

Manuscript Number: JAPG-D-10-00104R1

Title: Using predictive models as a spatially explicit support tool for managing cultural landscapes.

Article Type: Article

Keywords: Rural abandonment; LANDSAT imagery; Socio-economic drivers; predictive modeling.

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**Abstract:** Due to the high sensitivity of mountain landscapes to environmental changes, the study of land cover dynamics has become an essential tool for guiding management policies. Since the second half of the twentieth century, the Cantabrian Mountains (NW Spain) have been substantially altered by the loss of traditional management practices and, more recently, by the new environmental schemes developed by the Regional Government. This area is a biodiversity hotspot, representing the south-western-most distribution limit for a large number of species in Europe. Therefore, small changes in landscape patterns can result in biodiversity losses. In this study, we analyzed land cover changes in the Cantabrian Mountains from 1991 to 2004 by means of remote sensing techniques, identifying the main driving forces and classifying the territory according to its risk of land cover change. Forest expansion and loss of shrublands were the two major trajectories of change apparent during this period. When modeling the occurrence of these land cover changes, we found that performance of models was related to the nature of the change. The most accurate models were associated with processes of secondary succession, i.e. forest expansion (78.6%), while the least accurate models related to changes linked with management decisions, i.e. loss of shrubs (61.8%). The main drivers of change were variations in the number of goats (for the forest expansion model) and changes in the number of head of sheep and cattle (for the loss of shrubs model). Topographic conditions (altitude and slope) were relevant in both models. Our approach proposes an explicit decision support tool for landscape managers, allowing better identification of the areas where they should focus their attention.

**Using predictive models as a spatially explicit support tool for managing cultural landscapes.**

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1 **Using predictive models as a spatially explicit support tool for managing cultural landscapes**

2

3 **ABSTRACT**

4

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23 attention.

24

25 **KEY WORDS:** Rural abandonment; LANDSAT imagery; Socio-economic drivers; predictive  
26 modeling.

27

28 **1. INTRODUCTION**

29

30 Land cover and land use changes (LCLU) have been widely studied worldwide (Reid et al., 2000;  
31 Achard et al., 2006; Seabrook et al., 2007; Izquierdo and Ricardo, 2009; Townsend et al., 2009).  
32 Understanding the relationships between land cover patterns and their associated processes is  
33 extremely important for scientists, landscape managers and policy makers designing nature  
34 conservation strategies aimed at preserving some of the unique characteristics of landscapes (Kates

35 et al., 2001). In the European context, there is increasing concern about detecting landscape changes  
36 and their ecological consequences in mountain systems (MacDonald et al., 2000; Mottet et al., 2006;  
37 Gellrich et al., 2007), since these systems provide important ecosystem services (cultural,  
38 provisioning, regulating and supporting) contributing to both highland and lowland economies.  
39 Mountain systems constitute important biodiversity hotspots, since their biota is adapted to specific,  
40 narrow environmental limits, which makes them extremely sensitive to slight perturbations  
41 (Millennium Ecosystem Assessment, 2003). Therefore, early detection of changes in land cover  
42 patterns has become an important target in these ecological systems since it allows identification of  
43 the main landscape drivers and, consequently, the design of realistic management policies.

44

45 Through the centuries, human activity has played a decisive role in managing and shaping the  
46 landscape of Mediterranean mountain systems (Grove and Rackham, 2000). Studies related to land  
47 cover trends in these systems have focused mainly on changes resulting from agricultural  
48 abandonment. These are widespread, having begun in the early 20th century (Rey-Benayas et al.,  
49 2007). In the Iberian Peninsula, additional pressures result from declines in the transhumance system  
50 (Molinillo et al., 1997; Gómez and Lorente, 2004; Vicente-Serrano et al., 2005), which have been  
51 especially noteworthy in the Cantabrian Mountains range. These have involved a gradual loss of  
52 traditional management (based on grazing, cutting and burning; Calvo et al., 2007), favouring a  
53 process of landscape homogenisation that impacts biodiversity and threatens cultural landscape  
54 heritage (Jongman, 2002).

55

56 Remote sensing techniques have become essential tools for land cover studies at regional scales  
57 because of their capacity to provide a temporal series of information on the terrestrial land surfaces  
58 and, thus, give an integrated understanding of changing processes in the landscape (see for example  
59 Michalski et al., 2008). Predictive models, such as those based on regression, may provide a  
60 framework for identifying the driving forces behind land cover changes (Serra et al., 2008). The  
61 occurrence of land cover change can be successfully predicted across space by combining statistical  
62 models with spatially explicit data in a geographical information system (GIS) environment  
63 (Schneider and Pontius Jr., 2001). This combination of techniques and data represents a powerful  
64 tool for defining priority areas in terms of land management and biodiversity conservation (Lehmann  
65 et al., 2002).

66

67 Within the framework of the European Union (EU) and the Natura 2000 Network requirements  
68 (Habitats Directive, 92/43/EEC; Annon, 1992), such models can provide important input to the

69 design and application of integrated management strategies. Land use planning in mountain areas,  
70 which has traditionally focused on local actions and their short-term consequences, could then be  
71 replaced by unified policies addressing the preservation of the natural spaces network as a whole.  
72 Furthermore, maps illustrating predicted changes over time could empower land users to understand  
73 long-term outcomes of decisions (see for example, Binkley and Duncan, 2009), helping to connect  
74 people and ecology.

75

76 In this study, we evaluated land cover changes in the Cantabrian Mountains during the period 1991  
77 to 2004 using LANDSAT images. We then developed spatially explicit models of land cover change  
78 in order to predict where future transitions may occur in the landscape, as well as to define the main  
79 forces (biophysical and human) driving the observed changes. The results provide a useful support  
80 tool for landscape managers, since it allows the identification of priority areas in terms of  
81 conservation.

82

## 83 **2. METHODS**

84

### 85 **2.1 Study area**

86

87 The study area is located at the southern slope of the Cantabrian Mountains in the León province  
88 (NW Spain) (Figure 1). It includes 28 municipalities, covering 3,266 km<sup>2</sup>. Altitude ranges from 877  
89 to 2,412 m.a.s.l. This area lies on the boundary between the Atlantic/Eurosiberian and Mediterranean  
90 biogeographical regions, where four bioclimatic belts ranging from supramediterranean to subalpine  
91 can be identified (Rivas-Martinez et al., 1987). Average annual rainfall varies from 700 to 1,573 mm.  
92 Mean annual temperature varies from 8.2° C to 9.9° C. Atlantic vegetation is generally located on  
93 shaded and humid northern slopes. It mainly consists of deciduous forests (*Fagus sylvatica*, *Betula*  
94 *pubescens*, *Quercus petraea*, *Q. robur*) and heathlands of *Calluna vulgaris*. Mediterranean  
95 vegetation (*Quercus pyrenaica*, *Q. ilex*) mostly occurs on sunny and drier slopes. The lithology is  
96 also diverse, from massive Carboniferous limestones to slate with coal, sandstones, crystal quartzites  
97 and conglomerates (Gómez and Rodríguez, 1992). Among the driving forces that have shaped the  
98 landscape of this area over the centuries, transhumance has played an important role. It consists of  
99 the movement of flocks of thousands of sheep and goats from the south-Iberian “dehesa” systems to  
100 the Cantabrian pastures above the treeline during the summer. This activity has provided an  
101 important source of income for most of the municipalities of this area for centuries (Gómez and  
102 Rodríguez, 1992). Due to the complex orography, agricultural activities are concentrated on the

103 slopes close to the villages and in valley bottoms. Timber has traditionally been extracted from  
104 Atlantic forests for a range of purposes. Since the beginning of the twentieth century, the decline in  
105 the transhumance system, the abandonment of agricultural areas due to their lower profitability and  
106 the process of population emigration from the countryside to the cities (especially marked since  
107 1960), have resulted in the loss of traditional management practices across the territory. Furthermore,  
108 other activities, such as the opening of coal and opencast talc mines, construction of large reservoirs  
109 and afforestation of thousands of hectares with conifers, have transformed the landscape.

110

## 111 **2.2 Data sources**

112

113 Land cover was mapped using a temporal series of LANDSAT images for the years 1991, 1995,  
114 2000 and 2004 (Table 1). We selected images acquired during the summer season in order to obtain  
115 the lowest cloud and snow cover (the latter being present sometimes even in late spring).

116

117 LANDSAT images were geometrically corrected following the polynomial method proposed by Palá  
118 and Pons (1995), which uses ground control points extracted from aerial photographs as references  
119 and a 30 m resolution Digital Elevation Model (DEM) to minimize geometric errors. It was  
120 implemented using Miramon software (Pons, 2002). Around 60 ground-control points per image  
121 were used for geometric correction. Two thirds of these were used to correct the images; the  
122 remaining points were used to validate the results. The Root Mean Square Error (RMSE) was lower  
123 than the pixel size in all images ( $RMSE \pm SD = 16.16 \pm 4.78$ ). Radiometric correction was based on the  
124 algorithms developed by Markham and Barker (1986) and Morán et al. (1992), while atmospheric  
125 correction followed the transmittance model (COST) proposed by Chavez (1996). Down-welling  
126 transmittance values for bands five and seven were taken from Gilabert et al. (1994), since  
127 atmospheric conditions in their study area were more similar to ours than the area used by Chavez  
128 (1996). In order to compensate for differential solar illumination due to the shape of the terrain, a  
129 topographic correction was applied following the non-Lambertian C-Correction method (Teillet et  
130 al., 1982; Riaño et al., 2003). As each individual image was classified independently, the image  
131 series was not normalised.

132

133 Other data sources used in this study include a DEM at a 30-meter resolution and several vector  
134 layers showing urban areas, water surfaces and coniferous afforestation (see Table 2). Since these  
135 vector layers are inaccurate because of their coarse scale (1:200,000), they were edited and corrected  
136 on screen using high resolution orthophotographies. Socio-economic data accounting for changes in

137 livestock density (number of heads of sheeps, cows and goats) and human population density were  
138 recorded at the municipality level. All vectorial data were rasterized and resampled to match the  
139 LANDSAT 30-m spatial resolution.

140

### 141 **2.3 LANDSAT image classification**

142

143 A supervised classification (Maximum Likelihood method; Conese and Maselli, 1992; Martin et al.,  
144 1998; Shalaby and Tateishi, 2007; Schulz et al., 2010) was applied to produce a land cover map per  
145 year of study (1991, 1995, 2000, 2004). The variables involved in the process (see Table 2) were: (i)  
146 LANDSAT bands from 1 to 7 (excluding band 6 because of its coarse resolution). (ii) Two  
147 vegetation indices derived from LANDSAT images: the Normalized Differenced Vegetation Index  
148 (NDVI) (Rouse et al., 1973) and the standard Greenness Index (GI) of Tasseled Cap Transformation  
149 (Kauth and Thomas, 1976), as a measure of total photosynthesis and vegetation productivity. (iii) A  
150 spatial enhancement variable (texture), calculated as the average of the variance from the third band  
151 of each image measured within a mobile window 3x3 pixels. (iv) Topographic variables (altitude and  
152 slope) derived from the DEM.

153

154 Initially, we defined nine land cover categories: water, rock/bare ground, meadows, climatic  
155 pasturelands, heathlands, shrublands dominated by *Genista* spp., coniferous afforestations, forests  
156 (including deciduous and evergreen formations) and urban areas. After several preliminary  
157 classifications, we identified various conflicting assignments associated with the spatial complexity  
158 and heterogeneity of the landscape mosaic in the study area. Particularly relevant were problems of  
159 misclassification when dealing with the category “coniferous afforestations”, since it includes a wide  
160 range of development states, from mature to recently planted patches showing confusion with other  
161 land cover class as shrublands. This uncertainty was especially relevant in recently disturbed areas  
162 (young plantations). For this reason, coniferous afforestations, together with water and urban areas,  
163 were masked out and removed from the classification process. The remaining categories were  
164 grouped into four final classes: rock/ bare ground, herbaceous vegetation (including meadows and  
165 pasturelands), shrublands (including shrublands and heathlands) and forests.

166

167 High-resolution orthophotography (years 2000 and 2004) and fieldwork data (2005) were used to  
168 define at least 20 training polygons per category with a size of 50 pixels (4.5 ha), which were  
169 distributed throughout the study area following a stratified sampling design. Using the same data

170 sources, as well as Spanish Forest Inventories, we created a set of validation layers containing 100  
171 points per category and year.

172

173 Classification accuracy was assessed using a confusion matrix, which allowed validation points to be  
174 compared with the classified land covers. In order to interpret the matrix, we evaluated persistence  
175 and “swaps” (transitions between gains and losses in categories), according to Pontius Jr et al.  
176 (2004). Since coniferous plantations, water and urban areas were considered as constant land covers  
177 during the study period, we only assessed dynamics within rock/bare ground, herbaceous vegetation,  
178 shrubland and forest.

179

## 180 **2.4 Modeling land cover changes**

181

182 Principal Components Analysis (PCA) has been widely used in pre-classification change-detection  
183 approaches (see examples in Lu et al., 2004; Cakir et al., 2006; Pu et al., 2008; Deng et al., 2008),  
184 but less often in post-classification analyses. We applied a PCA on the temporal series of classified  
185 LANDSAT images (1991, 1995, 2000 and 2004) to enhance the detection of regions of change under  
186 the following assumption: We assigned values of 1 to 4 to the land cover categories, considering  
187 them as continuous, incremental stages of a secondary succession process: rock/bare ground (1),  
188 herbaceous vegetation (2), shrubland (3) and forest (4). Therefore, higher values will always mean  
189 greater complexity of community structure and ecosystem functioning. Consequently, landscape  
190 trends involving evolution towards more complex ecosystem structures would imply a shift from 1,  
191 2, or 3 towards 4. On the other hand, land cover changes from 4, 3 or 2 towards 1 would imply a loss  
192 in complexity of ecosystem structure backwards in the ecological succession due to perturbations.  
193 Subsequently, an unsupervised classification (ISODATA) was carried out on the first four principal  
194 components obtained from the previous step. The resulting cluster classes, corresponding to different  
195 categories of land cover change, were used in further analyses. For any given cluster class, a pixel in  
196 the landscape will be classified as “1” (present), belonging to their class, or “0” (absent) not  
197 belonging.

198

199 A sample of 20,000 systematic sample points was then generated throughout the study area to record  
200 different trajectories of land cover change (i.e. cluster classes). The sampling size was proportional  
201 to the surface corresponding to each change. Topographic and socio-economic data (see Table 2)  
202 were also assigned to those locations and recorded in a database structured around the cluster  
203 category. For each of these trajectories, we selected a prevalent data sample within each



204 presence/absence class but with equal sample numbers in each class. We then applied binary logistic  
205 regression (BLR) to model the probability of the occurrence of the main land cover changes as a  
206 function of the independent variables.

207

208 Before running the regression analysis, we checked for high Spearman correlations among the  
209 topographic and socio-economical variables, which would hinder the stepwise selection procedure.  
210 Finally, we assessed the significance of each of the independent variables, as a function of “change”  
211 or “no change”, using Mann–Whitney *U*-tests. Only significant variables ( $p < 0.05$ ) were retained in  
212 the final modeling analysis.

213

214 The selection of variables that best fitted into our models was made by means of a backwards  
215 stepwise regression. The analysis begins with a full model, where independent variables are removed  
216 in an iterative process (Hosmer and Lemeshow, 1989) based on a Wald algorithm. The ability of the  
217 model’s predictions to discriminate between the response classes was evaluated using Relative  
218 Operating Characteristics (ROC) (see Pontius Jr and Schneider, 2001; Braimoh and Vlek, 2005;  
219 Mathew et al., 2009). ROC values range from 0.5 (for a model that assigns the probability at  
220 random) to 1 (for a model that perfectly assigns the probability of observing the trajectory in the  
221 landscape). The logit function of the probability obtained from the models was converted, through an  
222 inverse logistic transformation, into a map showing the probability of change occurrence on a scale  
223 of 0 to 1.

224

225 GIS analyses were done using ERDAS® IMAGINE 8.5 and IDRISI KILIMANJARO 14.1 and  
226 statistic analyses were performed with SPSS 16.0.

227

### 228 **3. RESULTS**

229

#### 230 **3.1 Classification results and accuracy assessment**

231

232 Table 3 shows LANDSAT classification accuracy for the complete temporal series. In all cases, the  
233 average accuracy was greater than 85%, which indicates a good level of reliability. The lowest  
234 producer’s accuracy level corresponded with herbaceous vegetation, which was under-classified  
235 (values ranging from 73.91 to 85.22%); while the highest value was for rock/bare ground (values  
236 ranging from 87.13 to 97.09 %). The lowest user’s accuracy corresponded to shrublands, which were  
237 over-classified; while the highest value was for the rock/bare ground category.

238

### 239 **3.2 Land cover change monitoring**

240

241 Fig. 2 and Table 3 show that, at the beginning of the 1990s, the landscape in the study area consisted  
242 of a shrubland matrix (42.99% of the total area), with patches of different land cover. Forest patches  
243 represented 13.99% of the area and patches directly linked with human activities occupied  
244 respectively the 21.46 % (grasslands), 0.77% (water reservoirs) and 1.12% (urban areas). Rock and  
245 bare ground occupied 11.91% and coniferous plantations covered 7.77% of the study area.

246

247 From 1991 to 2000 the area occupied by shrublands only increased from 42.99% to 43.09% (less  
248 than one percent), while rock/bare ground and herbaceous vegetation showed an increase in area by  
249 3.28 % and 5.41 %, respectively. These increases corresponded with forests reduction from 13.99%  
250 to 12.34% cover. The most remarkable changes in these vegetation categories occurred during the  
251 period 2000-2004, when the cover of both herbaceous vegetation and shrublands decreased (5.31%  
252 and 5.93% respectively), while the area of rock/bare ground and forest increased by 13.69% and  
253 16.63%, respectively. For the study period as a whole, shrubland cover decreased a 5.72%, while  
254 both rock/bare ground (17.69%) and forests (2.88%) increased. Note that these percentages of  
255 change were calculated based on the surface occupied by each land cover in 1991. The area occupied  
256 by herbaceous vegetation underwent a slight reduction through the study period.

257

258 The cross-tabulation matrix between 1991 and 2004 (Table 4) provides information about systematic  
259 transitions between land cover types. For example, herbaceous vegetation, which did not undergo  
260 significant net changes (less than 1% decrease), was very dynamic (extensive swapping). In 2004,  
261 only 53.26% of herbaceous cover remained invariant from 1991, with 16.90% changing to  
262 shrubland, 5.94% to forest and 15.90% to rock/bare ground. Concurrently, 27.06% of the initial  
263 shrubland cover, 10.68% forest and 9.00% rock/bare ground shifted to herbaceous vegetation,  
264 making the net change of this land cover category almost null.

265

266 The 2.88% net change in forest cover was mainly associated with a swap from shrubland to forest  
267 (33.50%) and from herbaceous vegetation and rock/bare ground to forest (5.94 % and 1.55 %  
268 respectively). During the whole study period, forest mainly change towards shrubland (8.73%) and  
269 herbaceous vegetation (10.68%).

270

### 271 **3.3 Land cover change modeling**

272

273 We obtained 12 cluster classes (i.e. possible land cover changes from 1991 to 2004), which were  
274 interpreted according to the temporal sequence of land covers detected for the study period. Five  
275 cluster classes represented non-change situations, with the remaining seven classes representing  
276 different trends of change. Two of these classes of change corresponded with balanced situations  
277 between herbaceous-shrublands and shrublands-forests (23.83 and 18.74% of the sample points  
278 respectively). A 9.3% of the points represented areas of random change through time, corresponding  
279 with two cluster classes. Another cluster category (5.13%) recorded the processes of perturbation  
280 involving the loss of vegetation cover between 1991 and 1995, followed by a later recovery. The two  
281 remaining cluster classes corresponded with forest expansion and a consistent loss of shrubland  
282 throughout the whole timeframe (4.82% and 4.9% of the sample data respectively). Only the latest  
283 two classes were considered in the following statistical analyses.

284

### 285 *3.3.1 Forest expansion model*

286

287 Mann–Whitney *U*-tests on the explanatory variables showed that all of the following variables could  
288 significantly explain forest expansion changes: altitude ( $p < 0.01$ ), slope ( $p < 0.01$ ), change in  
289 population density ( $p < 0.01$ ) and temporal shifts in number of head of cattle ( $p < 0.01$ ), sheep ( $p <$   
290  $0.02$ ) and goats ( $p < 0.01$ ). On average, the change “increase of forest cover” predominantly occurred  
291 at altitudes of around 1,255 m (ranging from 1,241 to 1,267 m) and slopes of 5.09 degrees (ranging  
292 from 5.46 to 7.72). Moreover, this change was associated with sites characterized by larger  
293 reductions in both population and number of head of sheep than areas where forest did not increase.  
294 The Spearman test did not detect strong correlations among variables ( $r < 0.8$ ). Therefore, all of the  
295 independent variables were included in the binary logistic regression analysis (BLR).

296

297 Using backwards stepwise regression, only three variables were retained: altitude, slope and number  
298 of head of goats. The estimated regression coefficients are shown in Table 5. Positive values of the  
299 standardized logit coefficients indicate that higher values of the independent variables increase the  
300 probability of observing the trajectories. The “odds ratio”,  $\text{Exp}(\beta_1)$ , measures the likelihood of  
301 observing a trajectory if the independent variable is increased by one unit. When  $\beta > 0$ ,  $\text{Exp}(\beta) > 1$ ,  
302 indicating that the odds of observing the trajectory increase, and when  $\beta < 0$ ,  $\text{Exp}(\beta) < 1$ , meaning the  
303 likelihood of observing the trajectory decreases. When  $\beta = 0$ ,  $\text{Exp}(\beta) = 1$ , and the likelihood of  
304 observing the trajectory is not affected. The discrimination of the model, estimated through the area  
305 under the ROC curve (AUC), was 0.79. The probability map derived from the logistic function is

306 shown in Figure 3. The highest probability of forest expansion was mainly found in two locations:  
307 the whole southern part of the study area, corresponding with the lower peaks of the Cantabrian  
308 mountain range in the province of León, and valley bottoms in the northern part of the study area. In  
309 the latter, increasing the distance from valley bottoms reduced the probability of observing this  
310 change.

311

### 312 *3.3.2 Loss of shrub model*

313

314 Changes in population density ( $p= 0.12$ ) and number of head of goats ( $p= 0.17$ ) were excluded from  
315 the subsequent analyses according to the Mann–Whitney  $U$ -test. The remaining variables were taken  
316 into account in successive analyses because they were uncorrelated according to the Spearman test  
317 ( $r<0.8$ ): altitude ( $p< 0.01$ ), slope ( $p< 0.01$ ), number of head of cattle ( $p< 0.01$ ) and sheep ( $p< 0.01$ ).  
318 Loss of shrubland cover occurred in areas with a mean slope of 8.5 degrees, characterized by  
319 significant losses in the number of head of sheep and, at a lower extent, in the number of head of  
320 cattle.

321

322 The regression model was fitted as a function of the variables altitude, slope and number of head of  
323 both cattle and sheep (Table 5). The model discrimination was 0.62, which was lower than the fit of  
324 the forest expansion model. The probability map derived from the logistic function is shown in  
325 Figure 4. In this case, there were no clear patterns of spatial distribution of the change in the study  
326 area.

327

## 328 **4. DISCUSSION**

329

### 330 **4.1 Land cover change monitoring**

331

332 Land cover changes in the Cantabrian Mountains of León have followed the same trajectories  
333 observed in other Mediterranean mountain ranges since the beginning of the 20th century. The loss  
334 of traditional management practices (grazing, burning and cutting) have led to abandonment of both  
335 pastures and crops, resulting in shrub and forest encroachment (MacDonald et al., 2000; Lasanta-  
336 Martínez et al., 2005; Rey-Benayas et al., 2007; Pelorosso et al., 2009; Geri et al., 2010). We  
337 observed that, at the beginning of 1990s, almost half of the study area was covered by shrublands as  
338 the result of more than one hundred years of decline of the transhumance system (Rodríguez, 2005),  
339 increasing depopulation and an ageing population in the countryside (Collantes, 2001). This process

340 continued in the Cantabrian Mountains until 2000, when the trend started to change. The decrease in  
341 shrubland cover from 2000 to 2004 can be directly related to new conservation policies adopted in  
342 the study area. Four protected areas have been declared since 1990, covering 38% of the Cantabrian  
343 Mountains. In these protected areas, specific silvicultural measures have been introduced since 2000  
344 (Gil and Torre, 2007) to favour the regeneration of pastures to support extensive grazing and, at the  
345 same time, to create firebreaks to control both the risk and extent of fire. Such measures (particularly  
346 shrubland clearance to increase pastureland) have been successfully applied in other regions of Spain  
347 (Andalucía, Asturias, Galicia and La Rioja), as well as in other Mediterranean areas (Lasanta et al.,  
348 2009). Even in the few years since their introduction, these management strategies have had  
349 noticeable effects in the Cantabrian Mountains at regional scale. These include a reduction in arson  
350 fires in the study area (Head of Forest Fire Prevention, personal communication). The decrease in the  
351 area affected by forest fires can partly explain the 2.88% increase in forest cover recorded throughout  
352 the study period. Another key factor was the establishment of restrictive policies in the protected  
353 areas, involving a reduction in the incidence of some traditional management practices, such as  
354 burning. This is expected to drive secondary succession towards forest stages, as experienced in  
355 other protected areas in Spain (Peñuelas and Boada, 2003).

356

357 At this point, it is necessary to consider the interpretation of change from satellite images when  
358 comparing data from different months. Variations in the spectral behavior of the vegetation, due to  
359 its leaf water content, may lead to a certain level of confusion between land cover types, particularly  
360 in boundary areas, where the uncertainty is higher (Roy, 2000). Therefore, pixels on the border  
361 between shrublands and forests may be classified as a different land cover type depending on leaf  
362 moisture content. This effect has been detected in the study area, related to the fact that in 2000, the  
363 registered rainfall was 1655.1 mm, which represents less than one half of the value recorded in 2004  
364 (3817.4 mm) (Morán-Ordóñez, unpublished data). Even considering these sources of error, the trend  
365 of increase in forest cover (linked with abandonment) compares well with results reported over the  
366 last fifty years in other mountain ranges of northern Spain, including the Pyrenees (Roura-Pascual et  
367 al., 2005), as well as other areas of the Cantabrian Mountains (Rescia et al., 2008). Moreover, similar  
368 results were obtained by the Third National Forest Inventory 1992-2003 (Ministry of the  
369 Environment) for the Province of León.

370

371 The amount of herbaceous vegetation remained almost constant during the study period, despite the  
372 regional policies applied in the Cantabrian Mountains aimed at increasing pasture areas and  
373 enhancing extensive grazing system to economically and ecologically sustainable levels (Celaya et

374 al., 2007). This pattern may result from the compensatory effect of areas where shrub-cutting has  
375 been intensive (mainly in the more Atlantic municipalities) and areas where the successional trend  
376 linked with the abandonment of agricultural fields is continuing (mainly the most Mediterranean  
377 municipalities).

378

379 The extent of bare ground also increased over the study period, mainly due to the opening of three  
380 large quarries in the area since 1995. Silvicultural measures have also increased the percentage of  
381 bare ground in the study area. Shrub clearance has resulted in the affected areas apparently remaining  
382 as bare ground before the recovery of pasture species (especially in areas where *Genista* spp. and  
383 *Cytisus purgans* have been cleared).

384

#### 385 **4.2 Land cover change modeling**

386

387 A general goal of ecologists studying patterns of land cover change is to develop useful predictive  
388 models from many possible explanatory variables (e.g. Guisan and Zimmerman, 2000; Suárez-  
389 Seoane et al., 2002) to identify drivers of change. These models can be used as tools allowing  
390 managers to develop spatially-explicit environmental policies aimed at managing specific types of  
391 land cover to maintain biodiversity and the services they provide. In this sense, the binary logistic  
392 regression model successfully identified the drivers that have controlled the two main land cover  
393 changes under study (forest expansion and loss of shrubs). This knowledge is essential for defining  
394 regional strategies in the Cantabrian Mountains. Nowadays, the management of this area is shared  
395 among three administrative sections. Land cover changes, ecological processes and their drivers can  
396 differ between sections. Different authorities are responsible for each section, meaning that  
397 management decisions can be designed and performed independently from the others. However, the  
398 new challenges for conservation determined by EU policies will require an integrated understanding  
399 of the processes in the protected areas (Natura 2000 sites), whose boundaries do not correspond to  
400 administrative sections. Therefore, spatial models like the ones developed in this study can help  
401 managers to: i) understand what the main land cover processes in the whole mountain range are and  
402 where they are taking place; ii) identify the factors driving those changes as well as the extent at  
403 which they are acting; iii) integrate local-focused management and regional plans aimed at  
404 preserving areas of natural importance as a whole.

405

406 Forest expansion was best explained by topographic variables (altitude and slope), together with  
407 variations in the number of goats. Negative standardized logit coefficients indicated that the

408 probability of observing the analyzed trajectory decreases at higher altitudes and slopes. This may be  
409 due to the fact that forest recovery has occurred mainly in areas at medium altitude and with low  
410 slope close to the valley bottoms, where deeper and more fertile soils are found (Gil and Torre,  
411 2007). The loss of traditional management, based on timber extraction, and the abandonment of  
412 agricultural fields, located close to the villages, have favoured an increase in forest in lower areas.  
413 However, the logit coefficient for reductions in the number of goats indicated a positive relationship  
414 with the probability of forest expansion. Goats use not only herbaceous vegetation, but also woody  
415 species (Papachristou et al., 2005), whereas cattle and sheep only use herbaceous vegetation. This  
416 fact should be taken into account to understand the role played by goats in keeping both the forest  
417 understory clean of ground fuels and grassland areas clean of shrubs and wooded patches (Verdú et  
418 al., 2000; Celaya et al., 2007; Sebastián-López et al., 2008).

419

420 In contrast, the model for the loss of shrubland cover had low accuracy (AUC=0.62), probably  
421 because the change it describes depends not only on biophysical or socio-economic factors, but also  
422 on decisions made by managers at a regional level. The opening of pastoral areas by means of shrub  
423 clearing has occurred only in municipalities where the neighborhood council demanded them.  
424 Shrublands are distributed throughout the study area, across a wide range of environmental  
425 conditions. The locations of shrubland clearances are only dependent on the specific place where  
426 pastures are required for sheep and cattle grazing and the feasibility of the terrain as a source of  
427 short-term pasture. Therefore, even if this land cover change is clearly detected by LANDSAT  
428 images, it is difficult to model using logistic regression. The model, in spite of its low accuracy,  
429 provides a general description of the main drivers influencing the observed changes. Changes in  
430 cattle numbers were the most important variable in the model, reflecting the increased use of pastures  
431 for this kind of livestock, which has become more and more popular in the Cantabrian Mountains of  
432 León, as in other areas of the Cantabrian range (Rescia et al., 2008). As a result of the abandonment  
433 of the transhumance system, summer pastures have progressively been occupied by cows (even from  
434 neighboring provinces) due to their easier management: farmers can leave the cattle to roam free in  
435 the pastures for days, which imply a lower effort than having sheep or goats. Changes in the number  
436 of sheep were also important in the model because, as mentioned above, sheep together with cattle  
437 are responsible of the demand for shrub cutting.

438

## 439 **5. CONCLUSIONS**

440

441 After more than fifty years of rural abandonment and loss of traditional management in León  
442 Cantabrian Mountains, important land cover changes can be detected: an increase in bare ground,  
443 loss of shrublands and increase in forest cover. These trends have become more significant since  
444 2000, when modification in forestry policies introduced important changes aimed at substituting for  
445 the loss of traditional management practices (mainly shrub clearance). LANDSAT images were an  
446 important tool for analyzing these changes at a regional scale in mountain areas with high  
447 heterogeneity. Binary logistic regression models allowed the main drivers linked with these changes  
448 to be identified. In general terms, predictive models such as these could be used as a spatially explicit  
449 tool to address management strategies. Based on this information, managers can focus their attention  
450 on areas with a high risk of change and declare them as priority areas in terms of conservation and  
451 management. Knowledge about the drivers of change can also help in developing particular policies  
452 aimed at promoting the maintenance of traditional activities, which could be essential for preserving  
453 the cultural landscapes in the Cantabrian Mountains.

454

## 455 **6. ACKNOWLEDGEMENTS**

456

457 The study was supported by the Junta de Castilla y León (project number: LE021A08) and the  
458 Ministry of Science and Education (project number: CGL2006-10998-C02-01/BOS). The Ministry  
459 of Education of Spain provided the PhD-Scholarship for Alejandra Morán-Ordóñez. The authors  
460 would like to thank J.M. Alvarez for his help. We also are grateful to Althea Davies, Stefano  
461 Canessa and Jane Elith for their help in improving the language, and to the Cartography Support  
462 Service of the University of León and the forest engineers and rangers of the Autonomous Regions  
463 of Castilla y León for their support and comments. Finally, we wish to thank the Environmental and  
464 Livestock Sections of the Junta de Castilla y León for providing digital geographical and socio-  
465 economical data. The authors thank the anonymous referees for valuable comments and corrections.

466

467

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- LANDSAT-based classification and modelling identify land cover changes and drivers.
- Forest expansion and loss of shrublands are the major trajectories of change.
- Forest expansion is mostly linked to land abandonment and livestock changes.
- Loss of shrub cover is mostly linked to management decisions (shrub clearance).
- Predictive models can be used as a spatially explicit support tool for land managers.



Figure1

[Click here to download high resolution image](#)

Figure 1. Location of the study area in the north of León province, Spain.

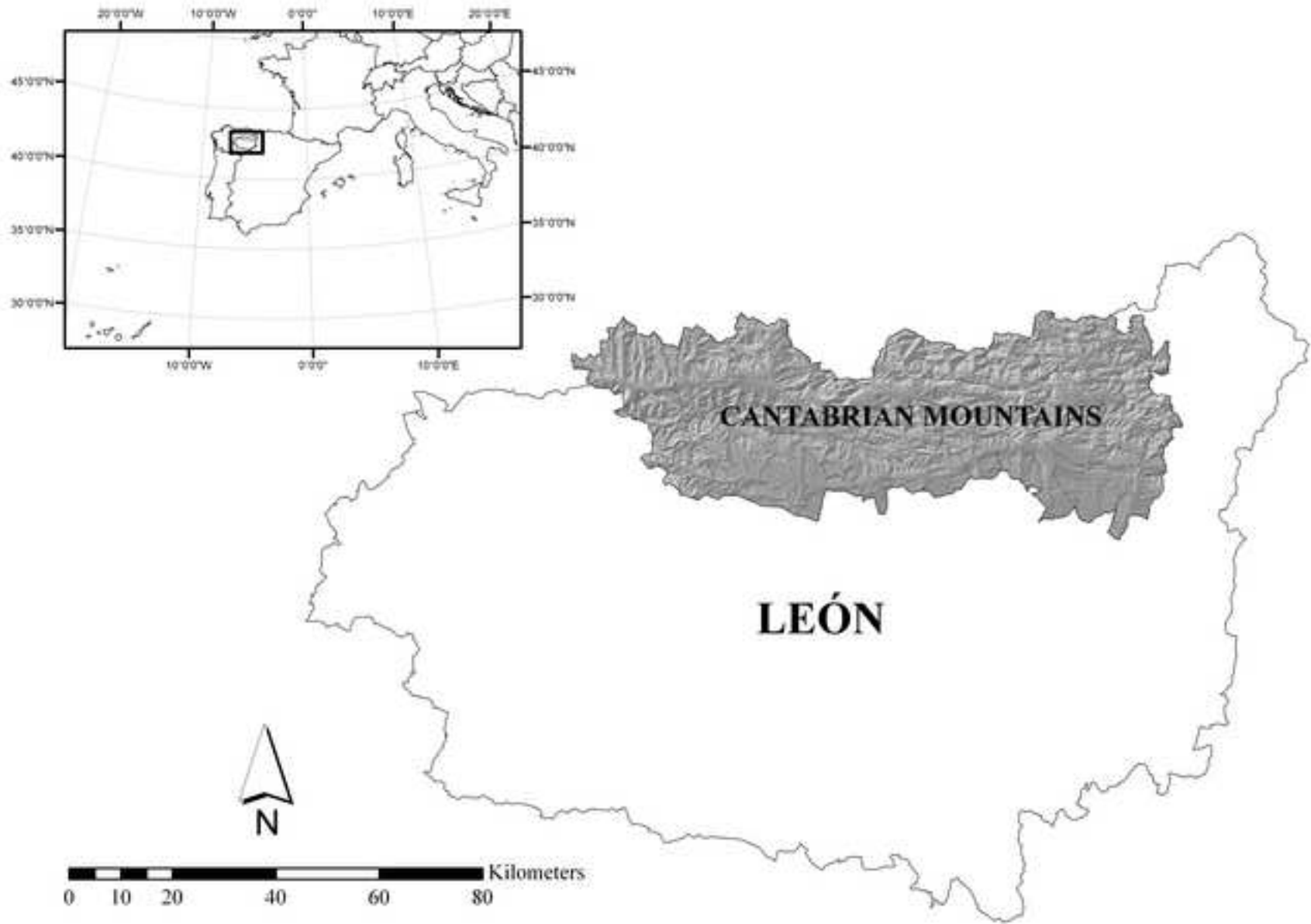


Figure 2. The four categorical land cover maps derived from the LANDSAT scenes used in the analysis (1991, 1995, 2000 and 2004).

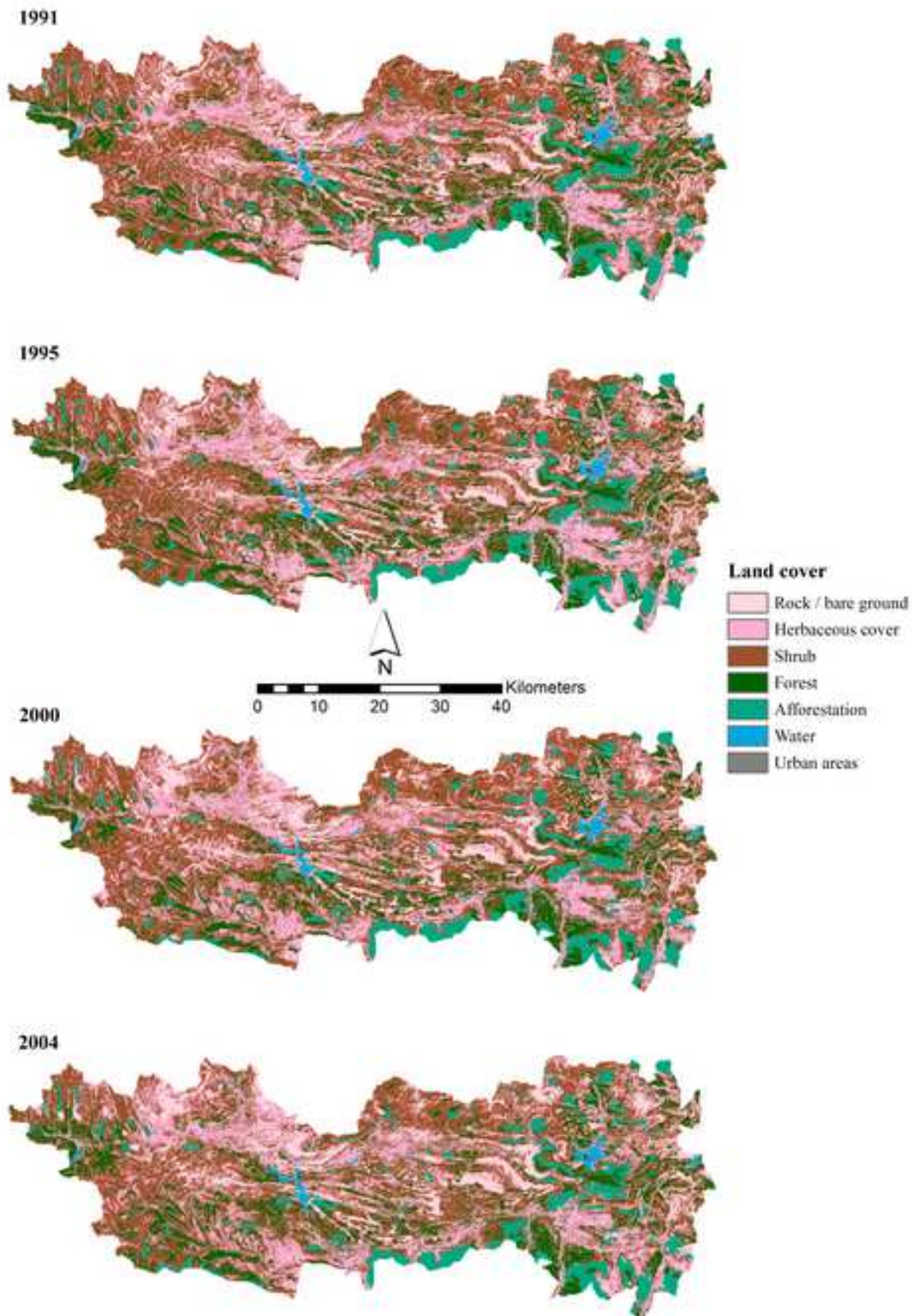


Figure 3. Probability of forest cover expansion

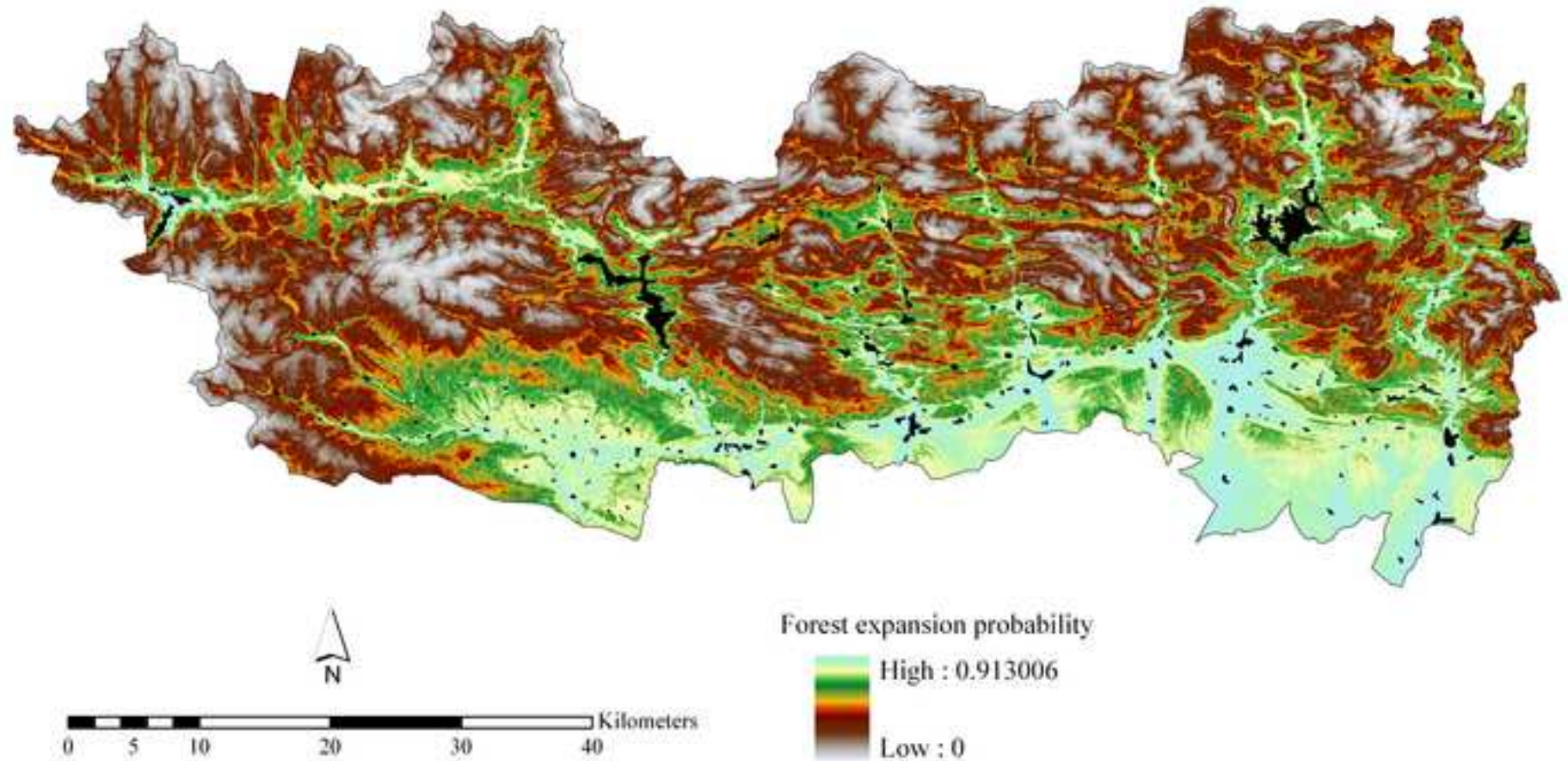




Figure 4. Probability of loss of shrub cover.

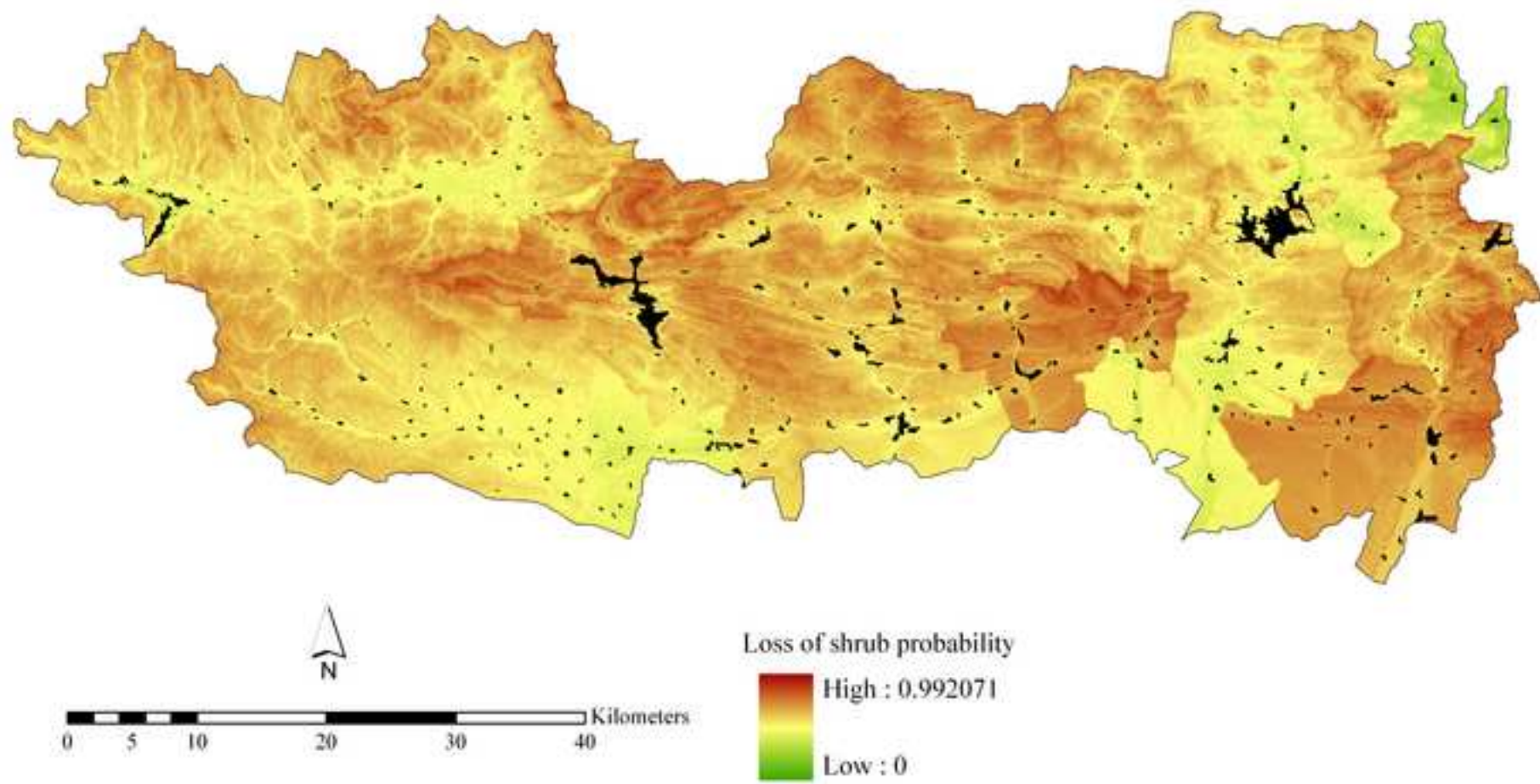


Table 1. LANDSAT images used in the land cover change analysis showing dates of acquirement, type of sensor and sun elevation angle expressed in degrees units (S. E. A).

Date	Sensor	S. E. A
08-04-1991	TM	54.15
08-15-1995	TM	48.87
09-05-2000	ETM+	49.45
09-24-2004	TM	42.72

Table 2. Data sources and variables used for LANDSAT image classification and analyses of land cover change.

Type	Data source, scale and spatial resolution	Date	Code	Variable definition
Remote sensing variables	LANDSAT images (30m)	1991, 1995 2000, 2004	<i>Bx</i>	Bands from 1 to 7 (excluding band 6)
			<i>NDVI</i>	Normalized Differenced Vegetation Index (NDVI), calculated as $(NIRC - NR) / (NIRC + NR)$ or $(BAND\ 4 - BAND3) / (BAND4 + BAND\ 3)$ .
			<i>GI</i>	Greenest Index calculates as $(NIRC / NG - 1)$ or $(BAND\ 4 / BAND2 - 1)$
			<i>TEX</i>	Texture: variable which enhances texture differences between categories. Calculated from the third band of each image.
Topographic variables	Digital Elevation Model (5, 30 m), Junta Castilla y León		<i>DEM</i>	Altitude
			<i>SLO</i>	Slope (degrees)
Land cover variables	Vectorial layers at 1:200,000 scale, Junta Castilla y León	2000	<i>URB</i>	Urban areas
			<i>WAT</i>	Reservoirs, lakes and pools
	Spanish Ministry of the Environment (Second and Third National Forest Inventories at 1:200,000 scale)	1996 2006	<i>CON</i>	Patches of conifer plantation established from 1900 to 1996.
			<i>NFI2</i>	Vegetation
Socio-economic variables	Spanish Statistics Institute, Caja España	1991-2004	<i>POP</i>	Changes in human population density (municipality level) by Ha
	Junta Castilla y León, sanitary campaigns	1999-2005	<i>CAT</i> <i>SHE</i> <i>GOA</i>	Change in number of head of cattle, sheep and goats (municipality level) by Ha

Table3

Table 3. Producer's accuracy (P.A.) and user's accuracy (U.A.) values specified per land cover category and year. The percentages of the total study area occupied each year per land cover category are also detailed. NC91/04 represents the percentage of net change for the period 1991-2004 (note that these percentages of change were calculated on the basis of the surface occupied by each land cover in 1991).

	Rock/bare ground			Herbaceous			Shrub			Forests			Overall accuracy
	P.A.	U.A.	%	P.A.	U.A.	%	P.A.	U.A.	%	P.A.	U.A.	%	
1991	96.12	95.19	11.91	84.16	94.44	21.46	93.33	85.22	42.99	94.34	94.34	13.99	92.05
1995	97.09	96.15	13.37	81.25	89.66	21.03	89.42	86.92	42.41	92.38	88.18	13.55	90.20
2000	87.13	97.78	12.30	78.50	88.42	22.63	96.12	77.95	43.09	90.00	90.91	12.34	87.83
2004	93.88	94.74	14.01	79.57	91.85	21.42	93.50	83.60	40.53	91.00	87.03	14.39	89.10
NC91/04			+17.69			-0.19			-5.72			+2.88	

Table 4. Cross-tabulation matrix analyses between the main land covers (values expressed in percentages).

1991	2004			
	Rock/bare ground	Herbaceous vegetation	Shrubs	Forests
Rock/bare ground	67.36	9.00	8.94	1.55
Herbaceous vegetation	15.90	53.26	16.90	5.94
Shrubs	16.00	27.06	65.42	33.50
Forests	0.74	10.68	8.73	59.01



Table 5. Main drivers retained in the final BLR models and their estimated coefficients.

	<b>Variable</b>	<b><math>\beta_1</math></b>	<b>SE</b>	<b>Wald</b>	<b>Sig.</b>	<b>Exp (<math>\beta_1</math>)</b>
Forest expansion	Altitude ( <i>DEM</i> )	-0.004	0.000	164.352	0.000	0.996
	Slope ( <i>SLO</i> )	-0.099	0.018	29.491	0.000	0.906
	Goat change ( <i>GOA</i> )	10.686	5.280	4.096	0.043	43759.825
	Constant	5.787	0.381	230.285	0.000	326.154
Loss of shrub cover	Altitude ( <i>DEM</i> )	0.001	0.000	9.704	0.002	1.001
	Slope ( <i>SLO</i> )	0.044	0.012	13.104	0.000	1.045
	Cattle change ( <i>CAT</i> )	5.332	1.689	9.965	0.002	206.751
	Sheep change ( <i>SHE</i> )	-3.781	1.063	12.657	0.000	0.023
	Constant	-1.313	0.311	17.824	0.000	0.269

$\beta_1$ : Coefficient, SE: Standard error of estimate, Exp ( $\beta_1$ ): Exponential coefficient/odds ratio