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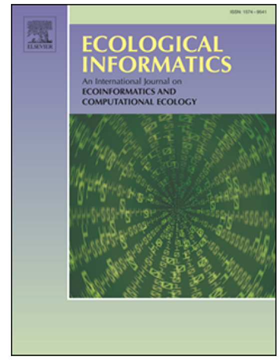

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A multi-temporal approach in MaxEnt modelling: a new frontier for land use/land cover change detection

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Abstract

Land-cover change, a major driver of the distribution and functioning of ecosystems, is characterized by a high diversity of patterns of change across space and time. Thus, a large amount of information is necessary to analyse change and develop plans for proper management of natural resources. In this work we tested MaxEnt algorithm in a completely remote land-cover classification and change analysis. In order to provide an empirical example, we selected Italian southern Alps as test region. We classified two Landsat images (1976 and 2001) in order to forecast probability of occurrence for unsampled locations and determining the best subset of predictors (spectral bands). A difference map for each land cover class, representing the difference between 1976 and 2001 probability of occurrence values, was realised. In order to better address the analysis of change patterns, we put together difference maps and topographic variables, since, in the study area, they are considered as the main environmental characteristic driving the land-use change topographic variables, in connection with climate change. Our results indicate that the selected algorithm, applied to land cover classes, can provide reliable data, especially when referring to classes with homogeneous texture properties and surface reflectance. The performed models had satisfactory predictive performance, showing relatively clear patterns of difference between the two time steps considered. The development of a methodology that, in the absence of field data, allow to obtain data on land use change dynamics, is of extreme importance for land planning and management.

Keywords: GIS, Land-cover change, Machine learning, MaxEnt, Probability distribution, Remote sensing.

1. Introduction

Land-cover change is considered to be the major driving force of transformation in ecosystem function and dynamics in many regions of the world (Gillanders, Coops, Wulder, Gergel, & Nelson, 2008). Land-cover change is characterized by a high diversity of patterns of change across space and time as a function of specific driving factors at a certain location (Mottet, Ladet, Coqué, & Gibon, 2006; Meyfroidt, Lambin, Erb, & Hertel, 2013; Lawler et al., 2014). A large amount of information is necessary to analyse land-cover change and develop plans for proper management of natural resources (Pelorosso, Leone, & Boccia, 2009). Traditional methods (e.g. field surveys, literature reviews, map interpretation and collateral and ancillary data analysis), however, are not effective to acquire land cover data at landscape scale, since they are time consuming, date lagged and often too expensive. Consequently remote sensing might represent an essential technology to study vegetation cover changes, especially over large areas (Green, Kempka, & Lackey, 1994; Stow et al. 2004; Lunetta, Knight, Ediriwickrema, Lyon, & Dorsey Worthy, 2006). Because of the potential for systematic observations at various scales, remote sensing technology extends possible data archives from present time to several decades ago (Brink

& Eva, 2009; Mallinis, Emmanoloudis, Giannakopoulos, Maris, & Koutsias, 2011; Fichera, Modica, & Pollino, 2012). For this advantage, enormous efforts have been made by researchers and application specialists to delineate land-cover change by applying remote sensing image time series (Verburg, Neumann, & Nol, 2011).

In the remote sensing literature, several methodologies have been reported for automatic classification. Many of them are based on Bayesian theory as it offers a theoretically robust foundation for the classification of remotely sensed data (Robin, Mascle-Le Hégarat & Moisan, 2005; Rocchini et al., 2017). MaxEnt (Phillips, Anderson, & Schapire, 2006), the current state-of-the-art of machine-learning algorithm traditionally used in distribution modelling (Elith & Graham, 2009; Peterson, Papes, & Eaton, 2007; Warren & Seifert, 2011), represent an appealing alternative to common "soft" classifiers because it can be trained with presence-only data, treating land cover classes the same way as a single species or habitat (Mack et al., 2016). The use of models which imply presence-only methods, represent a fascinating challenge since they allow for the mapping of uncertainty in the form of suitability maps instead of binary presence/absence (Rocchini et al., 2015), overcoming the problems derived from a crisp view of landscapes and taking into account the complexity of land cover classes.

Maxent has been used for one-class land cover classification in applied studies or to compare different distribution algorithms (see e.g. Li & Guo, 2010; Lin, Liu, Li & Li, 2014; Maclaurin & Levk, 2016; Mack & Waske, 2017), but its application in remote sensing remains rare. The theoretical foundation of MaxEnt consists in the maximum-entropy principle (Jaynes, 1957): when approximating an unknown probability distribution, the best approach is to ensure that the approximation satisfies any constraints on the unknown distribution that we are aware of, and that the distribution, the subject to those constraints, should have maximum entropy. Hence, the MaxEnt principle is to estimate a probability distribution by calculating the maximum entropy subject to a set of constraints that represent our incomplete information about the target distribution (Phillips, Anderson, & Schapire, 2006). Following this principle, MaxEnt, given the constraints derived from the data, estimates the most uniform distribution (maximum entropy) of sampling points compared to background locations (Baldwin, 2009; Phillips et al., 2009). The maximum entropy algorithm is deterministic and will converge to the maximum entropy probability distribution (Phillips, Anderson, & Schapire, 2006). Therefore, the resultant output represents how much better the model fits the location data than would a uniform distribution (Philips & Dudik, 2008; Baldwin, 2009).

The basic aim of this work is to disentangle the opportunities for future application of distribution models in multi-temporal remote sensing classification, in the absence of field data. Here we specifically concentrated on testing the MaxEnt algorithm in land cover classification and land-cover change detection. We expect that the tested algorithm, combined with GIS-based spatial analysis, would allow for completely remote land-cover classification and change detection analysis, providing reliable data, especially when referring to land cover classes with homogeneous texture properties and surface reflectance (Amici, 2011). Aware that there are no classification algorithms that could apply universally and that classifiers may also be assumed to have complementary capabilities (Matsuyama, 1987), through our work we aim to propose a rapid and cost-effective methodological approach that can be replicated for remote sensing-based multi-temporal classifications at landscape scale.

2. Material and methods

2.1 Spectral response-based MaxEnt classification

In order to provide an empirical example, we decided to make use Italian Southern Alps (Trentino region) as a test region (Figure1), with an extremely complex landscape ranging from agricultural land (mainly vineyards) at lower elevations, to broadleaf and coniferous forest and grasslands at higher elevations (> 2000 m) (refer to Rugani and Rocchini 2016 for additional information). We divided the classification framework into two major steps: *i*) remote sensing imagery and occurrence data collection, and *ii*) model building, to forecast probability of occurrence for unsampled locations (Yost et al., 2008). As for the first step, an ortho-Landsat MSS image (path

208, row 028, acquisition date August, 1976) and an ortho Landsat ETM+ image (path 192, row 028, acquisition date August, 2001) were acquired and converted to ASCII format for use in MaxEnt. In order to guarantee the comparability between the datasets in terms of spatial resolution, the Landsat images have been resampled at pixel resolution of 50m x 50m. Subsequently, the overlap area between the ETM+ and MSS images, comprising the test area identified, has been clipped and used in the classification procedure (model building). Then, through the overlay between Corine Land Cover 2000 dataset and satellite images, and the on screen photo interpretation of 1976 and 2001 images, we identified nine land-cover classes on the basis of the Corine legend (Tab.1). Subsequently, we selected 20 training pixels (where the uncertainty linked to visual classification was lower) for each class and for both time steps (1976-2001). In order to estimate the probability distribution of the land cover classes based on the spectral information provided by the Landsat images, we relied on MaxEnt software v.3.3 (http://www.cs. princeton.edu/~schapire/MaxEnt/; Last accessed on March 5, 2011), a free software package based on the maximum-entropy approach (Phillips, Anderson, & Schapire, 2006; Baldwin, 2009). The MaxEnt approach apply the principle of maximum entropy on presence-only data to relate environmental variables and habitat suitability in order to approximate the species' niche and potential geographic distribution (Phillips, Anderson, & Schapire, 2006; Ficetola et al., 2010). In principle maximum entropy seeks a marginal suitability function for each variable that *i*) matches the empirical data, *ii*) is maximally uninformative elsewhere, and *iii*) has a mean equal to that from the empirical data (Warren & Seifert, 2011). However, strict adherence to this requirement can lead to models that overfit input data. For this reason, MaxEnt uses a process called L1 regularization to constrain modelled distributions to lie within a certain interval around the empirical mean rather than matching it exactly (Phillips, Anderson, & Schapire, 2006). Hence, the entropy measured by MaxEnt on a grid cell containing an occurrence record of a known feature, for which we want to estimate the distribution, is expected to be low, whereas the entropy measured on a grid cell on which we do not know all the ecological constraints is expected to be high (Phillips & Dudik, 2008). Then, MaxEnt model evaluates the suitability of each grid cell as a function of environmental variables and generates an estimate of probability of presence that varies from 0 to 1, where 0 is the lowest and 1 the highest probability. The 180 selected training points and six spectral layers (Landsat bands) were here used in MaxEnt to model the distribution of the nine selected land-cover classes. In order to assess the predictive performance of the MaxEnt models (Land cover distribution probabilities), the Receiver Operating Characteristic curves (ROC) have been used (Hanley & McNeil, 1982; Zweig & Campbell, 1993). A ROC curve is obtained by plotting sensitivity (true positive rate) on the y axis and 1-specificity (false positive rate) on the x-axis for all possible thresholds. The Area Under the ROC Curve (AUC) value indicates the model accuracy and was used here as a standard measure of model quality (Elith et al., 2011). For random prediction, AUC is 0.5. The main advantage of ROC analysis is that the AUC provides a single measure of model performance, independent of any particular choice of threshold. In this work a bootstrap replicated run has been performed to do multiple runs (100) for the same land cover class; through this method the training data is selected by sampling with replacement from the presence points (random test samples equal to 25%), with the number of samples equaling the total number of presence points. MaxEnt models were run on separately to produce 18 datasets of probability of occurrence (9 for 1976 and 9 for 2001) of each land cover type within the study area.

2.2 Land-cover change analysis

A difference map for each land cover class (representing the difference between 1976 and 2001 probability of occurrence values), was obtained using the Raster map calculator module of GRASS GIS (GRASS Development Core Team, 2011; Neteler et al., 2012). Then, using GRASS GIS, was built a mask on pixels of each 2001 maps and, then, each mask was applied on 1976 maps, calculating the mean of frequency distribution of pixel values for each land use class. Thus was obtained a contingency matrix with average value of probability of belongings to 1976 classes for each of 2001 classes. In order to link land use changes and topographic variables (altitude and slope), a 75m Digital Elevation Model (DEM) was acquired. Subsequently the DEM was resampled at a spatial resolution of 50m, in order to enable the spatial overlay analysis between land-cover map data (difference between 2001 and 1976 models) and topography. Afterwards a slope raster map was obtained through the *r.slope.aspect* module of GRASS GIS. In the study area, topographic variables, like elevation and slope, in connection with climate change, are considered as the main environmental characteristic driving the land-use change patterns at landscape scale (see e.g. Tappeiner, Tasser, & Tappeiner, 1998; Dirnbock, Dullinger, & Grabherr, 2003; Gehrig-Fasel, Guisan, & Zimmermann, 2007; Tasser, Walde, Tappeiner, Teutsch, & Noggler, 2007; Randin et al., 2009). The difference maps were overlaid with the altitude and slope layers in order to analyse pattern of land-cover change in relation to topography.

The spatial data relatively to the slope, altitude and difference maps for the nine land use, were imported in the R software (R Development Core Team, 2011) from GRASS GIS, using the package *spgrass6*. To display as best as possible both the frequency distributions of nine difference maps and their relationships with geomorphological variables, we used the kernel density estimation, the commonest way to estimate the probability density function of a random variable (Venables & Ripley, 2002). We performed, on each class, a simple normal kernel estimation of difference values distribution, joined with the number of lost and gained pixels, to investigate the land use changes between 1976 and 2001. Then, to study the relationships between land use changes and the two considered geomorphological variables, we applied a two-dimensional kernel density estimation, algebraically defined how:

$$f(x,y) = \frac{\sum \phi\left(\left(x - x_s\right)/h_x\right)\phi\left(\left(y - y_s\right)/h_y\right)}{n h_x h_y} \quad \text{Eq. 1}$$

where x and y are the difference values and the geomorphological variable values, respectively, φ is the normal kernel function and h is the smoothing parameter for the two variables, called the bandwidth, here calculated using the rule-of-thumb indicated by Venables & Ripley 2002. Eq. 1, implemented by the R function *kde2d*, was performed between land use classes, taken one at once, and one of the two environmental variables. Then, the calculated kernel distributions were drawn using perspective plots, built with the R function *persp*, implemented into the *rgl* package (Adler & Murdoch, 2011). Following this procedure, we built 18 3D-density plots between land use classes and geomorphological variables distributions.

The choice to analyze the distribution of probability values of land use change with respect to topographic variables, not including them in the model process itself, has been dictated by the need to provide a further verification of the reliability of the difference models performed, by avoiding potential circular analysis, which is known to generally affect the ecological explanation of the patterns achieved from the modelling techniques (Ginzburg & Jensen, 2004).

3. Results

The MaxEnt classification output resulted in 18 maps showing the mean probability of occurrence for each land cover class for the two temporal steps. The MaxEnt model's internal test of variable importance showed that the MSS' near infrared bands represent the most important layer in classifying the distribution of forest cover classes (coniferous forests and broadleaved forests), water bodies, rock and bare soil, grasslands and pastures and artificial areas, while the MSS' green and red bands were the most important variables in explaining the distribution of agricultural areas (croplands, orchards, vineyards). Focusing on the test of variable importance for ETM+ bands, the middle-infrared bands resulted the most important layer in explaining the distribution of croplands, artificial areas, coniferous forests, water bodies and grasslands, while the near infrared band for orchards and broadleaves and red band for vineyards. The relative contributions of each band to each land cover model are reported in Table 2, showing relatively high values for the bands in the near infrared (1976 and 2001) and mid infrared (2001) regions of the electromagnetic spectrum (band 4and 5) for all models, while green and red regions showed high values for grasslands and vineyards models respectively in 1976.

The predictive quality of all models can be considered good with AUC values (average of 100 replicate runs) ranging from 0.93 to 0.99 and a standard deviation ranging from 0.003 to 0.19 (Tab.3). The land cover classes that have highest AUC values for both time steps considered are Water bodies and Artificial areas. The performed difference maps (2001-1976) allowed to evaluate the rate of land cover change in terms of probability of occurrence values: values equalling 0 correspond to no change, values greater than 0 correspond to a gain, while values less than 0 correspond to a loss (Fig. 2). The distribution of gain, loss or maintenance values for each land cover map is summarized by the frequency distribution curves represented in Figure 3, relating the values of loss (<0), gain(>0) or maintenance (=0) for each land use class to its frequency of occurrence. The curves highlights that the loss of probability of occurrence (loss of surface) was most pronounced in the "Croplands", "Water bodies", "Grasslands and Pastures" and "Rock and bare soil" classes, while the gain of probability of occurrence (gain of surface) was more pronounced for "Coniferous forests", "Broadleaved forests" and "Vineyards" classes.

A qualitative analysis of the data (direction of change) was obtained through the cross-classification analysis, which, in conjunction with the results obtained with regard to the rate of change, allowed an overall analysis of land cover change process. Linking the contingency matrix between 1976 and 2001 land cover models (Tab.4) to the frequency distribution curves (Fig.3), it is possible to highlight that the study area has been undergoing a significant increase in forest areas to the detriment of Croplands, Grasslands and Bare soil.

The relationships between change processes and topography have been summarised by the 3D-density plots between land use classes and geomorphological variables showed in figure 4 (Elevation) and 5 (Slope). Through the 3D-density plots it is possible to highlight that the increase in Broadleaved forests has occurred mainly at altitudes between 600 and 1200 meters with a slope peak corresponding to medium-high values (20-30°), while the increase in Coniferous forest has occurred in higher altitudes (1000 and 2000 meters). On the other hand the major decreases of cropland has occurred in connection with lowest altitude values (0-200 meters), while the decrease of grassland and pastures has occurred at altitudes between 1000 and 2000 meters and low slope values. The orchards were characterized by a slight increase at hilly altitudes and low slope values while the vineyards have been characterized by a slight loss with low slope values.

4. Discussion

In this paper, we applied a distribution model to land cover classes instead of species or habitats, presenting a novel approach in this framework and extending along the methods to multi-temporal data, which implies an analysis of change patterns for each model. The tested algorithm combined with GIS-based spatial analysis could represent a promising tool in land cover mapping and change analysis, as it allows to obtain multi-temporal suitability maps that better reflect the uncertainty proper of natural ecosystems than the division into discrete classes proper of crisp maps.

Our results indicate that MaxEnt, which typically has been used for estimating habitat suitability for plant and animal species in natural areas, can also provides reasonable estimates of land cover classes distribution and land use change detection, as can be seen from the AUC values obtained for all the models (Table 3).

Moreover, it is notable that the performed MaxEnt models had strong predictive performance even if restricted to spectral reflectance as explanatory variables, showing relatively clear patterns of difference between 2001 and 1976 probability of occurrence scores (see Figure 2).

In fact, the probability of occurrence for the nine land cover classes is clearly not randomly distributed, with regions of high values being found in correspondence of lowland or hilly areas for Croplands, Artificial areas, Orchards and Vineyards and in correspondence of Mountain areas, for forest classes and grasslands. As for the performance of the models, in terms of variability of suitability scores as well as AUC scores, this is dependent upon the land cover class take into exam. How close the AUC is to its potential maximum, can ultimately only be assessed if we consider how homogeneous and specialized are the environmental characteristics of the areas occupied by each land cover class, because a more heterogeneous and inclusive class (i.e a wider niche if we consider species or habitats) as it is defined in the classification process, corresponds generally with a lower AUC value (Phillips, Anderson, & Schapire, 2006; Elith et al., 2011). In fact higher values of AUC are related to Coniferous forests, Broadleaved forests and Grassland and pastures, which represent the classes that occupy the better defined niche in the study area. While, for more heterogeneous classes, AUC values are lower due to partial overlap of occupied environmental niche and of the spectral unmixing that characterizes the Landsat images (Van der Meer, 1995).

Focusing on the emerged change patterns, the data we obtained through this work are consistent with the literature, which highlights how the abandonment of traditional primary activities, a process due to various environmental and economic consequences, played a significant role in land cover changes in European mountains (MacDonald et al., 2000; Pelorosso, Leone, & Boccia, 2009; Kolecka et al., 2015; Orlandi et al., 2016). In particular, a process to be focused, for its profound implications in terms of natural resource management and biodiversity conservation, is the rapid expansion of forests and scrublands in abandoned agricultural areas, with the consequent variation in plant species composition, richness, and vegetation biomass (Amici et al., 2013; Dupouey, Dambrine, Laffite & Moares, 2002; Maccherini et al., 2013). This increase is due to ecological succession in abandoned lands, a non linear process that generally begins with the replacement of annual plants by perennial plants to reach a closed canopy by woody species (Bartha, Meiners, Pickett & Cadenasso, 2003; van Breugel, Bongers & Martínez-Ramos, 2007; Walther, Petersen & Pott, 2002).

Our results revealed a substantial functional reorganization of the land mosaic in terms of land use in the time span considered, that confirms what. The detected changes are connected with an increase in artificial surfaces (mostly residential buildings, farm sheds and roads) at the expense of arable land and vineyards and a significant growth in forest areas at the expense of agriculture areas, grasslands and baresoil, overall considering grasslands at higher elevations. In particular it should be reported a substantial increase of broadleaves in conjunction with situations of high gradients (10°-40°) and altitude between 600 and 1500 m.s.l.m. This seems to be confirmed by the forest management that has emerged in last decades, for which the cutting areas are selected from among the most accessible and more easily workable areas (Plieninger & Schaar, 2008) and a contemporary abandonment of pastures in the most inaccessible areas, as part of a more general trend of expansion of forest areas in mountainous and hilly areas due to the expansion of industrialized agriculture and the abandonment of traditional agricultural areas (Pelorosso, Leone, & Boccia, 2009; Geri, Amici, & Rocchini, 2010; Orlandi et al., 2016). The coniferous forests showed a similar trend, with the only difference that the increase in surface area took place mainly at the expense of grasslands. The expansion of coniferous forests is probably regulated by the same hypothesized drivers for deciduous forests, only translated in the altitudinal direction (between 1000 and 2000 m a.s.l., see Figure 4), following the ecological requirements of the alpine conifers, together with small scale microclimate changes (Pauli, Gottfried, Reiter, Klettner, & Grabherr, 2007). A decrease in terms of surface in the last decades was found for grassland areas and other open areas that, along with patches of sparse or dense forests are part of the traditional landscape mosaic, can be mainly found in the subalpine and alpine belt (Garbarino, Lingua, Subira, & Motta, 2011; Garbarino, Sibona, & Lingua, 2014). The forest patches can be considered as the most dynamic elements of the traditional heterogeneous alpine landscapes (Höchtl, Lehringer, & Konold, 2005), while the surfaces of open areas tend to reduce due to trees encroaching on the abandoned land (Cousins, Lavorel, & Davies, 2003; Dullinger, Dirnböck, Greimler, & Grabherr, 2003). This secondary succession process is particularly evident in the Italian Alps (Motta & Garbarino, 2003; Höchtl, Lehringer, & Konold, 2005; Garbarino & Pividori, 2006) where enclosed herbaceous patches, traditionally grazed during the summer are at risk of disappearing due to the abandonment of traditional practices (Grossi, Chevanier, Delcros, & Brun, 1995) and the subsequent secondary succession processes that are particularly fast and abrupt due to favourable climate and soil fertility. This process has mainly affected patches located at altitudes between 1000 and 2000 meters and steep slopes (10 to 40), where the strongest have been the effects of a more general reorganization of agricultural spaces due to the industrialization of agricultural practices, which favoured the abandonment of traditional practices and of less productive terrains.

In this context, we detected a significant increase of vineyards surfaces in the valley or in hilly areas with low slope (0°-5°), associated with the potential increase of wine market production in the Alps regions (Odorici & Corrado, 2004).

5. Conclusions

This work proposed a new remote sensed approach to perform multi-temporal land cover classification of large areas, using the maximum entropy approach. Our findings suggest that MaxEnt, a machine learning algorithm traditionally used in species/habitat distribution modelling, can represent a useful and reliable approach for identifying multi-temporal landscape dynamics, a result that should encourage conservationists to add distribution modelling to their toolbox. Moreover, the data obtained here are consistent with those obtained in previous work for alpine areas (see e.g. Chemini & Rizzoli, 2003 Falcucci, Maiorano, & Boitani, 2007; Tasser, Walde, Tappeiner, Teutsch, & Noggler, 2007; Rutherford, Bebi, Edwards, & Zimmermann, 2008; Niedrist, Tasser, Lüth, Dalla Via, & Tappeiner, 2009; Zimmermann, Tasser, Leitinger, & Tappeiner, 2010; Monteiro, Fava, Hiltbrunner, Della Marianna, & Bocchi, 2011), confirming that reasonable models of land cover distribution and change for remotely sensed derived presence-only data represent a challenging outlook.

The development of a methodology that, in the absence of field data, allows to obtain reliable data on land use change dynamics, is of extreme importance for those institutions engaged with landscape planning and management. In particular, in a context of climate change and changes, producing multi-temporal data in a systematic and cost-effective way is vital to: *i*) explore potential ecological patterns driving ecological processes and *ii*) allow a more efficient monitoring of land resources.

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Tables

Table 1. Description of land cover classes with relative Corine Land Cover code.

Class	Corine Land cover (Level III)	Description
Atificial areas (ART)	111, 112, 121, 122, 124	*Areas mainly occupied by urban fabric and/or industrial, commercial and transport units.*
Boadleaved forests (BRO)	311	*Vegetation formation composed principally of trees, including shrub and bush understoreys, where broad-leaved species predominate*
Coniferous forests (CON)	312	*Vegetation formation composed principaly of trees, including shrub and bush understoreys, where coniferous species predominate.*
Croplands (CRO)	211, 212, 241, 242	*Areas of permanent or annual crops which are permanently or not irrigated.*
Grasslands and pastures (GRA)	231, 321	*Low productivity grassland and natural or semi-natural meadows, which are permanently used for fodder production.*
Orchards (ORC)	222	*Parcels planted with fruit trees, in particular orchards of apples.*
Rock and bare soil (ROC)	332, 333	*Cliffs, rock outcrops, incuding active erosion, rocks, sparsely vegetated and unstable areas of stones, boulders, or rubble on steep scope.*
Vineyards (VIN)	221	*Areas planted with vines.*
Water bodies (WAT)	511, 512	*Natural or artificial stretches of water, and natural or artificial water-courses.*

Table 2. Relative contribution (%) of each band to each land cover model. The following table gives estimates of relative contributions of the environmental variables to the MaxEnt model. To determine the first estimate, in each iteration of the training algorithm, the increase in regularized gain is added to the contribution of the corresponding variable, or subtracted from it if the change to the absolute value of lambda is negative. For land cover classes abbreviation see table1.

		ART	BRO	CON	CRO	GRA	ORC	ROC	VIN	WAT
1976 (MSS)	**Band1** 0.5-0.6 um (Green)	0.4	11.1	0.4	6	51.1	11.4	31.3	7	35.3
	Band2 0.6-0.7um (Red)	13.2	26.9	39.9	35.8	20	14.8	22.7	85.4	2.3
	Band3 0.7-0.8um (Near Infrared)	0.8	27.1	0.4	15.7	0	32.8	25.1	3	0.8
	Band4 0.8-1.1um (Near Infrared)	85.6	34.9	59.3	42.5	28.9	41	20.9	4.6	61.6
2001 (ETM+)	**Band1** 0.45-0.52 um (Blue-Green)	2.8	0.4	0.2	20.1	5.7	7.2	26.4	10.4	0
	Band2 0.53-0.61 um (Green)	6.2	0.3	0	0.7	3.1	5.5	0.3	0.5	0
	Band3 0.63-0.69 um (Red)	18.3	0.6	22.8	1	3.8	0.4	30.6	6.3	1.7
	Band4 0.78-0.90 um (Near Infrared)	61.7	11	31.7	0.8	35.7	11.8	24.4	3.1	21.2
	Band5 1.55-1.75 um (Mid Infrared)	5.8	85.1	5.7	74	25.8	24.3	12.9	53.6	42.9
	Band7 2.09-2.35 um (Mid Infrared)	5.2	2.6	39.6	3.4	25.9	51.2	5.4	26.1	73.2

Table 3. The average training AUC and the standard deviation values for each model.

Land use Class	AUC		SD	
	2001	***1976***	***2001***	***1976***
Artificial areas (ART)	0.930	0.940	0.007	0.004
Broadleaved forests (BRO)	0.981	0.980	0.005	0.006
Coniferous forests (CON)	0.989	0.986	0.004	0.005
Croplands (CRO)	0.931	0.926	0.008	0.007
Grasslands and Pastures (GRA)	0.984	0.978	0.005	0.011
Orchards (ORC)	0.972	0.965	0.009	0.008
Rock and bare soil (ROC)	0.944	0.940	0.006	0.017
Vineyards (VIN)	0.954	0.959	0.017	0.019
Water Bodies (WAT)	0.993	0.984	0.003	0.007

Table 4. Contingency matrix. It represents the average values of probability of belongings to 1976 classes for each of 2001 classes.

					1976					
		ART	**BRO**	**CON**	**CRO**	**GRA**	**ORC**	**ROC**	**VIN**	**WAT**
2001	**ART**	0.26	0.01<	0.01<	0.29	0.01<	0.05	0.01	0.28	0.06
	BRO	0.01<	0.30	0.01	0.18	0.13	0.05	0.12	0.01	0.01<
	CON	0.01<	0.01<	0.35	0.12	0.17	0.08	0.12	0.01	0.01<
	CRO	0.07	0.01<	0.01<	0.38	0.01<	0.11	0.01<	0.18	0.01
	GRA	0.01<	0.01	0.01	0.01<	0.42	0.01<	0.13	0.01<	0.01<
	ORC	0.07	0.04	0.01<	0.21	0.01<	0.33	0.06	0.11	0.05
	ROC	0.01<	0.01<	0.01<	0.03	0.13	0.01<	0.38	0.01<	0.11
	VIN	0.01<	0.01<	0.01<	0.18	0.01<	0.18	0.09	0.41	0.04
	WAT	0.01<	0.01<	0.01<	0.1	0.01<	0.01<	0.02	0.01<	0.48

Figures caption

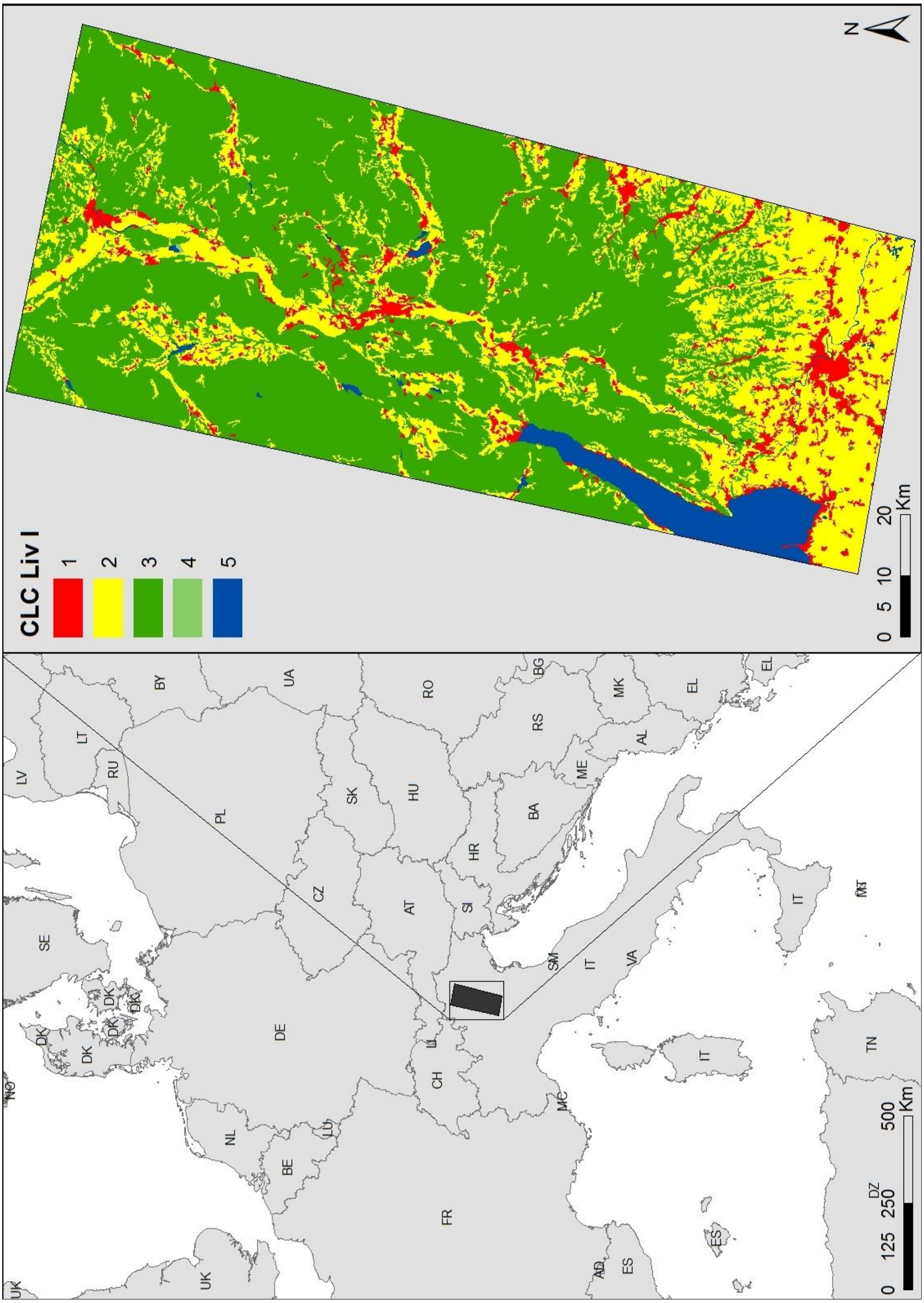

Figure 1. Study area.

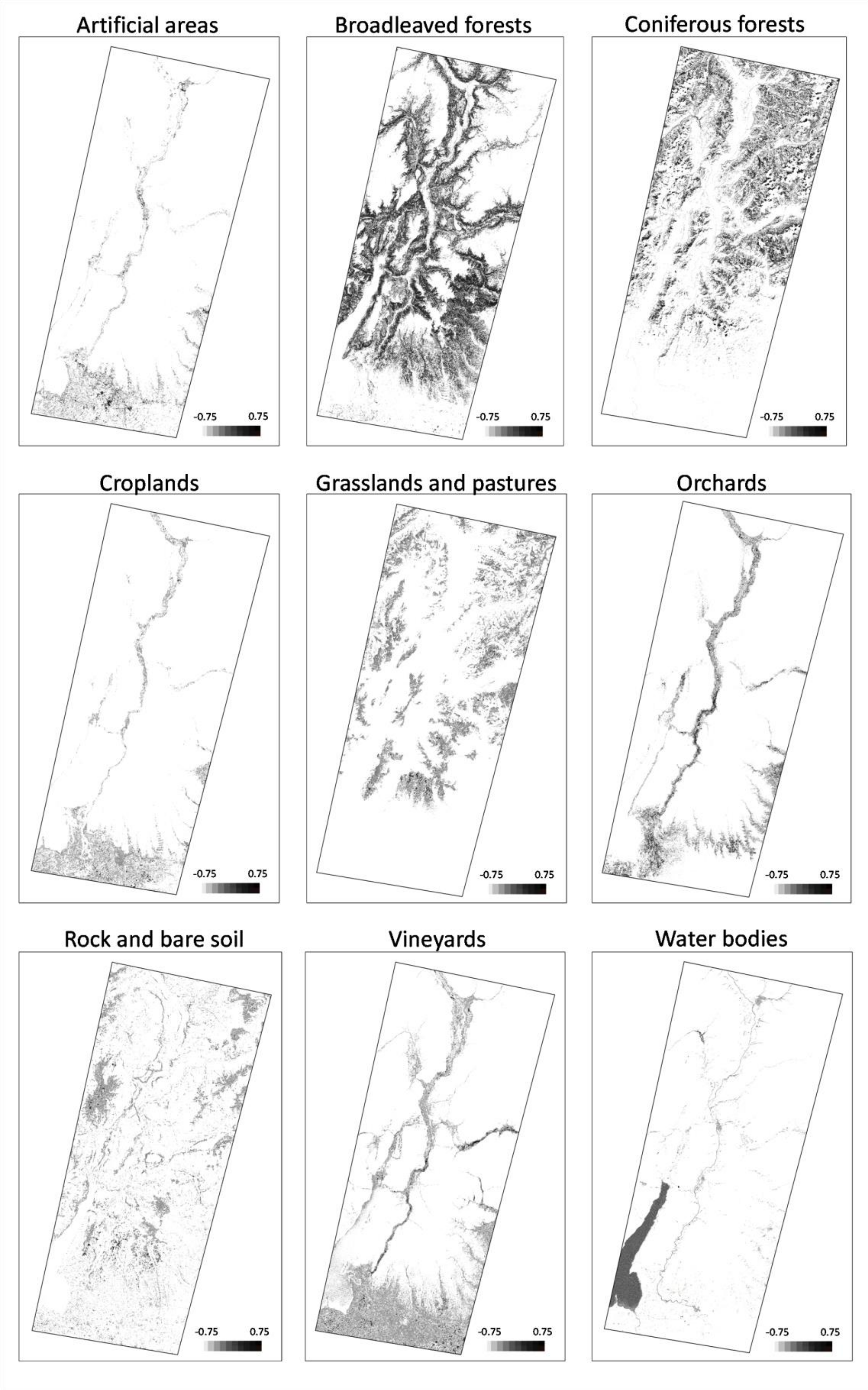

Figure 2. Difference maps (2011-1976) for each land cover class. The areas characterized by a significant increase of probability of occurrence values are represented trough dark grey tones of colour.

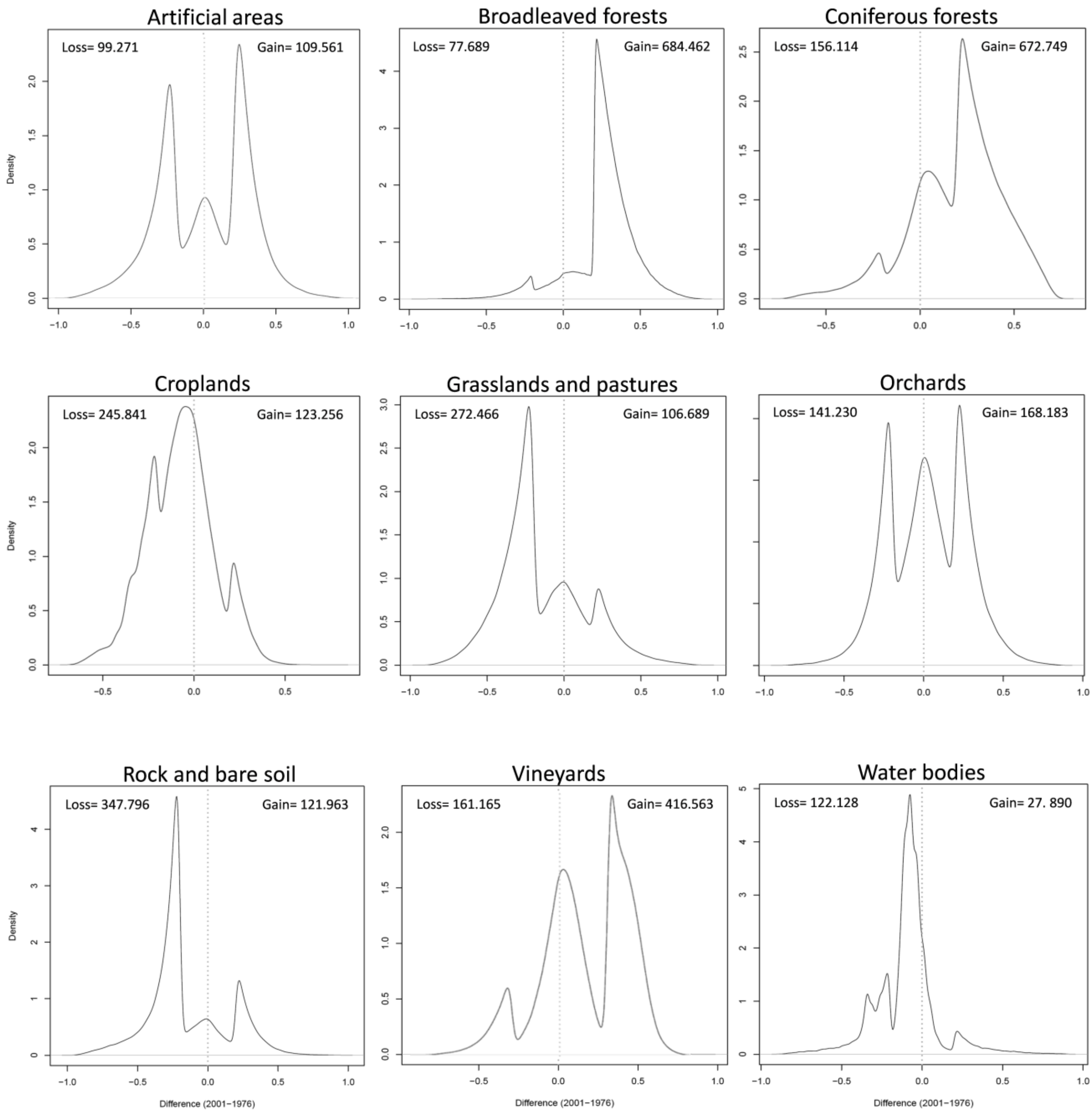

Figure 3. Frequency distribution curves relating the values of loss (<0), gain(>0) or maintenance (=0) for each land use class to its frequency of occurrence.

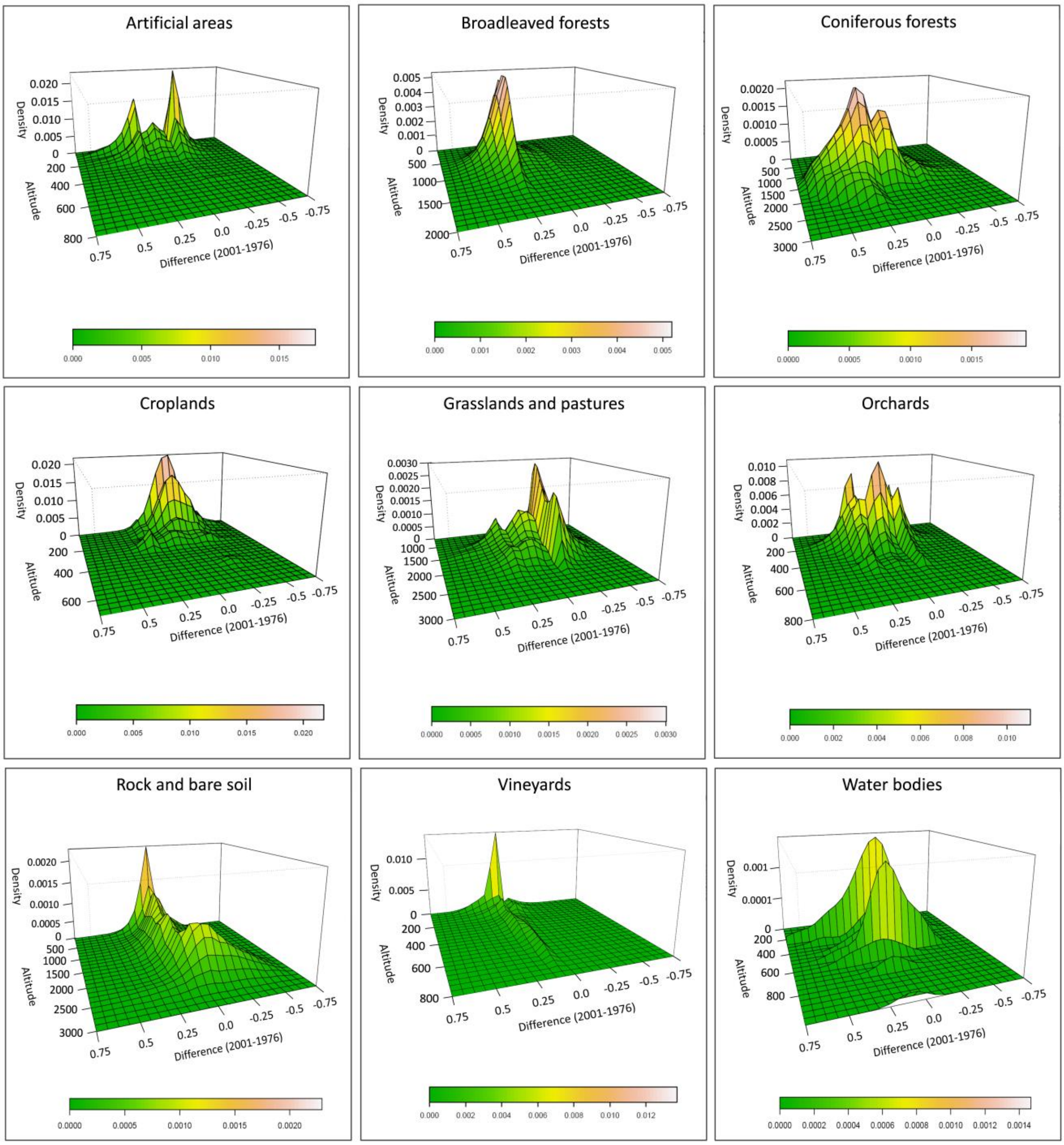

Figure 4. 3D-density plots between land use classes and Altitude.

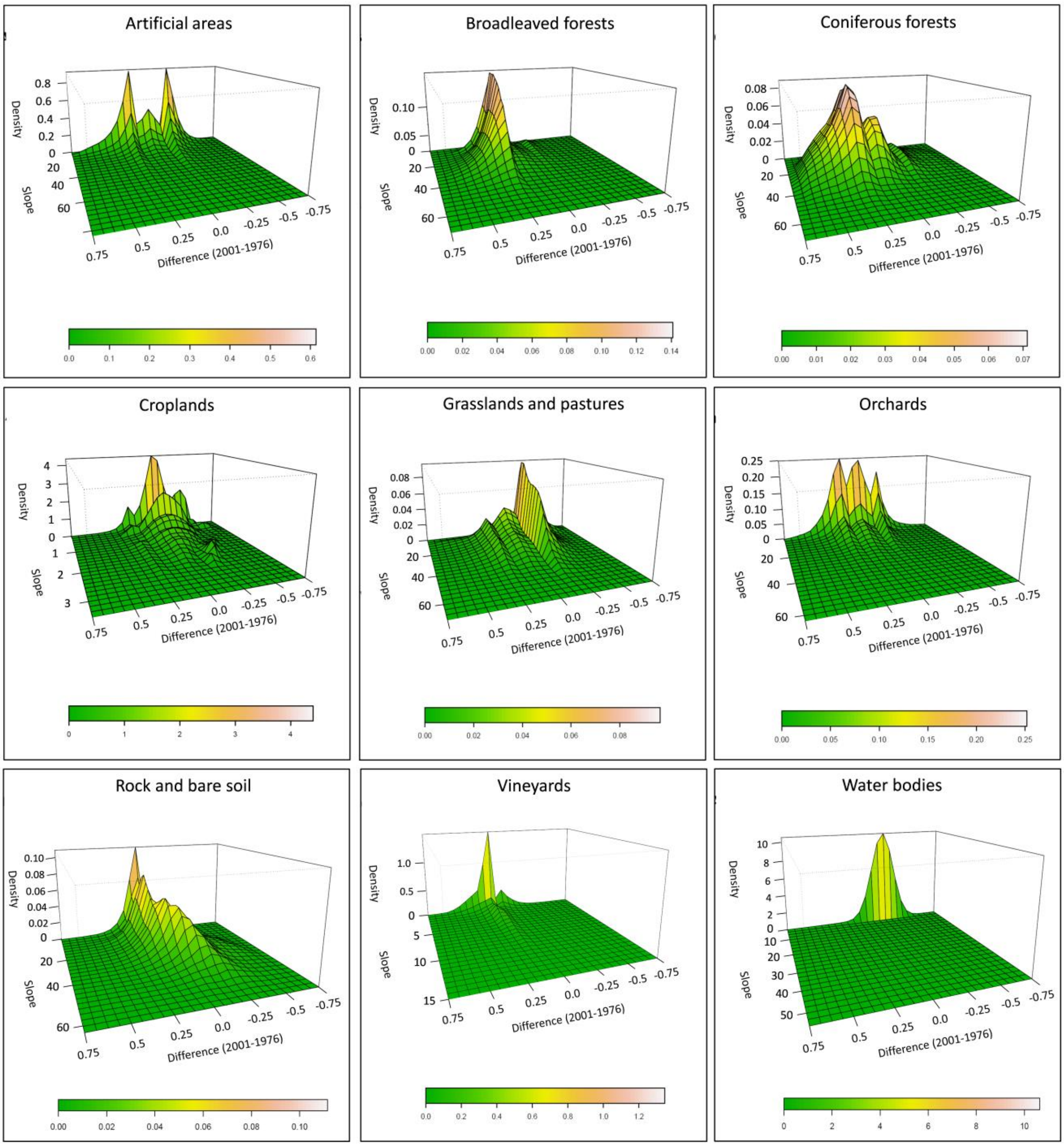

Figure 5. 3D-density plots between land use classes and Slope.

Highlights:

- Remote sensing is an essential technology to study land cover change over large areas
- MaxEnt algorithm allow to determine spatial distributions from incomplete data
- MaxEnt-based classification and detection of land cover changes is proposed
- MaxEnt may represent a useful tool for identifying multi-temporal landscape dynamics
- Results highlight the reliability of proposed method for land resources monitoring