463.

Danby, R. K. & Hik, D. S. (2007) Variability, contingency and rapid change in recent subarctic alpine tree line dynamics. *Journal of Ecology,* 95**,** 352-363.

Dullinger, S., Dirnbock, T. & Grabherr, G. (2003) Patterns of shrub invasion into high mountain grasslands of the Northern Calcareous Alps, Austria. *Arctic Antarctic and Alpine Research,* 35**,** 434-441.

Dullinger, S., Dirnbock, T. & Grabherr, G. (2004) Modelling climate change-driven treeline shifts: relative effects of temperature increase, dispersal and invasibility. *Journal of Ecology,* 92**,** 241-252.

Dullinger, S., Dirnbock, T., Kock, R., Hochbichler, E., Englisch, T., Sauberer, N. & Grabherr, G. (2005) Interactions among tree-line conifers: differential effects of pine on spruce and larch. *Journal of Ecology,* 93**,** 948-957.

Elmqvist, B., Ardo, J. & Olsson, L. (2008) Land use studies in drylands: an evaluation of object-oriented classification of very high resolution panchromatic imagery. *International Journal of Remote Sensing,* 29**,** 7129-7140.

FAO (2005) Extent of forest resources. [online] ftp://ftp.fao.org/docrep/fao/008/A0400E/A0400E03.pdf (Accessed Date: 2009.12.28)

Fox, J. (1997) *Applied regression analysis, linear models and related methods,* London etc., Sage.
Fox, J. (2002) *An R and S-PLUS companion to applied regression*, Sage Publications, Inc.
Gehrig-Fasel, J., Guisan, A. & Zimmermann, N. E. (2007) Tree line shifts in the Swiss Alps: Climate change or land abandonment? *Journal of Vegetation Science,* 18**,** 571-582.
Grace, J., Berninger, F. & Nagy, L. (2001) Impacts of climate change on the tree line. *Symposium on Plants in Cold Climates and Waterlogged Soils.* St Andrews, Scotland, Oxford Univ Press.
Guisan, A., Theurillat, J. P. & Kienast, F. (1998) Predicting the potential distribution of plant species in an Alpine environment. *Journal of Vegetation Science,* 9**,** 65-74.
Hay, G. J., Castilla, G., Wulder, M. A. & Ruiz, J. R. (2005) An automated object-based approach for the multiscale image segmentation of forest scenes. *International Journal of Applied Earth Observation and Geoinformation,* 7**,** 339-359.
Heiri, C., Bugmann, H., Tinner, W., Heiri, O. & Lischke, H. (2006) A model-based reconstruction of Holocene treeline dynamics in the Central Swiss Alps. *Journal of Ecology,* 94**,** 206-216.
Hoch, G. & Korner, C. (2009) Growth and carbon relations of tree line forming conifers at constant vs. variable low temperatures. *Journal of Ecology,* 97**,** 57-66.
Holtmeier, F.-K. (2009) *Mountain Timberlines* Springer Netherlands.
Kadmon, R. & Harari-Kremer, R. (1999) Studying long-term vegetation dynamics using digital processing of historical aerial photographs. *Remote Sensing of Environment,* 68**,** 164-176.
Karlsson, H., Hornberg, G., Hannon, G. & Nordstrom, E. M. (2007) Long-term vegetation changes in the northern Scandinavian forest limit: a human impact-climate synergy? *Holocene,* 17**,** 37-49.
Korner, C. (1998) A re-assessment of high elevation treeline positions and their explanation. *Oecologia,* 115**,** 445-459.
Korner, C. & Paulsen, J. (2004) A world-wide study of high altitude treeline temperatures. *Journal of Biogeography,* 31**,** 713-732.
Kullman, L. (2001) 20th century climate warming and tree-limit rise in the southern Scandes of Sweden. *Ambio,* 30**,** 72-80.
Lenoir, J., Gegout, J. C., Marquet, P. A., de Ruffray, P. & Brisse, H. (2008) A significant upward shift in plant species optimum elevation during the 20th century. *Science,* 320**,** 1768-1771.
Liu, H. Y., Tang, Z. Y., Dai, J. H., Tang, Y. X. & Cui, H. T. (2002) Larch timberline and its development in North China. *Mountain Research and Development,* 22**,** 359-367.
Lloyd, A. H. & Fastie, C. L. (2002) Spatial and temporal variability in the growth and climate response of treeline trees in Alaska. *Climatic Change,* 52**,** 481-509.

Maggi, M., Estreguil, C. & Soille, P. (2007) Woody vegetation increase in Alpine areas: a proposal for a classification and validation scheme. *International Journal of Remote Sensing,* 28**,** 143-166.

Majella, P. N. d. (2009) Inquadramento territoriale. [online] URL: http://www.parcomajella.it/PDF/carta_inquadramento_territoriale.pdf (Accessed Date: 08.25.2009)

Mas, J. F. (1997) Monitoring land-cover changes: a comparison of change detection techniques. *4th International Conference on Remote Sensing for Marine and Coastal Environments.* Orlando, Florida, Taylor & Francis Ltd.

McMahon, S. M., Dietze, M. C., Hersh, M. H., Moran, E. V. & Clark, J. S. (2009) A Predictive Framework to Understand Forest Responses to Global Change. *Year in Ecology and Conservation Biology 2009.* Oxford, Blackwell Publishing.

Melanie, A. H., Philip, E. H., Matt, S. M. & Richard, P. D. (2009) Are treelines advancing? A global meta-analysis of treeline response to climate warming. *Ecology Letters,* 9999.

Motta, R., Morales, M. & Nola, P. (2006) Human land-use, forest dynamics and tree growth at the treeline in the Western Italian Alps. *Annals of Forest Science,* 63**,** 739-747.

Motta, R. & Nola, P. (2001) Growth trends and dynamics in sub-alpine forest stands in the Varaita Valley (Piedmont, Italy) and their relationships with human activities and global change. *Journal of Vegetation Science,* 12**,** 219-230.

Müller-Schneider, P. (1986) *Verbreitungsbiologie der Blütenpflanzen Graubündens = Diasporology of the spermatophytes of the Grisons (Switzerland)*, Geobotanisches Institut der ETH, Stiftung Rübel.

Neteler, M. & Mitasova, H. (2004) Chapter 10: Processing of Aerial Photos *Open Source GIS: A Grass GIS Approach* Second Edition ed., Springer Science + Business Media, Inc. .

Okeke, F. & Karnieli, A. (2006) Methods for fuzzy classification and accuracy assessment of historical aerial photographs for vegetation change analyses. Part I: Algorithm development. *International Journal of Remote Sensing,* 27**,** 153-176.

Pachauri, R. K. & Reisinger, A. (2007) Climate Change 2007: Synthesis Report. Intergovernmental Panel on Climate Change (IPCC).

Palombo, C. (2009) INFLUENZE DELLE VARIAZIONI D'USO DEL SUOLO E DEI CAMBIAMENTI CLIMATICI SULLE DINAMICHE DEI POPOLAMENTI DI PINO MUGO DELLA MAJELLA. UNIVERSITÀ DEGLI STUDI DEL MOLISE.

Paulsen, J., Weber, U. M. & Korner, C. (2000) Tree growth near treeline: Abrupt or gradual reduction with altitude? *Arctic Antarctic and Alpine Research,* 32**,** 14-20.

Pekkarinen, A. (2002) A method for the segmentation of very high spatial resolution images of forested landscapes. *International Journal of Remote Sensing,* 23**,** 2817-2836.

Pignatti, S. (1982) *Flora d'Italia,* Bologna, Edagricole.

Platt, R. V. & Schoennagel, T. (2009) An object-oriented approach to assessing changes in tree cover in the Colorado Front Range 1938-1999. *Forest Ecology and Management,* 258**,** 1342-1349.

R-Development-Core-Team (2009) *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing. Vienna, Austria. ISBN 3-900051-07-0, URL http://www.R-project.org.

Richardson, D. M. (1998) *Ecology and biogeography of Pinus,* Cambridge, Cambridge University Press.

Rolland, C., Petitcolas, V. & Michalet, R. (1998) Changes in radial tree growth for Picea abies, Larix decidua, Pinus cembra and Pinus uncinata near the alpine timberline since 1750. *Trees-Structure and Function,* 13**,** 40-53.

Ronikier, A. (2009) Subalpine communities of dwarf mountain-pine: a habitat favourable for fungi. *Nova Hedwigia,* 89**,** 49-70.

Rossiter, D. & Loza, A. (2010) Technical Note: Analyzing land cover change with logistic regression in R (Version 2.2, First version April 2004) *Technical Report ITC.* Enschede, NL.

Rossiter, D. G. (2004) Technical Note: Statistical methods for accuracy assesment of classified thematic maps. Enschede (NL): International Institute for Geo-information Science & Earth Observation (ITC).

Smith, W. K., Germino, M. J., Johnson, D. M. & Reinhardt, K. (2009) The Altitude of Alpine Treeline: A Bellwether of Climate Change Effects. *Botanical Review,* 75**,** 163-190.

Stanisci, A., Pelino, G. & Blasi, C. (2005) Vascular plant diversity and climate change in the alpine belt of the central Apennines (Italy). *Biodiversity and Conservation,* 14**,** 1301-1318.

Takahashi, K. & Yoshida, S. (2009) How the scrub height of dwarf pine Pinus pumila decreases at the treeline. *Ecological Research,* 24**,** 847-854.

Theurillat, J. P. & Guisan, A. (2001) Potential impact of climate change on vegetation in the European Alps: A review. *Climatic Change,* 50**,** 77-109.

Tondi, E., Antonellini, M., Aydin, A., Marchegiani, L. & Cello, G. (2006) The role of deformation bands, stylolites and sheared stylolites in fault development in carbonate grainstones of Majella Mountain, Italy. *Journal of Structural Geology,* 28**,** 376-391.

UNFCCC (2001) Land use, land-use change and forestry (Decision 11/CP.7 of United Nations Framework Convention on Climate Change). [online] http://unfccc.int/files/meetings/workshops/other_meetings/application/pdf/11cp7.pdf (Accessed Date: 2009.12.12)

van Gils, H., Batsukh, O., Rossiter, D., Munthali, W. & Liberatoscioli, E. (2008) Forecasting the pattern and pace of Fagus forest expansion in Majella National Park, Italy. *Applied Vegetation Science,* 11**,** 539-546.

van Zonneveld, M., Jarvis, A., Dvorak, W., Lema, G. & Leibing, C. (2009) Climate change impact predictions on Pinus patula and Pinus tecunumanii populations in Mexico and Central America. *Forest Ecology and Management,* 257**,** 1566-1576.

Wieser, G., Matyssek, R., Luzian, R., Zwerger, P., Pindur, P., Oberhuber, W. & Gruber, A. (2009) Effects of atmospheric and climate change at the timberline of the Central European Alps. *Annals of Forest Science,* 66**,** 12.

Wild, J. & Winkler, E. (2008) Krummholz and grassland coexistence above the forest-line in the Krkonose Mountains: Grid-based model of shrub dynamics. *Ecological Modelling,* 213**,** 293-307.

Woodcock, C. E., Macomber, S. A., Pax-Lenney, M. & Cohen, W. B. (2001) Monitoring large areas for forest change using Landsat: Generalization across space, time and Landsat sensors. *Remote Sensing of Environment,* 78**,** 194-203.

Yu, Q., Gong, P., Clinton, N., Biging, G., Kelly, M. & Schirokauer, D. (2006) Object-based detailed vegetation classification. with airborne high spatial resolution remote sensing imagery. *Photogrammetric Engineering and Remote Sensing,* 72**,** 799-811.

Zhang, Y. J., Xu, M., Adams, J. & Wang, X. C. (2009) Can Landsat imagery detect tree line dynamics? *International Journal of Remote Sensing,* 30**,** 1327-1340.

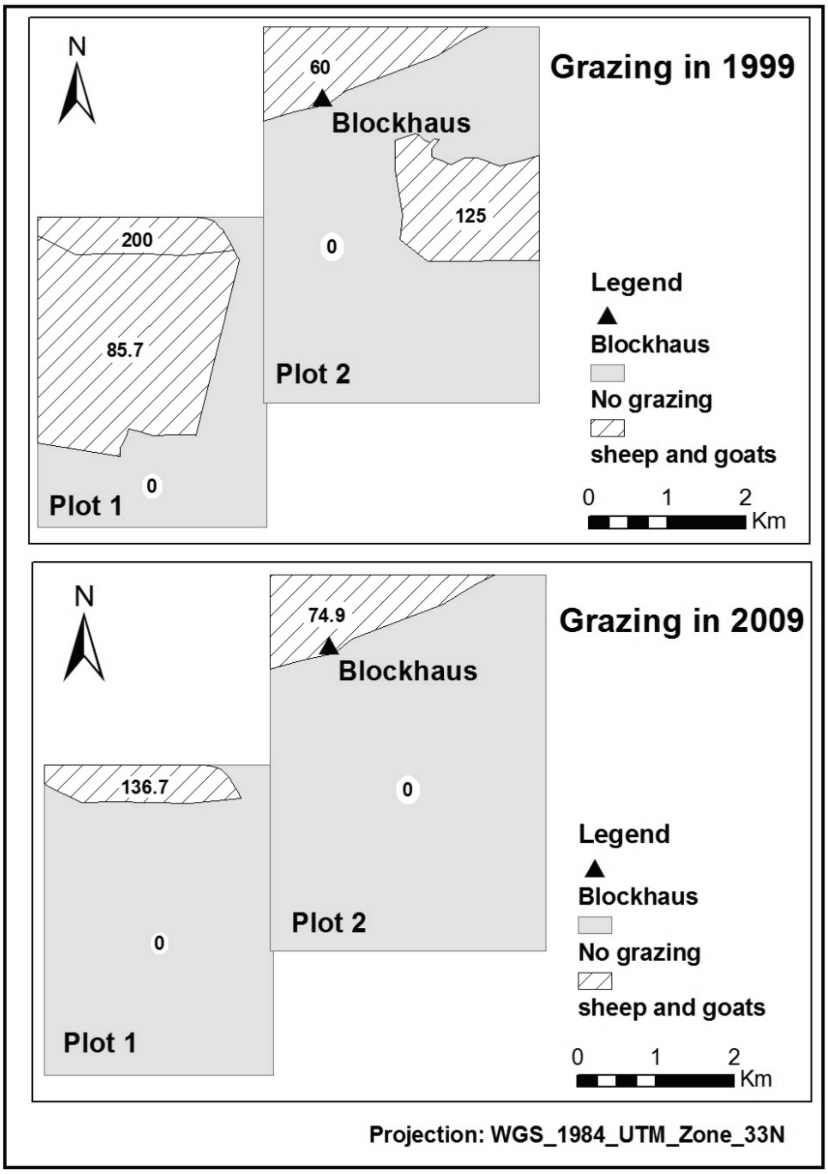
7. Abbreviations

L. --- Latin name or scientific name.
NP---National Park
GLM---Generalised Linear Model
VIF---Variance Inflation Factor
AIC---Akaike Information Criterion
ROC---Receiver Operating Characteristic
AUC---Area Under the ROC Curve

8. Appendices

Appendix I The grazing map of the study area. The value inside polygon is grazing intensity (number of sheep or goats/km^2).

Source: interview with Mr. Simone Angelucci, September of 2009 in Natioanl NP, Italy



Appendix II The field work data sheet

Point ID	

Basic information			
Name of recorder		Date:	/ (dd/mm)
Weather		Time:	

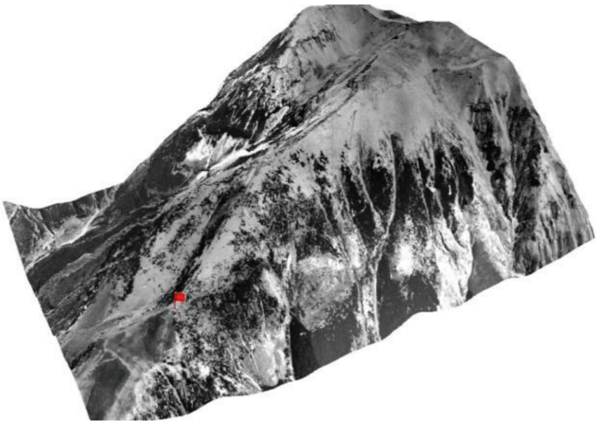
Geographical information		
coordinate	Latitude	
	Longitude	
Altitude (m)		
Slope (degree)		

Vegetation information				
Vegetation type	Beech (B)	☐	*Juniper nana* (Jn)	☐
	Pinus mugo (Pm)	☐	Grass (Gr)	☐
	Juniper sabina (Js)	☐	Bare ground (Bg)	☐
	Bracken Fern (BF)	☐	Others (Ot)	☐
Height (m)				

Canopy cover (point records)	P1		P9		P17		P25	
	P2		P10		P18		P26	
	P3		P11		P19		P27	
	P4		P12		P20		P28	
	P5		P13		P21		P29	
	P6		P14		P22		P30	
	P7		P15		P23		P31	
	P8		P16		P24		P32	
Surrounding description								

Grazing		
INDICATORS		description
Drinking water point	☐	
Grass height	☐	
Dropping	☐	
Animal track	☐	
Others	☐	
Other information		

Appendix III The aerial photos and changed detection results of plot-1 with 3D effect. The red flag represents the mountain of Rapina.

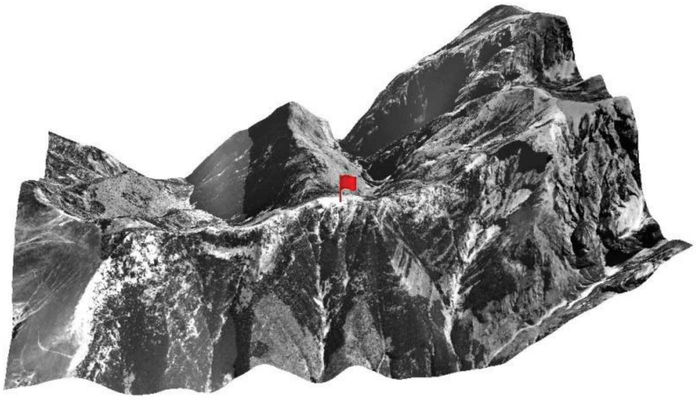


III.1 The aerial photos of 1954 in plot-1.

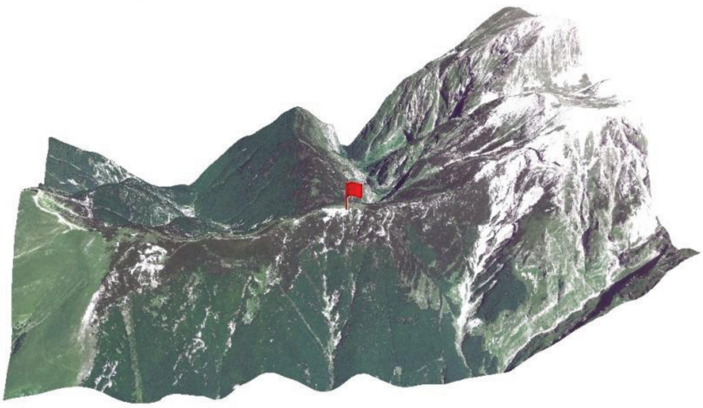
III.2 The aerial photos of 2007 in plot-1.

III.3 The change detection results of plot-1. Red colour represents where dwarf pine didn't change between 1954 and 2007; green colour represents where dwarf pine expanded between 1954 and 2007

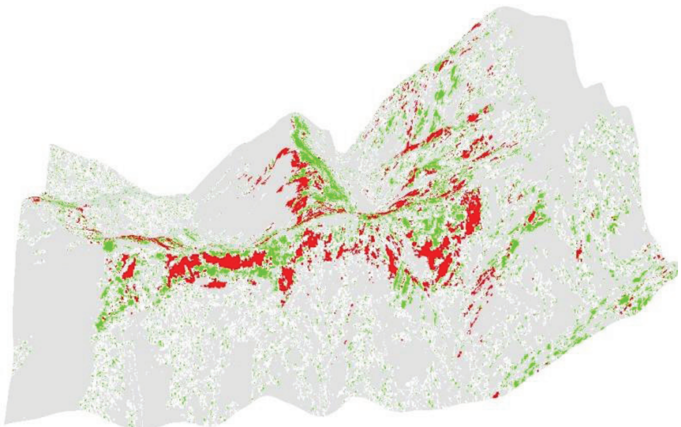
Appendix IV The aerial photos and changed detection results of plot-2 with 3D effect. The red flag represents the mountain of Cavallo.



IV.1 The aerial photos of 1954 in plot-2.



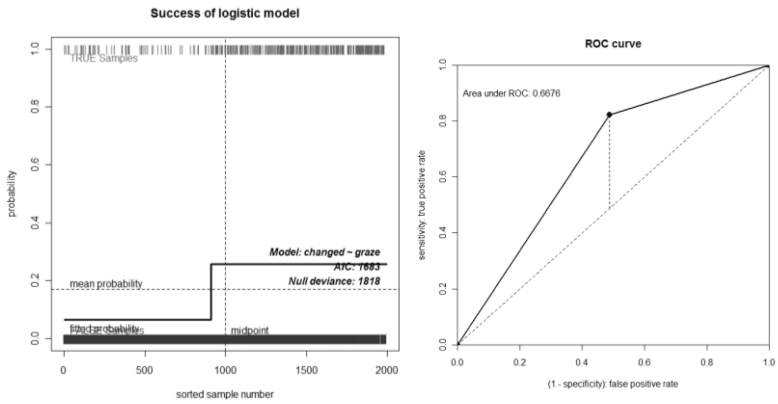
IV.2 The aerial photos of 2007 in plot-2.



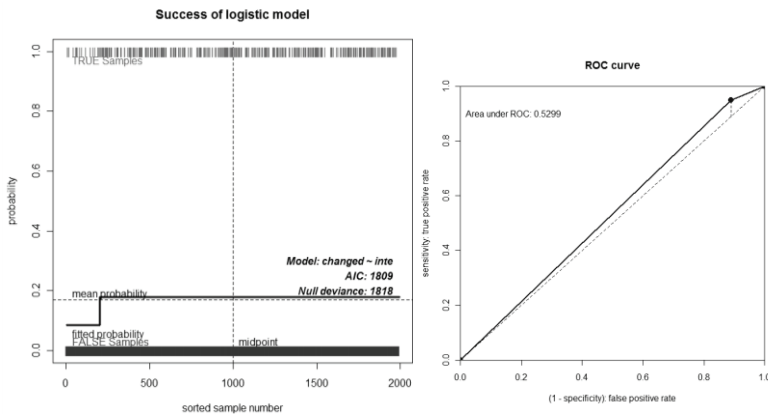
IV.3 The change detection results of plot-2. Red colour represents where dwarf pine didn't change between 1954 and 2007; green colour represents where dwarf pine expanded between 1954 and 2007

Appendix V The graph of logistic model and ROC curve for each single variable in Table 14.

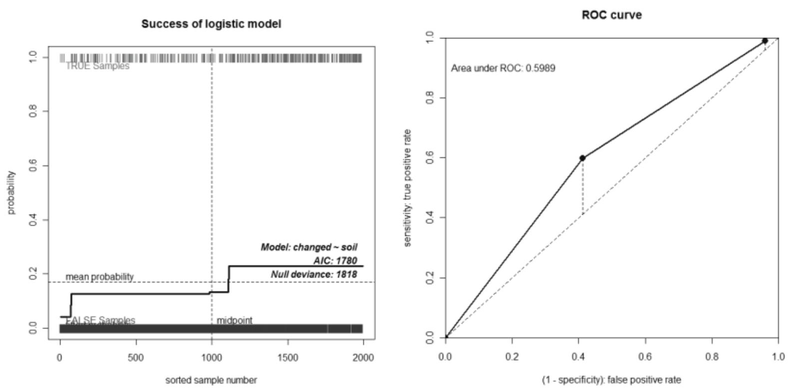
V.1 graze. AIC: 1638.4; AUC: 0.668.



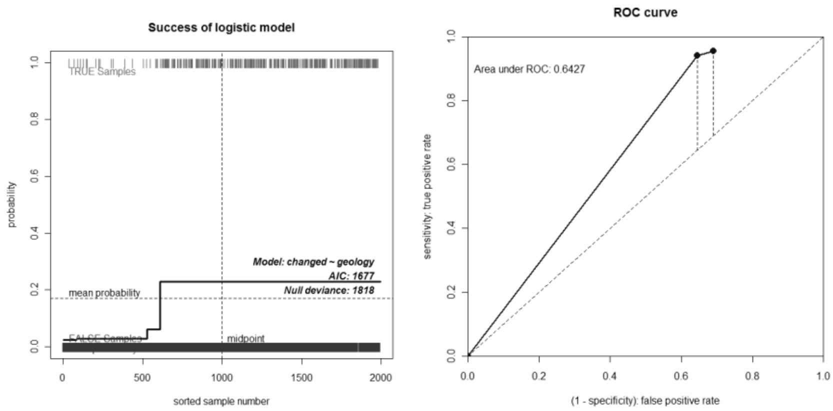
V.2 inte. AIC: 1808.7; AUC: 0.530.



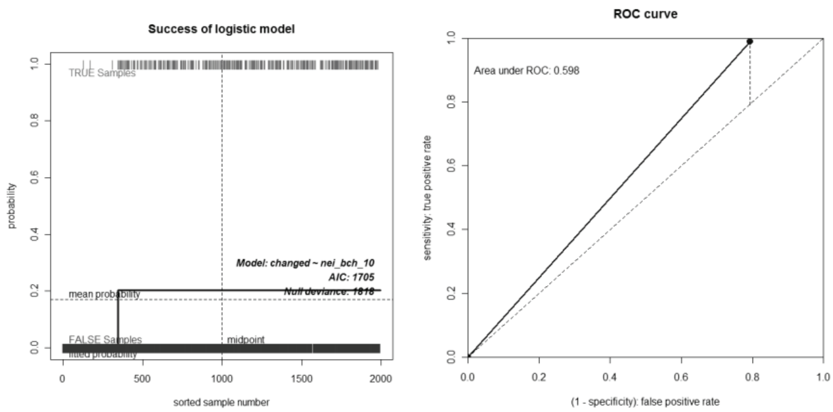
V.3 soil. AIC: 1780.4; AUC: 0.599.



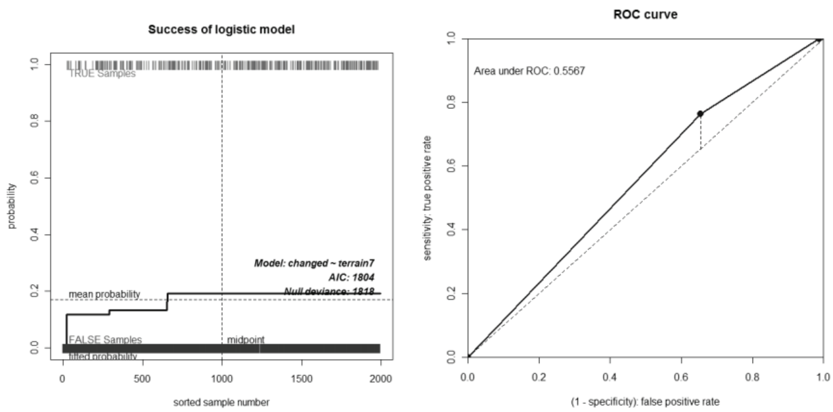
V.4 geology. AIC: 1676.7; AUC: 0.643.



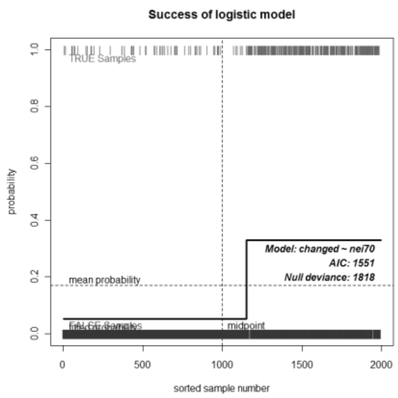
V.5 nei_bch_10. AIC: 1705.4; AUC: 0.598.

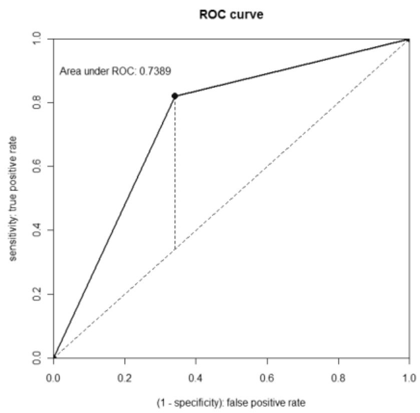


V.6 terrain. AIC: 1803.7; AUC: 0.557.

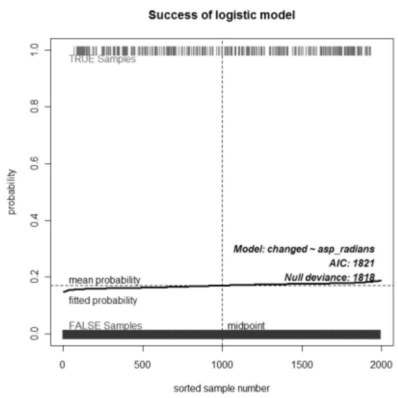


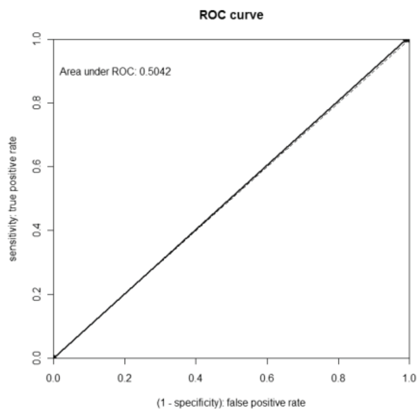
V.7 nei70. AIC: 1550.6; AUC: 0.739.



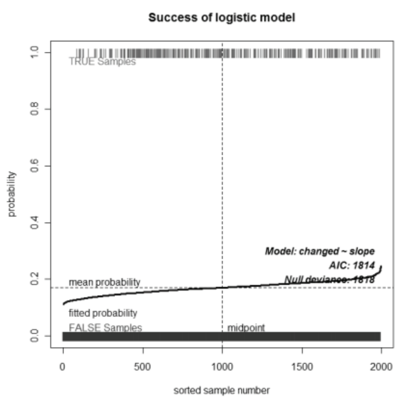


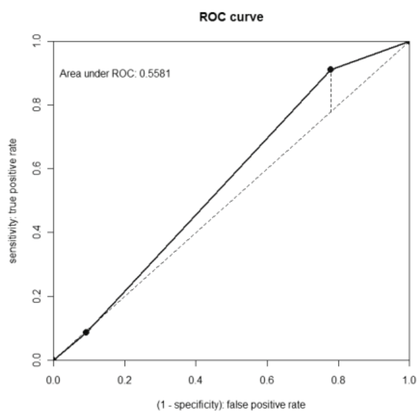
V.8 asp. AIC: 1820.8; AUC: 0.504.



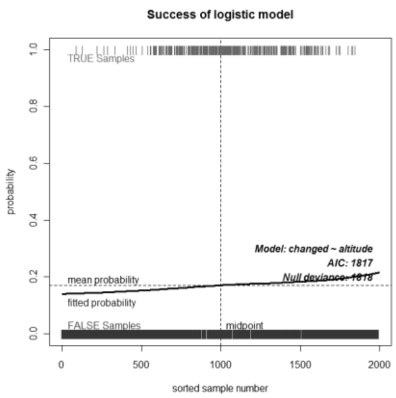


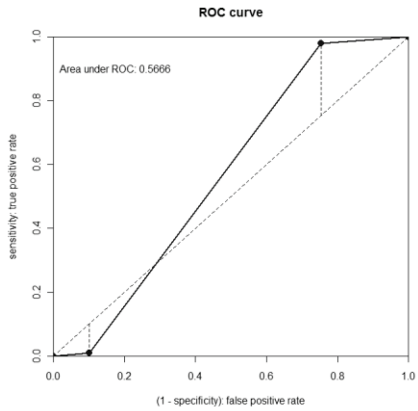
V.9 slope. AIC: 1814.2; AUC: 0.558.



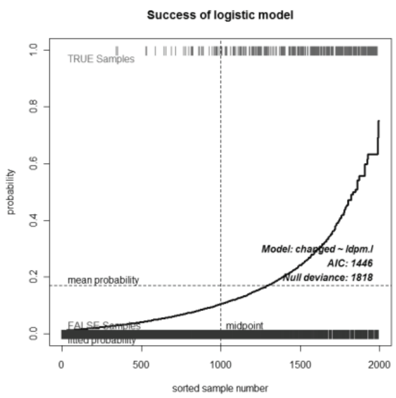


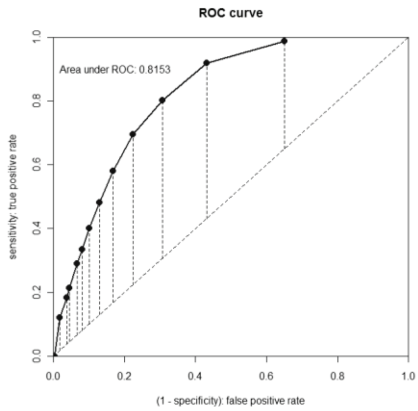
V.10 altitude. AIC: 1816.5; AUC: 0.567.



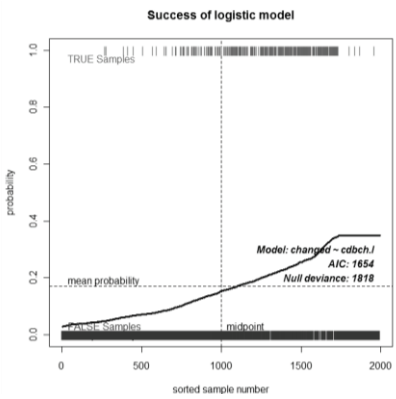


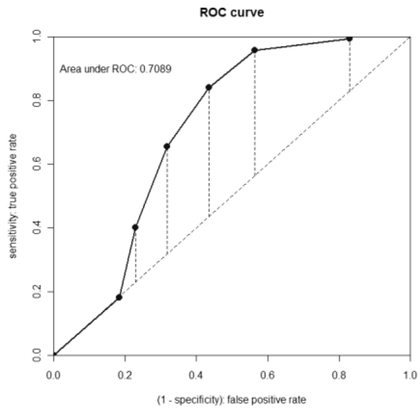
V.11 ldpm.l. AIC: 1446.0; AUC: 0.815.





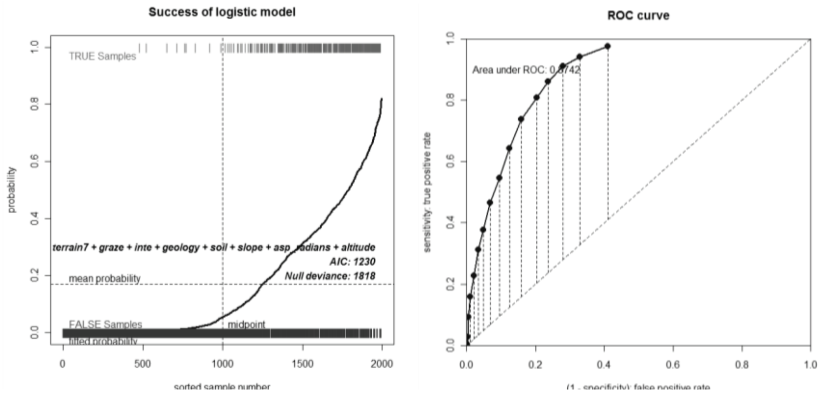
V.12 cdbch.l. AIC: 1654.5; AUC: 0.709.



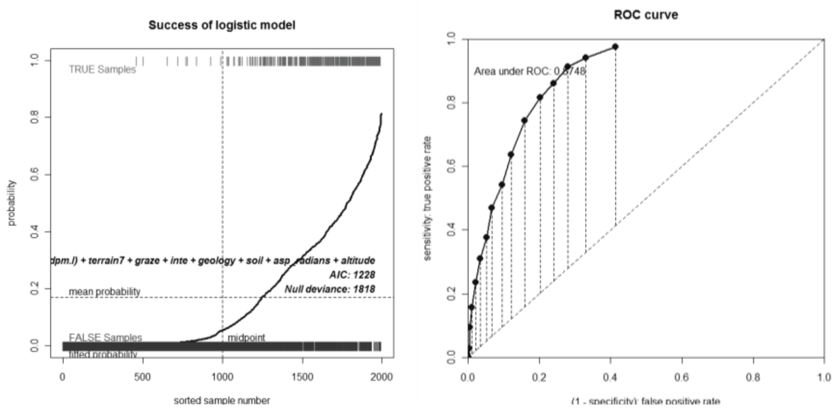


Appendix VI The graph of the logistic model and ROC curve for combined variables in Table 15

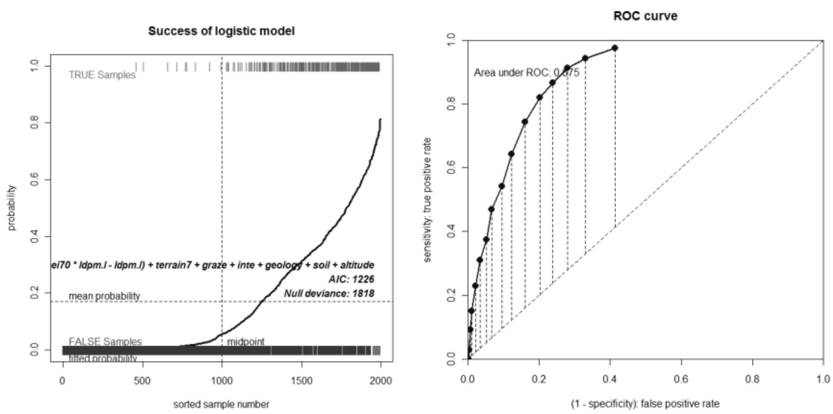
VI.1 The full model (*).AIC: 1229.6; AUC: 0.874.



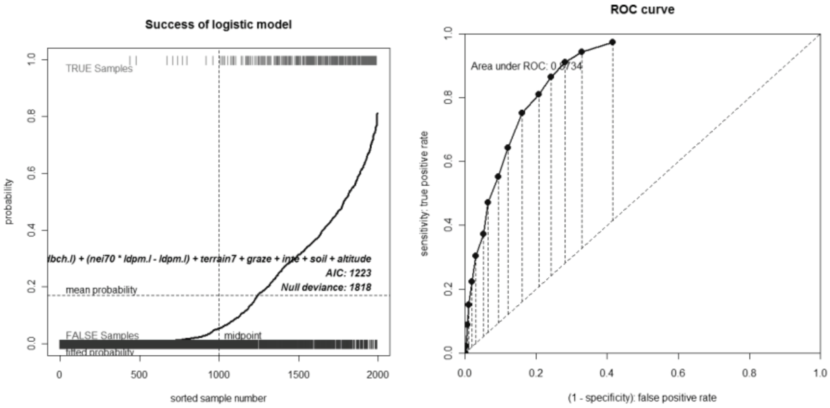
VI.2 *- slope. AIC: 1228.2; AUC: 0.875.



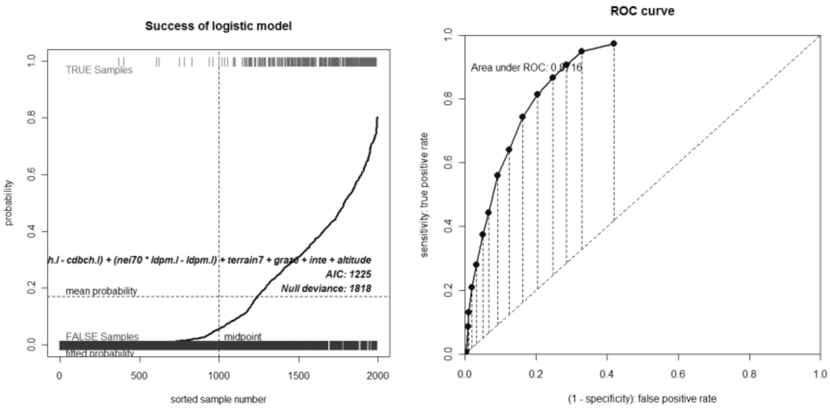
VI.3 *-slope-aspect. AIC: 1226.3; AUC: 0.875.



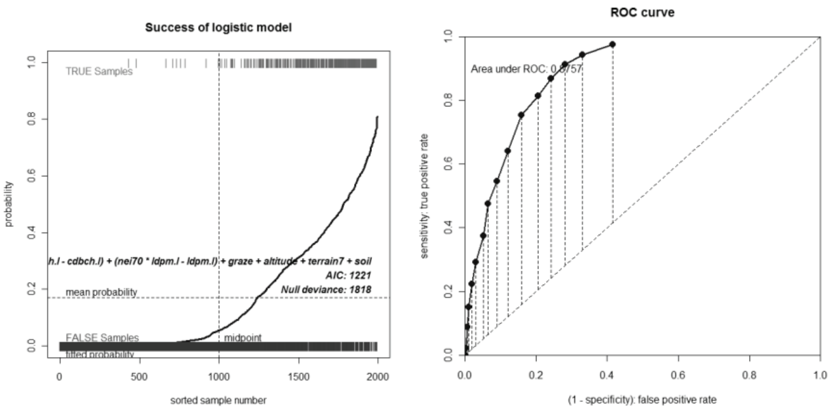
VI.4 *-slope-aspect-geology. AIC: 1222.9; AUC: 0.873.



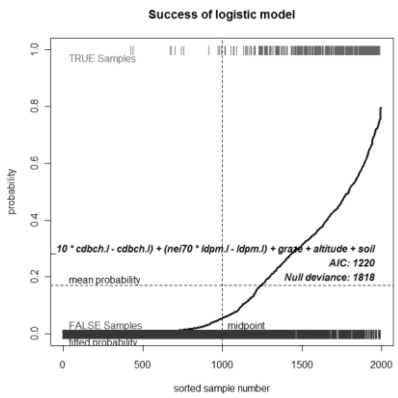
VI.5 *-slope-aspect-geology-soil. AIC: 1224.8; AUC: 0.872.

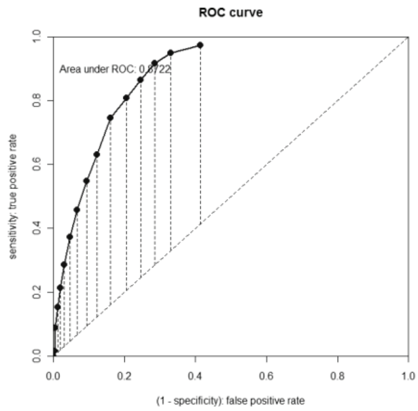


VI.6 *-slope-aspect-geology-inte. AIC: 1221.3; AUC: 0.876.



VI.7 *-slope-aspect-geology-inte-terrain. AIC: 1220.0; AUC: 0.872.





VI.8 *-slope-aspect-geology-inte-terrain-soil: this is the final model (see Figure 14 and Figure 15). AIC: 1222.2; AUC: 0.871.

VI.9 *-slope-aspect-geology-inte-terrain-soil-graze. AIC: 1235.1; AUC: 0.867.