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Linking land cover dynamics with driving forces in mountain landscape of the Northwestern Iberian Peninsula



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ABSTRACT

The mountainous areas of the northwestern Iberian Peninsula have undergone intense land abandonment. In this work, we wanted to determine if the abandonment of the rural areas was the main driver of landscape dynamics in Gerês-Xurés Transboundary Biosphere Reserve (NW Iberian Peninsula), or if other factors, such as wildfires and the land management were also directly affecting these spatio-temporal dynamics. For this purpose, we used earth observation data acquired from Landsat TM and ETM + satellite sensors, complemented by ancillary data and prior field knowledge, to evaluate the land use/land cover changes in our study region over a 10-year period (2000-2010). The images were radiometrically calibrated using a digital elevation model to avoid cast- and self-shadows and different illumination effects caused by the intense topographic variations in the study area. We applied a maximum likelihood classifier, as well as other five approaches that provided insights into the comparison of thematic maps. To describe the land cover changes we addressed the analysis from a multilevel approach in three areas with different regimes of environmental protection. The possible impact of wildfires was assessed from statistical and spatially explicit fire data. Our findings suggest that land abandonment and forestry activities are the main factors causing the changes in landscape patterns. Specifically, we found a strong decrease of the 'meadows and crops' and 'sparse vegetation areas' in favor of woodlands and scrublands. In addition, the huge impact of wildfires on the Portuguese side have generated new 'rocky areas', while on the Spanish side its impact does not seem to have been a decisive factor on the landscape dynamics in recent years. We conclude rural exodus of the last century, differences in land management and fire suppression policies between the two countries and the different protection schemes could partly explain the different patterns of changes recorded in these covers.

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Introduction

During the last century Europe's landscape has undergone major changes (Gerard et al., 2010). Some of these changes are a result of territory homogenization processes due to rural areas being abandoned and agricultural intensification (Navarro and Pereira, 2012; Suárez-Seoane et al., 2002). Many mountain rural areas in the northwestern Iberian Peninsula have been abandoned, and therefore, the agro-pastoral activities linked to the traditional rural

http://dx.doi.org/10.1016/j.jag.2014.11.010 0303-2434/© 2014 Elsevier B.V. All rights reserved. lifestyle have vanished (Gómez-Sal et al., 1993; Stellmes et al., 2013). These land cover and landscape changes affect biodiversity (Navarro and Pereira, 2012; Regos et al., in press; Sirami et al., 2007) and are a major causative component of global change (Verburg et al., 2011; Vitousek et al., 1997). It is essential to detect and quantify these potential changes in order to carry out the appropriate planning and management actions for conserving the environment in general and protected areas in particular. Furthermore, this type of analysis can be used in subsequent studies to assess the effect that these land cover and landscape changes have on biodiversity and ecosystem services (Suárez-Seoane et al., 2002; Regos et al., in press; Sirami et al., 2007; Navarro and Pereira, 2012).

Multispectral classification and photointerpretation of remote sensing data can be used to map vegetation and land cover (Cohen and Goward, 2004; Gerard et al., 2010). These data are particu-

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larly useful in mountainous areas where accessibility is limited (Shrestha and Zinck, 2001; Álvarez-Martínez, 2010). Over the past 40 years the images captured by Landsat satellites have been widely used to monitor these covers both at the landscape and regional scales (Chuvieco, 2008). The availability of long time-series, an appropriate spatial resolution for research at these scales and adequate spectral resolution for estimating vegetation properties make Landsat data very advantageous compared to other satellite data. Consequently, they have been widely used in a myriad of applications in ecology and other Earth sciences (Cohen and Goward, 2004).

However, in areas with strong topographic variations, the results obtained from the classification of Landsat images may not be good enough (Shrestha and Zinck, 2001; Xie et al., 2008). The main causes are illumination variations (topographic shadows and self-shadows) and atmospheric effects, among others. It is therefore necessary to preprocess the images, including appropriate topographic and radiometric corrections to substantially improve the outcome of the classification (Pons, 1990; Pons and Solé-Sugrañes, 1994; Salvador et al., 1996). Misclassification due the mixed pixels is also another important source of uncertainty when applying traditional hard classification techniques, especially in mountain areas characterized by highly fragmented and heterogeneous landscapes (Álvarez-Martínez et al., 2010). In addition, topographic variations affect microclimates, which may influence vegetation patterns (McGrath et al., 2012). In fact, a recent study have demonstrated that ecological processes behind forest expansion at the boundary between Eurosiberian and Mediterranean biogeographic regions is a complex undertaking because the influence of land use may be reinforced or constrained by abiotic factors such as climate (Álvarez-Martínez et al., 2014). It is therefore, necessary to introduce topographic and climate variables as ancillary information to improve the classification of vegetation classes (Shrestha and Zinck, 2001). In addition, the temporal resolution of Landsat images and the meteorological conditions of the study region, which has a lot of cloud cover on many days, reduce the availability of this satellite imagery. Two more important limitations are the Scan Line Corrector (SLC) problems of Landsat 7 Enhanced Thematic Mapper Plus (ETM+) from 2003 and the reduced availability of Landsat 5 Thematic Mapper (TM) before 2001 (NASA, 2013; Wulder et al., 2011). The incorporation of ancillary variables during the classification process could compensate for the lack of additional spectral information, thus improving the thematic accuracy of the resulting cartography (Campbell, 2008).

In this work we evaluated the land cover and landscape dynamics from 2000 to 2010 in a mountainous region of the northwestern Iberian Peninsula based on a post-classification comparison of Landsat-derived maps after taking into account all above mentioned shortcomings. Previous research based on the analysis of time-series of remote sensing data or aerial photography have already showed that land abandonment is one of the main drivers affecting the spatio-temporal dynamics during the second half of the 20th century (pre and post-1990's period) in marginal areas of Northwestern Iberian Peninsula (Calvo-Iglesias et al., 2009; Pôças et al., 2011; Stellmes et al., 2013). However, these previous studies do not address the potential impact of other driving forces that might be also affecting to these dynamics at regional levels. In our understanding, filling these gaps is essential to provide guidance to policy makers for developing coherent policies for effective land planning. New studies in early 21th century are also needed to test whether land abandonment processes are dominant in landscapes or whether, by the contrary, changes in natural disturbance regime, land planning, or forest policies are nowadays modulating these reported trends. Romero-Calcerrada and Perry (2004) demonstrated that the probability of fires occurring is higher in areas submitted to agricultural land abandonment. Increased fire

hazard is expected where land cover changes have promoted an increase in fuel load, such as those resulting from rural abandonment (e.g., vegetation succession on abandoned lands, pastures, or woodlands) or from afforestation activities (Loepfe et al., 2010; Moreira et al., 2011). During the second half of the last century most afforestation and reforestation processes that occurred in the Iberian Peninsula were the result of forest programs (Calvo-Iglesias et al., 2009; Moreira et al., 2011; Pausas et al., 2004). In our study region, oak forests are represented exclusively by native species and result from a natural succession process, while the pine plantations are a consequence of previous forestry management plans with social and economic interests (Macedo et al., 2009). Several of these native forestry species, together with some scrub communities and pastures, are protected by the conservation measures implemented for the protected sites. The main objective was therefore, to determine whether the abandonment of rural areas was the main driver of land cover and landscape dynamics in our study region, or whether other factors, such as wildfires or forest management were also directly affecting these spatio-temporal dynamics. We hypothesized that differences in forest management and fire suppression policies as well as different protection schemes may have caused different spatial patterns in the temporal dynamics of the land covers. To test this we conducted our study in three areas with different protection and territorial management regimes.

Material and methods

Study areas

We carried out the study in three areas included in the Gerês-Xurés Biosphere Reserve (about 176,000 ha in total). All of them are located in the NW Iberian Peninsula (Fig. 1), between latitudes of 41°38′51" and 42°8′58" and longitudes 7°38′39" and 8°25′43″. The first area is the Peneda Gerês National Park (PGNP) in Portugal, and the second is the Baixa Limia-Serra do Xurés Natural Park (XNP) in Galicia (NW Spain). The third area is the unprotected areas (UAA) adjacent to XNP (Fig. 1). The topographic relief is complex with an elevation ranging from 15 m to 1513 m, with an average slope of 13° (ranging between 0° and 66°). The region is located in the transition between the Mediterranean and Eurosiberian biogeographic zones close to the Atlantic coast. The climate is temperate oceanic sub-Mediterranean (Ninyerola et al., 2005). The most common type of vegetation is scrub communities. Forests are very fragmented and dominated by oaks and pines (Pulgar, 2005).

The study areas are representative of the mountainous landscapes in the northwestern Iberian Peninsula. Although this landscape has been intensely affected by human activity, the current density of the human population is quite low $(29.4 \text{ inhab/km}^2)$ (Macedo et al., 2009). The population settlements are administratively organized into six municipalities of Galicia and five of Portugal. The population dynamics have been largely influenced by the migrations of the past century, the low birth rate, and high mortality, especially in the early 1950s. As a consequence, the study region lost more than 14,000 inhabitants in the Galician municipalities included in the reserve since 1900. Nowadays, the current population is only 41% of the population in the year 1900. From 1991 to 2007 this area lost about 3000 inhabitants, mainly since 2001 (www.ine.es). The depopulation of the area has been accompanied by the abandonment of traditional agricultural and livestock activities.

Satellite imagery and ancillary data processing

The analysis described in this study (Fig. 2) spans a ten-year time period (2000–2010). The main data source consisted of five Landsat



Fig. 1. Location of the Gerês–Xurés biosphere reserve in the Iberian Peninsula showing the three mountain areas studied over the ten-year period (2000–2010). Coordinates are UTM, Zone 29N.

TM and ETM + images (8 June 2000, 24 June 2000, 20 March 2000, 19 May 2010, and 30 July 2010), acquired on very close dates to the fieldwork. Landsat scenes (e.g., March and June images) during spring and summer season were considered for seasonal discrepancies on the phenology of oaks (deciduous species). All these images are available from the U.S. Geological Survey (USGS) Center for Earth Resources Observation and Science (EROS) and were obtained by direct download from the GloVis facility (http://glovis.usgs.gov).

All downloaded images were L1T (a processing level that includes a geometric correction performed with ground control points (GCP) and the use of a digital elevation model) and projected in the UTM coordinate system (WGS 84 datum, UTM projection, Zone 29 North). The RMS was estimated from the GCP provided by the USGS for each image (average of 4.04 m). Once the images were geometrically reviewed we digitized masks to delineate areas affected by clouds and their shadows.

Through the radiometric correction, DNs (digital numbers) were converted into reflectance values using the sensor calibration parameters and other factors such as atmospheric effects and the solar incidence angle, taking into account the relief, cast- and self-shadows (by using the Global Digital Elevation Model, GDEM http://gdem.ersdac.jspacesystems.or.jp/, with a 30 m spatial resolution) (Pons and Solé-Sugrañes, 1994).

As mentioned above, the incorporation of ancillary data during the classification procedure could improve the overall accuracy of the resulting maps. Therefore, the classification process was based



Fig. 2. Flow diagram of the methodology used for spatio-temporal analysis of the land use/land cover types supported by supervised classification procedures. Input data are represented by boxes drawn in fine black lines filled in with light grey, processes are represented by boxes with bold lines and filled in with dark grey, and the change analyses are represented by white boxes.

on the radiometric information from reflective bands (reflectance bands 1–5 and 7 (LD7) plus NDVI (Rouse et al., 1974) and SAVI (Huete, 1988)), auxiliary variables (a Digital Terrain Model, DTM, which included the DEM and the Digital Slope Model, DSM, generated from the same source, distance to rivers and buildings from topographical maps, MDist, and climatic maps), and field knowledge. Field knowledge was crucial for selecting the most adequate training and test areas, as well as the most accurate maps. The mean, maximum and minimum temperatures, the precipitation rate and the solar radiation of June were considered in the climatic maps (according to the models developed by Ninyerola et al., 2000; Pons and Ninyerola, 2008).

To avoid a different weight in the classification process for the variables other than the percentage of reflectance, the variables were re-scaled in real data type between 0 and 100.

Finally, a selective filter was applied to the classification results, replacing unclassified values for a majority (modal) value within a convolution window of 5×5 cells. Preprocessing of the Landsat images and preparing the remaining variables was carried out using the MiraMon v. 7.0 software (Pons, 2010).

Training and validation areas

In order to obtain several Land Use/Land Cover (LULC) maps, we applied a maximum likelihood classifier, the most widelyused supervised classification strategy (Campbell, 2008), as well as other approaches that provided insights into the comparison of categorical maps (parallelepiped distance, minimum distance, Mahalanobis distance, artificial neuronal networks, and support vector machines). The map legend was established by selecting

Table 1

Number of samples (and total number of pixels) considered for the supervised classification and corresponding training areas and validation per thematic class and year.

Classes	Training area	S	Validation are	Validation areas			
	2000	2010	2000	2010			
Rocky areas	31 (578)	24 (471)	20 (534)	23 (569)			
Mixed rocky and scrub areas	34 (547)	25 (494)	17 (627)	22 (542)			
Scrublands	33 (721)	20 (363)	32 (702)	24 (377)			
Burned areas	12 (392)	16 (667)	12 (392)	9 (403)			
Sparse vegetation	6(318)	6 (400)	10 (439)	9 (417)			
Oak forests	20 (440)	23 (326)	21 (507)	19 (483)			
Pine forests	30(303)	32 (831)	23 (644)	20 (679)			
Meadows and crops	50 (311)	45 (184)	31 (190)	31 (123)			
Human settlements	40 (717)	43 (703)	22 (395)	41 (452)			
Dam reservoirs	19 (1427)	19 (925)	13 (1463)	13 (1284)			
Bare ground	14 (69)	12 (214)	12 (172)	21 (325)			
Total	289 (5823)	265 (5578)	213 (6065)	232 (5654)			

the 11 most relevant land use and vegetation cover types identified during the fieldwork in the study areas: (1) 'rocky areas' are rocky soils with less than 20% vegetation cover; (2) 'mixed rock' and scrub areas' are rocky soils with a range between 20–80% scrub; (3) 'scrublands' are areas with a range between 80–100% scrub; (4) burned areas; (5) 'sparse vegetation areas' are areas with poor soils with little vegetation but with a different spectral behavior from the other categories, and are probably previously burned areas; (6) 'oak forests' are native oaks forests, dominated by *Quercus robur* and *Quercus pyrenaica*, which constitute the climax vegetation of the region; (7) 'pine forests' are coniferous mature forests dominated by *Pinus sylvestris* and *Pinus pinaster*; (8) 'meadows and crops'; (9) 'human settlements' include rural and urban areas, buildings, and roads; (10) 'dam reservoirs'; and (11) 'bare ground' are edges of dam reservoirs, large sand roads, and open pit mines.

Training and validation areas were selected for each of the eleven classes considered. They consisted of a set of pixels identified over well-known homogeneous areas in each Landsat image, thus providing a reference spectral signature per class. A total of about 500 areas were defined independently for each year, distributed throughout all environmental conditions. The number of areas per land cover class increased with increasing heterogeneity of the area under analysis (Richards and Jia, 2006). Thus, 'meadows and crops' and 'human settlements' accounted for the greatest number (\sim 80), while the rest of them ranged between 30 and 60, only 'sparse vegetation areas' land category accounted for less than 20 each (\sim 15) (Table 1). According to Janssen and Van der Wel (1994) individual pixels are the most appropriate test sampling unit for pixel-based classification procedures. Thus, a total of 6065 and 5654 pixels were selected for the years 2000 and 2010 (Table 1). A statistically acceptable minimum number of validation pixels (>40) were established per class to ensure an efficient accuracy assessment (Congalton and Green, 2009; Kindu et al., 2013; Foody, 2002). The identification of training and validation areas for each class was supported by different RGB composites obtained by combining satellite bands, and airborne photography. Specifically, for the year 2000 we used digital orthophotos in natural color at a scale of 1:18 000 from the Plan Nacional de Ortofotografía Aérea (PNOA) of 2003, while for the year 2010 we used digital orthophotos of 2007. However, field surveys, carried out during May-June of 2000 and 2010 with 168 sampling plots, were crucial for improving training and defining test areas (Fig. 3). Fieldwork consisted of in situ characterization of the main (and eventually a secondary) habitat within a radius of approximately 100 m for each sampling point (Domínguez and Regos, 2010; Regos et al., 2013; Regos et al., in press). NDVI and 457

RGB composites were especially useful for discriminating 'burned areas' (Dorrego and Álvarez, 2009).

The transformed divergence was computed over the training areas to infer the statistical separability between the different classes (Richards and Jia, 2006). When the most usual formula is used the transformed divergence ranges between 0 and 2, with 0 representing a complete overlap between pairs of classes and 2 representing a perfect separability; a transformed divergence above 1.9 corresponds to good class separability (Richards and Jia, 2006). A comparative analysis was carried out to evaluate the improvement in the statistical separability of the different categories when new variables other than reflectances were introduced. The Envi 4.7 sp1 software was used to define training and validation areas and assess the statistical separability, classification procedures, and the subsequent accuracy of the generated maps.

Accuracy assessment

The accuracy of the LULC maps was assessed with confusion matrices based on the number of pixels classified per class and comparing the results obtained from different classification methods. This assessment was performed over independent test areas. The main quality parameters were overall accuracy (%), the Kappa index of agreement, and errors of omission and commission per category (Chuvieco, 2008; Richards and Jia, 2006). Each LULC map was visually compared with other data sources: (1) CORINE land cover data from 2000 (EEA, 2000); (2) knowledge of the study area from fieldwork; and (3) vector layers of buildings, roads, and rivers from topographic maps at a scale of 1:25,000.

In addition, to assess the uncertainty derived from potential erroneous allocations made by traditional hard classification techniques, we calculated uncertainty maps following a methodology based on fuzzy classification processes and confusion indices (CIs) developed in Álvarez-Martínez et al. (2010). The CI discriminates subareas with high uncertainty due to class overlapping, accepting that one pixel can belong to more than one class (e.g., mixed pixels). Thus, if one class clearly dominates above the others (CI approaches zero) there is little confusion in the classification process for that pixel. If CI approaches one, then there is confusion as to the land cover class to which the pixel certainly pertains. For each of the Landsat-derived maps (2000 and 2010), a map with the CI values was also calculated.

Change analysis

We addressed the study at two levels of analysis (i.e., extents): landscape and local level. We defined the landscape level as the whole study area (176,000 ha), in which we studied changes in the spatial extent of the land cover types identified in the study area. We used the survey plots as a local level (survey plot level; 3 ha) at which to analyze the temporal changes in the proportion of area associated with main land cover classes. To quantify LULC changes in the period 2000–2010 and to determine the spatio-temporal dynamics of these changes at the landscape level we performed a post-classification comparison of the maps obtained for the two years. Moreover, in XNP, where the fieldwork was carried out, we also considered an analysis at a local level to determine whether the drivers affecting the land cover dynamics at landscape level are also acting at survey plot scale. The methodology used to extract this land cover change information is illustrated in Fig. 2.

Landscape-level analysis

To analyze land cover changes at landscape level we crosstabulated the remote sensing data-derived maps in order to obtain a transition matrix for quantifying the spatial extent that had been lost or gained by a given land cover type over the entire study period

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Fig. 3. The 168 field sampling plots carried out in the XNP (Baixa Limia–Serra do Xurés Natural Park) helped to improve the definition of the training and test areas used during the supervised classification procedure.



Fig. 4. Spectral separability analysis using transformed divergence for different pairs of categories and variables. Variables: LD7 (reflective bands), NDVI, and SAVI (vegetation indices), DEM (digital elevation model), MDist (distance maps), ClimRAD (climatic maps). Land cover types: RA (rocky areas), RS (mixed rock and scrub areas), RS (mixed rock and scrub areas), RS (mixed rock and scrub areas), RC (meadows and crops), and HS (human settlements).

(from 2000 to 2010). We also calculated the total area (ha) for each thematic category and for both years. In addition, to assess temporal changes in the location of land cover categories we vectorized the raster maps and calculated the amount of overlap between polygons of the same category in different years with the relative area overlap index (RAO, Maruca and Jacquez, 2002):

$$\mathsf{RAO}_{ij} = \frac{a_{(i \cap j)}}{a_{(i \cup j)}}$$

where $a_{(i \cap j)}$ is the area of intersection and $a_{(i \cup j)}$ the union for polygons at the beginning (*i*) and at the end (*j*) of the time interval. For polygons that do not intersect, the RAO is zero while an increase in their values indicates a greater degree of overlap up to a maximum value of one.

Since we expected to find temporal changes, especially in the polygon boundaries, we also calculated the relative area generation (RAG) defined by Sirami et al. (2009) as:

$$\mathsf{RAG}_{ij} = \frac{(a_j - a_{(i \cap j)})}{a_{(i \cup j)}}$$

where a_j is the area of the polygon at the end of the time interval, and the relative area disappearance (RAD):

$$\mathsf{RAD}_{ij} = \frac{(a_i - a_{i \cap j})}{a_{(i \cup j)}}$$

Table 2

where a_i is the area of the polygon at the beginning of the time interval.

The transition matrices and the three indices were calculated for the 2000–2010 time interval for each category. We also carried out these change analyses separately for the three areas in which the study region was divided in order to compare their change dynamics. For these change analyses at the landscape level we used the ArcGIS 9.3 software (Environmental Systems Research Institute, Inc.).

Local-level analysis

This analysis consisted in determining land cover changes within a radius of 100 m around each sampling point. For this, we calculated the proportion of area associated with main land cover classes for 2000 and 2010 with buffer maps, where the maximum distance to each sampling point was 100 m. After testing for normality, a Student's test for paired samples was performed to determine whether there were significant differences (Quinn and Keough, 2002). This analysis was carried out with the MiraMon 7.0 software (Pons, 2010) and the R statistical package (R Core Team, 2012).

Estimating the impact of fires during the last decade

We considered the burned areas as a thematic class for each land cover map to assess the impact of fires on the land cover dynamics in the study areas during 2000–2010. Previous research have highlighted the need of high temporal resolution satellite data over large periods for undertaking land cover dynamics when dealing with highly heterogeneous and dynamic landscapes (Álvarez-Martínez et al., 2011; Stellmes et al., 2013). Taking into account that fire events and recovery of vegetation could have occurred in the period between dates, masking the real incidence of the wildfires, we also calculated areas burned between 2000 and 2009 from

Confusion matrices and statistical accuracy assessment defined for each land cover map. Both classification results (rows) and ground truth (columns), in percentage values.

Overall	accuracy: 8	9.65%; Kapp	a index: 0.8	8										
2000	RA	RS	SC	BA	SV	OF	PF	MC	HS	DR	BG	Total	CoE	UA
RA	455	91	0	0	0	0	0	0	1	0	7	554	17.87	82.13
RS	61	503	40	49	6	11	4	2	13	0	10	699	28.04	71.96
SC	3	21	618	0	5	27	2	16	1	0	5	698	11.46	88.54
BA	0	0	0	318	0	0	0	0	0	0	0	318	0	100
SV	1	9	5	0	421	0	0	7	0	0	7	450	6.44	93.56
OF	0	0	38	0	0	454	2	15	1	0	1	512	11.33	88.67
PF	0	0	1	0	0	5	636	0	0	0	0	642	0.93	99.07
MC	0	0	0	0	0	10	0	148	42	0	0	200	26	74
HS	1	2	0	25	7	0	0	1	287	0	0	331	13.29	86.71
DR	0	0	0	0	0	0	0	0	0	1463	8	1463	0	100
BG	13	1	0	0	0	0	0	1	50	0	134	198	32.32	67.68
Total	534	627	702	392	439	507	644	190	395	1463	172	6065		
OE	14.79	19.78	11.97	18.88	4.1	10.45	1.24	22.11	27.34	0	22.09			
PrA	85.21	80.22	88.0	81.12	95.9	89.55	98.7	77.89	72.66	100	77.91			

Overall accuracy: 90.57%; Kappa index: 0.89

2010	RA	RS	SC	BA	SV	OF	PF	MC	HS	DR	BG	Total	CoE	UA
RA	426	1	0	0	0	0	0	0	1	0	0	428	0.47	99.53
RS	143	472	19	1	7	2	25	0	2	0	21	692	31.79	68.21
SC	0	43	297	0	0	21	16	5	4	0	48	434	31.57	68.43
BA	0	0	0	399	0	0	0	0	0	0	9	408	2.21	97.79
SV	0	3	24	1	408	0	1	0	1	0	7	445	9.88	91.69
OF	0	23	37	2	0	456	1	3	12	0	9	506	8.31	90.12
PF	0	0	0	0	1	4	636	0	0	0	0	678	6.19	93.81
MC	0	0	0	0	0	0	0	105	9	0	0	114	7.89	92.11
HS	0	0	0	0	0	0	0	10	423	0	0	450	6	94
DR	0	0	0	0	0	0	0	0	0	1284	16	1284	0	100
BG	0	0	0	0	1	0	0	0	0	0	215	215	0	100
Total	569	542	377	403	417	483	679	123	452	1284	325	5654		
OE	25.13	12.92	21.22	0.99	2.16	5.59	6.33	14.63	6.42	0	33.85			
PrA	74.87	87.08	78.78	99.01	97.8	94.41	93.6	85.37	93.58	100	66.15			

Land cover types: RA (rocky areas), RS (mixed rocky and scrub areas), SC (scrublands), BA (burned areas), SV (sparse vegetation areas), OF (oak forests), PF (pine forests), MC (meadows and crops), HS (human settlements), DR (dam reservoirs), and BG (bare ground).

available cartography of the Portuguese territory. Portugal is the only country in Europe that has systematic mapping of their fires since 1990 obtained from Landsat images (DGRF, 2012). From these spatial data, we calculated the extension of burned areas for each year and analysed the land cover types most affected by fire in PGNP from the LULC map of 2000. For the Galician site, the impact of the wildfires on land covers over the last decade was assessed from statistical data. The Spanish government annually provides fire data at a municipal level; these data are recorded on the ground at the time of the fire event and are stored in a database (MAGRAMA, 2013).

Results and discussion

Class separability and overall accuracy

The problems of spectral separability among pairs of classes could be solved by including auxiliary variables in the analysis. The results showed that the introduction of the ancillary data increased the capacity to discriminate between classes (Fig. 4); therefore, all variables were used during the classification process. Thus, if we only considered Landsat bands, the statistical separability between classes such as 'rocky areas' and 'human settlements' was too low (a transformed divergence of 1.792 in this case), while if we added other auxiliary variables (vegetation indices, terrain digital models, and climatic variables) the separability between these classes reached the maximum value (2.000) (Fig. 4). The separability between 'meadows and crops' and 'oak forests' was also higher when we introduced distance-to-buildings and distance-to-rivers maps. All these variables also led to better discrimination between 'mixed rock and scrub areas' and 'scrubland'. Since the results of the separability tests were satisfactory (values higher than 1.90), the set of classes defined above was maintained and the classification algorithm based on the selected training areas was implemented.

We used confusion matrices based on the generated LULC maps to assess the classification accuracy of each year. Six classification methods were compared in order to choose the procedure with the best results (further information on the comparison between algorithms in Appendix A). The LULC maps were finally generated with the Mahalanobis distance algorithm for the year 2000 (89.65%) and 2010 (90.57%) (Table 2). The resulting overall accuracy was always contrasted with a threshold of acceptance. The proposed threshold for individual classifications is 85% (Campbell, 2008), but a first estimation of the overall accuracy of the land cover change analysis was obtained by multiplying the overall accuracy of each LULC map $(85 \times 85 = 72.25\%)$, in a theoretical case) (Serra et al., 2003). Therefore, in our case, the change analysis had a thematic accuracy of 81.19% (89.65×90.57).

Uncertainty maps showed clear spatial differences across the study area (Fig. 5). The highest confusion was associated with those areas dominated by 'mixed rock and scrub areas' and 'scrubland' while 'dam reservoirs', 'pine forests', and 'burned areas' had the lowest confusion values (exactly those classes with the highest spectral separability results). The rest of the land cover classes showed an intermediate situation (Fig. 5). This is also in agreement with the confusion matrices results since 'mixed rock and scrub areas' and 'scrubland' are the thematic classes with the highest commission errors and lowest user's accuracy values (Table 2). The overall pattern of uncertainty was consistent for the both years, as the inter-annual differences were related to real land cover changes. In light of our results, we conclude Landsat data analysis allows to determine general patterns across long periods, but not to characterize land cover transitions at least in ecotones areas. Although the inclusion of ancillary data have considerably improved our classification outcomes, visual interpretation of oldto-new aerial photographs and automatic classification of high resolution satellite images may provide more reliable land cover maps at detailed spatial scales, not subject to uncertainty issues, allowing proper comparisons among land cover maps at different scales.

Change analysis

Landscape-level analysis

A recent study of land cover changes based on the analysis of time-series of remote sensing data with high temporal resolution demonstrated that the biomass increased in marginal areas of Spain due to land abandonment (decreased human pressure) between 1989 and 2004 (Stellmes et al., 2013). In our study region, we detected a strong decrease in 'meadows and crops' and 'sparse vegetation areas' in favor of oak forest and scrublands (RAG values up to 42.9 and 59.7%, respectively). Specifically, we found that 'meadows and crops' decreased by 34% between 2000 and 2010 (Table 3). This trend is in agreement with the results obtained from the agricultural census between 1999 and 2009 (www.ine.es). According to these data, in Galician municipalities included in the study areas, arable lands decreased by 40%, a decline very close to the trend



Fig. 5. Confusion index (CI) maps for 2000 and 2010: High CI value (approaches 1) means high uncertainty in the pixel allocation. Low CI value (approaches 0) implies low uncertainty.



Fig. 6. Final classification maps derived from Landsat images and ancillary data for each study area: UAA (unprotected adjacent areas), XNP (Baixa Limia–Serra do Xurés Natural Park), and PGNP (Peneda Gerês National Park).

recorded in XNP and UAA (average value of 34%). The decline in 'meadows and crops' is clearly related to depopulation and subsequent abandonment of traditional agro-pastoral activities. In the Montealegre municipality (partially included in our study area) Pôças et al. (2011) showed that annual crops decreased by 43.46% between 1979 and 2002, which is practically the same as the trend recorded in PGNP (43%) (Table 3). In northern Galicia, croplands have also lost importance with regard to grasslands, the use of

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Table 3

Changes at landscape level for the whole area, Gerês–Xurés biosphere reserve. For each category, the following indicators are provided: area occupied by each land cover type in 2000 and 2010, in hectares (ha) and % (in bold); trend between 2000 and 2010, measured in %, increasing (\uparrow) or decreasing (\downarrow).

	2000		2010		Trend	
Rocky areas	12355.29	7.15	7529.2	4.36	-39.06	\downarrow
Mixed rocky and scrub areas	56226.96	32.54	66887.75	38.71	18.96	↑
Scrublands	37726.92	21.84	28987.45	16.78	-23.17	\downarrow
Burned areas	4615.92	2.67	2392.02	1.38	-48.18	\downarrow
Sparse vegetation	9568.62	5.54	3909.06	2.26	-59.15	\downarrow
Oak forests	21126.33	12.23	32739.73	18.95	54.97	↑
Pine forests	13112.19	7.59	16729.53	9.68	27.59	↑
Meadows and crops	10536.48	6.10	6966.3	4.03	-33.88	\downarrow
Human settlements	7504.47	4.34	6411.76	3.71	-14.56	\downarrow

scrublands has become marginal and forestry has increased during the second half of the 20th century (Calvo-Iglesias et al., 2009). Other Mediterranean mountain landscapes also show a decline in extensive agriculture and a reduction in meadowlands mainly due to land abandonment followed by scrubland and later woodland recovery (Pelorosso et al., 2009; Romero-Calcerrada and Perry, 2004). Thus, in areas affected by land abandonment and not regulated by effective regional and local agricultural policies, woodland recovery is the endpoint of a secondary succession process. Our findings showed that at the same time that crops and meadows have decreased, scrublands, and forests have increased, which confirms this assumption. 'Mixed rock and scrub areas' also increased from 56,226 ha in 2000 to 66,887 ha in 2010 (from 32.5 to 38.7%) (Table 3). 'Scrublands' is the most dynamic cover: it has high RAG values in the three areas studied, which means new areas have been colonized by scrubs (Table 4). However, this category also has high RAD values, which means areas initially occupied by scrublands have disappeared (Table 4) and been substituted by forests (Table 5). Scrublands have been replaced by oak forests in some areas, while areas previously occupied by 'mixed rock and scrub areas' and 'meadows and crops' have been colonized by scrubs and forests as a consequence of a decrease in traditional agricultural and livestock activity (Table 5; Fig. 6). Thus, during the last ten years the extension of oak forests (represented exclusively by native species) increased from 21,126 ha to 32,739 ha, i.e., increased from 12.2% to 18.9% of the studied territory (Table 3). Oak forests are characterized by a high percentage of relative area generation (RAG values from 42% of UAA to 55.4% of PGNP), while the forests existing at the beginning of the period have not changed significantly (between 16.8 and 22.9% RAD) (Table 4). The regulation on the felling of oak forests in the 1990s by the Regional Ministry of the Environment, which attenuated forestry and agricultural pressures, has also probably helped to prevent a massive elimination of these woodlands (Calvo-Iglesias et al., 2009; Macedo et al., 2009). Similar trends

Table 4

Changes (in terms of area and temporal dynamics) at landscape level for the Baixa Limia–Serra do Xurés Natural Park (XNP), Peneda Gerês National Park (PGNP) and for the unprotected areas adjacent to the XNP (UAA). For each category the following indicators are provided: area occupied by each land cover type in 2000 and 2010, in hectares (ha) and % (in bold); trend between 2000 and 2010, measured in %, increasing (\uparrow) or decreasing (\downarrow); and temporal dynamics (measured in % by relative area overlap index, RAO, relative area generation, RAG, and relative area disappearance, RAD).

Covers	Area				Trend		Tempora	l dynamics	
XNP	2000		2010				RAO	RAG	RAD
Rocky areas	2693.61	9.27	421.90	1.45	-84.34	\downarrow	10.4	4.5	85.0
Mixed rocky and scrub areas	13454.91	46.30	15123.80	52.05	12.40	1	49.6	29.5	20.8
Scrublands	5873.67	20.21	5595.10	19.25	-4.74	Ļ	26.4	35.2	38.3
Burned areas	815.58	2.81	178.20	0.61	-78.15	\downarrow	0.5	13.7	64.4
Sparse vegetation	1184.58	4.08	337.59	1.16	-71.50	Ļ	1.0	21.4	77.6
Oak forests	2675.16	9.21	3789.70	13.04	41.66	1	33.9	44.6	21.5
Pine forests	1114.20	3.83	2576.40	8.87	131.23	1	18.2	64.3	17.5
Meadows and crops	757.35	2.61	429.60	1.48	-43.28	\downarrow	28.9	17.7	53.3
Human settlements	489.42	1.68	421.90	1.45	-13.80	\downarrow	8.9	41.5	49.5
PGNP									
Rocky areas	9572.67	10.30	7098.48	7.64	-25.85	\downarrow	34.8	22.6	42.6
Mixed rocky and scrub areas	38969.46	41.94	45920.34	49.42	17.84	1	50.7	30.8	18.5
Scrublands	12856.95	13.84	10470.33	11.27	-18.56	\downarrow	23.4	31.9	44.6
Burned areas	2011.50	2.16	1995.03	2.15	-0.82	\downarrow	1.8	48.9	49.3
Sparse vegetation	2879.91	3.10	205.65	0.22	-92.86	\downarrow	0.3	6.4	93.3
Oak forests	8385.39	9.02	14493.87	15.60	72.85	1	21.6	55.4	22.9
Pine forests	8629.65	9.29	7626.6	8.21	-11.62	\downarrow	27.3	32.4	40.3
Meadows and crops	4259.43	4.58	2425.86	2.61	-43.05	\downarrow	26.2	19.6	54.2
Human settlements	5356.53	5.76	2448	2.63	-54.30	\downarrow	14.6	21.4	64.1
UAA									
Rocky areas	89.01	0.18	8.82	0.02	-90.09	Ļ	0.0	9.0	91.1
Mixed rocky and scrub areas	3802.59	7.49	5843.61	11.50	53.67	1	20.1	52.6	27.2
Scrublands	18996.30	37.40	12922.02	25.44	-31.98	\downarrow	29.6	22.9	47.5
Burned areas	1788.84	3.52	218.79	0.43	-87.77	\downarrow	0.5	10.5	89.0
Sparse vegetation	5504.13	10.84	3365.82	6.63	-38.85	\downarrow	6.2	34.1	59.7
Oak forests	10065.78	19.82	14456.16	28.46	43.62	1	41.2	42.0	16.8
Pine forests	3368.34	6.63	6526.53	12.85	93.76	1	20.1	59.1	20.8
Meadows and crops	5519.70	10.87	4110.84	8.09	-25.52	\downarrow	33.6	23.4	42.9
Human settlements	1658.52	3.27	3541.86	6.97	113.56	\uparrow	15.9	63.0	21.0

Table 5

Transition matrices obtained from the remotely sensed data-derived maps from 2000 (rows) to 2010 (columns) (expressed in hectares) for the Baixa Limia–Serra do Xurés Natural Park (XNP), Peneda GerêsNational Park (PGNP) and for the unprotected areas adjacent to the XNP (UAA); land use and cover type acronyms are given in Table 1.

Rocky areas 293.8 2143 173 2.1 3.5 22.8 33.5 0.2 1.2 Mixed rocky and scrub areas 107.1 9482.1 1867 81.1 124.7 399.2 1247.9 24 105.4 Scrublands 3.2 1437.5 2393.9 43.9 147.9 1316.7 325.4 67.6 80.5 Burned areas 3.3 304.3 327.5 6.2 14 103.2 52.7 0.2 3.4 Oak forests 2.9 355.4 25.8 9 1639.6 202.9 41.7 30.3 Pine forests 0.2 288.6 128.7 4.6 15.9 53.1 568.1 1.9 6.9 Meadows and crops 0.4 104.1 78.5 0.5 2.7 211.4 8.9 266.3 82.9 Human settlements 0.2 224.6 48.2 5.9 3 14.5 85.8 162 75.2 PGN RA MR	XNP	RA	MR	SC	BA	SE	OF	PF	МС	UR
Mixed rocky and scrub areas 107.1 9482.1 1867 81.1 124.7 399.2 1247.9 24 105.4 Scrublands 3.2 1437.5 2393.9 43.9 147.9 1316.7 325.4 67.6 80.5 Sparse vegetation 10.3 749.7 211.3 6.9 15.4 25.7 43.2 10.5 28.5 Oak forests 2.9 359.2 355.4 25.8 9 1639.6 202.9 41.7 30.3 Pine forests 0.2 288.6 128.7 4.6 15.9 53.1 568.1 1.9 6.9 Meadows and crops 0.4 104.1 78.5 0.5 2.7 211.4 8.9 266.3 82.9 Human settlements 0.2 224.6 48.2 5.9 5.1 132 48.1 47 19.4 Rocky areas 4301.6 4623.5 280.2 55.9 5.1 132 48.1 47 19.4 Burned areas	Rocky areas	293.8	2143	173	2.1	3.5	22.8	33.5	0.2	1.2
Scrublands 3.2 1437.5 2393.9 43.9 147.9 1316.7 325.4 67.6 80.5 Burned areas 3.3 304.3 327.5 6.2 14 103.2 52.7 0.2 3.4 Sparse vegetation 10.3 749.7 211.3 6.9 15.4 25.7 43.2 10.5 28.5 Oak forests 2.9 359.2 355.4 25.8 9 1639.6 202.9 41.7 30.3 Pine forests 0.2 288.6 128.7 4.6 15.9 53.1 568.1 1.9 6.9 Meadows and crops 0.4 104.1 78.5 0.5 2.7 211.4 8.9 266.3 82.9 Human settlements 0.2 224.6 48.2 5.9 3 14.5 85.8 16.2 75.2 PGNP RA MR SC BA SE OF PF MC UR Burned areas 34.7 73 621.5 72.5 13.3 463.5 57.7 1.4 9.5 Sparse	Mixed rocky and scrub areas	107.1	9482.1	1867	81.1	124.7	399.2	1247.9	24	105.4
Burned areas 3.3 304.3 327.5 6.2 14 103.2 52.7 0.2 3.4 Sparse vegetation 10.3 749.7 211.3 6.9 15.4 25.7 43.2 10.5 28.5 Oak forests 2.9 355.2 355.4 25.8 9 1639.6 202.9 41.7 30.3 Pine forests 0.2 288.6 128.7 4.6 15.9 53.1 568.1 1.9 6.9 Meadows and crops 0.4 104.1 78.5 0.5 2.7 211.4 8.9 266.3 82.9 Human settlements 0.2 224.6 48.2 5.9 3 14.5 85.8 16.2 75.2 PGNP RA MR SC BA SE OF PF MC UR Rocky areas 4301.6 4623.5 280.2 55.9 5.1 132 48.1 4.7 19.4 Scrublands 127.7 3761.5 424.49 481.8 99 2861.6 591.1 245.9 255.5 55	Scrublands	3.2	1437.5	2393.9	43.9	147.9	1316.7	325.4	67.6	80.5
Sparse vegetation10.3749.7211.36.915.425.743.210.528.5Oak forests2.9359.2355.425.891639.6202.941.730.3Pine forests0.2288.6128.74.615.953.1568.11.96.9Meadows and crops0.4104.178.50.52.7211.48.9266.382.9Human settlements0.2224.648.25.9314.585.816.275.2PGNPRAMRSCBASEOFPFMCURRocky areas4301.64623.5280.255.95.113248.14.719.4Mixed rocky and scrub areas2405.128566.81743.5769.743.72710.52088252.1355.5Scrublands127.73761.54424.948.18992861.6591.1245.9215.1Burned areas34.7733621.572.513.3466.357.71.49.5Sparse vegetation85.31913432.971.69.483.999.521.9113.1Oak forests20.22243.1925.320.39.54071.2528.8242.5130Pine forests91.5121.91169.8164.98.71118.33489.827197.6Meadows and crops6.8430.7191.623.19	Burned areas	3.3	304.3	327.5	6.2	14	103.2	52.7	0.2	3.4
Oak forests 2.9 359.2 355.4 25.8 9 1639.6 202.9 41.7 30.3 Pine forests 0.2 288.6 128.7 4.6 15.9 53.1 568.1 1.9 6.9 Human settlements 0.2 224.6 48.2 5.9 3 14.5 85.8 16.2 75.2 PGNP RA MR SC BA SE OF PF MC UR Rocky areas 4301.6 4623.5 280.2 55.9 5.1 132 48.1 4.7 19.4 Nixed rocky and scrub areas 2405.1 285668 1743.5 769.7 43.7 2710.5 2088 252.1 355.5 Scrublands 127.7 3761.5 4424.9 481.8 99 2861.6 591.1 245.9 215.1 Burned areas 34.7 733 621.5 72.5 13.3 466.3 57.7 1.4 9.5 Sparse vegetation 85.3<	Sparse vegetation	10.3	749.7	211.3	6.9	15.4	25.7	43.2	10.5	28.5
Pine forests0.2288.6128.74.615.953.1568.11.96.9Meadows and crops0.4104.178.50.52.7211.48.9266.382.9Human settlements0.2224.648.25.9314.585.816.275.2PGNPRAMRSCBASEOFPFMCURRocky areas430.64623.5280.255.95.113248.14.719.4Mixed rocky and scrub areas2405.128566.81743.5769.743.72710.52088252.1355.5Scrublands127.73761.54424.9481.8992861.6591.1245.9215.1Burned areas34.7733621.572.513.3466.357.71.49.5Sparse vegetation85.31913432.971.69.483.999.521.9113.1Oak forests20.22243.1925.3202.39.54071.2528.8242.5130Pine forests91.52129.71169.8164.98.71118.33489.827197.6Meadows and crops6.8430.7191.623.191747.189.71387.4369.8Human settlements12.71415.7622141.37.51273.5610.2236.2993ADDRAMRSCBASEOF <td>Oak forests</td> <td>2.9</td> <td>359.2</td> <td>355.4</td> <td>25.8</td> <td>9</td> <td>1639.6</td> <td>202.9</td> <td>41.7</td> <td>30.3</td>	Oak forests	2.9	359.2	355.4	25.8	9	1639.6	202.9	41.7	30.3
Meadows and crops Human settlements0.4104.178.50.52.7211.48.9266.382.9PGNPRAMRSCBASEOFPFMCURRocky areas4301.64623.5280.255.95.113248.14.719.4Mixed rocky and scrub areas2405.128566.81743.5769.743.72710.52088252.1355.5Scrublands127.73761.54424.9481.8992861.6591.1245.9215.1Burned areas34.7733621.572.513.3466.357.71.49.5Sparse vegetation85.31913432.971.69.483.999.521.9113.1Oak forests20.22243.1925.3202.39.54071.2528.8242.5130Pine forests91.52129.71169.8164.98.71118.33489.827197.6Meadows and crops6.8430.7191.623.191747.189.71387.4369.8ADDRAMRSCBASEOFPFMCURADDRAMRSCBASE0.51.24.77.10.53.3ADDRAMRSCBASEOFPFMCURMixed rocky and scrub areas3.71615.5657.714205.1282.6	Pine forests	0.2	288.6	128.7	4.6	15.9	53.1	568.1	1.9	6.9
Human settlements0.2224.648.25.9314.585.816.275.2PGNPRAMRSCBASEOFPFMCURNixed rocky areas4301.64623.5280.255.95.113248.14.719.4Mixed rocky and scrub areas2405.128566.81743.5769.743.72710.52088252.1355.5Scrublands127.73761.54424.9481.8992861.6591.1245.9215.1Burned areas34.7733621.572.513.3466.357.71.49.5Sparse vegetation85.31913432.971.69.483.999.521.9113.1Oak forests20.22243.1925.3202.39.54071.2528.8242.5130Pine forests91.52129.71169.8164.98.71118.33489.827197.6Meadows and crops6.8430.7191.623.191747.189.71387.4369.8Human settlements12.71415.7622141.37.51273.5610.2236.2993AADDRAMRSCBASEOFPFMCURRocky areas0.141.422.80.51.24.77.10.53.3Mixed rocky and scrub areas3.71615.5657.714205.12	Meadows and crops	0.4	104.1	78.5	0.5	2.7	211.4	8.9	266.3	82.9
PGNPRAMRSCBASEOFPFMCURRocky areas4301.64623.5280.255.95.113248.14.719.4Mixed rocky and scrub areas2405.128566.81743.5769.743.72710.52088252.1355.5Scrublands127.73761.54424.9481.8992861.6591.1245.9215.1Burned areas34.7733621.572.513.3466.357.71.49.5Sparse vegetation85.31913432.971.69.483.999.521.9113.1Oak forests20.22243.1925.3202.39.54071.2528.8242.5130Pine forests91.52129.71169.8164.98.71118.33489.827197.6Meadows and crops6.8430.7191.623.191747.189.71387.4369.8Human settlements12.71415.7622141.37.51273.5610.2236.2993AADDRAMRSCBASEOFPFMCURNixed rocky and scrub areas3.71615.5657.714205.1282.6848.631.6139.2Scrublands1.21664.77282.5105.31931.344972025.4623.9843.4Burned areas0332.6490.99.7138<	Human settlements	0.2	224.6	48.2	5.9	3	14.5	85.8	16.2	75.2
Rocky areas4301.64623.5280.255.95.113248.14.719.4Mixed rocky and scrub areas2405.128566.81743.5769.743.72710.52088252.1355.5Scrublands127.73761.54424.9481.8992861.6591.1245.9215.1Burned areas34.7733621.572.513.3466.357.71.49.5Sparse vegetation85.31913432.971.69.483.999.521.9113.1Oak forests20.22243.1925.3202.39.54071.2528.8242.5130Pine forests91.52129.71169.8164.98.71118.33489.827197.6Meadows and crops6.8430.7191.623.191747.189.71387.4369.8Human settlements12.71415.7622141.37.51273.5610.2236.2993AADDRAMRSCBASEOFPFMCURRocky areas0.141.422.80.51.24.77.10.53.3Mixed rocky and scrub areas3.71615.5657.714205.1282.6848.631.6139.2Scrublands1.21664.77282.5105.31931.344972025.4623.9843.4Burned areas0332.6490.9 <t< td=""><td>PGNP</td><td>RA</td><td>MR</td><td>SC</td><td>BA</td><td>SE</td><td>OF</td><td>PF</td><td>MC</td><td>UR</td></t<>	PGNP	RA	MR	SC	BA	SE	OF	PF	MC	UR
Mixed rocky and scrub areas2405.128566.81743.5769.743.72710.52088252.1355.5Scrublands127.73761.54424.9481.8992861.6591.1245.9215.1Burned areas34.7733621.572.513.3466.357.71.49.5Sparse vegetation85.31913432.971.69.483.999.521.9113.1Oak forests20.22243.1925.3202.39.54071.2528.8242.5130Pine forests91.52129.71169.8164.98.71118.33489.827197.6Meadows and crops6.8430.7191.623.191747.189.71387.4369.8Human settlements12.71415.7622141.37.51273.5610.2236.2993ADDRAMRSCBASEOFPFMCURRocky areas0.141.422.80.51.24.77.10.53.3Mixed rocky and scrub areas3.71615.5657.714205.1282.6848.631.6139.2Scrublands1.21664.77282.5105.31931.344972025.4623.9843.4Burned areas0332.6490.99.7138477.2263.151.825Sparse vegetation0.711132151.7	Rocky areas	4301.6	4623.5	280.2	55.9	5.1	132	48.1	4.7	19.4
Scrublands 127.7 3761.5 4424.9 481.8 99 2861.6 591.1 245.9 215.1 Burned areas 34.7 733 621.5 72.5 13.3 466.3 57.7 1.4 9.5 Sparse vegetation 85.3 1913 432.9 71.6 9.4 83.9 99.5 21.9 113.1 Oak forests 20.2 2243.1 925.3 202.3 9.5 4071.2 528.8 242.5 130 Pine forests 91.5 2129.7 1169.8 164.9 8.7 1118.3 3489.8 27 197.6 Meadows and crops 6.8 430.7 191.6 23.1 9 1747.1 89.7 1387.4 369.8 Human settlements 12.7 1415.7 622 141.3 7.5 1273.5 610.2 236.2 993 AADD RA MR SC BA SE OF PF MC UR Rocky areas 0.1 41.4 22.8 0.5 1.2 4.7 7.1 0.5 3.3	Mixed rocky and scrub areas	2405.1	28566.8	1743.5	769.7	43.7	2710.5	2088	252.1	355.5
Burned areas34.7733621.572.513.3466.357.71.49.5Sparse vegetation85.31913432.971.69.483.999.521.9113.1Oak forests20.22243.1925.3202.39.54071.2528.8242.5130Pine forests91.52129.71169.8164.98.71118.33489.827197.6Meadows and crops6.8430.7191.623.191747.189.71387.4369.8Human settlements12.71415.7622141.37.51273.5610.2236.2993AADDRAMRSCBASEOFPFMCURRocky areas0.141.422.80.51.24.77.10.53.3Mixed rocky and scrub areas3.71615.5657.714205.1282.6848.631.6139.2Scrublands1.21664.77282.5105.31931.344972025.4623.9843.4Burned areas0332.6490.99.7138477.2263.151.825Sparse vegetation0.711132151.738.4514.6289.2665.1328.4334.4Oak forests0.524.49743.620.7218.6715.9715.9715.9715.4715.9	Scrublands	127.7	3761.5	4424.9	481.8	99	2861.6	591.1	245.9	215.1
Sparse vegetation 85.3 1913 432.9 71.6 9.4 83.9 99.5 21.9 113.1 Oak forests 20.2 2243.1 925.3 202.3 9.5 4071.2 528.8 242.5 130 Pine forests 91.5 2129.7 1169.8 164.9 8.7 1118.3 3489.8 27 197.6 Meadows and crops 6.8 430.7 191.6 23.1 9 1747.1 89.7 1387.4 369.8 Human settlements 12.7 1415.7 622 141.3 7.5 1273.5 610.2 236.2 993 AADD RA MR SC BA SE OF PF MC UR Rocky areas 0.1 41.4 22.8 0.5 1.2 4.7 7.1 0.5 3.3 Mixed rocky and scrub areas 3.7 1615.5 657.7 14 205.1 282.6 848.6 31.6 139.2 Scrublands 1.2 1664.7 7282.5 105.3 1931.3 4497 2025.4 623.9	Burned areas	34.7	733	621.5	72.5	13.3	466.3	57.7	1.4	9.5
Oak forests 20.2 2243.1 925.3 202.3 9.5 4071.2 528.8 242.5 130 Pine forests 91.5 2129.7 1169.8 164.9 8.7 1118.3 3489.8 27 197.6 Meadows and crops 6.8 430.7 191.6 23.1 9 1747.1 89.7 1387.4 369.8 Human settlements 12.7 1415.7 622 141.3 7.5 1273.5 610.2 236.2 993 AADD RA MR SC BA SE OF PF MC UR Rocky areas 0.1 41.4 22.8 0.5 1.2 4.7 7.1 0.5 3.3 Mixed rocky and scrub areas 3.7 1615.5 657.7 14 205.1 282.6 848.6 31.6 139.2 Scrublands 1.2 1664.7 7282.5 105.3 1931.3 4497 2025.4 623.9 843.4 Burned areas 0 332.6 490.9 9.7 138 477.2 263.1 51.8	Sparse vegetation	85.3	1913	432.9	71.6	9.4	83.9	99.5	21.9	113.1
Pine forests 91.5 2129.7 1169.8 164.9 8.7 1118.3 3489.8 27 197.6 Meadows and crops 6.8 430.7 191.6 23.1 9 1747.1 89.7 1387.4 369.8 Human settlements 12.7 1415.7 622 141.3 7.5 1273.5 610.2 236.2 993 AADD RA MR SC BA SE OF PF MC UR Rocky areas 0.1 41.4 22.8 0.5 1.2 4.7 7.1 0.5 3.3 Mixed rocky and scrub areas 3.7 1615.5 657.7 14 205.1 282.6 848.6 31.6 139.2 Scrublands 1.2 1664.7 7282.5 105.3 1931.3 4497 2025.4 623.9 843.4 Burned areas 0 332.6 490.9 9.7 138 477.2 263.1 51.8 25 Sparse vegetation 0.7 1113 2151.7 38.4 514.6 289.2 665.1 328.4 <td>Oak forests</td> <td>20.2</td> <td>2243.1</td> <td>925.3</td> <td>202.3</td> <td>9.5</td> <td>4071.2</td> <td>528.8</td> <td>242.5</td> <td>130</td>	Oak forests	20.2	2243.1	925.3	202.3	9.5	4071.2	528.8	242.5	130
Meadows and crops 6.8 430.7 191.6 23.1 9 1747.1 89.7 1387.4 369.8 Human settlements 12.7 1415.7 622 141.3 7.5 1273.5 610.2 236.2 993 AADD RA MR SC BA SE OF PF MC UR Rocky areas 0.1 41.4 22.8 0.5 1.2 4.7 7.1 0.5 3.3 Mixed rocky and scrub areas 3.7 1615.5 657.7 14 205.1 282.6 848.6 31.6 139.2 Scrublands 1.2 1664.7 7282.5 105.3 1931.3 4497 2025.4 623.9 843.4 Burned areas 0 332.6 490.9 9.7 138 477.2 263.1 51.8 25 Sparse vegetation 0.7 1113 2151.7 38.4 514.6 289.2 665.1 328.4 353.4 Oak foreets 0.5 284.9 743.6 207 218.6 7152.9 788.8 410.9	Pine forests	91.5	2129.7	1169.8	164.9	8.7	1118.3	3489.8	27	197.6
Human settlements12.71415.7622141.37.51273.5610.2236.2993AADDRAMRSCBASEOFPFMCURRocky areas0.141.422.80.51.24.77.10.53.3Mixed rocky and scrub areas3.71615.5657.714205.1282.6848.631.6139.2Scrublands1.21664.77282.5105.31931.344972025.4623.9843.4Burned areas0332.6490.99.7138477.2263.151.825Sparse vegetation0.711132151.738.4514.6289.2665.1328.4353.4Oak forests0.5284.9743.620.7218.67152.9788.8410.9431.4	Meadows and crops	6.8	430.7	191.6	23.1	9	1747.1	89.7	1387.4	369.8
AADDRAMRSCBASEOFPFMCURRocky areas0.141.422.80.51.24.77.10.53.3Mixed rocky and scrub areas3.71615.5657.714205.1282.6848.631.6139.2Scrublands1.21664.77282.5105.31931.344972025.4623.9843.4Burned areas0332.6490.99.7138477.2263.151.825Sparse vegetation0.711132151.738.4514.6289.2665.1328.4353.4Oak forests0.5284.9743.620.7218.67152.9788.8410.94314	Human settlements	12.7	1415.7	622	141.3	7.5	1273.5	610.2	236.2	993
Rocky areas0.141.422.80.51.24.77.10.53.3Mixed rocky and scrub areas3.71615.5657.714205.1282.6848.631.6139.2Scrublands1.21664.77282.5105.31931.344972025.4623.9843.4Burned areas0332.6490.99.7138477.2263.151.825Sparse vegetation0.711132151.738.4514.6289.2665.1328.4353.4Oak forests0.5284.9743.620.7218.6715.2788.8410.9431.4	AADD	RA	MR	SC	BA	SE	OF	PF	МС	UR
Mixed rocky and scrub areas 3.7 1615.5 657.7 14 205.1 282.6 848.6 31.6 132.2 Scrublands 1.2 1664.7 7282.5 105.3 1931.3 4497 2025.4 623.9 843.4 Burned areas 0 332.6 490.9 9.7 138 477.2 263.1 51.8 25 Sparse vegetation 0.7 1113 2151.7 38.4 514.6 289.2 665.1 328.4 353.4 Oak forests 0.5 284.9 743.6 207 218.6 7152.9 788.8 410.9 431.4	Rocky areas	0.1	41.4	22.8	0.5	12	47	71	0.5	33
Scrublands 1.2 1664.7 7282.5 105.3 1931.3 4497 2025.4 623.9 843.4 Burned areas 0 332.6 490.9 9.7 138 477.2 263.1 51.8 25 Sparse vegetation 0.7 1113 2151.7 38.4 514.6 289.2 665.1 328.4 353.4 Oak forests 0.5 284.9 743.6 20.7 218.6 7152.9 788.8 410.9 431.4	Mixed rocky and scrub areas	3.7	1615 5	657.7	14	205.1	282.6	848.6	31.6	139.2
Burned areas 0 332.6 490.9 9.7 138 477.2 263.1 51.8 25 Sparse vegetation 0.7 1113 2151.7 38.4 514.6 289.2 665.1 328.4 353.4 Oak forests 0.5 284.9 743.6 20.7 218.6 7152.9 788.8 410.9 431.4	Scrublands	1.2	1664.7	7282.5	105.3	1931.3	4497	2025.4	623.9	843.4
Sparse vegetation 0.7 1113 2151.7 38.4 514.6 289.2 665.1 328.4 353.4 Oak forests 0.5 284.9 743.6 20.7 218.6 7152.9 788.8 410.9 431.4	Burned areas	0	332.6	490.9	9.7	138	477.2	263.1	51.8	25
Dak forests 0.5 284.9 743.6 20.7 218.6 7152.9 788.8 410.9 431.4	Sparse vegetation	0.7	1113	2151.7	38.4	514.6	289.2	665.1	328.4	353.4
	Oak forests	0.5	284.9	743.6	20.7	218.6	7152.9	788.8	410.9	431.4
Pine forests 0 400.1 758.5 18.6 177.7 219.2 1656.5 16.7 64.3	Pine forests	0	400.1	758.5	18.6	177.7	219.2	1656.5	16.7	64.3
Meadows and crops 0.2 171.8 501.8 1.9 107.1 1372.1 56.4 2422.4 882.7	Meadows and crops	0.2	171.8	501.8	1.9	107.1	1372.1	56.4	2422.4	882.7
Human settlements 0.5 178.1 214.7 4.4 59.9 133 167.1 162.2 714.2	Human settlements	0.5	178.1	214.7	4.4	59.9	133	167.1	162.2	714.2

were reported in the Cantabrian Mountains since 1956-2010 by a detailed photointerpretation, where the rate of forest expansion was significantly higher in natural basins and, particularly, on shaded slopes. The mean elevation of new forest patches increased during the study period, which was particularly evident on natural sunny slopes (Álvarez-Martínez et al., 2014). Pine forests have also increased significantly in XNP and UAA, while they have lost occupation in some zones of PNPG (40.3% RAD) (Table 4; Fig. 6). In 2000, pine forests occupied 13.112 ha, while in 2010 the occupied extension was 16.728 ha (Table 3). Considering that pine forests in the study region are a consequence of previous forestry management oriented to social and economic interests (in fact, regional and local programs have helped afforestation and reforestation) (Macedo et al., 2009) we can conclude that rural abandonment and forestry management are the main factors affecting the spatio-temporal landscape dynamics in the study areas. Nonetheless, the study areas have been subject to massive land abandonment since the middle of the 20th century, similarly to other areas of the Iberian Peninsula (Calvo-Iglesias et al., 2009; Pôças et al., 2011; Romero-Calcerrada and Perry, 2004; Stellmes et al., 2013). Thus, recently observed processes of land cover change could, at least partially, be a consequence of changes in land use that occurred long before 2000.

Local-level analysis

The results derived for XNP from the local-level analysis are similar to the results obtained from the analysis at landscape level. Specifically, pine and oak forests increased significantly in the percentage of occupation from 7.1 and 6.9% in 2000 to 14.0 and 10.4% in 2010, respectively, (t = -3.735, p < 0.001, t = -3.933, p < 0.001) (Table 6) while the extension of the 'meadows and crops' and 'rocky areas' categories decreased from 3.4 and 7.0% to 1.1 and 0.5%, respectively, (t = 2.900, p = 0.004; t = 1176, p < 0.001) (Table 6). The 'urban settlements' and 'mixed rock and scrub areas' remained

unchanged (from 3.3 and 46.8% to 1.9 and 49.2%, respectively) (t = 1.775, p = 0.07; t = -0.732, p = 0.465)(Table 6). The 'burned areas' and 'sparse vegetation areas' decreased significantly (from 1.5 and 3.9% to 0.4 and 1.2%)(t = 2.281; p = 0.02; t = 3.885, p < 0.001)(Table 6) during the last decade. However, it is important to note that the comparison between landscape and local level was addressed using the same Landsat data, so these findings could partially be a generalization of changes at plot level. Further research based on high-resolution satellite data would be helpful in finding driving forces of changes at finer scales.

Estimating the impact of fires during the last decade

The results derived from comparing the LULC maps showed the fire-affected area was similar in 2010 and 2000 in PGNP, while in the Galician site it was significantly less in 2010 than in 2000. In

Table 6

Changes at local level for the Baixa Limia–Serra do Xurés Natural Park (XNP): % proportion of area associated with main land cover classes for 2000 and 2010; *T*-value; *p*-value of *T*-test analysis; increasing (\uparrow) or decreasing (\downarrow) trend between 2000 and 2010.

Land cover classes	2000	2010	T-value	<i>p</i> -value	Trend
Rocky areas	7	0.5	1176	< 0.001	↓****
Mixed rocky and scrub areas	48.6	49.2	-0.73	0.465	-
Scrublands	18.4	20.2	-1.02	0.307	-
Burned areas	1.5	0.4	2.28	0.02	↓*
Sparse vegetation	3.9	1.2	3.89	< 0.001	↓****
Oak forests	6.9	10.4	-3.93	< 0.001	↑***
Pine forests	7.1	14	-3.74	< 0.001	↑***
Meadows and crops	3.4	1.1	2.90	0.004	↓**
Human settlements	3.3	1.9	1.78	0.07	-

* p<0.05.

^{**} p<0.01.

^{***} *p* < 0.001.

order to determine a clear trend of area affected along the study period we also indicate the number and extension of largest fire events reported along this decade from statistical and spatially explicit fire data. According to findings obtained from available cartography, in the period between 2000 and 2009 the impact of fires in the Portuguese territory was invariable: fire devastated 28,874 ha in PGNP, particularly 5596 ha in 2002, 8477 ha in 2006, and 3725 ha in 2009 (DGRF, 2012). In the Galician area, the extension of fire-affected areas considerably decreased from 2006 (MAGRAMA, 2013). In particular, only three fires (<500 ha each one) affected the municipalities included in the study area between 2006 and 2009. Consequently, in rocky areas with less than 20% vegetation (called 'rocky areas' in this work) we found two opposite trends: (1) in XNP the RAG values were lower than 5% (RAD values were higher than 85% and these areas were mainly replaced during the last decade by 'mixed rock and scrubs'; Table 4 and 5); and (2) in the PGNP, the RAG values were higher than 20% (with RAD value of 42%; Table 4). Thus, the huge impact of wildfires on the Portuguese side have generated new 'rocky areas', while on the Spanish side its impact does not seem to have been a decisive factor on the landscape dynamics in recent years. Recent studies in the northeastern corner of Spain found that fire suppression is a major factor leading to prevailing fire regimes, and has identified interactions between the fire regime and fire suppression based on landscape patterns (Brotons et al., 2013; Regos et al., 2014a). This is consistent with the assumption that in the Galician area the fires did not affect the land cover dynamics as strongly as they did during the previous decades, unlike in the Portuguese area. We suggest that the differences in the total amount of area burned in our study areas during the last years could be due to a strong and effective fire suppression policy in the Galician area. Specifically, the new 'rocky areas' generated in 2010 derived from 'mixed rocky with scrub areas' and 'scrublands' (see Table 5), which turned out to be the main land covers affected by wildfires during this period (49 and 15%, respectively), followed by pine and oak forests (8.8 and 8.7%) and 'rocky areas' (7%). These fires have therefore impeded the natural process of secondary succession and favored the increase in 'rocky areas' in the Portuguese area. Our results are in agreement with previous studies of spatial patterns of fire occurrence carried out in southern Europe (Álvarez-Martínez et al., 2010; Moreira et al., 2001; Nunes et al., 2005; Oliveira et al., 2013). According to these authors, the scrublands, grasslands, and sparse vegetation areas are the land covers most prone to fire. Specifically, in Portugal scrublands were found to be more susceptible to burning, followed by other forest cover types (Moreira et al., 2001; Nunes et al., 2005). Furthermore, deciduous forest cover is the result of the colonization of former 'meadows and crops' and 'scrublands' but also the result of colonization of previously burned areas (Table 5). A previous study in Cantabrian Mountains analyzed the post-fire regeneration response of Q. pyrenaica, one of the most abundant and characteristic oak species in our study area. The abundance of this species varied as a function of pre-fire abundance, but an increase of its mean cover from 3.6% to 42.6% was found in forest communities for a period of 6 years after the disturbance (Calvo and Tarrega de Luis, 1999). Therefore, the wildfires help to explain the sharp increase in hardwoods due to their ability to re-sprout.

Conclusions

The findings of our land cover change analysis support and reflect the outcomes of various studies that address different aspects of land-use change in Southern Europe during the second half of the 20th century (pre and post-1990's period). Therefore, land cover dynamics in early 21th century are still being affected by the rural exodus of the last century. Furthermore, our study complements those works previously carried out in other marginal areas of Iberian Peninsula providing new insights into the driving forces determining land cover dynamics, as well as contributes to add value to Landsat data-based analysis into land dynamics science. Specifically, the preprocessing of the images, that included appropriate topographic and radiometric corrections, was adequate to avoid the illumination variations and atmospheric effects. The incorporation of ancillary variables during the classification process compensated for the lack of additional spectral information, thus improving the thematic accuracy of the resulting cartography (see Appendix B for more detailed information). In addition, the comparison among different classification algorithms helped to choose the procedure with the best results, allowing us to address the LULC changes analysis with an adequate thematic accuracy. Specifically, the findings derived from our remote sensing databased analysis showed that rural abandonment has encouraged the expansion of scrubland as well as the natural succession processes, favoring native forest species in our study area. Furthermore, the comparative analysis of the change patterns enabled us to find different trends in the land cover dynamics between the three study areas, and thus to infer the possible driving forces behind such patterns. The three relative area overlap indices, complemented by transition matrices, allowed us to understand, in a very intuitive manner, change patterns that otherwise it had been impossible to find. In particular, forest management has encouraged an increase in non-native pine species, even in protected areas. Moreover, the increase in scrubland has led to fuel accumulation, so that wildfires have been also playing a role in the dynamics of the land covers, which has only partially been offset in the Galician area through effective fire suppression policies. In light of these findings, we conclude that the differences in land management and fire suppression policies between the two countries and the different protection schemes may partly explain the different patterns of changes recorded in these covers. The extent to which these changes have affected the biodiversity and ecosystem services or have been affected by other climatic, structural or socio-economic factors are issues which should be addressed in future studies in order to gain a better understanding of the main threats to biodiversity and landscapes in Europe in recent decades.

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Appendix A.

Table A1 Accuracy results of the six methods used for the classification procedure, grouped by year and algorithm: overall accuracy (in bold) and Kappa coefficient.

	Parallelepiped distance	Minimum distance	Mahalanobis distance	Maximum likelihood	Artificial neuronal networks	Support vector machines			
Kerne	4					Radial basis function	Linear function	Polynomial function	Sigmoidal function
2000 2010	63.14(0.58) 68.32(0.64)	83.54(0.81) 65.74(0.61)	89.6(0.88) 90.57(0.89)	87.1(0.85) 89.9(0.88)	90.12(0.88) 88.09(0.86)	92.6(0.91) 87.26(0.85)	92.5(0.91) 88.15(0.86)	92.6(0.91) 87.33(0.85)	91.65(0.90) 86.31(0.84)

Six classification methods were compared in order to choose the procedure with the best results. The highest overall accuracy in 2000 (up to 90%) was obtained with support vector machine and artificial neural networks (ANN) considering all Landsat bands and all other variables. However, after visual assessment we found that the accuracy results of these procedures were not in agreement with the separability results. The 'dam reservoirs' or 'burned areas' categories (that showed a maximum spectral separability with the remaining categories) presented pixels mistakenly classified, so the learning machine algorithms were finally ruled out. The highest accurate scores in 2010 were found with Mahalanobis distance, the most consistent algorithm along the two dates.

Appendix B.

Table B1 Improvement of thematic accuracy of land cover maps by means of progressive inclusion of ancillary data during the classification procedure (using Mahalanobis distance algorithm) for year 2000: overall accuracy (in bold) and Kappa coefficient.

	Landsat data	+Vegetation indices	+Digital terrain models	+Distance maps	+Climate variables
Overall accuracy	83.06	84.91	87.29	88.28	89.6
(Kappa coefficient)	(0.80)	(0.82)	(0.85)	(0.86)	(0.88)

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