

Yolanda Pueyo (a) and Santiago Beguería (b)

^aInstituto Pirenaico de Ecología, CSIC, Campus de Aula Dei, P.O. Box 202, 50080
Zaragoza, Spain

^bDepartment of Physical Geography, GIS and Hydrology, Faculty of Geosciences,
Utrecht University, P.O. Box 80.115, 3508TC Utrecht, The Netherlands

1 **MODELLING THE RATE OF SECONDARY SUCCESSION AFTER**
2 **FARMLAND ABANDONMENT IN A MEDITERRANEAN MOUNTAIN AREA**

3

4 **Abstract**

5 Secondary succession after farmland abandonment has become a common process
6 in north Mediterranean countries, especially in mountain areas. In this paper a
7 methodology is tested which combines Markov chains and logistic multivariate
8 regression to model secondary succession after farmland abandonment in environments
9 where abiotic constraints play a major role, like mountain areas. In such landscapes a
10 decay in the succession rate with time is usually found, as the best locations are
11 progressively occupied. This is frequently addressed using non-stationary Markov
12 chains. Here, we test if the combination of logistic multivariate regression with Markov
13 chains, however, allows for spatially distributed transitions probabilities based on
14 abiotic factors and therefore it is able to reproduce the preferential colonization of the
15 most favourable locations. The model is tested in the Ijuez valley in the Spanish
16 Pyrenees, which underwent generalised land abandoned during the 50s. Results confirm
17 a substantial improve in the prediction success of the Markov-logistic model when
18 compared to the standard Markov chain approach. As a result, the decay in the
19 succession rate can be successfully modelled. The specific results for our study area are
20 discussed further in an ecological context. The methodology proposed is applicable to
21 any landscape where vegetation dynamics are constrained by environmental factors.
22 However, the inclusion of land use as an explanatory factor would be necessary in
23 human-managed landscapes.

24 **Keywords:** environmental constraints, logistic regression, Markov chains, *Pinus*
25 *sylvestris*, Pyrenees, succession rate.

26 **Introduction**

27 North Mediterranean countries are enduring rural depopulation since last century,
28 specially in marginal areas like mountains (Lasanta et al., 2005; Romero-Calcerrada and
29 Perry, 2004). Immediate consequences of this process are farmland abandonment and
30 decrease in livestock pressure (García-Ruiz et al., 1996; Lasanta et al., 2006; Pueyo and
31 Alados, in press), which enhances natural secondary succession and leads to
32 reforestation of previously occupied areas (Beguería, 2006a; Beguería et al., 2003;
33 Rocchini et al., 2006; Sickel et al., 2004).

34 There is large interest in applied ecology and environmental planning in
35 understanding the driving processes of secondary succession, because usually land use
36 changes (in type or intensity) lead to land cover change. For this reason, a considerable
37 amount of studies have been devoted to quantify the magnitude of changes in land cover
38 and the processes originating them, like rural abandonment and global warming
39 (Riebsame et al., 1994; Vicente-Serrano et al., 2004). At a finer scale, secondary
40 succession is constrained by physical conditions like topography (Pan et al., 1999). This
41 is specially true for mountain areas, where topography controls climatic gradients and
42 soil and water distribution (del Barrio et al., 1997; Villalba et al., 1994). After a large
43 disturbance, secondary succession is determined by the differential growth, survival and
44 colonization ability of plant species, which can differ largely depending on the
45 environmental conditions (Aragón and Morales, 2003; Mueller-Dombois, 2000; Myster
46 and Pickett, 1994). As a consequence, high variability in the succession rate has been
47 observed in highly heterogeneous areas like mountain landscapes (Prach, 1993).

48 There is hence great interest in the ability to model the process of secondary
49 succession. When conveniently calibrated for a given case study, spatially-explicit
50 simulation models can become a useful tool for decision making in landscape planning.

51 This is because they allow understanding the main driving factors in the process, but
52 they also provide ecological forecasting tools for scenario testing. In this context,
53 Markov chain models have been frequently used for modelling ecosystem dynamics,
54 and more specifically for vegetation succession processes (Acevedo et al., 1995;
55 Balzter, 2000; Callaway and Davis, 1993; Usher, 1979).

56 A Markov chain model describes the states of a system at successive times. The
57 system is characterized by a discrete variable which can adopt several states, and hence
58 the Markov chain describes its changes of state (transitions). In the context of vegetation
59 dynamics, the states of the system are the different vegetation types which characterize
60 the secondary succession sequence. A concept central to the Markov chain theory are
61 the transition probabilities, which quantify the likelihood of a given transition. In a
62 standard Markov chain approach, it is assumed that transition probabilities are constant
63 across space and stationary in time. These conditions are hardly found in nature. For this
64 reason, several authors have criticized their adequacy, and alternative models have been
65 proposed (Hill et al., 2002; Yemshanov and Perera, 2002).

66 Since transition probabilities are constant across space (usually obtained from
67 counts over the whole spatial domain), standard Markov models average the spatial
68 effects (Usher, 1981). Thus, they are not able to represent the spatial heterogeneity of
69 succession rates present in a real landscape, and consequently they fail in predicting
70 vegetation dynamics in heterogeneous environments. In order to solve this problem,
71 Yemshanov et al. (2002) defined various environmental domains in their study area and
72 derived specific transition matrices for each of them. An improved approach consists on
73 considering the transition probabilities as a continuous spatial variate, dependent on the
74 spatial variation of a set of explanatory variables. These transition probabilities have
75 been estimated using multivariate regression techniques (Augustin et al., 2001), and

76 artificial neural networks (Gullison and Bourque, 2001).

77 The assumption of stationarity of transition probabilities over time, i.e. that
78 transition probabilities remain constant during the succession process, is another
79 important issue which complicates the application of Markov chain models to the
80 analysis of natural systems (Childress et al., 1998; Usher, 1979). Observation often
81 contradicts the stationarity assumption, since succession rate tends to decrease with time
82 (Myster and Pickett, 1994; Shugart and Hett, 1973). Usher (1979) pointed out that
83 natural succession should be usually modelled as a non-stationary Markov process, i.e.,
84 allowing the transition probabilities to change with time. If observations are available at
85 different times, this can be approached by calculating different transition probabilities
86 for each observation interval (Benabdellah et al., 2003; Hill et al., 2002). However, this
87 approach fails to explain the reason why transition probabilities change in time. Besides,
88 it does not allow predicting future states of the system, since future transition
89 probabilities are not known. By including external abiotic factors in transition models it
90 could be possible to explain the decay of succession rate by natural ecological
91 processes, and thus to predict the future evolution of the succession process.

92 The aim of this work was to assess a methodology to predict the process of
93 secondary succession after farmland abandonment. This methodology was tested in a
94 small valley in the Pyrenees, the Ijuez RiverValley. We hypothesized that secondary
95 succession rate after farmland abandonment is not spatially homogeneous, but shows
96 important differences because of the spatial heterogeneity of the abiotic factors. Also we
97 hypothesized that succession rate would show a decay through the process of secondary
98 succession due to the decreasing availability of favourable locations as the process
99 advances.

100 We used a simple model which simulates the process of secondary succession

101 based on a stationary Markov chain. Transition probabilities were not spatially
102 homogeneous, but they were estimated using multivariate logistic regression from a set
103 of spatially distributed variables, to allow for spatial heterogeneity. We expected that
104 such a simple model would be able to predict both the temporal and the spatial patterns
105 of secondary succession better than the standard Markov approach.

106 This work will contribute to understand the process of secondary succession after
107 farmland abandonment on environments with strong abiotic constraints, such as
108 mountain areas. Although the specific results of our research (i.e. the vegetation
109 transition model) are in principle valid only for the specific conditions of the study area,
110 the theory and methods can be generalized for the analysis of secondary succession in
111 any other area. Modelling the process of secondary succession can be a useful tool for
112 environmental planning and forest managers, in Mediterranean mountain areas where
113 land abandonment has been a common landscape process in the last decades, but also at
114 a European scale, where landscape homogenization requires a scientific based landscape
115 planning to maintain cultural and ecological values (Jongman, 2002; Lasanta et al.,
116 2006).

117 **Materials and methods**

118 *Study area*

119 The study area corresponds to the Ijuez River Valley, a small tributary to the
120 Upper Aragón River in the Central Spanish Pyrenees, covering an area of 54.6 km².
121 The altitude of the valley ranges from 800 to 2200 m. a.s.l. (Fig. 1). The valley lies
122 within the Eocene Flysch sector, lithology consisting of a succession of thin, alternating,
123 heavy folded layers of marls and sandstones. Climate is of submediterranean type, with
124 average temperature ranging from 3.5° to 10° and annual rainfall ranging between 1000

125 and 2000 mm (Ibarra and De la Riva, 1996).

126 The Ijuez River valley supported a high human pressure until the last decades of
127 the 19th Century, with full occupation of the land available for cultivation and grazing.
128 According to Ibarra and De la Riva (1996) the depopulation process was slow but
129 steady in the first decades of the 20th century, so by 1950 the valley population was
130 62% of the population in 1900. In the years 1956 to 1960 the five villages in the valley
131 and most part of the arable lands were bought by the State Forest Service for land
132 reclamation. The population of the valley descended to 26.7% of the initial population
133 by 1960 and 4.4% in 1970. Some reforestation works were carried out mostly between
134 1956 and 1965 in the abandoned lands, and the rest of the valley underwent a process of
135 natural vegetation recovery. The forestry (natural or aforestations) is not managed for
136 timber production or other purposes. Currently there is no significant land use in the
137 valley except for some crops and meadows in the valley bottom (2% of the area) and
138 cow summer grazing in the alpine pastures (7% of the area). These conditions conform
139 an excellent scenario to study the influence of abiotic factors in secondary succession
140 with minimum interference of land use, which is a problem often encountered.

141 Potential vegetation in the valley is a forest of *Quercus faginea* Lam. below 1200-
142 1300 m, and *Pinus sylvestris* L. woodland (Scots pine) above this altitude (Montserrat,
143 1966). *P. sylvestris* has extended its potential area to lower altitude in detriment of *Q.*
144 *faginea* forest, favoured by aforestations and faster growing rates in secondary
145 succession (Montserrat, 1966).

146 Secondary succession after farmland abandonment in the study area leads to a fast
147 invasion by weeds (*Brachypodium pinnatum* (L.) P.Beauv., *Carex flacca* Schreb.,
148 *Bromus erectus* Huds., *Medicago lupulina* L.) in the first three years, and by shrubs
149 afterwards (*Genista scorpius* (L.) DC., *Juniperus communis* L., *Rosa sp.* and *Crataegus*

150 *monogyna* Jacq.). Finally, *P. sylvestris* colonizes the shrublands, usually developing a
151 monospecific forest, although it can be mixed with *Q. faginea* specially in south
152 oriented slopes where pines grow slower (Gracia et al., 2002). As a consequence,
153 secondary forest in the study area consists mostly on *P. sylvestris* along the whole
154 altitude range.

155 *Assessing land cover change*

156 We built a GIS database based on the analysis of a sequence of aerial photos
157 dating from 1957 (black and white images at aprox. 1:32000 scale), 1977 (black and
158 white images at aprox. 1:18000 scale) and 2002 (digital color orthophoto with a
159 resolution of 1 m). The older photos were orthorectified using the 2002 image as
160 reference and a 10 m digital terrain model (DTM) with Erdas Imagine 8.5, for a final
161 resolution of approximately 1 m.

162 Areas that were cultivated before 1957 were identified and mapped based on the
163 1957 aerial photos and information on the abandonment process from a previous study
164 by Ibarra & de la Riva (1996). The sucesional state of patches that were abandoned
165 was assessed on consecutive images. The abandoned patches were determined and
166 classified into three categories: shrubland, secondary forest and reforestation. Due to
167 difficulties in recognizing shrubland composition in the old aerial photos, only one
168 shrubland category was identified which includes from early to more mature stages of
169 shrubland development. A patch was classified as forest when presenting a percentage
170 of soil covered by trees greater than 60%. Artificial reforestation was identified very
171 clearly, thus not leading to any uncertainty.

172 Since the interest of this work was the natural succession process, we identified
173 and removed from the analysis the human-promoted transitions (i.e. conversion of
174 natural cover into croplands, which was in any case very limited, and reforestation;

175 Figure 3). Thus, our analysis was restricted to abandoned farmland areas, isolating the
176 process of natural secondary succession from human-induced changes. Usually, it is
177 difficult to separate abiotic factors from human land use, because they are closely
178 interrelated (Poyatos et al., 2003). However, considering the abrupt depopulation of the
179 Ijuez valley in the decade between 1955 and 1965, we consider that these problems
180 have been reduced to a reasonable minimum in this study.

181 *Assessing the temporal pattern of secondary succession by a standard Markov chain*

182 In a standard Markov chain model, stationary transition probabilities are applied
183 recursively each time step to simulate the changes of state of the system being
184 modelled. This requires the construction of a transition matrix, which includes the
185 transition probability for each possible change between two states (Caswell, 2001). The
186 transition matrices are usually inferred from empirical evidences of the state of the
187 system at various times. From the transition matrix it is possible to predict the
188 proportion of the different vegetation classes at any time, average transition times from
189 one class to another and the average time to reach the final (absorbing) state. In our case
190 we considered only the transition from abandoned fields to shrubland, and from these to
191 incipient secondary forest (the absorbing state). We calculated three transition matrices
192 counting the spatial units (grid cells), n_{ij} , that changed from state i to state j ($i = j =$
193 {abandoned field, shrubland, secondary forest}) between two consecutive land cover
194 maps.

195 We tested for non-stationarity of transition probabilities using the Anderson–
196 Goodman test (Anderson and Goodman, 1957),

$$197 \quad -2 \ln(\lambda) = 2 \sum_i \sum_j \sum_t n_{ij}(t) \ln(p_{ij}(t)/p_{ij}) \quad (1)$$

198 where $n_{ij}(t)$ and $p_{ij}(t)$ are the frequency and transition probabilities at time t , and p_{ij} is

199 the average transition probability from i to j . $-2 \ln(\lambda)$ follows a χ^2 distribution with
200 $m(m-1)(t-1)$ degrees of freedom, m being the number of possible states. The null
201 hypothesis tested is that $p_{ij}(t)$ is constant and equal to p_{ij} .

202 *Assessing the spatial pattern of secondary succession by multivariate logistic regression*

203 The use of averaged transition probabilities as calculated in the transition matrix
204 has the drawback of masking the spatial heterogeneity in secondary succession rate that
205 usually exists in real landscapes. For this reason, we used multivariate logistic
206 regression to estimate transition probabilities from spatially distributed variables, in a
207 similar way that was proposed by Augustin et al. (2001). We performed logistic
208 regressions for the transitions between every two consecutive maps. We used forward
209 and backward stepwise procedures to choose only the variables that were relevant to the
210 models. We looked at the variables entering the models and their importance for
211 transition probabilities through their Wald statistics (Hair et al., 1998). Overall fitting of
212 the models was evaluated by the receiver operating characteristic (ROC) curve and
213 computing the area under the curve, AUC (Beguería, 2006b; Swets, 1988). Then, we
214 derived forest transition probability maps for each time period from the regression
215 models, as well as a transition time map.

216 The explanatory variables were derived from a DTM with 10 m resolution. The
217 variables were the elevation (km), the slope gradient ($m\ m^{-1}$), the topographic index,
218 and the potential radiation (kJ). Elevation strongly determines temperature and rainfall
219 in mountain areas (Barry, 1922), and thus it is broadly used as a proxy for climatic
220 gradients (Arroyo and Marañón, 1990; Fernandez et al., 2004). In the study area the
221 temperature gradient with altitude can be determinant, because secondary succession by
222 *P. sylvestris* is observed in its natural range and also at lower elevation. Slope gradient

223 and the topographic index account for water and nutrient availability in the soil. Slope
224 gradient represents the potential energy available at a point, and controls hydrological
225 and erosion processes in the soil (Florinsky et al., 2002). The topographic index $\ln(A_s/\beta)$
226 (non-dimensional) is calculated from the relative accumulated drainage area, A_s , (i.e.
227 the total upslope area draining to a certain pixel divided by the area of the pixel) and the
228 slope gradient, β (Beven and Kirkby, 1979). The topographic index has been
229 extensively used to express the accumulation of water and soil in the landscape
230 (Gómez-Plaza et al., 2001). Annual potential radiation influences soil temperature and
231 evaporation and hence soil water content, and thus it may also be a decisive factor for
232 determining the succession rate. Potential radiation was estimated using the Potrad 5.1
233 model, written in the PCRaster dynamic modelling language.

234 As a result of this stage, the logistic models were translated into maps showing the
235 spatial distribution of the transition probabilities from shrubland to forest for the three
236 observation intervals.

237 *Stochastic simulation of the secondary succession process*

238 In order to assess the capability of the above transition models to adequately
239 represent the time development of the succession process, we performed a stochastic
240 simulation using the transition probability map obtained from the first observation
241 interval. The transition probabilities were applied recursively to the cells corresponding
242 to the abandoned fields, which were initially set to shrubland. The simulation period
243 was set to 1950-2002, corresponding to the observation time, and it was subdivided into
244 a number of equal timesteps. At each time step a random field was generated, and the
245 state of each cell was either changed to forest if the random value at the cell was equal
246 or lower than the transition probability, or left as shrubland in the opposite case. Cells

247 changed to forest were not changed in subsequent time steps. For comparison purposes,
248 an alternative simulation was made using the average transition probabilities obtained
249 from the transition matrices, which represents a standard Markov chain approach. The
250 ability of the Markov-logistic stochastic simulation to predict the observed spatial
251 distribution of vegetation in 2002 was assessed. The statistic employed was the success
252 rate, computed as the percentage of pixels that were well predicted in 2002 (Fielding
253 and Bell, 1997). We also compared the proportion of forest predicted by both models at
254 the three moments with real observations. This allowed us to determine which model
255 best predicted the decay in secondary succession rate. Due to the stochastic nature of the
256 modelling approach, a different final configuration is obtained each time a new
257 simulation is run. In order to obtain reliable validation statistics we used a Monte Carlo
258 technique, consisting on performing a high number (1000) of simulation runs and using
259 the most frequent final state (shrub or forest) for each pixel to compute the statistic
260 (Manly, 1997).

261 **Results**

262 The analysis of the sequence of aerial images confirmed that secondary forest
263 succession following land abandonment has been the dominant process during the
264 second half of the 20th century in the Ijuez Valley (Fig. 2). From the initial state in
265 which 61% of the territory was cultivated, a big part of the farmland (74%) had already
266 been abandoned around 1957 (Fig. 3). 56% of the abandoned fields remained in the
267 shrubland stage, and only 6% of the abandoned surface had reached the incipient forest
268 state by 1957. The other 12% of the surface had been reforested. By 1977 only 14% of
269 the remaining farmland was maintained, while 11% presented a shrubland cover and 9%
270 had evolved towards secondary forest. Important reforestation works were performed on
271 this period, which affected 66% of the abandoned farmland. During the same period,

272 24% of the shrubland (fields abandoned in the previous interval) evolved into forest,
273 and 65% remained in the same state. From 1977 to 2002 there was no more land
274 abandonment, but secondary succession continued in the shrubland areas. By 2002
275 croplands were nearly inexistent, only appearing on the valley bottom (around 2% of the
276 total territory). Incipient secondary forest dominated the landscape, although shrub still
277 remained in large areas (21% of the territory; Fig 2).

278 From the previous analysis on the land cover changes in the valley transition
279 matrices were calculated only for the patches that were abandoned and led to natural
280 succession (Table 1). That is, artificial reforestation of former farmland and the
281 continuity of crops were excluded from the analysis. The period 1957 to 1977 allows
282 comparing the transition probabilities to secondary forest from recent and old
283 abandoned fields (Table 1, panel b). According to the results, the transition probability
284 is lower for the recently abandoned fields, supporting the hypothesis of a decay in the
285 succession rate with time. The same result is found when comparing transition from
286 shrubland to secondary forest (Table 1, panels b and c), for which it was found that the
287 transition probability was reduced from 0.27 to 0.15 between 1957 and 2002. If this
288 probability is referred to a period of one year to correct for the different time spans
289 between the images, the reduction in the transition probability becomes more evident
290 (0.0135 and 0.006). This represents a decay in the average succession rate, which was
291 confirmed by the Anderson-Goodman test of stationarity ($\chi^2 = 1406$, $p < 0.001$).

292 In order to obtain transition probabilities dependent on abiotic conditions (and
293 thus, spatially variable), three logistic models were adjusted to the transitions observed
294 starting from abandoned fields in 1957, from shrubland in 1957 and from shrubland in
295 1977. The three models showed a good fit to the data, with AUC equal to 0.77, 0.83 and
296 0.76 for models a, b and c, respectively (Table 2).

297 Selection of variables by the two stepwise methods (forward and backward) was
298 consistent, resulting in identical sets of predictor variables. According to the Wald
299 statistic the most important variable in all the three models was potential radiation,
300 having a negative effect on forest transition probability. This results confirm that solar
301 radiation exerts a negative effect on secondary succession rate in our study area.
302 Elevation was the second variable in importance in the first model (Table 2a), but it did
303 not appear in the next two models. Slope gradient and the topographical index, showing
304 positive relation to transition probability, appeared to be much less important in the
305 model. After potential solar radiation, the most important variable in the second and
306 third models was slope gradient, inversely related to transition probability (Table 2b and
307 2c). The topographic index showed decreased importance with respect to the previous
308 model.

309 Three maps showing the spatial distribution of transition probabilities were
310 derived from the logistic models (Fig. 4). It can be observed that locations showing high
311 transition probabilities on one moment tend to be occupied by forest in the next step,
312 and thus excluded from the analysis. On the contrary, locations with low transition
313 probabilities tend to appear in subsequent maps, showing slower succession rate. This
314 information can be presented in the form of transition times, i.e. the estimated time to
315 reach the forest state (Fig. 5). Expected transition times to secondary forest in the study
316 area ranged between 25 years in the most favourable areas and more than 200 years in
317 the least favourable ones.

318 It must be noted that the transition probabilities show more or less the same values
319 at the same locations in the consecutive maps (Fig. 4). The faster occupation of the cells
320 with high transition probability is, thus, responsible for the reduction in the average
321 transition probability which was found previously. This result supports the hypothesis

322 that the succession process can be modelled by a stationary approach, i.e. using the
323 transition probability map from the first observation interval. The results of one such
324 stochastic simulations (Markov-logistic simulation) are shown in Figure 6. A good
325 agreement was found between the simulation results and the situation observed in 2002,
326 the success rate being 67%. For comparison, a standard Markov chain simulation with
327 averaged transition probabilities was not able to predict the spatial distribution of
328 succession states (Fig. 6c), and yielded a success rate of only 50%.

329 An important fact shown by the Markov-logistic stochastic simulation was the
330 faster colonisation of the most favourable locations. Locations with high transition
331 probability became scarcer as the process advances in time, which determines a decay in
332 the average transition probabilities in the Markov-logistic simulation (Fig. 7). This
333 contrasts with the standard Markov chain model, in which transition probabilities are
334 constant through time. If one compares the observed proportion of secondary forest in
335 the three aerial photos with the forest cover predicted by the two simulations (Fig. 8), a
336 better agreement is also found between the Markov-logistic model and the observation.
337 This has major importance if predictions are to be made about the future state of
338 vegetation in the area, for example in the context of a decision making process through
339 scenario testing. We prolonged the simulation up to year 2100, in order to compare the
340 percentage of forest cover predicted by the two models (Fig. 8). Compared to the
341 standard Markov model, the Markov-logistic simulation predicts a more realistic decay
342 in forest recovery rate, and hence the time to total recovery is significantly higher. The
343 decay curve can be adjusted by a logarithmic function (Fig. 8).

344 **Discussion**

345 This study has shown the existence of a strong relationship between transition
346 probability (and its reciprocal, the succession rate) and abiotic factors in a mountain

347 landscape. This agrees with the results obtained by other authors, which show that forest
348 succession rates can show large differences over relatively short distances in response to
349 environmental gradients (Aragón and Morales, 2003; Carmel and Kadmon, 1999;
350 Donnegan and Rebertus, 1999). This implies that the spatial pattern of secondary
351 succession can be successfully modeled upon the spatial distribution of the abiotic
352 factors.

353 Vegetation dynamics are very often addressed using Markov chain models, in
354 which transition probabilities are obtained from cross-counting between two correlative
355 vegetation surveys. Utility of Markov chains has been criticized to model future
356 transitions because observed succession rates are seldom stationary (Usher, 1981). In
357 practice, decay in succession rate is observed very often in natural ecosystems (Myser
358 and Pickett, 1994; Shugart and Hett, 1973).

359 We demonstrate that the decay in succession rate can be modelled using a
360 stationary first order Markov chain if factors determining transition probabilities and
361 their spatial distribution are included in the model. Temporal differences in the
362 succession rate can be explained by the spatial selection of the most favourable
363 locations for secondary succession, which can only be modelled if transition
364 probabilities are considered a continuous spatial variable.

365 The combination of Markov chains and multivariate analysis incorporating spatial
366 variables related with dispersal abilities has proved to be very useful in matching
367 observed spatial succession patterns (Augustin et al., 2001). Here, we show the utility of
368 this methodology in predicting successional processes in environments highly
369 dependent on abiotic constraints.

370 In our case study, both the transition matrices and the logistic models showed
371 evidences of non-stationarity. We interpreted the non-stationarity of transition matrices

372 as emerging from the process of vegetation succession in a heterogeneous landscape, in
373 which transition probabilities differ largely from one location to another. The shortage
374 of high favourable locations as the revegetation process advances in time is sufficient to
375 explain the decay in the succession rate observed in the sequence of aerial photos.
376 Accordingly, the results of our simple stochastic dynamic model based on spatially
377 distributed transition probabilities showed a good agreement with the field observations,
378 both in predicting the spatial distribution of secondary forest fifty years after
379 abandonment and the timing of the process for the whole study area.

380 Nevertheless, we encountered a methodological problem in order to validate the
381 results of the model, pixel-based, with the polygon maps drawn from the aerial
382 photographs, which could affect negatively the success rate. Moreover, the model would
383 be improved by adding neighbour information (Hersperger, 2006; Turner, 1987), seed
384 dispersal patterns and distance from seed sources (Prevosto et al., 2003), but a fully
385 pixel-based data would be required.

386 Previous models of *P. sylvestris* forest development did not take into account
387 environmental constraints (Prevosto et al., 2003), and thus they were not applicable to a
388 highly heterogeneous area such as the Pyrenees, where abiotic factors play a major role
389 on determining vegetation dynamics at landscape scale (del Barrio et al., 1997). For
390 heterogeneous areas our approach could be more useful. However, our proposed
391 approach should include explanatory variables related to human activities (i.e. grazing
392 and forest management) when landscapes with evidences of human use are taken into
393 consideration.

394 Furthermore, the relative importance of abiotic constraints can not be directly
395 extrapolated to other areas, as far as it is particular for the landscape analysed and the
396 plant species involved. In our study area elevation and potential solar radiation

397 determined the faster installation of *Pinus sylvestris* after land abandonment. Elevation
398 determines a climatic gradient in mountains (Donnegan and Rebertus, 1999), which
399 reproduces from bottom to top the changes in mean temperature observed from south to
400 north. Since the Pyrenees are located in the southernmost part of the geographical range
401 of *P. sylvestris*, high temperatures and water scarcity in summer are the limiting factors
402 for this species (Castro et al., 2004). Dispersal and establishment determine largely
403 survival of *P. sylvestris* (Castro et al., 2004; Prevosto et al., 2003). As seedling
404 germination take part in spring, high solar radiation reduces water availability and
405 decrease seedling survival during summer in Mediterranean mountains. Low summer
406 temperatures, large water retention and less solar radiation favour the establishment of
407 *P. sylvestris*, and thus increase secondary succession rate (Castro et al., 2004). Water
408 availability and high temperatures are decisive in the distribution of a large amount of
409 trees at the boundary between the summer drought Mediterranean zone and the cooler
410 and moister mountain and northern areas (Pigott and Pigott, 1993).

411 Accumulation of water and nutrients due to the topography played a secondary
412 role on determining succession rate, although in other mountain areas it has been found
413 to be a major factor determining succession (Donnegan and Rebertus, 1999). It can be
414 argued that in the southern limit of the geographic range of *P. sylvestris* high summer
415 temperature and insolation play a major role and outweigh other factors, which in more
416 temperate conditions would determine the succession rate. Also, it is likely that the
417 broad scale used in this study affected negatively the importance of these factors.

418 Where conditions are favourable to *P. sylvestris*, it tends to originate nearly
419 monospecific forest. The rapid growth rate of the pine impedes *Quercus faginea* to
420 colonize more mesic areas. It is expected that in locations where successional rates are
421 slower the establishment of *Q. faginea* would be allowed (Gracia et al., 2002).

422 Nevertheless, further study is needed to confirm this issue.

423 **Conclusions**

424 We propose a method to model the rate of secondary succession after farmland
425 abandonment based on Markov chains and incorporating the effect of abiotic factors
426 through multivariate analysis. This method was able to predict both the spatial and
427 temporal patterns of secondary succession in our study area. For secondary forest of *P.*
428 *sylvestris* in the Pyrenees, the most important factor determining rate of succession was
429 the gradient of temperature with elevation and potential solar radiation. Water and
430 nutrient availability due to local topographical conditions played a secondary role. The
431 results of this research can be useful for forest managers and environmental planners, in
432 order to decide the best practices after land abandonment. The application of this
433 methodology is suitable anywhere where there are evidences suggesting strong abiotic
434 constraints to secondary succession, such as mountain areas. In human-managed
435 landscapes, the inclusion of human use as explanatory variables (i.e grazing or forest
436 management) could improve predictive power of the model.

437 **Acknowledgements**

438 This study has been supported by the research projects PIRIHEROS - REN2003-
439 08678/HID, CANOA - CGL2004-04919-C02-01, REN2002-04668 and CGL2005-
440 01625/BOS, funded by CICYT (Spanish Ministry of Science and Technology), and by
441 RESEL (Spanish Ministry of Environment). Personal support for Y. P. was provided by
442 Government of Aragón and CSIC and personal support for S. B. was provided by the
443 Spanish Government Secretary for Education and Universities and the European Social
444 Fund.

445 **References**

446 Acevedo, M.F., Urban, D.L. , Ablan, M., 1995. Transition and gap models of
447 forest dynamics. *Ecol. Appl.* 5, 1040-1055.

448 Anderson, T.W. , Goodman, L.A., 1957. Statistical-inference about Markov-
449 chains. *Annals of Mathematical Statistics* 28, 89-110.

450 Aragón, R. , Morales, J.M., 2003. Species composition and invasion in NW
451 Argentinian secondary forest: effects of land use history, environment and landscape. *J.*
452 *Veg. Sci.* 14, 195-204.

453 Arroyo, J. , Marañón, T., 1990. Community Ecology and Distributional Spectra
454 of Mediterranean Shrublands and Heathlands in Southern Spain. *J. Biogeogr.* 17, 163-
455 176.

456 Augustin, N.H., Cummins, R.P. , French, D.D., 2001. Exploring spatial
457 vegetation dynamics using logistic regression and a multinomial logit model. *J. Appl.*
458 *Ecol.* 38, 991-1006.

459 Balzter, H., 2000. Markov chain models for vegetation dynamics. *Ecol. Model.*
460 126, 139-154.

461 Barry, R.G., 1922. *Mountain weather and climate*, 2nd ed. Meuthe, London.

462 Beguería, S., 2006a. Changes in land cover and shallow landslide activity: A
463 case study in the Spanish Pyrenees. *Geomorphology* 74, 196-206.

464 Beguería, S., 2006b. Validation and evaluation of predictive models in hazard
465 assessment and risk management. *Nat. Hazards* 37, 315-329.

466 Beguería, S., López-Moreno, J.I., Lorente, A., Seeger, M. , Garcia-Ruiz, J.M.,
467 2003. Assessing the effect of climate oscillations and land-use changes on streamflow in
468 the Central Spanish Pyrenees. *Ambio* 32, 283-286.

469 Benabdellah, B., Albrecht, K.F., Pomaz, V.D.L., Denisenko, E.A. , Logofet,

470 D.O., 2003. Markov chain models for forest successions in the Erzgebirge, Germany.
471 Ecol. Model. 159, 145-160.

472 Beven, K.J. , Kirkby, M.J., 1979. A physically based, variable contributing area
473 model of basin hydrology. Hydrolog. Sci. Bull. 24, 43-69.

474 Callaway, R.M. , Davis, F.W., 1993. Vegetation Dynamics, Fire, and the
475 Physical-Environment in Coastal Central California. Ecology 74, 1567-1578.

476 Carmel, Y. , Kadmon, R., 1999. Effects of grazing and topography on long-term
477 vegetation changes in a Mediterranean ecosystem in Israel. Plant Ecol. 145, 243-254.

478 Castro, J., Zamora, R., Hodar, J.A. , Gomez, J.M., 2004. Seedling establishment
479 of a boreal tree species (*Pinus sylvestris*) at its southernmost distribution limit:
480 consequences of being in a marginal Mediterranean habitat. J. Ecol. 92, 266-277.

481 Caswell, H., 2001. Matrix population models; construction, analysis and
482 interpretation, Sinauer Associates, Sunderland.

483 Childress, W.M., Crisafulli, C.M. , Rykiel, E.J., 1998. Comparison of
484 Markovian matrix models of a primary successional plant community. Ecol. Model.
485 107, 93-102.

486 del Barrio, G., Alvera, B., Puigdefabregas, J. , Diez, C., 1997. Response of high
487 mountain landscape to topographic variables: Central Pyrenees. Landscape Ecol. 12, 95-
488 115.

489 Donnegan, J.A. , Rebertus, A.J., 1999. Rates and mechanisms of subalpine forest
490 succession along an environmental gradient. Ecology 80, 1370-1384.

491 Fernandez, J.B.G., Mora, M.R.G. , Novo, F.G., 2004. Vegetation dynamics of
492 Mediterranean shrublands in former cultural landscape at Grazalema Mountains, South
493 Spain. Plant Ecol. 172, 83-94.

494 Fielding, A.H. , Bell, J.F., 1997. A review of methods for the assessment of

495 prediction errors in conservation presence/absence models. *Environ. Conserv.* 24, 38-
496 49.

497 Florinsky, I.V., Eilers, R.G., Manning, G.R. , Fuller, L.G., 2002. Prediction of
498 soil properties by Digital Terrain Modelling. *Environ. Modell. Softw.* 17, 295-311.

499 García-Ruiz, J.M., Lasanta, T., Ruiz-Flaño, P., Ortigosa, L., White, S.,
500 Gonzalez, C. , Marti, C., 1996. Land-use changes and sustainable development in
501 mountain areas: A case study in the Spanish Pyrenees. *Landscape Ecol.* 11, 267-277.

502 Gómez-Plaza, A., Martínez-Mena, J., Albadalejo, J. , Castillo, V.M., 2001.
503 Factors regularing spatial distribution of soil water content in small semiarid
504 catchments. *J. Hydrol.* 253, 211-226.

505 Gracia, M., Retana, J. , Roig, P., 2002. Mid-term successional patterns after fire
506 of mixed pine-oak forests in NE Spain. *Acta Oecol.* 23, 405-411.

507 Gullison, J.J. , Bourque, C.P.A., 2001. Spatial prediction of tree and shrub
508 succession in a small watershed in northern Cape Breton Island, Nova Scotia, Canada.
509 *Ecol. Model.* 137, 181-199.

510 Hair, J.F.J., Anderson, R.E., Tatham, R.L. , Black, W.C., 1998. Multivariate data
511 analysis with readings, Prentice Hall, New Jersey.

512 Hersperger, A.M., 2006. Spatial adjacencies and interactions: Neighborhood
513 mosaics for landscape ecological planning. *Landscape Urban Plann.* 77, 227-239.

514 Hill, M.F., Witman, J.D. , Caswell, H., 2002. Spatio-temporal variation in
515 Markov chain models of subtidal community succession. *Ecol. Lett.* 5, 665-675.

516 Ibarra, P. , De la Riva, J., 1996. Dinámica de la cubierta del suelo como
517 resultado de la despoblación y de la intervención del estado: el valle de la Garcipollera
518 (Huesca), in: J.L. Acín , V. Pinilla (Eds.), *Pueblos abandonados ¿un mundo perdido?*
519 *Rolde de Estudios Aragoneses, Zaragoza*, pp. 55-78.

520 Jongman, R.H.G., 2002. Homogenisation and fragmentation of the European
521 landscape: ecological consequences and solutions. *Landscape Urban Plann.* 58, 211-
522 221.

523 Lasanta, T., Gonzalez-Hidalgo, J.C., Vicente-Serrano, S.M. , Sferi, E., 2006.
524 Using landscape ecology to evaluate an alternative management scenario in abandoned
525 Mediterranean mountain areas. *Landscape Urban Plann.* 78, 101-114.

526 Lasanta, T., Vicente-Serrano, S.M. , Cuadrat, J.M., 2005. Mountain
527 Mediterranean landscape evolution caused by the abandonment of traditional primary
528 activities: a study of the Spanish Central Pyrenees. *Applied Geography* 25, 47-65.

529 Manly, B.F.J., 1997. Randomization, bootstrap and Monte Carlo methodology in
530 Biology, Chapman & Hall/CRC, London.

531 Montserrat, P., 1966. Vegetación de la cuenca del Ebro. *Publicaciones del*
532 *Centro pirenaico de Biología experimental* 1, 1-22.

533 Mueller-Dombois, D., 2000. Rain forest establishment and succession in the
534 Hawaiian Islands. *Landscape Urban Plann.* 51, 147-157.

535 Myster, R.W. , Pickett, S.T.A., 1994. A Comparison of Rate of Succession over
536 18 Yr in 10 Contrasting Old Fields. *Ecology* 75, 387-392.

537 Pan, D.Y., Domon, G., de Blois, S. , Bouchard, A., 1999. Temporal (1958-1993)
538 and spatial patterns of land use changes in Haut-Saint-Laurent (Quebec, Canada) and
539 their relation to landscape physical attributes. *Landscape Ecol.* 14, 35-52.

540 Pigott, C.D. , Pigott, S., 1993. Water as determinant of the distribution of trees at
541 the boundary of the Mediterranean zone. *J. Ecol.* 81, 557-566.

542 Poyatos, R., Latron, J. , Llorens, P., 2003. Land use and land cover change after
543 agricultural abandonment - The case of a Mediterranean Mountain Area (Catalan Pre-
544 Pyrenees). *Mt. Res. Dev.* 23, 362-368.

545 Prach, K., 1993. On the rate of succession. *Oikos* 66, 343-346.

546 Prevosto, B., Hill, D.R.C. , Coquillard, P., 2003. Individual-based modelling of
547 *Pinus sylvestris* invasion after grazing abandonment in the French Massif Central. *Plant*
548 *Ecol.* 168, 121-137.

549 Pueyo, Y. , Alados, C.L., in press. Effects of fragmentation, abiotic factors and
550 land use on vegetation recovery in a semi-arid Mediterranean area. *Basic Appl. Ecol.*
551 doi:10.1016/j.baae.2006.03.009.

552 Riebsame, W.E., Meyer, W.B. , Turner, B.L., 1994. Modelling land use and
553 cover as part of global environmental change. *Climatic Change* 28, 1-10.

554 Rocchini, D., Perry, G.L.W., Salerno, M., Maccherini, S. , Chiarucci, A., 2006.
555 Landscape change and the dynamics of open formations in a natural reserve. *Landscape*
556 *Urban Plann.* 77, 167-177.

557 Romero-Calcerrada, R. , Perry, G.L.W., 2004. The role of land abandonment in
558 landscape dynamics in the SPA 'Encinares del rio Alberche y Cofio, Central Spain,
559 1984-1999. *Landscape Urban Plann.* 66, 217-232.

560 Shugart, H.H. , Hett, J.M., 1973. Succession - Similarities of Species Turnover
561 Rates. *Science* 180, 1379-1381.

562 Sickel, H., Ihse, M., Norderhaug, A. , Sickel, M.A.K., 2004. How to monitor
563 semi-natural key habitats in relation to grazing preferences of cattle in mountain
564 summer farming areas - An aerial photo and GPS method study. *Landscape Urban*
565 *Plann.* 67, 67-77.

566 Swets, J.A., 1988. Measuring the accuracy of diagnostic systems. *Science* 240,
567 1285-1293.

568 Turner, M.G., 1987. Spatial simulation of landscape changes in Georgia: a
569 comparison of 3 transition models. *Landscape Ecol.* 1, 29-36.

570 Usher, M.B., 1979. Markovian approaches to ecological succession. *J. Anim.*
571 *Ecol.* 48, 413-426.

572 Usher, M.B., 1981. Modelling ecological succession, with particular reference to
573 Markovian models. *Vegetatio* 46, 11-18.

574 Vicente-Serrano, S.M., Lasanta, T. , Romo, A., 2004. Analysis of spatial and
575 temporal evolution of vegetation cover in the spanish central pyrenees: Role of human
576 management. *Environ. Manage.* 34, 802-818.

577 Villalba, R., Veblen, T. , Ogden, J., 1994. Climatic influences on the growth of
578 subalpine trees in the Colorado Front Range. *Ecology* 75, 1450-1462.

579 Yemshanov, D. , Perera, A.H., 2002. A spatially explicit stochastic model to
580 simulate boreal forest cover transitions: general structure and properties. *Ecol. Model.*
581 150, 189-209.

582

583

584

585

586

586 Table 1. Transition matrices for natural secondary succession on abandoned farmland
587 between around 1950 and 1957 (a), 1957 and 1977 (b), 1977 and 2002 (c).

588

a	Shrubland	Forest
Abandoned fields	0.90	0.10
b	Shrubland	Forest
Abandoned fields	0.55	0.45
Shrubland	0.73	0.27
c	Shrubland	Forest
Shrubland	0.85	0.15

589

589 Table 2. Logistic models specifications: *a*, transition from abandoned fields to forest
 590 1977; *b*, transition from shrublands 1957 to forest 1977; *c*, transition from shrublands
 591 1977 to forest 2002.

592

a	Variable	B	se	Wald	sign.
	Intercept	-1.007	0.164	37.5	<0.001
	elevation	5.136	0.114	2039.8	<0.001
	slope gradient	1.767	0.261	46.0	<0.001
	topographic index	0.134	0.012	127.6	<0.001
	potential radiation	-0.604	0.013	2157.3	<0.001
b	Parameter	B	se	Wald	sign.
	Intercept	9.711	0.232	1757.0	<0.001
	slope gradient	-7.036	0.361	380.7	<0.001
	topographic index	0.050	0.014	12.4	<0.001
	potential radiation	-0.870	0.017	2473.1	<0.001
c	Parameter	B	se	Wald	sign.
	Intercept	7.539	0.255	871.6	<0.001
	slope gradient	-6.328	0.385	270.3	<0.001
	topographic index	-0.123	0.018	48.7	<0.001
	potential radiation	-0.622	0.019	1101.7	<0.001

593 se: standard error

594

595

595 **Figure captions**

596

597 Figure 1. Location of the study area and relief. Contour interval is 100 m. The area
598 under study (abandoned farmland that undergone natural succession) is shown in grey.

599 Figure 2. Land cover maps from 1950 (*a*, inferred from 1957 photo and Ibarra & de la
600 Riva (1996), 1957 (*b*), 1977 (*c*) and 2002 (*d*). Legend: 1, mature forest; 2, arable lands;
601 3, shrubland; 4, secondary forest; 5, reforestation; 6, other.

602 Figure 3. Transitions tree. In black, the transitions considered in the model.

603 Figure 4. Forest transition probability maps. *a*, transition from abandoned fields to
604 forest (1977); *b*, transition from shrubs (1957) to forest (1977); *c*, transition from shrubs
605 (1977) to forest (2002).

606 Figure 5. Expected transition time (years to forest state).

607 Figure 6. Secondary succession on abandoned fields, land cover in 2002: *a*, observed; *b*,
608 simulated, Markov - logistic model; *c*, simulated, standard Markov chain model.
609 Legend: 1, secondary forest; 2, shrubland.

610 Figure 7. Average transition probabilities for the standard Markov model (plain line)
611 and the Markov-logistic simulation (dots). Dashed line: adjusted power curve ($y =$
612 $5.22 \cdot 10^{40} x^{-12.32}$).

613 Figure 8. Rate of forest recovery, percentage of the abandoned surface. Big squares,
614 observed; small squares, standard Markov model; dots, Markov-logistic simulation;
615 dashed line, adjusted logarithmic curve ($y = -0,67 + 0,29 \ln(x-1938,7) \forall x-x_0 > 0$).

616

617 Table 1. Transition matrices for natural secondary succession on abandoned farmland

618

between 1950 and 1957 (a), 1957 and 1977 (b), 1977 and 2002 (c).

619

a	Shrublands	Forest
Abandoned croplands	0.91	0.09

b	Shrublands	Forest
Abandoned croplands	0.35	0.65
Shrublands	0.73	0.27
Forest	0	1

c	Shrublands	Forest
Shrublands	0.85	0.15
Forest	0	1

620

621

621 Table 2. Logistic models specifications. *a*, transition from abandoned fields to forest
 622 1977; *b*, transition from shrublands 1957 to forest 1977; *c*, transition from shrublands
 623 1977 to forest 2002.

624

a	Parameter	B	se	Wald	sign.
	Intercept	-1.007	0.164	37.5	<0.001
	elevation	5.136	0.114	2039.8	<0.001
	slope gradient	1.767	0.261	46.0	<0.001
	topographic				
	index	0.134	0.012	127.6	<0.001
	potential				
	radiation	-0.604	0.013	2157.3	<0.001
b	Parameter	B	se	Wald	sign.
	Intercept	9.711	0.232	1757.0	<0.001
	slope gradient	-7.036	0.361	380.7	<0.001
	topographic				
	index	0.050	0.014	12.4	<0.001
	potential				
	radiation	-0.870	0.017	2473.1	<0.001
c	Parameter	B	se	Wald	sign.
	Intercept	7.539	0.255	871.6	<0.001
	slope gradient	-6.328	0.385	270.3	<0.001
	topographic				
	index	-0.123	0.018	48.7	<0.001
	potential	-0.622	0.019	1101.7	<0.001

radiation

625

se: standard error

626

627

627 **Figure captions**

628

629 Figure 1. Location of the study area and relief. Contour interval is 100 m. The area
630 under study (abandoned farmland that undergone natural succession) is shown in grey.

631 Figure 2. Land cover maps from 1950 (*a*, inferred from 1957 photo and Ibarra & de la
632 Riva (1996), 1957 (*b*), 1977 (*c*) and 2002 (*d*). Legend: 1, mature forest; 2, arable lands;
633 3, shrubland; 4, secondary forest; 5, reforestation; 6, other.

634 Figure 3. Transitions tree. In black, the transitions considered in the model.

635 Figure 4. Forest transition probability maps. *a*, transition from abandoned fields to
636 forest (1977); *b*, transition from shrubs (1957) to forest (1977); *c*, transition from shrubs
637 (1977) to forest (2002).

638 Figure 5. Expected transition time (years to forest state).

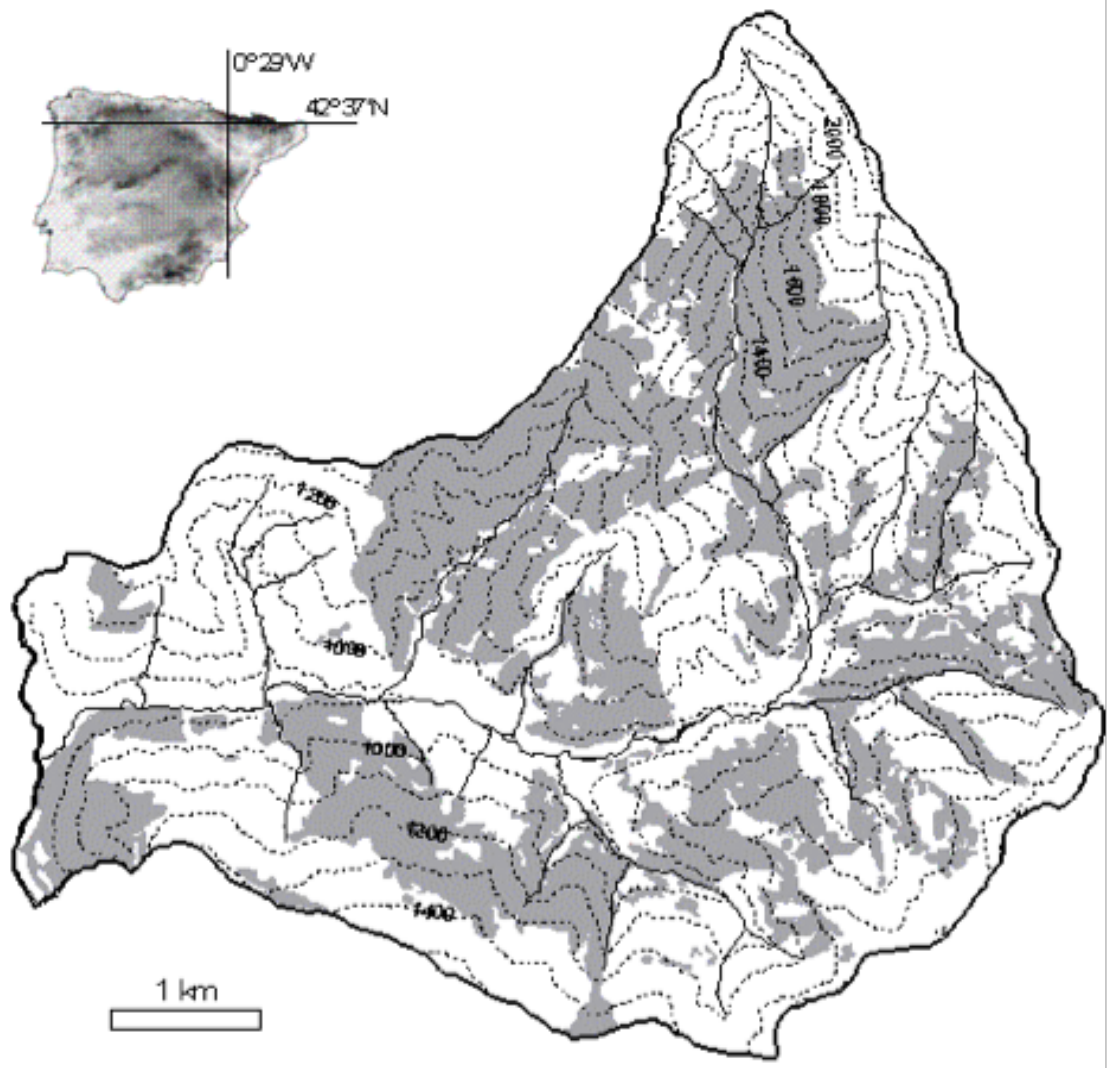
639 Figure 6. Secondary succession on abandoned fields, land cover in 2002: *a*, observed; *b*,
640 simulated, Markov - logistic model; *c*, simulated, standard Markov chain model.

641 Legend: 1, secondary forest; 2, shrubland.

642 Figure 7. Average transition probabilities for the standard Markov model (plain line)
643 and the Markov-logistic simulation (dots). Dashed line: adjusted power curve ($y =$
644 $5.22 \cdot 10^{40} x^{-12.32}$).

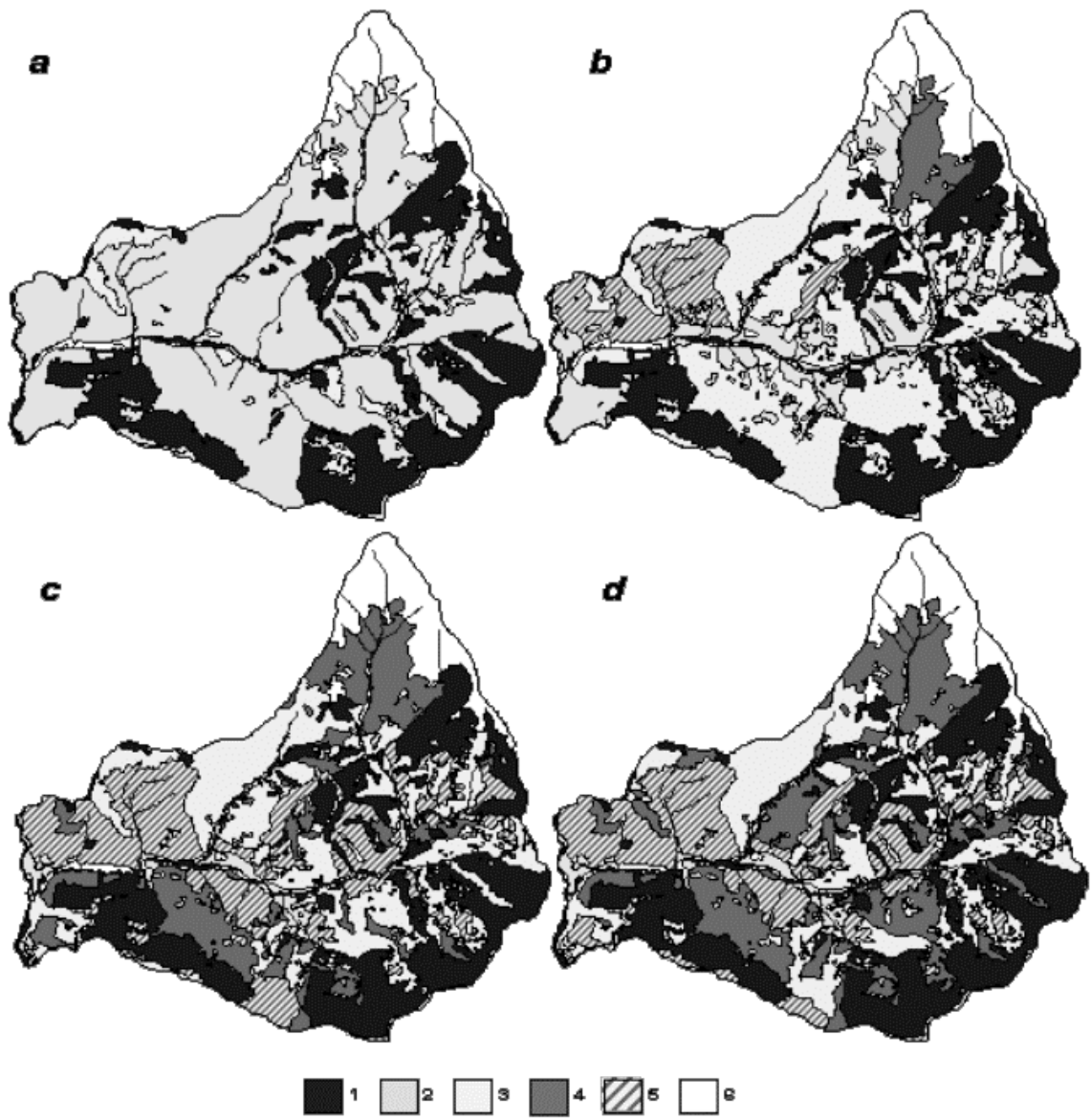
645 Figure 8. Rate of forest recovery, percentage of the abandoned surface. Big squares,
646 observed; small squares, standard Markov model; dots, Markov-logistic simulation;
647 dashed line, adjusted logarithmic curve ($y = -0,67 + 0,29 \ln(x-1938,7) \forall x-x_0 > 0$).

648



649
650
651
652
653
654
655
656
657

Fig. 1



658

659

660

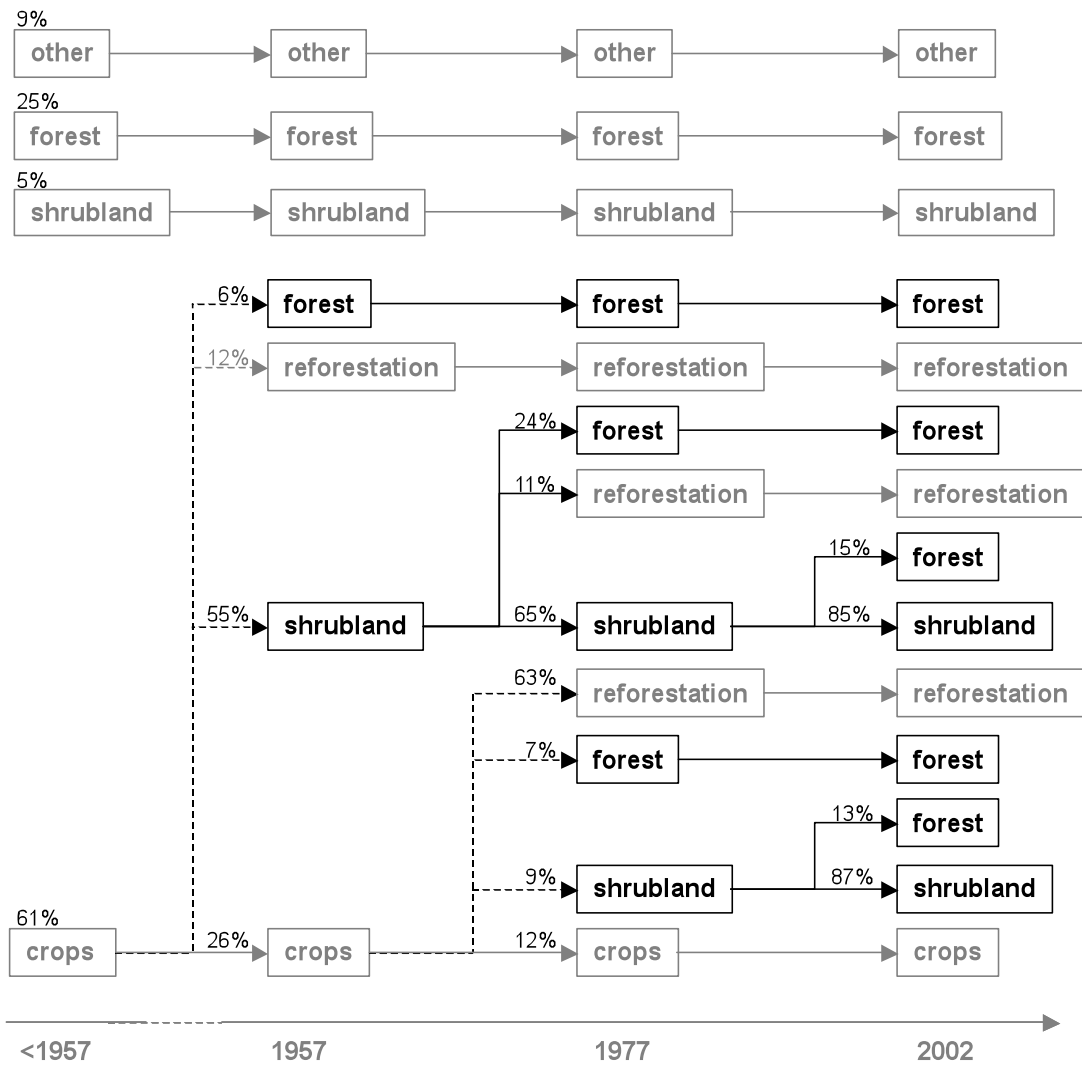
661

662

663

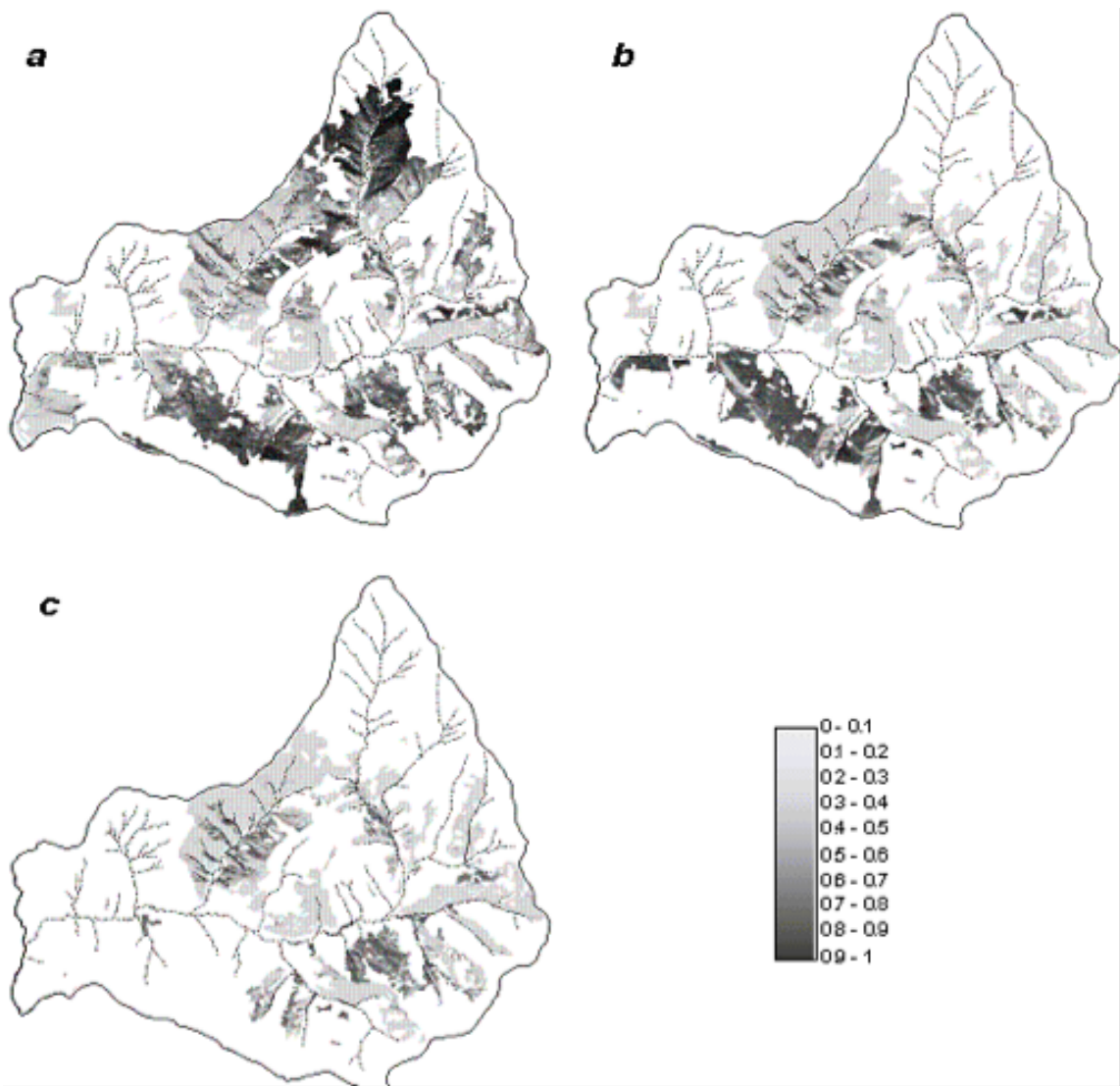
664

Fig. 2



664
 665
 666
 667
 668
 669
 670
 671
 672
 673
 674
 675

Fig. 3



676

677

678

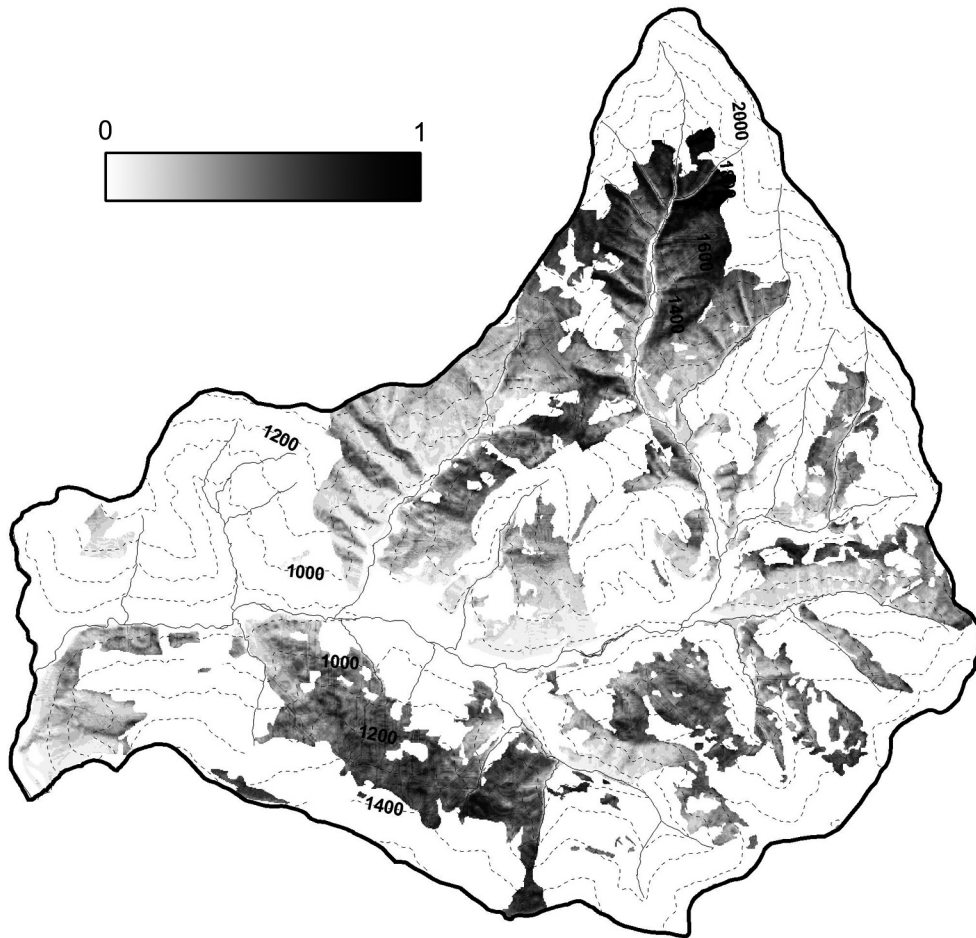
679

680

681

682

Fig. 4



682
683
684
685
686
687
688
689
690
691
692
693
694
695
696
697

Fig. 5

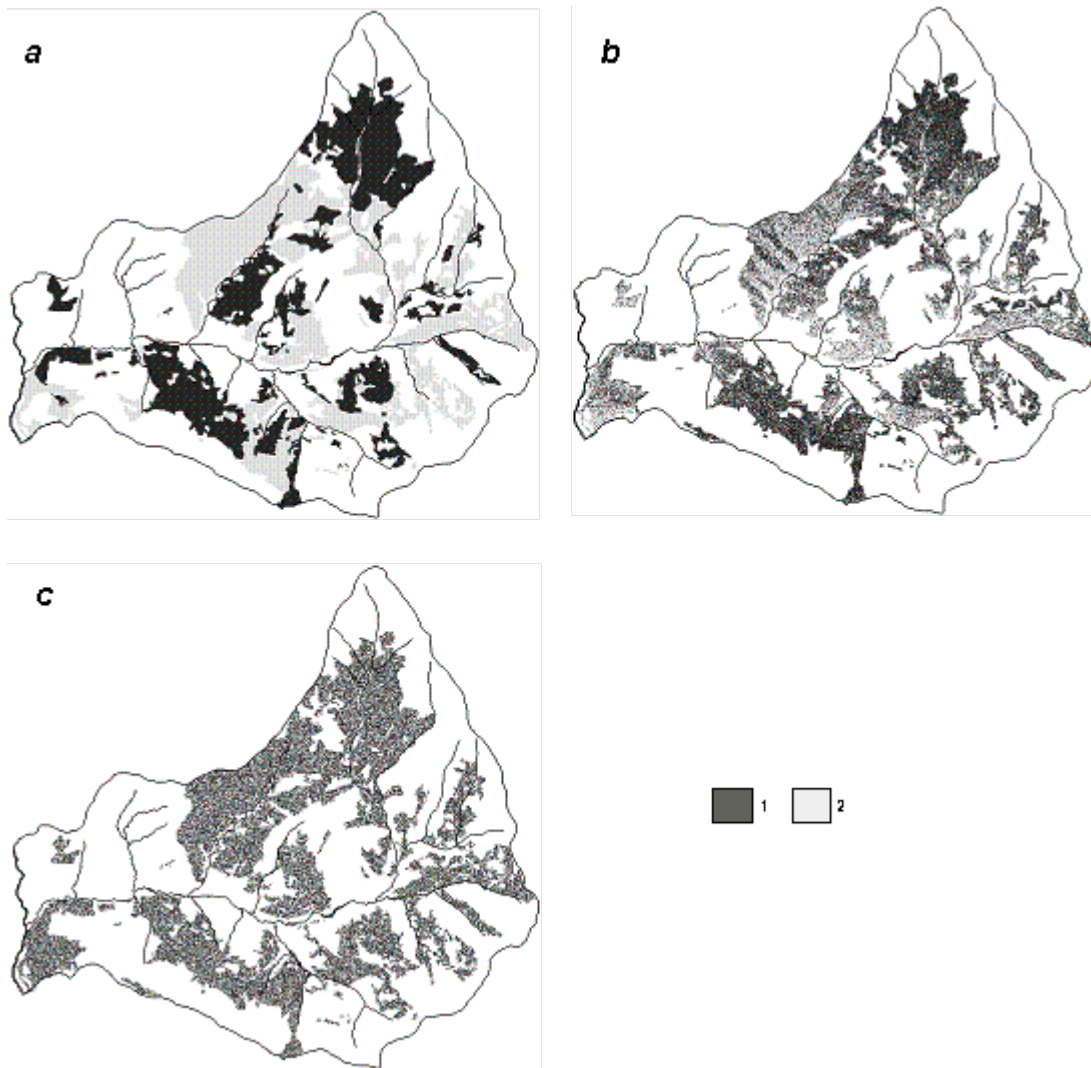
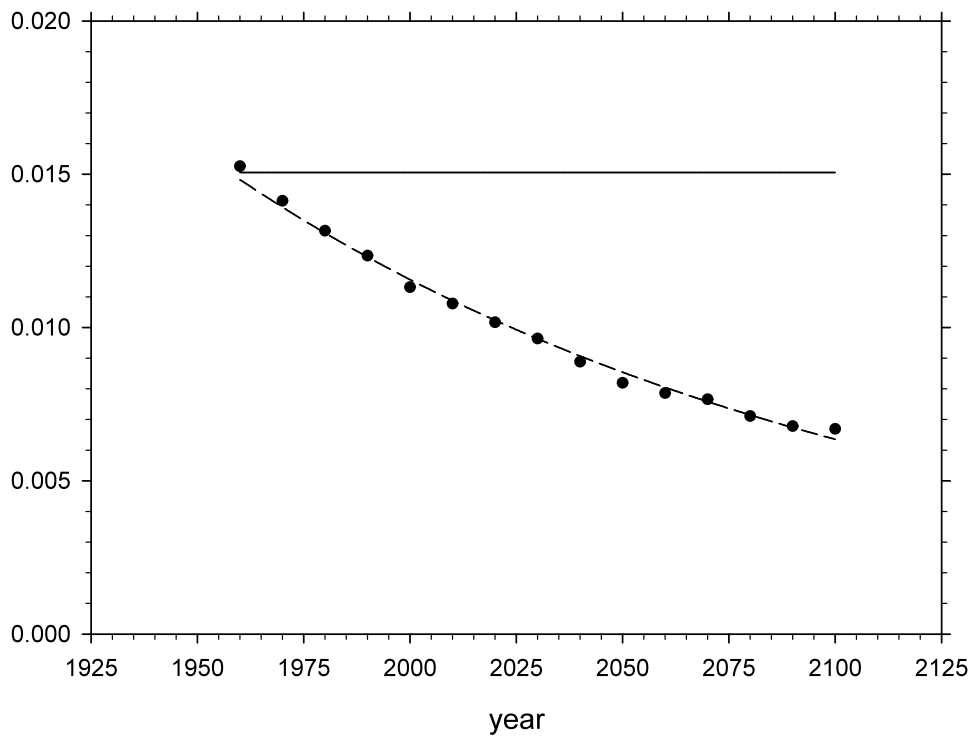
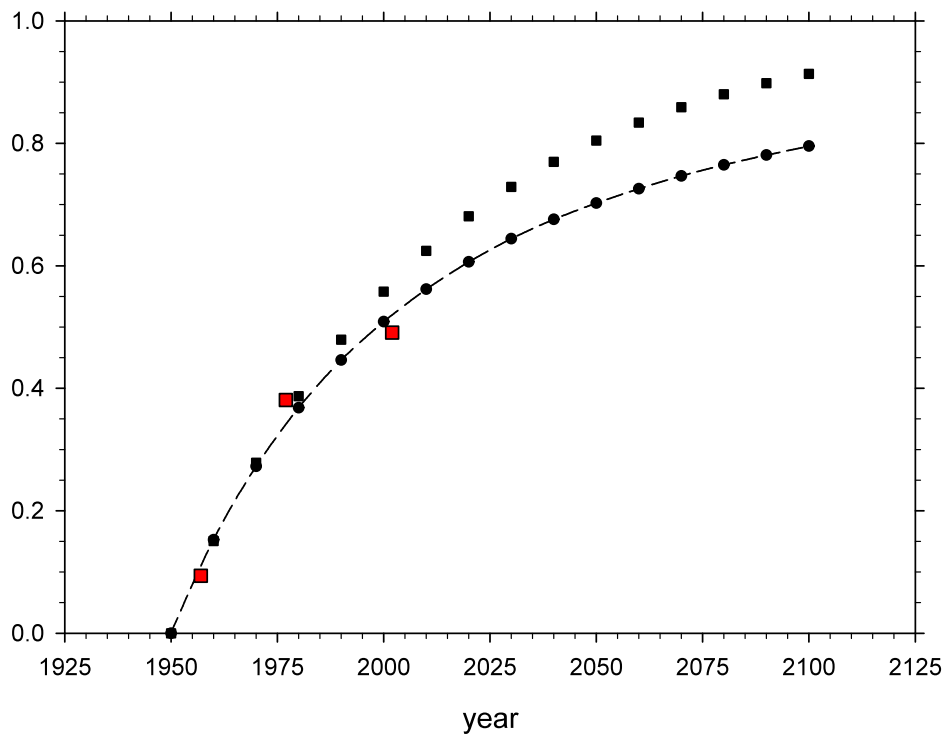


Fig. 6



706
707
708
709
710
711
712
713
714
715
716
717
718

Fig. 7



718
719
720
721
722
723
724
725
726
727
728
729
730
731
732
733

Fig. 8